LABOR MARKET SEGREGATION
AND THE WAGE DIFFERENTIAL
BETWEEN RESIDENT AND MIGRANT WORKERS IN CHINA

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by
LU Ruosi

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ABSTRACT

Labor Market Segregation
and the Wage Differential
between Resident and Migrant Workers in China

by

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Master of Philosophy

This thesis looks at the effect of industrial and occupational segregation on the wage differential between resident and migrant workers in China. It extends the work of Meng and Zhang (2001) by considering the possible employment segregation of resident and migrant workers by both industry and occupation. I contend that industry segregation is at least as important as occupational segregation for Chinese migrant workers, as most migrant workers in China have come from the countryside to fuel the booming labor-intensive manufacturing and construction industries in the cites. Due to the *hukou* policy (a household registration system) in China, migrant workers normally face more constraints in searching for jobs in other sectors. My empirical study confirms that the proportion of the resident-migrant worker wage differential that is explained by industrial segregation is much larger than that explained by occupational segregation. Taking both industrial and occupational segregation into account explains the substantial wage differential between resident and migrant workers, which indicates the influence of industrial and occupational barriers on the wage differential in China.

Keywords: Industry, occupation, segregation, wage differential, migrant workers.

DECLARATION

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original work based primarily on my own research, and I warrant that all citations of previous research, published or unpublished, have been duly acknowledged.

(LU Ruosi)
August 26, 2008

CERTIFICATE OF APPROVAL OF THESIS

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It has been a year since the first version of my thesis was done in last May. There is not much improvement in it, and this pity cannot be removed in the left few days.

I have to admit that I always have innumerable pities like this in my past life. The reason is the same: I only want to start working when everything has been prepared well, and I am weak in controlling my work progress and daily life.

However, life in Lingnan is the best one I have ever had in universities. Here I become increasingly conscious of my bad work habit or personality, and my misunderstanding of real freedom, which is my aim, though hard to attain. Another point is that I began to realize my dream of living as a scholar in these two years, though I ever asked myself thousands of times whether I am suitable to do such a hard but interesting job. I come to look at doing research as a life-long job, instead of some finish-after-examination missions. I am learning how to put all my best into studying once I begin the work. The progress is slow. However, in this semester my CV is no longer filled up with blank like before. Besides, I enjoy spending every day peacefully in the University's quiet library: reading, thinking, writing, and dreaming. In this small but pretty campus, I even learned how to swim, a dream from my childhood.

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Chapter 1. Introduction

After 30 years of economic reform, China has been transformed from a predominantly agricultural economy into an industrial powerhouse. Its urban population has increased from about 12% of the total population in the late 1970s to 40% in 2006 (China Statistical Year Book), a result not only of the rapid rate of urbanization but also of a dramatic increase in the rural to urban migration rate. It is now estimated that there are approximately 0.18 billion rural migrant workers working in the cities who account for more than 50% of the labor force in China's industrial sector[1].

Despite such a fast rate of industrialization and urbanization, income inequality in China as measured both in terms of coastal versus inland and urban versus rural workers has been widening since the mid-1980s. According to the estimation of Lin, Wang, and Zhao (2004), the coast-inland income ratio rose from 1.31 in 1985 to 1.65 in 2000, and the urban-rural income ratio rose from 1.82 in 1985 to 2.42 in 2000. Such a rise in inequality may appear at odds with conventional economic theory, which predicts factor price equalization accompanied by the movement of labor from the countryside to the city or from agricultural activities to industrial activities. As has been repeatedly shown by previous researchers in this area, an important factor that contributes to this anomaly is the government's special control on internal migration through the household registration system, or *hukou* system in China (For example, Yang 1999, Whalley and Zhang 2004, Lu and Chen 2006). In brief, China's

[1] See the reports by Xinhua News Agency on January 18 and February 24, 2006 (www.xinhuanet.com). According to Cai (2007), kinds of information also shows there are about 0.103 or 0.118 billion rural migrants in 2004. According to the National Bureau of Statistic (2008), at the end of 2006, rural migrants are about 0.132 billion. And Ministry of Labour and Social Security reports they may reach 0.12 billion (Laodong He Shehui Baozhang Bu Diaoyanzu 2006).

household registration system specifies that individuals must register with the local authority at their place of birth, and only registered local people are entitled to the various welfare programs provided by the local government, which include housing, education, health care, unemployment benefits, and income support. Various unemployment reduction policies are also targeted at local residents only. This system greatly disadvantages migrant workers, and helps to create a two-tier labor market in the cities. For example, according to recent surveys (see footnote 1 for the source), rural migrant workers are highly concentrated in low-end, labor-intensive jobs. The survey in 2007 by Ministry of Agriculture also shows manufacturing, construction and catering service industry contained 67% of all rural migrants (Ji 2007). *The Summary Report of Rural Migrant Workers in China* (Zhongguo Nongmingong Wenti Yanjiu Zong Baogao Qicao Zu 2006) suggests that in 2004 30.3% of rural migrants work in manufacture industry, and 22.9% of them in construction industry. The research team of Ministry of Labour and Social Security (Laodong he Shehui Baozhang Bu Diaoyanzu 2006) reports that the manufacture industry consists of 68% rural migrants and the number in the construction one is almost 80%. When it comes to the catering service, personal services and domestic work, and the dustman job, the number increases to above 90% (Nongye Bu Diaoyanzu 2006). These percentages contrast sharply to the average level all over the country in the way that from 1998 to 2006, the percentage of the employees in service sector is increasing faster than that in manufacturing one[2] (China Statistics Yearbook). Other surveys indicate that rural migrant workers seldom signed formal labor contracts with their employers, and their average wage is just more than half of resident urban workers'. Many migrant workers are not paid on time and have to

[2] In 1998, the percentage of employees in the manufacturing sector is 23.5% of the sum of employees in all sectors and that in the service sector is 26.7%. In 2006, the former is 25.2% while the latter increases to 32.2%.

work extremely long hours without overtime pay[3].

The status and treatment of these rural migrant workers is so alarming that it is now high on the policy agenda of the central government[4]. However, the issue of wage inequality between urban resident and rural migrant workers is complicated by the fact that the average educational level of rural migrant workers is also significantly lower than that of their urban counterparts. Any government policies that aim to reduce the wage inequality between these two groups must carefully distinguish the wage differential that is created by institutional or discriminative forces from that generated by normal market forces. Thus far, there have been only several empirical studies to estimate the exact impact of potential labor market segregation on wage inequality between urban and rural migrant workers.

The work of Meng and Zhang (2001) is pioneering in this respect. They utilize the data from two surveys conducted in 1999 for Shanghai and the methodology developed by Brown *et al.* (1980) to decompose wage differential into the productivity effect, occupational segregation effect, and wage discrimination effect. Their decomposition shows that occupational segregation only contributes roughly

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[3] For example, according the survey in Cai and Du (2007), during 2003 and 2005, the average wage of rural migrant workers increases from 781 Yuan to 953, while that for urban residents is from 1170 to 1534 Yuan (pp. 23-30). A piece of news in 2005 says that in the recent 12 years, rural migrants' wage only rise by 68 Yuan (Yangcheng Wanbao 2005). In the survey of Ministry of Agriculture (Nongye Bu Diaochazu 2006), the average wage of migrant workers is 60% of that for their resident counterpart, and in 2004 only 12.5% of migrants have labor contracts with their employers. Wage delay is still popular among migrant workers and average work time for them is 11 hours per day, and over 26 days per month. 76% of them never enjoyed overtime pay (Zhongguo Nongmingong Wenti Yanjiu Zong Baogao Qicao Zu, 2006). Only 47.78% of migrant workers got their wage on time (Zhu and Tao 2006).

[4] During the National People's Congress and meetings of the National Committee of the CPPCC in 2004, Premier Wen Jiabao pledged to tackle the thorny issue of defaulted construction costs and wage arrears for migrant workers in the construction sector in his government work report. On January 18, 2006, the central government announced No. 10 gazette in 2006 ("Zhonghua Renmin Gongheguo Guowuyuan Gongbao 2006 Nian Di 10 Hao") named "Guowuyuan Guanyu Jiejue Nongmingong Wenti de Ruogan Yijian (Government's suggestions about settling the problem of rural migrant workers)". The Vice-minister of Labor and Social Security also declared "we will exert our utmost to tackle the farm workers' wage arrears issue and provide them with the same social security protection as their urban peers."

4.85% of the total wage differential, whereas intra-occupational factors account for 82%. This rather surprising finding rejects the assumption that occupational segregation is an important factor leading to the wage gap. On the other hand, Wang (2005b) argues that the insignificant impact of labor market segregation on wage differentials in Meng and Zhang (2001) is caused by the improper segregation measure they adopt. Wang (2005b) suggests that, besides occupation, ownership of enterprises is also an important factor contributing to labor market segment of China since the state-owned enterprises are more likely to hire local residents. Following Meng and Zhang (2001), she uses a year 2002 dataset from five cities[5] and divides the sample into four types according to both occupation and ownership: people self-employed, people working in the state-owned enterprises, and blue- and white-collar workers in non-state-owned enterprises, respectively. She finds that 58.73% of the wage gap is due to the between-sector factors, in which 26.93% of the gap is caused by between-sector discrimination. On the other hand, 15.96% is by within-sector discrimination. This new classification improves the influence of labor market segregation dramatically, which is now a more important reason than wage discrimination to explain the wage gap.

Different from the above two studies, Sylvie *et al.* (2008) argue that migrants and residents have contrasted occupational distribution across different types of ownership of enterprises, which also have different wage-setting structures, thus they adopt only type of ownership of enterprises as the measure of labor market segregation. Their data are from twelve provinces[6] of China in 2002, covering the main economy areas. They employ the extended form of Brown *et al.* (1980)

[5] They are Shanghai, Wuhan, Fuzhou, Xi'an, and Shenyang.
[6] The twelve provinces are Anhui, Beijing, Chongqing, Gansu, Guangdong, Henan, Hubei, Jiangsu, Liaoning, Shanxi, Sichuan and Yunnan.

decomposition, adding a new item of hourly wage effect to account for the effect of working time. Their conclusion is that the main source of wage gap is the endowment difference between migrants and residents (explains 138% of the wage gap), that is to say, on-job discrimination, including both wage discrimination (46%) and labor market segregation (2%), may not be important at all. They also propose an explanation for the insignificant segregation effect in the former studies: it is because migrants and residents have different comparative advantage in private sector and public sector, respectively. The migrant population has higher return to their characteristics in the private sector than residents, thus increasing migrants' participation into the public sector does not necessarily improve their average earnings. (Sylvie *et al.* 2008)

My thesis will adopt traditional theoretical framework based on occupations and follow Meng and Zhang (2001)'s analysis. Careful investigation of the labor market segregation that rural migrant workers in China are faced would give rise to another perspective that industry segregation is an important factor that may lead to wage gap. Industry premium has been seen as one of the sources of wage differentials for a long time[7]. The best example is the education industry: the blue-collar workers in the education industry may have high wage, while workers in the same occupation of manufacturing industry may earn much less. Investigation shows in 2002, the highest average industrial wage is 19135 Yuan, being three times as much as the lowest one (6398 Yuan). In fact, the wage differentials leading by industrial segregation keep increasing in recent years, and become even more obvious than that leading by regional difference (Cai *et al.* 2006). Therefore the consideration of only

[7] Please refer to the literature review part in Krueger and Summers (1988).

occupational segregation will underestimate the influence of the segregation factor to the wage gap. Besides, since state-owned enterprises monopolize many high-earnings- and high-welfare-industries in service sector, such as banking and insurance, education and research institutions, media industry, and government or party agencies, adopting ownership as a measure of segregation can also be seen as introducing industry factor to some extent[8]. At last, China's *hukou* system offers a good institutional background for the study of industry-occupational segregation because persons who belong to the same race and nation are treated differently when looking for jobs just because they have different *hukou* locations following their parents.

It is by considering the industry factor that the current study makes its contribution. More specifically, I extend the Brown *et al.* (1980) approach by taking into account both the industry and occupational segregation effects. In so doing, I separate workers into four groups: blue-collar workers in the industrial sector, white-collar workers in the industrial sector, blue-collar workers in the service sector, and white-collar workers in the service sector. Furthermore, my study utilizes data from a 1998 survey conducted by the Fafo Institute for Applied International Studies in Oslo and the National Research Center for Science and Technology for Development (NRCSTD), which was the first integrated survey of resident and migrant workers covering several major Chinese cities. The survey also collected detailed information on the personal and job characteristics of the respondents, which enables me to better estimate the first-stage multinomial logit models of job attainment. My results show that 47% of the wage differential is attributable to between-group effects, and 20% is

[8] Though Sylvie *et al*. (2008) adopt extension of Brown *et al.* (1980), their approach is much different from others and mine. Thus I will not consider their results here.

associated with industry and occupational segregation (unexplained between-group effects). This finding confirms that labor market segregation is indeed an important factor that contributes to the wage inequality between urban resident and rural migrant workers.

The remainder of the thesis is as follows. I outline my empirical methodology in Chapter 2. Chapter 3 tells the story of industrial segregation in China. Chapter 4 describes the data and sample characteristics. I present and discuss my empirical findings in Chapter 5, 6, and 7. Chapter 8 concludes the thesis.

Chapter 2. Methodology

The Blinder-Oaxaca (1973) decomposition approach is the most popular method for analyzing the wage differential. The implementation of this approach requires the estimation of a wage determination equation, and the specification of the wage equation is mainly based on the human capital theory. The rationale of this approach is that a wage differential can be decomposed into two parts: one that can be explained by human capital factors and the other that cannot be explained by observed individual productivity characteristics and is hence ascribed to labor market discrimination. However, as Oaxaca and Neuman (1998) point out, there exist two obvious deficiencies in Blinder-Oaxaca (1973) approach: one is that as discrimination can take the form of both unequal access to jobs and unequal treatment in the same job, this method is unable to distinguish which form contributes more to the observed wage differential. The other is that though job status will influence the wage level, the latter may also contribute to access to different jobs, and lead to the endogeneity problem. To settle the first problem, Brown *et al.* (1980) decomposition may work, while to the second one, Inverse Mill's Ratio (IMR) in Heckman (1976 and 1979)' and Lee (1983)'s selectivity correction method will help.

Brown *et al.* (1980) extend the Blinder-Oaxaca approach by explicitly incorporating the effect of occupational segregation in their decomposition. They assume that there may be unequal access to occupations for minority or disadvantaged workers in the labor market. As long as the factors that determine a worker's choice of occupation are not completely the same as those that influence a worker's wage, the Blinder-Oaxaca type of wage decomposition may be biased. Similarly, if one believes that there is unequal access to industries for rural migrant workers in China, then potential bias may also arise if industry choice is not controlled for. In this thesis, I extend the method of Brown *et al.* (1980) by explicitly taking into account the choice of both industry and occupation when estimating the wage equation and decomposing wage differentials.

More specifically, let us assume the wages for urban resident and rural migrant workers are determined by the following Mincerian wage equations.

$$\ln w_j^k = X_j^k \beta_j^k + \varepsilon_j^k \qquad k = u, r \text{ and } j = 1, \ldots, J, \tag{1}$$

where the superscripts u and r denote urban resident and rural migrant workers, respectively; w is the earnings of a worker in job j (for simplicity, I suppress the individual subscript i in the equation) and j is an industry-occupation indicator; X is a vector of the individual and job characteristic variables that affect a worker's pay; β is the unknown parameter to be estimated; and ε is the error term.

Next, I assume that the individual industry or occupation choice is determined by the following multinomial logit model.

$$p_{nj}^k = prob(y_n^k = j) = \frac{\exp(Z_n^k \gamma_n^k)}{\sum_{h=1}^{J} \exp(Z_n^k \gamma_n^k)} \qquad k = u, r;\ n = 1, \ldots, N \text{ and } j = 1, \ldots, J, \tag{2}$$

where p_{nj}^k is the probability that individual n is working in the jth category of the industry-occupation; N is the sample size; J is the total number of industry-occupation categories; Z represents a vector of the exogenous variables that affect labor supply and demand; and γ is its coefficient. As each individual must select one industry-occupation, only J–1 sets of coefficients are uniquely defined. I choose to normalize the coefficients for the first industry-occupation category (blue-collar workers in the industrial sector) to be zero.

Following Brown *et al.* (1980), the wage differential of urban residents and rural migrant workers can be decomposed as:

$$\overline{\ln w}^{u} - \overline{\ln w}^{r} = \underbrace{\sum_{j=1}^{J} p_j^r \hat{\beta}_j^u (\overline{X}_j^u - \overline{X}_j^r)}_{WE} + \underbrace{\sum_{j=1}^{J} p_j^r \overline{X}_j^r (\hat{\beta}_j^u - \hat{\beta}_j^r)}_{WU} + \underbrace{\sum_{j=1}^{J} \overline{\ln w}^{u} (p_j^u - \hat{p}_j^r)}_{BE} + \underbrace{\sum_{j=1}^{J} \overline{\ln w}^{u} (\hat{p}_j^r - p_j^r)}_{BU}$$

The upper bars denote the average, and the upper hats denote the predicted values. The term *WE* is the explained wage differential due to differences in personal characteristics; *WU* is the unexplained wage differential due to differences in the coefficients of the estimated resident and migrant wage equations; *BE* is the explained between-industry-occupation wage differential due to differences in qualifications in an industry-occupation group; and *BU* is the unexplained wage differential due to differences in the structures of industry-occupational attainment. Therefore, the foregoing wage decomposition approach takes into account not only the wage discrimination that arises from doing the same job (*WU*), but also the wage discrimination that arises from unequal access to jobs (*BU*). These two parts reflect two basic rights in *Discrimination (Employment and Occupation) Convention*[9]: equal pay and equal access (Li 2006). As an extension of Brown *et al.* (1980), I define jobs by both occupation and industry, which allows me to take into account the labor market segregation that arises both from occupation barriers and industry barriers.

The estimation of (1) and (2) will be more efficient if we also take into account the fact that there may be unobserved variables that affect both the wage and industry-occupation choices of workers, and thus the error terms of (1) and (2) may

[9] China has subscribed this convention in August, 2005.

be correlated (Heckman 1976 and 1979, Lee 1983). To consider this fully, a two-stage selectivity model will be estimated. In the first stage, (2) is estimated, and in the second stage the following wage equation is estimated.

$$\ln w_j^k = X_j^k \beta_j^k + \alpha_j^k \lambda_j^k + e_j^k \, , \tag{3}$$

where λ_j^k is the estimated IMR from the first stage of the estimation. I estimate this multinomial selectivity model separately for urban resident and rural migrant workers. To further improve the efficiency of the estimation, (2) and (3) are both estimated by the maximum likelihood method using LIMDEP. However, the achieved IMR could be problematic since it is difficult to find out variables that are fully exogenous. In order to assure the robustness of the outcome, I will report two sets of empirical results, without and with selectivity correction respectively. Comparison will be made between them and finally I will choose the results with selectivity correction.

Chapter 3. The industrial segregation in China

There are three aspects about the industrial segregation in China. First, the appearance of industrial segregation has its historical reason. Second, the pattern for nowadays migrants to search for jobs is easy to lead them to crowd into limited industries. Third, other points may help us understand this situation better, such as government policy and low substitutability between migrant and resident workers. Notice that since my data are gathered at the end of 1998, I will adopt information around 2000 to depict the situation at that time. However, the latest data is also employed when possible to help understanding.

3.1. The historical reason

At the early period of the economic reform (1984-1988), rural migrant workers are introduced mainly by the government into labor-intensive industries. This can be understood from the aspects of labor demand and supply. As for labor demand, it increases rapidly in urban areas based on a boom of the manufacture industry and service sector, such as urban construction (Zhao, Yaohui 2000), textile industry, retail sales, nursemaiding (Mallee 2000), etc.. They engender an urgent hunger for un- and semi-skilled, low-paid, and flexible labor (Solinger 1999b, pp. 47 and pp. 198-199). As for labor supply, there are several reasons. First, the employment problem of city youth was just settled (Xue 1988) and under the protection of the “iron rice bowl” institutional arrangement, urban residents keep a high employment rate though with moderate wage. Second, the improvement in living standards in the cities, as well as the new employment opportunities appearing in foreign-capital enterprises (Feng and

Jiang 1988), leads urban residents to become unwilling to work for those traditional jobs with relatively low pay and poor working conditions (Zhao, Yaohui 2000). Coupled with the slowdown of urban natural population increase, appears a shortage of urban labor supply (Mallee 2000). On the other hand, third, millions of rural laborers are released by the agriculture reform, which means the abundant rural labor supply (Taylor 1988). Because of the above two perspectives of labor demand and supply, also to avoid the heavy pressure on public facilities and services, the government permits the rural laborers to work in several urban industries first, and then opens the other ones gradually (Zhao, Yaohui 2000). Thus, the initial rural-urban migrants are concentrated in limited industries, all of which are physically exhausting, dangerous and dirty[10].

3.2. The low bargaining power for migrants

After 1988, rural migrants are able to work in cities more and more freely, and "tide of rural laborers" appears at the beginning of 1990s. There are mainly four ways for migrants to find their jobs (Zhao, Shukai 2000). The most important way is through relatives and local fellows who have arrived in the city, i.e. social network. *Migrant networks offer money for loans, company for the trip, a welcome mat upon arrival, reduction in the psychological costs of moving, food the migrant was accustomed to, and, most important of all, a job* (Roberts 2000). Usually pioneers go to the city and find jobs first and then introduce their relatives and friends to the same jobs in the same industry (For example, Knight 2002, Mallee 2000, Solinger 1999b, pp. 176-178, Zhao 1997, Zhao, Shukai 2000, Zhao 2001). Though this trend has weakened, today

[10] "According to Banister and Taylor (1989), there were already 5 million rural construction workers in urban areas in 1988." Cited from Zhao, Yaohui (2000).

65% of rural migrant workers still depend on social network to find their urban jobs (Laodong He Shehui Baozhang Bu Diaoyanzu 2006). This pattern also consists with that of international migration (Boyd 1989, Hugo 1981, Mckenzie and Rapoport 2007). The second way is through enterprise recruitment with the help of local government or just through the co-operation among governments, which follows the traditional method at the very beginning of the reform (Solinger 1999b, pp.178-182). The third one is to take advantage of employment agencies (Solinger 1999b, pp.182-184). Because of the relatively high service fee, only a small part of migrants choose this approach. However, as the government attaches increasing importance to rural migrants' employment problem in recent years, the fee is lowered and thus more and more migrants begin to consider this approach. The last is to search for jobs by oneself. We may infer from common sense that the person adopts the fourth method, to some extent, has more ability than the one who is through other three methods.

Though having the above four ways, instead of the relatively simple method (only through government) before 1988, most of the migrants still have to be kept in manufacturing industry because of their low bargaining power. For the historical reason of industrial concentration I mentioned, migrants depending on social network seem most inclined to enter manufacturing industry following their pioneers. Also, it is still true for the traditional way through government and enterprises. The other two methods depend on market and are likely to have more job choices and chances than the first two. However, two existing factors limit migrants' ability to bargain with employers: One is their lack of citizenship, and the other is restricted financial support at their first arriving in the city. The content of the citizenship includes kinds of social welfare, like unemployment insurance[11], medical insurance and other government support and public goods rationing (Solinger 1999b, Wang 1999). Whether a person deserves the citizenship from local government relies on the possession of local household registration (*hukou*). This institutional barrier makes China's internal migrants comparable to undocumented international immigrants in other countries (Roberts 2000, Solinger 1999a and 1999b, pp.5). On one hand, migrants without local *hukou* are kept from those social welfare; on the other hand, they need pay kinds of extra fees on their living and attaining jobs, enduring possible exploitation from local bureaucracy (Liu 2006, Roberts 2000, Solinger 1999b, pp.75-77, Zhao, Yaohui 2000). As Zhao, Yaohui (2000) says, *according to a sample survey by the MOL (Ministry of Labor) on rural migrant workers in large cities, these cards and certificates cost a migrant worker 223 yuan per year in 1996. This is much higher than the cost standards set by the MOL that totaled at most 20 yuan. It implies that these new regulations became new possibilities for over-charging migrants by all levels of government*. Furthermore, most of them have no more than 400 Yuan when entering the city at the end of 1990s (Cai 1997), only twice as much as the lowest urban living standard per month even without considering accommodations[12]. Taking into account other disadvantages resulting from rural-urban migration, it is natural for migrants to find jobs as soon as possible and thus lower their reserve wages.

Some evidence on migrants' job search costs may help us understand the above

[11] The unemployment insurance for urban residents consists of three parts: unemployment insurance, basic living standard for urban life, and for state-owned lay-off employees.
[12] In 2001, the average lowest living standard in Beijing is 280 Yuan per month; it is 180 Yuan in Nanjing, the capital of Jiangsu province and 300 Yuan in Guangzhou, the capital of Guangdong province. Refer to People's Daily on line: http://www.people.com.cn/GB/shenghuo/200/8492/8493/index.html. The average lowest living standard in cities all over the country is 182.4 Yuan at the end of 2007, referring to the website of Ministry of Civil Affairs of the PRC, http://cws.mca.gov.cn/accessory/200801/1201 050645191.htm

situation better. In a survey of Beijing, there are 78.52% of migrants spending less than 100 Yuan on job search (Zhu and Tao 2006). In another survey, the average search cost for migrants in Pearl River Delta is 370 Yuan, and that in Yangtze River Delta is 353 Yuan (Zhonghua Gongshang Shibao 2006). The span to get jobs, in the data I use, is average 6.21 weeks and 78% of them find work within 2 weeks. Such low search cost and short search span imply that, to some extent, migrants can afford limited searching cost.

Thus with weak bargaining power, most of migrants, no matter attaining their jobs through social network and government or through employment agency and oneself, have to restrict themselves to those flexible and low-paid jobs, at least when they first come to the city. The data I employ will give specific illustration to this[13]. 53.17% of migrants find their jobs before migration, among whom 5.6% find their jobs by themselves in 7 industries, 7.9% through government and agency in 11 industries and the left through social network in 14 industries (there are 15 specific industries altogether). If we choose manufacture, construction and social service industries as examples (the most concentrated three industries for migrant workers (Roberts 2000)), we will find the percentages in these three industries of different migrant groups are quite similar. The percentage in manufacture sector (manufacture plus construction industries) of the group finding job by oneself (68.66%) is a little lower than that for through government (83.06%) and through social network (73.07%). At the same time, the percentage in service sector (social service) of the first group (16.42%) is higher than the other two (3.17% and 12.71%). Among migrants obtaining job after migration, 10.44% find jobs by oneself in 9 industries,

[13] The percentages of the methods to find jobs are the same as the trend in other studies (Roberts 2000, Zhao, Shukai 2000).

2.67% are through government and agency in 7 industries and 86.89% through social network in 14 industries. In these three industries, we will find the same trend for migrants' finding job before migration: The percentage of manufacture sector for the first group (68.52%) is lower than the other two (70.00% and 73.62%) and that of service sector (19.15%) is higher than the other two (16.67% and 10.89%). These small differences in percentages among different methods to find jobs do not change the fact that there are far more migrants in manufacture sector than in service one.

Furthermore, the first urban job is important for migrants' career afterward (Li 1999). Except working experience, they will also establish new social networks mainly through co-worker relationships (Zhao, Shukai 2000). Hence the industrial segregation from the beginning becomes more and more obvious. Solinger (1999b) sums up six typical occupations for rural migrants: construction; manufacturing; garment processing; nursemaiding; marketing, crafts, and services; and begging or scrap collecting. Among them, except the last one, the first three occupations belong to manufacture sector and the other two belong to service sector. In a survey in 2007, though migrant workers are hired by more diverse industries, half of them still concentrate in only four ones, three of which belong to manufacturing sector and contain 41.5% of migrants (construction, electronics manufacturing and garment manufacturing industry) (Cai and Du 2007, pp.5).

Notice that after entering an industry, since a worker's skill can be improved, rise in occupational ladder is easier than changing to another better industry. So we will find a large proportion of migrants existing in white-collar-manufacture sector. This is consistent with Meng and Zhang (2001)'s conclusion that occupational segregation is not so important as wage discrimination between rural and resident workers. That is also why I choose four sectors instead of two sectors (blue- and white-collar). Table 1 shows that there about 18% of migrants have white-collar jobs in manufacturing sector, even more than those with blue-collar ones in service sector (about 13%).

3.3. Other perspectives

Other perspectives will help us to understand better industrial-occupational segregation of labor market. First, the policy of the central government and the whole bureaucracy do not direct towards rural migrants before 2000. Migrants' labor is desired, but their presence is not (Roberts 2000). Urban-biased policy before the reform and the limitation imposed on free migration after the reform courage the industrial-occupational segregation between rural migrants and urban residents. The typical policy tool is *hukou* system. Using *hukou*, migrants (no matter from rural or urban areas) and residents are divided clearly into two groups and enjoy totally different welfare treatment and public goods in their own country (Solinger 1999b, pp.4). For the central government, order and stabilization is its first consideration and controlling migration flow is one of the methods; for municipal government, since quite a part of welfare and public goods are related to local finance, it has incentive to take advantage of *hukou* to hold back the equal civilization treatment from migrants. Also, municipal bureaucracy may attain benefits from migrant controlling (Solinger 1999b, pp.9). According to the study of Project Group from Renmin University Law Faculty (2006), from 1995 to 2004, departments of central government (such as the Central People's Government, and Ministry of Labor and Social Security) at least issue 9 regulations and announcements including the discrimination items against employment of migrants. Beijing and Guangdong province issue at least 7 regulations separately and it is 10 for Shanghai. Those regulations require enterprises should only hire migrants when local laborers are not enough; limit occupations and industries to keep from migrants; ask migrants to have extra train and certificates before employment and thus increase the labor cost of enterprises (Solinger 1999b, pp.79-84, Zhao, Shukai 2000, Project Group from Renmin University Law Faculty 2006, Zhou 2006). And it is especially obvious from 1994 to 1998, when *xiagang* (laid-off) problem becomes severe accompanying the advance of the reform. Most of cities announce policies to prevent migrants entering "good" jobs (Zhou 2006, Zhao, Yaohui 2000). For example, in 1995, Beijing government divides all jobs into three catalogues A, B, and C according to the reference of resident workers. The new policy prohibits migrant workers to enter A, and limits them to undertake B and encourages C. Jobs in catalogue A and B include segregation of both industry and occupation and quite a lot concentrate on service sector (Zhou 2006). Many migrants are fired at that time, even a large number of enterprises are willing to hire them (Knight 1999); and migrants in Beijing decreases dramatically.

Second, there is low substitutability between rural migrant and resident workers (Appleton 2004, Knight 1999), especially in manufacture sector. Urban-biased policies give urban residents long-time priority over rural migrants, and the beginning concentration of rural workers mentioned above, as well as the negative image of migrants from the press (Davin 2000, Zhao, Yaohui 2000), deepens such impression. Hence they prefer unemployment to those dirty and dangerous jobs since they will lose face if they accept the latter. The social welfare related to *hukou* and relative good living condition also provide economic support to such priority.

Third, institutions and state-own enterprises, especially those with high wage and welfare, or having monopoly on some industry, employ workers mainly according to *hukou* and the social network among the insiders (Cai 2004), while rural migrants often have not such social relationship. Those enterprises often concentrate in service sector, such as industries of communications, banking and finance, and government agencies.

Thus, given the special circumstances in China, the labor market segregation for rural migrants may take the form of both occupational crowding and industry crowding[14], as reflected by the figures in Table 1.

The data we use were collected in 1998, when the unemployment problem became most serious and the labor market segregation was abundantly clear. From 2000, local governments began to cancel discrimination policies against migrants and rural migrants' civil rights became one of the focuses of the central government (Project Group from Renmin University Law Faculty 2006). Some changes privileging migrants also happened to the *hukou* system, though its nature of controlling migration kept still. Despite of the above situation, the basic pattern does not change and industrial-occupational segregation is still an important problem today.

[14] Hirsch and Schumacher (1992) put forward the same argument for the labor market segregation of blacks in the United States.

Chapter 4. Data

4.1. The survey

The study utilizes data from the 1998 Survey of Occupational Mobility and Migration collected by the Fafo Institute for Applied International Studies in Oslo and the National Research Center for Science and Technology for Development (NRCSTD) in Beijing. The former is an independent and non-profit-making research institute, and the latter is a branch institute of the Ministry of Science and Technology of China. The survey was carried out in three Chinese cities: Beijing, Wuxi, and Zhuhai (see Appendix 1 for the locations of these three cities). As pointed out by the survey organizers, these three cities were not randomly chosen, but were selected to "explore the effects of the transition in cities of different scale, region, and with different economic profiles" (Drury and Arneburg 2001, p. 4). Beijing, as the capital of China, is dominated by the public service sector and large state enterprises. Its labor market is more diversified due to its size, but is less open compared with the market in the other two cities. Wuxi is a flourishing industrial city near Shanghai in the Yangtze River Delta area of Jiangsu province, and has followed a model of development that is based on collective and township-village enterprises. It is also a city chosen by the central government to test its new state enterprise reform policies. Zhuhai, as one of the earliest special economic zones in China, is dominated by joint-venture and foreign investment firms, and has the most developed labor market of the three. All three cities have absorbed a large inflow of rural immigrant workers due to their fast economic development, and together give a good representation of well-developed cities in China[15].

The survey samples were selected randomly in the three cities, with selection being carried out separately for local and migrant workers. A two-stage cluster sampling approach was used to obtain the local resident sample. In the first stage, a random stratification sample of Residential Committees[16] was selected based on location and size. In the second stage, a random sample of households within each Residential Committee was chosen to take part in a household survey. A separate group of clusters based on the neighborhood-level police stations was selected to obtain the migrant sample, and a random sample of migrant households was then selected to take part in the survey.

The survey questionnaire had two parts. The first part was conducted at the household level and aimed to collect information about all of the household members, and the second part was for a randomly selected household member aged 16 or above. As migrants are minorities in the city, these individuals had to be over-sampled to achieve a suitably sized migrant sample. The detailed working history information over the previous five years (1994-1998) was collected from the selected individuals. Together, the two parts of the survey obtained both detailed household information and detailed working history information of an adult member within each household. I use this data for my study because the survey was the first major integrated survey of residents and migrants in cities in China.

[15] One survey in 2007, covering 25 provinces and including 5130 observations, shows that 20.9% of migrant workers are absorbed by Pearl River Delta, and 11.6% by Yangtze River Delta, and 11.9% by around Bohai Sea economics area. Totally nearly 50% of rural migrant workers gather in these three regions. Refer to Cai and Du (2007), pp.4.Also in report from the Ministry of Agriculture (2006), Guangdong, Beijing and Jiangsu are the first three districts absorbing the quantity of rural migrants in 2003.

[16] Residential Committees are neighborhood-level administrative units in China. Each Residential Committee consists of 400 to 1,000 households.

4.2. Statistical summary

The target sample size of the survey was 7,835 households, and the final completed sample contained 7,326 households. The sample sizes for Beijing, Wuxi, and Zhuhai were 2,446, 2,437, and 2,443, respectively. Several steps are adopted to handle the sample. First, about missing variables, almost half of the observations have problem of missing information, which are mainly on occupation, industry, monthly wage, and weekly work hours. There are 165 observations that do not report their education level, either. In those observations with missing information, about 90% of them are resident, nearly 60% are women, and half of them receive education no more than 9 years. Missing wage and missing work hours, missing industries and occupations are consistent. Besides, they distribute evenly among three cities. Thus there does not seem to be any systematic bias generated by deleting those observations directly except that most of the deleted observations are residents. However, those residents may either be out of work or have special jobs, such as those with especially high or low earnings. Second, about dropping variables, in order to keep the analysis simple and clear, I delete observations who work in farming industry or whose occupations are farming, fishing, and the like. Those jobs self-employed[17] and unable to classify are also dropped. In fact, the rest sample just keeps workers in manufacturing and service sector. My final sample contains 3,886 workers, of which 1,682 are migrant workers and 2,204 resident workers.

The over-crowding-in-manufacturing-sector problem of migrants is not alone as shown in my data. It is common from the very beginning of the reform to now. Kinds

[17] Self-employed migrants are a special group, as Meng (2001) and Sylvie *et al.* (2008) indicate. Thus their earnings and working hours are difficult to define.

of surveys, as cited in my Introduction part, have proved this.

The industrial distribution in the statistical yearbooks of three cities may also support that my final sample probably has no systematic bias. Two points need be noticed. One is that the survey was held in main urban districts of three cities, not including counties and rural districts that belong to them, so I will use the statistics on *employment of urban districts*. The other is that since the whole employment in my thesis is the summation of that in manufacturing and service sector, not adding farming sector, I will also follow this rule when using statistics summary in the yearbooks. In 1998, Beijing has 37.46% of employment in manufacturing industry and 62.54% in service one in urban districts (Beijing statistical yearbook 1999, pp.84, form 3-1). Compared with the distribution in my thesis (42.45% of all observations, including migrants and residents), the real proportion of manufacturing sector is similar but a little lower. Considering the statistics in the yearbook also include foreign laborers, self-employed persons, and those who have unclassified jobs, proportion for manufacturing sector may increase and be more close to that in my thesis. Besides, higher distribution for manufacturing sector and lower for service one in my thesis will underestimate discrimination, instead of overestimate. In 1998, employment in manufacturing sector of urban districts in Wuxi is 65.31% of employed workers and that for service one is 34.69% (Wuxi statistical yearbook 2001, form 2-7). The distributions of Wuxi in my thesis are 63.52% for manufacturing industry and 36.48% for service one. Thus they are very close. And for Zhuhai they are 48.12% for manufacturing sector and 51.88% for service one (Zhuhai statistical yearbook 1999, pp.90, form 3-8). Compared with proportions in my thesis, the former is lower (in my thesis it is 64.34%) and the latter is higher

(35.66% in my thesis). The difference is not small, though the trend is the same as Beijing.

As mentioned, I define four industry-occupation groups: (1) blue-collar workers in the industrial sector[18]; (2) white-collar workers in the industrial sector; (3) blue-collar workers in the service sector; and (4) white-collar workers in the service sector. The classification of industries into either the industrial sector or the service sector closely matches the standard broad definition of sectors used by the China Statistical Bureau, i.e. the primary sector (agriculture), the secondary sector (manufacturing, construction, and public utilities), and the tertiary sector (the service sector). It should be noted that my use of the term "industrial sector" covers the whole secondary sector, not just the manufacturing industry. This broad definition of industry and occupation groups is based on two considerations: first, the classification of four groups is clear enough to show industry-occupational segregation. According to Table 1, we may see that the wage gap between migrants and residents is obvious, no matter of the same group or cross groups. Second, because of the limited sample size, I do not want to end up with industry or occupation cells that contain only a handful of observations. In fact, the most ideal classification should include eight groups in that industrial and service industries are divided into top-end and low-end, respectively[19]. Table 1d delivers the average wage

[18] Blue-collar workers consist of commercial/ social service workers and manufacturing/ transport workers, and white-collar includes leading cadre in government, professional/ technical and related worker, and clerical workers. Industrial sector consists of 4 industries: mining and quarrying, manufacturing, electricity gas and water production and supply, construction. Service sector includes 10 industries: geological prospecting, water conservancy; transport storage and communications; wholesale/ retail trade, restaurants; banking and insurance; real estate; social services; health care sporting and social welfare; education culture arts and media; scientific research/ polytechnic services; government/ party agencies and social organizations.

[19] Top-end industrial sector is electricity gas and water production and supply. Low-end industrial sector includes mining and quarrying, manufacturing, and construction. Notice that because of lack of detailed information, I can not distinguish top-end manufacturing industry, say, electronics, from low-end, say, catering. Top-end service sector includes 7 industries. Some of them are with high wages though without respectable social status: transport storage and communications; banking and insurance; real estate; education culture arts and media; scientific

of 8 groups and shows a clearer segregation. In order to include observations as many as possible, I do not drop the missing variables of education, state-own, and etc. Thus there are 4463 observations totally in Table 1d and more than that in the regression sample.

The data in Table 1 show that rural migrant workers are far more concentrated in the blue-collar and industrial sector group (64.21%) and far less represented in the white-collar and service sector (3.86%) than their urban counterparts (the corresponding figures for the latter are 28.77% and 33.08%, respectively). Furthermore, the mean log hourly wage for blue-collar workers in the industrial sector is the lowest and that for white-collar workers in the service sector the highest for both rural migrant and urban resident workers. These raw data indicate that our classification of industry-occupation groups captures the main thrust of labor market segregation in China well. Furthermore, the regressions in the following chapters show that most of the city dummies are significant. However, because of limited sample size, running regressions for each city separately is insignificant or even impossible[20]. Thus I will only list the descriptive statistic for three cities, respectively.

From Tables 1a, 1b, and 1c, we may see that the basic patterns for sector distributions and log wage of three cities are almost the same as that for all observations in Table 1. The distribution of migrants in Beijing is most close to the average, and the proportion of white-collar migrants in service sector increases to 7.43%, double of

research/ polytechnic services; health care sporting and social welfare; government/ party agencies and social organizations. The left three are not top-end: geological prospecting, water conservancy; wholesale/ retail trade, restaurants; social services.

[20] For Beijing, the migrant observations of white-collar job in service industry are 26. For Wuxi, they are 8 and for Zhuhai, they are 31.

the average level. In Wuxi, an industrial city, about 92% of migrants concentrate in manufacturing sector, and that for residents are 62%. Thus migrant white-collar workers in service sector are especially low (1.82%). Zhuhai, as a newly-rising city, is flourishing in service sector, so it has more migrants than other two cities working in the service industry (about 23%), while inside which the proportion for white-collar jobs (3.47%) is even lower than that of Beijing. In fact, the wage differentials between migrants and residents in four sectors, respectively, are highest in Zhuhai among the three cities. Another point on wage differential is that except Zhuhai, the pattern of hourly wage for migrants are different from that of residents. In the service sector of Beijing, blue-collar workers earn more than white-collar ones. And this is also the case for migrants in both industries of Wuxi. Though there exists difference among cities, residents' sector-distribution and hourly log wage are obviously distinguished from migrants'.

For the multinomial logit model of industry-occupation selection, the vector of the independent variables Z should include those variables that affect both the labor supply and demand for a job. The factors influencing an individual's supply of labor are wealth, preferences, and job search costs, whereas the factors that determine the demand for labor are mainly those affecting an individual's productivity. I thus include in Z years of work experience, years of schooling, a dummy variable for gender, a dummy variable for marital status, dummy variables that indicate whether the respondent's father is a party cadre or is self-employed (owns a business), a dummy variable for working in a state-owned enterprise, a dummy variable for getting the job through state allocation, and dummy variables for the three cities. The human capital variables that are included are meant to control for both an individual's productivity and wealth, whereas the family background variables are proxies for individual preferences. The dummy variable for getting a job through state allocation and the city dummies are related to the job search costs. I believe that the family background variables and the dummy for whether the respondent obtained a job through state allocation are the main identification variables that should be included in the industry-occupation choice equation, but not the wage equation.

The specification of our wage equation follows the usual human capital theory. It includes a dummy for gender, years of work experience and its square, years of schooling, a dummy that indicates whether an individual is a party cadre, a dummy for working in a state-owned enterprise, and two city dummies[21].

The variable definition and descriptive statistics are reported in Table 2. As shown in the table, on average the migrants earn roughly 38% less than the residents, and also tend to have less human capital (years of schooling) and lower status (cadre[22]). The fewer years of work experience and lower probability of being married among the migrants are mainly due to their younger age profile compared with the residents. Furthermore, the migrants are less likely to have a father who is a Party cadre, less likely to work in a state-owned enterprise, and less likely to have gotten their job

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[21] I also run the specification with the martial status dummy included, but it remains insignificant.

[22] According to Drury and Arneburg (2001), "Cadre", with "Workers" and "Farmers", is a concept coming from the traditional system. "Generally, the cadre identity is gained once people owns the academic credentials of the secondary technical school or that of the higher grades and works in a state unit. It includes the cadres of state organizations, social groups and the cadres, the technical personals of the state enterprise, the news agency and the institutions such as researching organizations, schools, hospitals (i.e. the science, education, culture, and health departments) ".

In order to have a clearer understanding of "Cadre", the concepts of "Workers" and "Farmers" will also be illustrate. "Workers" refers to "the people who work in the formal unit of the city without the cadre identity and are registered residents in city". Hence "Worker" should be only urban residents. "Farmers" refer to "the people who are registered residents in country. They may be engaged in agriculture or work in city". Hence the identity of rural migrants is usually "Farmer". However, after checking the data, I find that many migrant respondents consider themselves as "Worker". It is also reasonable to doubt the "Cadre" identity. So here I will just treat "Cadre" as a higher social identity than "Farmers" and "Workers".

through state allocation. However, they are more likely to have a self-employed father.

The most interesting difference between the migrant and resident workers in this study is obviously the wage differential. In what follows, we examine the extent to which this differential can be explained by potential labor market segregation.

Chapter 5. Empirical results: Logit model of group-entry

As mentioned in chapter 2, there are two steps to decompose the wage differentials. In this part, I will deliver the results of the first step: equations of group-entry separately for residents and migrants. To clarify the importance of the industry factor, two binary logit models with only occupation or industry alone will be estimated, which are followed by a multinomial logit model co mbining industries with occupations.

5.1. Binary logit model of occupation or industry alone

The left two columns of Table 3 contain the estimation of occupation attainment alone. I simply divide occupation status into blue-collar and white-collar, and choose blue-collar occupation as base group. Hence in these two binary choice models for migrants and residents respectively, the coefficients of blue-collar are both set to zero and only those for white-collar are reported, which will be interpreted by comparison with the base group, blue-collar.

Most of the coefficients for the two samples are quite different. Compared with female, male residents are less likely to get a white-collar job, while male migrants have more chance of that (getting a white-collar job) than female migrants. This is consistent with the fact that female migrants encounter double discrimination of both gender and *hukou* constraint in occupation mobility (Huang 2001). Besides, there are more residents than migrants in service sector industry, in which female is more concentrated. Years of schooling has a positive and significant effect on both migrants and residents, and the value of the former is larger than the latter, indicating that the return of education is higher for migrants. Work experience has different impact on migrants and residents, indicated by the difference in the signs and significant levels. This is the same as the age variable (a proxy for work experience) in Meng and Zhang's (2001). Marital status seems to have no obvious influence on job attainment for both samples. Working in a state-owned enterprise will decrease the chance of migrants to become white-collar workers while increase that of residents. Though not significant, to some extent they suggest the existence of institution barrier for migrants in the state-owned enterprises. Migrants' jobs allocated by the government significantly tend to be blue-collar, which may because that one of the main ways for state-owned enterprises to hire migrants is recruitment through migrants' local government (Zhao, Yaohui 2000). As for family background, a father's identity being a cadre will obviously increase the chance to be enrolled as white-collar workers, both for migrants and residents. However, if a father is a business man, the migrant will significantly have even higher probability to be white-collar than blue-collar, compared with that of the resident, whose coefficient is much smaller and insignificant. This may happen because a stable and formal job is still important in urban areas of China, though till 1998 the economic reform has lasted for 20 years. Differences among cities are obvious. Working in Beijing or Wuxi will both have negative effect on attainment of white-collar jobs for migrants and residents. Besides Zhuhai's highly market-oriented economy and the dominance of service industry, other two reasons may contribute to this: as for migrants' coefficients, the relatively large migrant sample of Zhuhai may be concerned, since according to Table 1, the proportion of white-collar jobs of migrants in Zhuhai is in fact much smaller than that of other two cities. Drury and Arneburg (2001) also indicates that migrants' situation is worst in Zhuhai among the three cities. On the other hand, coefficients on residents are negative may be because of the high proportion of white-collar jobs in residents of Zhuhai (see Table 1c, 71%). Finally, the constant item in migrants' equation is more negative than that in residents', revealing that under the same condition, migrants face as twice as much of entry barrier of white-collar jobs than residents.

The right two columns of Table 3 contain the estimated results for industry alone. The same as occupation, manufacturing industry is chosen as base group and the coefficients of service sector industry will be interpreted relative to it. There still exists difference between two sets of coefficients for migrants and residents, which, however, is distinguished from that of occupation. Male workers of both samples are obviously more likely to enter manufacturing industry, since female often concentrate in the service sector. So compared with occupation, the coefficient of male for migrants in industry equation becomes negative and significant. Years of schooling for both samples appears insignificant and much smaller (about 2.3%) than that in occupation equations (about 23%). The fact is that though the non-technical labor is more popular in manufacturing industry, blue-collar jobs included in service sector need not much skill, either. Different from that in occupation, work experience is significant for migrants, as is the case in marital status. However, the signs for two experience items are the reverse of that in occupation, which may be due to the reason that most of the experience for migrants is farming and physical work after entering cities. The cadre identity no longer helps migrants to enter service sector, and the impacts for both samples decrease much, compared with occupation equations. Since service sector includes both white-collar and blue-collar job, it is understandable.

There also exists the same pattern for coefficients of occupation and industry, though the reason behind may differ from each other. Like occupation equations, state-owned enterprises are more likely to provide residents with jobs in service sector industry, and have no impact on migrants. Job attainment by the government allocation also obviously decreases migrants' chance to enter service sector. Both of these two factors reflect the disadvantageous institution arrangement for migrants. A father's cadre identity will help both migrants and residents to get jobs in service sector. Residents in Beijing and Wuxi are significantly less likely to enter service sector than those in Zhuhai. This may be because Zhuhai is a newly rising city and does not have old industry foundations as the other two. The constant is again much more negative for migrants than for residents, indicating the entry barrier.

The first part in Table 5 (also in Table 11, the same) and Table 6 (also in Table 12, the same) presents the observed distribution, the predicted distribution, and the difference between them, respectively, for occupation and industry alone. Item 1 and 2 are the observed distribution for residents and migrants. Item 5 shows the difference between these two items. Comparing item5 in Table 5 and Table 6, we may see that the difference in industry is larger than that in occupation. Item 3 and 4 are the estimated distributions predicted by the coefficients in Table 3. $\hat{p}^{u}$ denotes the proportion of urban residents if they would face the same treatment of migrants, by inserting the values of residents' characteristics into migrants' group-attainment equation. And $\hat{p}^{r}$ denotes the proportion of rural migrants if they would face residents' treatment when applying for jobs. Regarding occupation, the predicted proportion of white-collar jobs for migrants is about 5% higher than the original, which is close to Meng and Zhang's (2001) result, 5.89%; regarding industry, the predicted proportion of service sector for migrants increases nearly by 30%. Thus the industrial segregation seems much higher than occupational segregation. This is even more obvious by comparing item 6 and item 7 in two tables. Item 6 denotes the difference of distributions between migrants and residents if they would face the same group-entry condition, which means the human capital difference. Item 7 denotes the extent of segregation, using the difference between migrants' observed and predicted distribution. The weight of the values of item 6 and item 7 is just reversed in two tables. As for occupation, the explained difference (item 6) is much higher than the residual difference (item 7), while for industry, the former is much lower than the latter. The impact of those segregations on wage differentials will be illustrated in the next chapter.

From the above comparisons of group-entry equations between migrants and residents, as well as between occupation and industry classification, we may see there exist different patterns not for migrants and residents, but for occupation and industry. A Chow test is also exerted for occupation and industry entry specifications separately. The test value for occupation is 46.84, and for industry is 262.38. Both of them are significant at 1% level, and the structure difference existing in industry classification is much more obvious than that in occupation. Thus, the combination of occupation and industry is reasonable.

5.2. Multinomial logit model of industry-occupation attainment

Multinomial logit model for residents and migrants separately is the first step to decompose the wage differentials using industry-occupation classification. The results are presented in Table 7, and just like binary model, the coefficient for the base group – blue-collar workers in the industrial sector – is set to zero and only the estimated coefficients for the rest three industry-occupation groups are reported. All of the coefficients should also be interpreted by comparison with the base group.

Compared with former occupation or industry classification alone, the new four-sector model shows several differences. First, the coefficient of male for residents keeps its sign and significance unchanged as in the equations of occupation and industry alone. On the other hand, male's positive and insignificant impact on migrants in former occupation classification becomes negative and significant in white-collar job in manufacturing industry, and keeps positive and insignificant in white-collar job in service sector industry. Though both for white-collar, the direction of male's effect between two industries is different. Second, years of schooling has a positive and significant effect on an individual's chance of entering service sector, including both blue-collar and white-collar jobs. And the return of education for migrants is still larger than that for residents, and it is higher in service sector (about 22%-34%) than in manufacturing industry (about 0.2%-1%). Furthermore, in the former industry classification, education is not significant at all, which is the same as in its present coefficients of white-collar job in manufacturing industry. Third, different from former occupation and industry classification, a father's cadre identity can only obviously increase migrants' enrollment as white-collar workers in service sector. Meanwhile its effects on residents hold and become even stronger. At last, the existence of entry barrier for migrants in state-owned enterprises is not so obvious as in form occupation and industry classification. Furthermore, state-owned enterprises are more likely to provide white-collar jobs in the service sector for both migrants and residents, but this may simply reflect the fact that the government still monopolizes top-end service activities in China.

Not surprisingly, several variables keep the same pattern in present four-sector equation as in former occupation and industry equations. First, work experience seems to still have no significant impact on industry-occupation attainment, as is the case with marital status. Second, being a cadre's offspring still significantly increases an individual's chances of working in the service sector or as a white-collar worker, though the extent for migrants decreases a little and that for residents increases much compared with before. Third, if migrants' job is allocated by the government, it will still tend to be blue-collar in manufacturing industry. Fourth, residents in Beijing and Wuxi are more likely to have blue-collar jobs in manufacturing industry than those in Zhuhai. The positive effect on migrants' enrollment in manufacturing industry and negative in service sector are consistent with Beijing and Wuxi's characteristics of old industry foundations. At last, constant is negative and the absolute value for migrants is much greater than that for residents to the extent which increases as the sector becomes better and better.

The first part in Table 9 (also in Table 14, the same) presents the observed distribution, the predicted distribution, and the difference between them for four industry-occupation sectors. Item 5 illustrates the difference of observed proportion between migrants and residents. The most obvious difference exists in blue-collar workers in the manufacturing industry and white-collar workers in the service sector, the worst and the best. The explained difference, item6, and residual difference, item 7, give a clearer illustration. We can see that the predicted proportion of rural migrant workers working as blue-collar workers in the industrial sector is far below the actual proportion, whereas the predicted proportion of rural migrant workers working as white-collar workers in the service sector is far higher than the actual proportion. In contrast, the predicted proportion of urban resident workers working as white-collar workers in the service sector is much less than the actual proportion. In other words, other things being equal, rural migrant workers are more likely to end up as blue-collar workers in the industrial sector, and urban resident workers are more likely to be found in white-collar jobs in the service sector. This indicates that there is indeed labor market segregation in China for urban resident and rural migrant workers.

Thus the patterns of sector-entry for migrants and residents are distinguished from each other. And a Chow test is also exerted for sector-entry specifications. The test value is 305.36, indicating structure difference between migrants and residents is significant at 1% level.

Chapter 6. Empirical results: Group specific earnings functions

The second step of Brown *et al.* (1980) approach is earnings functions for migrants and residents respectively. As mentioned in Chapter 2, the endogeneity problem caused by sample selection that may exist in this step can be settled by Heckman's (1973) method. However, the fully exogenous instruments are hard to find. Besides, a Hausman Test suggests that only half of wage equations below encounter the significant endogeneity problem. In order to check the robustness of the decomposition results, I will consider two sets of earnings functions: One uses the general Brown *et al.* (1980) approach and the other is modified by selectivity correction.

6.1. Earnings functions without selectivity correction

6.1.1. Occupation/ industry specific earnings functions without selectivity correction

The selectivity-corrected wage equations for occupation or industry alone are reported in Table 4. The left four columns contain the estimated coefficients of occupation groups for migrants and residents respectively. Human capital variables have expected sign and except squared experience item in white-collar jobs for migrants, all of them are significant. Male residents in blue-collar jobs have much higher return than that for migrants. The return of schooling and cadre identity are higher for migrants than those for residents. The former is consistent with occupation entry equation in Chapter 5 and Meng and Zhang (2001)'s results. This may be because migrants are more likely to concentrate in newly-rising and market sector where the rate of return to education is higher (Dinh and Maurer-Fazio 2004, Fan

2001). The return of experience is larger for migrants, while the increase in it is slower than that for residents in blue-collar jobs. The reason may be that blue-collar migrants are more likely to take jobs with high mobility. If a migrant's identity is a cadre, his premium will be higher than that of a resident. Perhaps migrants have more difficulties to attain such identity than residents, so the elite effect is more obvious in them. Individuals in Zhuhai earn more than those in Beijing and Wuxi. The constant item for migrants is much lower than that for residents, indicating that controlling for the above characteristics, migrants will earn lower wage than residents. This is the same case in Meng and Zhang (2001). Notice that migrants in state-owned enterprises earn less than those in non-state-owned ones. Though it is not significant, it may indicate the institution barrier to some extent.

The right four columns in Table 4 contain the estimated coefficients of industry groups for migrants and residents respectively. As in occupation groups, human capital variables have expected sign, and except squared experience item in service sector for migrants, all of them are significant. In fact, the coefficients themselves, as well as the difference between migrants and residents in industry group, do not distinguish much from that in occupation group. One exception is state-owned enterprises in manufacturing industry. Migrants under such condition have significantly higher wage than residents. This indicates that state-owned enterprises provide much better protection for migrants than non-state-owned ones do. However, it does not mean that migrants have advantages over residents in state-owned enterprises. The *state-own* coefficient of service sector shows that residents earn as much as almost seven times than migrants; furthermore, the premium is insignificant for the latter.

A Chow Test is exerted on both sectors for occupation and industry respectively. As for occupation equations, the test value for blue-collar jobs is 14.50, and for white-collar jobs is 13.98. Both are significant at 1% level. As for industry equations, the test value for manufacturing industry is 13.73, and for service sector industry is 7.68. Both of them are significant at 1% level. Compared with sector-entry ones, the structure difference between migrants and residents in earnings functions seems much less.

6.1.2. Industry-occupation specific earnings functions without selectivity correction

The selectivity-corrected wage equations for industry-occupation sectors are reported in Table 8. Those combine the results in former earnings functions of occupation and industry alone and deliver a more detailed illustration. There still exists some difference between the wage determination patterns of migrants and residents. First, male residents earn higher wage than migrants in blue-collar jobs of manufacturing industry, while male migrants earn more than residents in white-collar jobs of service sector, though insignificant. Second, except blue-collar jobs in manufacturing industry, the return of schooling for migrants (3.7%-8.6%) is obviously larger than that for residents (3.5%-4.9%), just like earnings functions of occupation and industry alone show. Third, work experience brings higher wage for migrants than for residents. However, different from the regressions of two sectors, more than half of the coefficients become unobvious. This insignificant impact of experience is consistent with previous findings for China and is probably due to the fact that older workers had a much smaller wage increment before the reform era (Meng and Kidd 1997, Dong *et al*. 2002). Fourth, when a migrant's identity is a cadre, the premium for him will be as twice as much than that for a resident, both in blue-collar jobs of manufacturing industry and white-collar jobs of service sector. This impact is larger than that in earnings functions of occupation and industry alone. Fifth, state-owned enterprises incline to provide higher wages for migrants in blue-collar jobs of manufacturing industry, indicating better protection for migrant workers than in non-state-owned enterprises. However, the premium of working in state-owned companies is much higher for residents than for migrants in white-collar jobs of both industries. This suggests that residents have obvious advantage through institutional arrangement. At last, all of the constant items for migrants are significantly smaller than that for residents, indicating high unexplained premium for urban residents. Notice that the adjusted R-square for migrants in white-collar jobs of manufacturing is especially small than others, which shows that the wage determination of this sector is complicated than others.

A Chow Test is exerted separately for each sector. The test values are 6.55, 4.65, 5.80, and 1.60 for blue-collar and white-collar jobs in manufacturing industry and service sector respectively. Though only the last one is insignificant, the value of former three are also much smaller than that of four-sector entry functions, indicating the wage determination structure of migrants and residents is much more similar to each other than entry one. Thus it is reasonable to consider wage equations with selectivity correction.

6.2. Earnings functions with selectivity correction

6.2.1. Occupation/ industry specific earnings functions with selectivity correction

Table 10 contains separately the occupation and industry specific wage functions with selectivity correction. The left four columns are the estimated coefficients of occupation groups. The new item λ is Inverse Mill's Ratio. Compared with results without correction, more than half of the coefficients become insignificant, especially for migrant: except schooling, other coefficients of migrants are not significant at all. At the same time, most of the human capital coefficients for residents keep significant, no matter for blue-collar or for white-collar workers. This may indicate migrants are influenced much by the occupation-entry conditions. None of the significant coefficients change their signs in equations without correction. And the values of them do not change much.

The right four columns are the estimated coefficients of industry groups. Compared with results without correction, most of the coefficients are still significant, especially for residents. As for return of schooling and premium of cadre identity, migrants still have higher coefficient values than residents in both industries, just like the equations without selectivity correction. However, changes happen in service sector. Male migrants now earn a little less than male residents. The return of experience of migrants is almost the same as that of residents, though in the uncorrected equations, it is higher for migrants than residents. Migrants in Wuxi earn less, instead of higher in former functions, than residents. These may indicate that compared with manufacturing industry, service sector is more likely to be influenced by sector-entry condition.

I run the specification with the two family background dummies (whether an individual's father is a cadre and whether an individual's father owns a business) and the state job allocation dummy included in the wage equation, but most of them are insignificant. At the same time, more than half of these dummies appear to be significant in binary logit models. I therefore assert that these selectivity models meet the identification condition.

6.2.2. Industry-occupation specific earnings functions with selectivity correction

The selectivity-corrected wage equations for the various occupation-industry groups are reported in Table 13. Except one (experience square item for blue-collar migrants in service sector), all of the human capital variables have their expected signs. The rates of return to education range from 3% to 9%, and are higher for migrants in the service sector. Work experience always enters positively, but like functions without correction, is only significant in three out of the eight regressions. Finally, state-owned enterprises tend to pay workers – both residents and migrants – more in the industrial sector, but almost the opposite is true in the service sector. This is because the main large enterprises in industrial sectors are still owned by state and all their workers have “enterprise premium”. (Meng and Perkins 1998, Meng 2002, Wu 2002)

Compared with the model without correction, I have reasons to choose the one with multinomial selection. First, the selectivity model meets the identification condition. In the wage equation, I run the specification with the two family background dummies and the state job allocation dummy included, but most of them are insignificant. Besides, in most of the multinomial logit models, I find that the dummy for whether an individual’s father is a cadre are significant. The dummy for whether the respondent obtained his or her current job through state allocation are significant in two models (white-collar workers in the manufacturing industry and blue-collar workers in the service industry), and the dummy for whether an individual's father owns a business also appears to be significant in one model (blue-collar workers in the service industry). Together, these results show that those identification variables for the selectivity model play a significant role in the job attainment equations.

Another reason is the significance of coefficients and the increase of R-squares. In the earnings functions with multinomial selection, three human capital variables become significant compared with those of former model, including squared experience item of blue-collar resident workers in manufacturing industry, work experience variable of white-collar resident workers in manufacturing industry, and the dummy of male for migrant workers in service sector. Though four coefficients become insignificant, they concentrate in the dummy of cadre. Since the identity of cadre is not recognizable enough, this adjustment can be accepted. Besides, five out of eight R-squares become higher than functions without selectivity correction. Thus I consider earnings equations with multinomial selection to be more robust.

Chapter 7. Empirical results: Wage decomposition

To perform the Brown *et al.* (1980) wage decomposition outlined in the methodology section, we need use the predicted nondiscriminatory proportion attained from group-entry equations in Chapter 5, and the coefficients of earnings functions in Chapter 6. Since there are two sets of coefficients in last chapter, I will also report two decomposition outcomes, with and without selectivity correction respectively.

7.1. Wage decomposition without selectivity correctio*n*

7.1.1. Wage decomposition of occupation or industry alone

Table 5 delivers the results for occupational segregation alone. The wage differentials are decomposed into four parts: the estimated within-group explained wage differential (WE), the estimated within-group unexplained wage differential (WU), the estimated between-group explained wage differential (BE), and the estimated between-group unexplained wage differential (BU). The summation of item 11 is equal to WE, and that of item 12, item 13, and item 14 are corresponding to WU, BE, and BU part respectively. WE is -0.0355, or -9.26% of the total wage differential. The negative sign means if migrants had been treated in the same way as residents, their wage would have been higher than that of residents, which may be because migrants have some special characteristics. WU is much higher and equals to 0.2861, or 74.61% of the total wage differential. This may be viewed as the upper bound of the on-the-job wage discrimination against migrant workers. BE is 0.1112, or 29% and BU is 0.0216, or 5.64%. These two items explain the wage differentials across occupations, and BU part indicates labor market segregation or unequal access to different occupations. Notice the two components of BU in item 14. The first negative value belongs to the blue-collar job and means that there are too many migrants crowding into it. The second positive value illustrates the entry barrier of white-collar for migrants.

This composition results are similar to Meng and Zhang (2001)'s. First, the largest part is WU and the smallest part is BU, which shows that wage discrimination is the main reason of wage gap between migrants and residents, while occupational segregation is a relatively minor cause. Second, WE part is a negative value, suggesting migrants' some special characteristics advantage over residents. The total unexplained part (WU and BU) is much larger than the total explained one, indicating the severe discrimination again migrants.

Table 6 delivers the decomposition of industrial wage gap. WE is 0.0151, or 3.91% of the total wage differential. WU, the upper bound of wage discrimination, is still very high and equal to 0.2731, or 70.94% of the total wage differential. BE is 0.0155, or 4.02% and BU is 0.0814, or 21.13%. The two components of BU in item 14 also include a negative value and a positive one, indicating migrants' crowding in manufacturing industry and the entry barrier of service sector for them.

There are some points in this result. First, there exists obvious difference between industrial and occupational decomposition. Though the largest part is still WU, the proportion of BU increases dramatically and becomes the second large part, which means industrial segregation is also an important factor leading to wage differentials. Second, two reasons may contribute to the above change. One is that the structure difference between migrants and residents across industry entries is much more obvious than that across occupation entries, which can be proved by the Chow Test in Chapter 5. Another reason is the different weights between item 6 and item 7 in Table 5 and Table 6. That is, the residual difference in Table 6 is much higher than that in Table 5, while the explained difference in the former is much lower than that in the latter. Third, the industrial decomposition is closer to the intuition than the occupational one. The WE part becomes slightly positive, which is consistent with the statistical characteristics of residents: more work experience, higher education level, and more local social relationship.

7.1.2. Wage decomposition of industry-occupation sectors

Table 11 shows the decomposition of industry-occupation wage gap. WE is again negative and equals to -0.0253, or -6.57% of the total wage differential. WU, the upper bound of wage discrimination, equals 0.2299, or 59.70% of the total wage differential. BE is 0.1025, or 26.61% and BU is 0.0780, or 20.25%. As the Chow Test exerted in Chapter 6, the structure difference of wage determination pattern between migrants and residents is much less than that of sector-entry, and in the last sector, white-collar job in service sector, there is even no such difference. Item 12 shows this trend to some extent since the WU part for white-collar service sector job is the smallest one in the four WU components. As for sector segregation, the two negative values in item 14 show that migrants are crowding in the blue-collar jobs in both industries and have entry barrier in the white-collar jobs. The final decomposition of four sectors combines the results of occupation and industry alone since the WU is still the largest part and BU is the second largest one, while WE is negative. We may see that after adding industry factor, the importance of sector-segregation in explaining the wage gap improves significantly. Though it is still not so important as wage discrimination factor, the proportion of segregation increases to 1/3 of WU, instead of less than 1/14 in occupation classification alone.

However, one may argue that since BU equals the summation of item 14, then the more classifications the decomposition has, the higher the BU part is. This can be explained by two things. First, Kidd and Shannon (1996) find that sector segregation does not change much with the level of sector aggregations. Second, though Meng and Zhang (2001) only have occupation classification (blue-collar and white-collar), they divide blue-collar jobs into three groups and thus there are also four sectors in their decomposition process.

7.2. Wage decomposition with selectivity correction

7.2.1. Wage decomposition of occupation or industry alone

In Table 11, I present the results for a binary logit selectivity-adjusted wage model that uses occupation alone as the labor market segregation measure, and the estimated total between-occupation wage differential drops to 29.07%, lower than results without correction (34.64%). More interestingly, the estimated between-occupation unexplained wage differential is only 4.73%, which is even smaller than the 4.85% estimated by Meng and Zhang. This indicates that after binary selection, the impact of labor market segregation on the wage differential due to occupational segregation is still negligible. However, the proportion of wage discrimination (WU) decreases to 56.48% compared with former 74.61% and WE becomes positive (14.45%).

In Table 12, I estimate the binary logit selectivity-adjusted wage model with selectivity correction using industry alone as the labor market segregation measure. Although the estimated total between-sector wage differential is still samll and accounts for only 21.22% of the total wage differential, the estimated between-sector unexplained wage differential keeps relatively large (17.81%) with respect to occupational segregation, indicating a significant labor market segregation effect on the wage differential due to unequal access to industries. And just as the results reported in occupation wage gap decomposition, this proportion decreases compared with that without correction. WE and WU parts change much. The former jumps up to 100.67% and the latter drop dramatically to -21.89%, suggesting there is no wage discrimination within industry and the main reason of wage gap is difference in human capital between migrants and residents, which, however, is not consistent with intuition.

7.2.2. Wage decomposition of industry-occupation sectors

In Table 14, WE is 0.1042, or 27% of the total wage differential. WU, the upper bound of wage discrimination, is almost the same, at 0.1004, or 26% of the total wage differential. BE is also quite close and occupies 0.1025, or 26.61%, which is a little larger than labor market segregation part BU of 0.0780, or 20.25%. This latter figure shows that unequal access to industry-occupation contributes as much as 20.25% of the observed wage differential between resident and migrant workers. Compared with decomposition results without correction, only WE and WU parts have some change. The proportion of WE almost increases by 34% and WU decreases that much.

This new results here are also significantly different from those obtained by Meng and Zhang (2001). First, the estimated between-sector wage differential represents almost 47% (26.61% + 20.25%) of the total wage differential, whereas the estimation of Meng and Zhang, which is based on occupational segregation alone, is only 12%. The second, and perhaps the most important, difference is that the estimated labor market segregation effect accounts for almost the same proportion as wage discrimination, which is in sharp contrast to the 105.74% (WU) versus 4.85% (BU) figure estimated by Meng and Zhang. I ascribe the significant difference between the two studies to the use of both industry and occupation to define labor market segregation. One point is that BU part may be lower bound of the labor market segregation since once there exists obvious entry barrier, migrants may give up endeavor to enter those "good" job.

7.3. The extension of wage decomposition with selectivity correction

There are two extended forms of the wage differential decomposition with selectivity correction using both occupation and industry. One is for male, and the other adopts industry and ownership to define the labor market segregation.

Table 15 delivers the decomposition result for male. Studies have shown that there exists obvious gender wage gap in the labor market of China (Meng 1998, Wang 2005a, Cai and Du 2007, pp.25) and female migrants encounter double discrimination. Thus the decomposition with only the male sample may show the segmented labor market of residents and migrants more clearly. In Table 15, compared with Table 14, WE increases from 27.05% to 35.43%, suggesting an obvious human capital difference between male migrants and residents. WU decreases slightly to 25.63% and BU also drops to 16.60%, and they are still close to each other. Wage differentials explained by between sectors factor account for about 39% (22.35+16.60%) totally, less than 47% for the whole sample. This indicates segmented labor market is indeed an important factor leading to wage gap between migrants and residents. On the other hand, female migrants are more likely to encounter barrier of sector access with respect to their male counterparts.

Table 16 shows the wage decomposition for the whole sample with selectivity correction, while measuring the labor market segregation by industry and ownership according to "enterprise premium" mentioned in Chapter 6. I should have considered industry-occupation sector and ownership, but because of limited sample, I just present two factors of the above. Thus the four sectors are non-state-owned enterprises[23] and state-owned enterprises in the manufacturing industry respectively, and non-state-owned enterprises and state-owned enterprises in the service sector industry respectively. In the final decomposition results, WE is negative (-14.56%). WU increases much and occupies again the largest proportion (79.81%), and BU (21.18%) is about 1/4 of WU. However, BU part is still much larger than Meng and Zhang (2001)'s. Furthermore, it is reasonable to consider that much of wage discrimination is caused by occupation difference (blue-collar and white-collar). To illustrate clearly, Table 17 summarizes the percentage distributions and mean log hourly wage of resident and migrant workers by occupation-industry and ownership groups. In manufacturing industry, the wage differentials between migrants and residents are larger in state-owned-enterprises than that in their counterpart. However,

[23] Non-state-owned enterprises include collective and private ones.

this situation is not obvious in service industry.

Chapter 8. Conclusions

To conclude, I extend the wage decomposition framework of Brown *et al.* (1980) by taking into account potential segregation in both industry and occupation. I apply this framework to decompose the wage differential between urban resident and rural migrant workers in China using data from the 1998 Survey of Occupational Mobility and Migration collected by the Fafo Institute for Applied International Studies in Oslo and the National Research Center for Science and Technology for Development (NRCSTD). In contrast to earlier findings by Meng and Zhang (2001), I find labor market segregation in China as measured by both industry and occupational segregation to contribute significantly (up to 20%) to the observed wage differential between these two groups of workers.

I also perform my analyses using extensions of decomposition in order to keep my result robust. One extension is to use industry or occupation alone as the measure for labor market segregation, and the results show that the main effect of labor market segregation on the wage differential comes from industry, rather than occupational, segregation. I believe that this finding fits intuition well. Because of the household registration system in China, rural migrant workers face more difficulties in searching for jobs in cities and hence are less likely to switch industries. However, it may be less difficult for them to climb up the occupational ladder within the same firm or industry. Another extension is to decompose the wage differentials without using selectivity correction. Though under this condition the segregation effect is not so important as that using correction, the proportion of labor market segregation is still obviously improved than Meng and Zhang (2001)'s. Besides, regressions show that results with correction is more reasonable. The other two extensions are to use male sample and to combine industry and ownership as the measure of segregation. For the former, the impact of segregation is as important as that for the whole sample. For the latter, the impact decreases since I do not consider the occupation factor.

My findings provide useful policy implications for the government. They show that the household registration system is a major obstacle for migrant workers in gaining equal access to good jobs, and thereby lowers their wages. If the government intends to reduce the earnings gap between resident and migrant workers, then it must abandon this policy, because it increases labor market rigidity and reduces efficiency.

There exist three problems when I use the Brown *et al.* (1980) approach. First, there exist the statistic discrimination and other factors that are hard to control. For example, the quality of education is hard to control, and the residents' advantage in local social network may be helpful to some occupations. We may look at the proportion of unexplained part as the upper bound of discrimination. Second, as Sylvie *et al.* (2008) mention, the Brown *et al.* (1980) approach uses average log wages of different sectors to decompose the wage gap, however, those average wage will change according to the classification of sectors and thus will influence the final decomposition. While method using in Sylvie *et al.* (2008) is not as general as in Brown *et al.* (1980), I still adopt approach in the latter. Third, an obvious characteristic in all of the data sets is that migrants are much younger than residents on average. For example, in Meng and Zhang (2001), the difference of age between two groups is about 15 years, and in Wang (2005), that of work experience is about 8.8 years. In mine, it is about 10 years. The survey in 2007 also shows that 58.2% of jobs for migrants only contain young people aged 18-25 (Cai and Du 2007, pp.16). Thus consideration may appear that the factors influencing migrants' age may be related with the ones contributing to both industry-occupation choice and wage, and then there perhaps exists the problem of sample selection, which is expected to handle in late studies.

Table 1. Percentage distributions of resident and migrant workers by occupation-industry groups

Occupation-industry	Migrants	Residents
Blue collar in manufacture industry	64.21% (0.4795)	28.77% (0.4528)
Mean log hourly wage	1.0667 (0.5040)	1.2420 (0.5580)
White collar in manufacture industry	18.37% (0.3874)	24.36% (0.4294)
Mean log hourly wage	1.0971 (0.6514)	1.4078 (0.6769)
Blue collar in service sector industry	13.56% (0.3424)	13.79% (0.3449)
Mean log hourly wage	1.4357 (0.5475)	1.6414 (0.5851)
White collar in service sector industry	3.86% (0.1928)	33.08% (0.4706)
Mean log hourly wage	1.6666 (0.8136)	1.8222 (0.6623)
Total	100%	100%
Sample	1682	2204

Note: numbers in the brackets are standard deviations.

Table 1a. Percentage distributions of resident and migrant workers by occupation-industry groups in Beijing

Occupation-industry	Migrants	Residents
Blue collar in manufacture industry	51.14% (0.0268)	21.26% (0.0148)
Mean log hourly wage	1.0965 (0.5413)	1.3565 (0.4922)
White collar in manufacture industry	32.57% (0.0251)	27.43% (0.0162)
Mean log hourly wage	1.1177 (0.6064)	1.3837 (0.6625)
Blue collar in service sector industry	8.86% (0.0152)	13.12% (0.0122)
Mean log hourly wage	1.5890 (0.6699)	1.7239 (0.5824)
White collar in service sector industry	7.43% (0.0140)	38.19% (0.0176)
Mean log hourly wage	1.4818 (0.7031)	1.7171 (0.6619)
Total	100%	100%
Sample	350	762

Note: numbers in the brackets are standard deviations.

Table 1b. Percentage distributions of resident and migrant workers by occupation-industry groups in Wuxi

Occupation-industry	Migrants	Residents
Blue collar in manufacture industry	68.79% (0.0221)	43.28% (0.0167)
Mean log hourly wage	1.0809 (0.4420)	1.1252 (0.4999)
White collar in manufacture industry	23.92% (0.0204)	18.42% (0.0130)
Mean log hourly wage	1.0304 (0.7390)	1.1420 (0.6199)
Blue collar in service sector industry	5.47% (0.0109)	14.92% (0.0120)
Mean log hourly wage	1.4673 (0.5822)	1.4029 (0.5058)
White collar in service sector industry	1.82% (0.0064)	23.39% (0.0142)
Mean log hourly wage	1.1540 (0.8136)	1.4523 (0.6623)
Total	100%	100%
Sample	439	885

Note: numbers in the brackets are standard deviations.

Table 1c. Percentage distributions of resident and migrant workers by occupation-industry groups in Zhuhai

Occupation-industry	Migrants	Residents
Blue collar in manufacture industry	67.08% (0.0157)	15.98% (0.0155)
Mean log hourly wage	1.0505 (0.5218)	1.5351 (0.7359)
White collar in manufacture industry	10.08% (0.0101)	29.62% (0.0194)
Mean log hourly wage	1.1287 (0.5975)	1.7009 (0.6355)
Blue collar in service sector industry	19.37% (0.0132)	12.93% (0.0142)
Mean log hourly wage	1.4038 (0.5163)	1.9640 (0.5432)
White collar in service sector industry	3.47% (0.0061)	41.47% (0.0209)
Mean log hourly wage	1.9526 (0.8802)	2.2862 (0.4891)
Total	100%	100%
sample	893	557

Note: numbers in the brackets are standard deviations.

Table 1d. Percentage distributions of resident and migrant workers by 8 occupation-industry (top-end and low-end) groups

Occupation-industry	Migrants	Residents
Blue collar in top-end manufacture industry	0.05%	1.32%
Mean log hourly wage	0.7306 (0.0000)	1.8645 (0.4846)
Blue collar in low-end manufacture industry	64.55%	27.18%
Mean log hourly wage	1.0726 (0.5041)	1.2195 (0.5449)
White collar in top-end manufacture industry	0.05%	0.58%
Mean log hourly wage	0.8440 (0.0000)	2.1930 (0.5157)
White collar in low-end manufacture industry	12.80%	12.83%
Mean log hourly wage	1.4309 (0.5379)	1.6067 (0.5765)
Blue collar in top-end service sector industry	3.35%	7.73%
Mean log hourly wage	1.1401 (0.7225)	1.5605 (0.6636)
Blue collar in low-end service sector industry	15.02%	16.32%
Mean log hourly wage	1.0548 (0.6327)	1.2801 (0.7102)
White collar in top-end service sector industry	1.77%	25.82%
Mean log hourly wage	1.5525 (0.7493)	1.8064 (0.6517)
White collar in low-end service sector industry	2.12%	7.77%
Mean log hourly wage	1.6706 (0.8511)	1.8010 (0.7424)
Total	100%	100%
sample	2031	2432

Note: numbers in the brackets are standard deviations.

Table 2. Variable meaning and descriptive statistics

Variable	Definition	Means and Standard Deviations	
		Migrants	Residents
Log wage	Log hourly wage	1.1443 (0.5770)	1.5294 (0.6712)
Male	Dummy=1 for male	0.6141 (0.4869)	0.5345 (0.4989)
Married	Dummy=1 for currently married	0.4584 (0.4984)	0.8353 (0.3710)
Schooling	Years of schooling	9.2718 (2.5921)	11.196 (3.2556)
Experience	Years of working experience	9.0690 (8.0275)	19.568 (10.318)
Cadre	Dummy=1 for party cadre	0.0517 (0.2215)	0.3312 (0.4708)
State-owned	Dummy=1 for working in a state-owned enterprise	0.2366 (0.4251)	0.6175 (0.4861)
Allocated	Dummy=1 for getting the job through state allocation	0.0357 (0.1855)	0.2078 (0.4058)
Father-cadre	Dummy=1 if the respondent's father is a party cadre	0.1195 (0.3245)	0.3530 (0.4780)
Father-business	Dummy=1 if the respondent's father owns business	0.0470 (0.2116)	0.0191 (0.1368)
Beijing	Dummy=1 if the sample is from Beijing	0.2081 (0.4061)	0.3457 (0.4757)
Wuxi	Dummy=1 if the sample is from Wuxi	0.2610 (0.4393)	0.4015 (0.4903)
Sample size		1682	2204

Table 3. Binary logit model of occupation/ industry attainment

Variable	Occupation		Industry	
	Migrants	Residents	Migrants	Residents
	White collar	White collar	Service sector	Service sector
Male	0.02891 (0.859)	-0.64851 (0.000)	-0.45434 (0.001)	-0.38000 (0.000)
Schooling	0.25491 (0.000)	0.22935 (0.000)	0.02280 (0.398)	0.02595 (0.159)
Experience	0.06149 (0.051)	-0.01153 (0.577)	-0.05633 (0.039)	-0.02511 (0.149)
Experience^2	-0.00022 (0.786)	0.00010 (0.025)	0.00217 (0.002)	0.00077 (0.041)
Married	0.27493 (0.187)	0.16928 (0.352)	0.50502 (0.006)	0.06913 (0.645)
Cadre	2.18740 (0.000)	2.64677 (0.000)	0.25230 (0.373)	0.69786 (0.000)
Stateown	-0.33565(0.147)	0.00527 (0.965)	0.04090 (0.786)	0.34736 (0.001)
Allocate	-0.68097(0.082)	-0.17440 (0.234)	-0.63300 (0.094)	0.10468 (0.379)
Father-cadre	0.43099 (0.039)	0.32497 (0.008)	0.37132 (0.063)	0.26815 (0.010)
Father-business	0.58909 (0.063)	0.05229 (0.899)	0.19634 (0.494)	-0.18420 (0.587)
Beijing	-0.69346 (0.001)	-0.84307 (0.000)	1.47824 (0.000)	-0.47735 (0.000)
Wuxi	-1.32619 (0.000)	-0.77232 (0.000)	0.82863 (0.000)	-1.26286 (0.000)
Constant	-4.53805(0.000)	-2.98760 (0.000)	-1.93262 (0.000)	0.43270 (0.113)
N	1682	2204	1682	2204

Note: Figures in parentheses indicate *p*-values.

Table 4. Occupation/ Industry specific wage functions without selectivity correction

Variable	Blue collar		White collar		Manufacturing industry		Service industry	
	Migrants	Residents	Migrant	Residents	Migrants	Residents	Migrants	Residents
Male	0.17728	0.30638	0.11727	0.12171	0.11483	0.19942	0.27876	0.20685
	(0.000)	(0.000)	(0.098)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Schooling	0.04315	0.04270	0.08753	0.04311	0.06173	0.05165	0.05494	0.04775
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Experience	0.03441	0.01603	0.02808	0.01659	0.03951	0.01331	0.01913	0.01449
	(0.000)	(0.001)	(0.013)	(0.002)	(0.000)	(0.020)	(0.077)	(0.003)
Experience^2	-0.00084	-0.00043	-0.00036	-0.00045	-0.00080	-0.00023	-0.00039	-0.00047
	(0.000)	(0.000)	(0.233)	(0.000)	(0.000)	(0.083)	(0.185)	(0.000)
Cadre	0.35443	0.30476	0.23650	0.18573	0.36135	0.24054	0.48254	0.26792
	(0.001)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Stateown	0.10096	0.13280	-0.09905	0.04956	0.07814	0.02177	0.02321	0.14325
	(0.006)	(0.000)	(0.313)	(0.198)	(0.043)	(0.541)	(0.764)	(0.000)
Beijing	-0.08338	-0.38701	-0.04436	-0.56729	-0.10898	-0.37879	-0.15220	-0.53957
	(0.038)	(0.000)	(0.631)	(0.000)	(0.011)	(0.000)	(0.082)	(0.000)
Wuxi	-0.06674	-0.52100	-0.13497	-0.76967	-0.07447	-0.56498	-0.19000	-0.67599
	(0.060)	(0.000)	(0.210)	(0.000)	(0.036)	(0.000)	(0.037)	(0.000)
Constant	0.39887	0.88578	0.22436	1.37759	0.25494	0.91518	0.45976	1.13556
	(0.000)	(0.000)	(0.180)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)
Adjusted R^2	0.1183	0.2564	0.2400	0.3311	0.1922	0.2797	0.1775	0.3614
N	1389	1171	293	1033	1308	938	374	1266

Figures in parentheses indicate *p*-values.

Table 5. Wage decompositions for occupation segregation alone without selectivity correction

Occupation	Observed distribution		Predicted distribution		Observed difference	Explained difference	Residual difference
Group	p^u	p^r	$\hat{p}^u$	$\hat{p}^r$	$p^u - p^r$	$p^u - \hat{p}^r$	$\hat{p}^r - p^r$
	1	2	3	4	5	6	7
Blue-collar	0.5313	0.8258	0.6064	0.7779	-0.2945	-0.2466	-0.0479
White-collar	0.4687	0.1742	0.3936	0.2221	0.2945	0.2466	0.0479
	$\ln \overline{w}^u - \ln \overline{w}^r$	$\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$p^r \hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$p^r \overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$\ln \overline{w}^u(p^u - \hat{p}^r)$	$\ln \overline{w}^u(\hat{p}^r - p^r)$
	8	9	10	11	12	13	14
Blue-collar	0.2459	-0.0223	0.2662	-0.0184	0.2198	-0.3250	-0.0632
White-collar	0.2823	-0.0981	0.3805	-0.0171	0.0663	0.4362	0.0848
Total wage differentials			WE		WU	BE	BU
0.3834			-0.0355 (-9.26%)		0.2861 (74.61%)	0.1112 (29.00%)	0.0216 (5.64%)

Table 6. Wage decompositions for industry segregation alone without selectivity correction

Industry	Observed distribution		Predicted distribution		Observed difference	Explained difference	Residual difference
Group	p^u	p^r	$\hat{p}^u$	$\hat{p}^r$	$p^u - p^r$	$p^u - \hat{p}^r$	$\hat{p}^r - p^r$
	1	2	3	4	5	6	7
Manufacturing	0.4256	0.7776	0.6241	0.4818	-0.3520	-0.0562	-0.2958
Service	0.5744	0.2224	0.3759	0.5182	0.3520	0.0562	0.2958
	$\ln \overline{w}^u - \ln \overline{w}^r$	$\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$p^r \hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$p^r \overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$\ln \overline{w}^u(p^u - \hat{p}^r)$	$\ln \overline{w}^u(\hat{p}^r - p^r)$
	8	9	10	11	12	13	14
Manufacturing	0.2404	-0.0439	0.2843	-0.0341	0.2210	-0.0771	-0.4056
Service	0.4553	0.2211	0.2342	0.0492	0.0521	0.0926	0.4870
Total wage differentials			WE		WU	BE	BU
0.3850			0.0151 (3.91%)		0.2731 (70.94%)	0.0155 (4.02%)	0.0814 (21.13%)

Table 7. Multinomial logit model of industry-occupation attainment

Variable	Migrants			Residents		
	White collar in M industry	Blue collar in S industry	White collar in S industry	White collar in M industry	Blue collar in S industry	White collar in S industry
Male	-0.63532 (0.000)	-0.16138 (0.366)	0.18119 (0.581)	-0.28550 (0.023)	-0.54370 (0.001)	-0.93956 (0.000)
Schooling	0.01491 (0.625)	0.24539 (0.000)	0.33519 (0.000)	0.00214 (0.935)	0.22466 (0 .000)	0.23567 (0.000)
Experience	-0.02693 (0.378)	0.09938 (0.006)	-0.07166 (0.204)	-0.04536 (0.055)	-0.03472 (0.233)	-0.03563 (0.171)
Experience^2	0.00146 (0.068)	-0.00114 (0.243)	0.00365 (0.006)	0.00105 (0.043)	0.00138 (0.029)	0.00165 (0.004)
Married	0.53357 (0.008)	0.33675 (0.139)	0.50688 (0.220)	0.19847 (0.327)	0.36391 (0.157)	0.21525 (0.340)
Cadre	0.73545 (0.113)	2.56722 (0.000)	1.87175 (0.000)	0 .81190 (0.002)	3.00903 (0.000)	3.14551 (0.000)
Stateown	-0.19271(0.242)	-0.87515 (0.002)	0.54312 (0.124)	-0.04514 (0.730)	-0.61999 (0.000)	0.33218 (0.028)
Allocate	-1.06657(0.036)	-1.02112 (0.021)	-0.57286 (0.339)	0.07501 (0.647)	-0.28896 (0.167)	-0.04888 (0.786)
Father-cadre	0.13213 (0.590)	0.26078 (0.271)	1.09607 (0.002)	0.30552 (0.035)	0.38362 (0.029)	0.53963 (0.001)
Father-business	0.26975 (0.391)	0.65291 (0.062)	0.62222 (0.342)	-0.32912 (0.480)	-0.08331 (0.881)	-0.15577 (0.761)
Beijing	1.58736 (0.000)	-0.54177 (0.037)	0 .55342 (0.123)	-0.37801 (0.036)	-0.83130 (0.000)	-1.20716 (0.000)
Wuxi	0.88666 (0.000)	-1.14450 (0.000)	-0.92398 (0.052)	-1.49212 (0 .000)	-1.02356 (0.000)	-1.81820 (0.000)
Constant	-1.89254(0.000)	-4.52627 (0.000)	-7.06480 (0.000)	0.87510 (0.020)	-2.82366 (0.000)	-2.29381 (0.000)
N		1682			2204	

Note: Figures in parentheses indicate *p*-values. M denotes for industrial sector and S for service sector.

Table 8. Industry-occupation specific wage functions without multinomial selection

Variable	Blue collar in M industry		White collar in M industry		Blue collar in S industry		White collar in S industry	
	Migrants	Residents	Migrant	Residents	Migrants	Residents	Migrants	Residents
Male	0.14755	0.28260	0.27139	0.34045	0.05744	0.08534	0.30396	0.13055
	(0.000)	(0.000)	(0.000)	(0.000)	(0.425)	(0.115)	(0.135)	(0.001)
Schooling	0.04439	0.04884	0.03656	0.03539	0.07881	0.04325	0.08601	0.04352
	(0.000)	(0.000)	(0.016)	(0.001)	(0.000)	(0.000)	(0.030)	(0.000)
Experience	0.04069	0.01540	0.01672	0.01031	0.02079	0.01135	0.03084	0.01948
	(0.000)	(0.035)	(0.166)	(0.159)	(0.116)	(0.220)	(0.288)	(0.003)
Experience^2	-0.00097	-0.00026	-0.00045	-0.00044	-0.00012	-0.00025	-0.00073	-0.00056
	(0.000)	(0.143)	(0.194)	(0.005)	(0.746)	(0.227)	(0.296)	(0.000)
Cadre	0.39303	0.13649	0.24522	0.37199	0.17395	0.23477	0.39227	0.15102
	(0.003)	(0.181)	(0.265)	(0.000)	(0.056)	(0.001)	(0.127)	(0.001)
Stateown	0.12327	0.08766	0.05789	0.17638	-0.09549	-0.08845	-0.23379	0.07827
	(0.002)	(0.042)	(0.486)	(0.001)	(0.420)	(0.164)	(0.260)	(0.120)
Beijing	-0.13333	-0.33562	-0.03924	-0.39888	0.07202	-0.34306	-0.41561	-0.61658
	(0.004)	(0.000)	(0.681)	(0.000)	(0.504)	(0.000)	(0.055)	(0.000)
Wuxi	-0.07225	-0.44479	-0.07777	-0.54800	-0.01975	-0.65161	-0.57081	-0.77413
	(0.055)	(0.000)	(0.419)	(0.000)	(0.858)	(0.000)	(0.058)	(0.000)
Constant	0.36678	0.72394	0.54409	1.06610	0.34133	1.27540	0.48711	1.40660
	(0.000)	(0.000)	(0.003)	(0.000)	(0.053)	(0.000)	(0.332)	(0.000)
Adjusted R^2	0.1436	0.2018	0.0649	0.2914	0.2114	0.2610	0.2930	0.3501
N	1080	634	309	537	228	304	65	729

Figures in parentheses indicate *p*-values. M denotes for industrial sector, and S for service sector.

Table 9. Wage decompositions without multinomial selection

Occupation-industry group	Observed distribution		Predicted distribution		Observed difference	Explained difference	Residual difference
	p^u	p^r	$\hat{p}^u$	$\hat{p}^r$	$p^u - p^r$	$p^u - \hat{p}^r$	$\hat{p}^r - p^r$
	1	2	3	4	5	6	7
B-M	0.2877	0.6421	0.4026	0.3739	-0.3544	-0.0862	-0.2682
W-M	0.2436	0.1837	0.2130	0.3904	0.0599	-0.1468	0.2067
B-S	0.1379	0.1356	0.2224	0.0915	0.0023	0.0464	-0.0441
W-S	0.3308	0.0386	0.1621	0.1442	0.2922	0.1866	0.1056
	$\ln \overline{w}^u - \ln \overline{w}^r$	$\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$p^r \hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$p^r \overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$\ln \overline{w}^u(p^u - \hat{p}^r)$	$\ln \overline{w}^u(\hat{p}^r - p^r)$
	8	9	10	11	12	13	14
B-M	0.1753	-0.0326	0.2079	-0.0209	0.1335	-0.1070	-0.3331
W-M	0.3166	0.0806	0.2360	0.0148	0.0434	-0.2067	0.2910
B-S	0.2057	-0.1384	0.3441	-0.0188	0.0467	0.0761	-0.0723
W-S	0.1562	-0.0099	0.1661	-0.0004	0.0064	0.3401	0.1924
Total wage differentials			WE		WU	BE	BU
0.3850			-0.0253 (-6.57%)		0.2299 (59.70%)	0.1025 (26.61%)	0.0780 (20.25%)

Note: B-M denotes for blue-collar in industrial sector, W-M for white-collar in industrial sector. B-S for blue-collar in service sector, and W-S for white-collar in service sector.

Table 10. Occupation/ Industry specific wage functions with selectivity correction

Variable	Blue collar		White collar		Manufacturing industry		Service industry	
	Migrants	Residents	Migrant	Residents	Migrants	Residents	Migrants	Residents
Male	0.11652	0.17623	0.10824	0.22918	0.32126	0.31257	0.32714	0.33655
	(0.108)	(0.000)	(0.230)	(0.001)	(0.002)	(0.000)	(0.001)	(0.002)
Schooling	0.05471	0.02462	0.04201	0.00615	0.05285	0.03824	0.05204	0.03512
	(0.050)	(0.013)	(0.257)	(0.742)	(0.000)	(0.000)	(0.001)	(0.025)
Experience	0.01839	0.01753	0.01378	0.01766	0.02069	0.01941	0.02047	0.02055
	(0.177)	(0.002)	(0.435)	(0.028)	(0.063)	(0.005)	(0.075)	(0.080)
Experience^2	-0.00026	-0.00052	-0.00021	-0.00058	-0.00051	-0.00063	-0.00053	-0.00067
	(0.415)	(0.000)	(0.604)	(0.002)	(0.157)	(0.000)	(0.152)	(0.017)
Cadre	-0.02514	-0.08911	-0.15592	-0.32851	0.44693	0.08133	0.43858	0.03550
	(0.908)	(0. 454)	(0.617)	(0.163)	(0.004)	(0.397)	(0.007)	(0.837)
Stateown	-0.05292	0.05328	-0.04227	0.04983	0.02312	0.04702	0.02181	0.02290
	(0.618)	(0.178)	(0.748)	(0.388)	(0.766)	(0.457)	(0.789)	(0.836)
Beijing	0.03687	-0.49504	0.06234	-0.43136	-0.27866	-0.41724	-0.30839	-0.38609
	(0.744)	(0.000)	(0.662)	(0.000)	(0.236)	(0.000)	(0.207)	(0.004)
Wuxi	0.03418	-0.70262	0.09515	-0.64483	-0.26382	-0.31988	-0.27858	-0.24238
	(0.839)	(0.000)	(0.657)	(0.000)	(0.092)	(0.051)	(0.080)	(0.408)
Constant	1.06370	1.90360	1.66970	2.63130	0.78005	1.66840	1.01580	2.21670
	(0.105)	(0.000)	(0.122)	(0.000)	(0.178)	(0.000)	(0.219)	(0.002)
λ	-0.32854	-0.33364	-0.78591	-0.93606	-0.20047	-0.81260	-0.43219	-1.5220
	(0.185)	(0.014)	(0.172)	(0.025)	(0.562)	(0.021)	(0.490)	(0.119)
Adjusted R^2	0.2423	0.3345	0.2453	0.3367	0.1760	0.3651	0.1765	0.3667
N	1389	1171	293	1033	1308	938	374	1266

Figures in parentheses indicate *p*-values.

Table 11. Wage decompositions for occupation segregation alone with selectivity correction

Industry	Observed distribution		Predicted distribution		Observed difference	Explained difference	Residual difference
Group	p^u	p^r	$\hat{p}^u$	$\hat{p}^r$	$p^u - p^r$	$p^u - \hat{p}^r$	$\hat{p}^r - p^r$
	1	2	3	4	5	6	7
Blue-collar	0.5313	0.8258	0.6064	0.7779	-0.2945	-0.2466	-0.0479
White-collar	0.4687	0.1742	0.3936	0.2221	0.2945	0.2466	0.0479
	$\ln \overline{w}^u - \ln \overline{w}^r$	$\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$p^r \hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$p^r \overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$\ln \overline{w}^u(p^u - \hat{p}^r)$	$\ln \overline{w}^u(\hat{p}^r - p^r)$
	8	9	10	11	12	13	14
Blue-collar	0.2459	0.0778	0.2551	0.0642	0.2107	-0.3250	-0.0632
White-collar	0.2823	0.0102	0.2720	0.0018	0.0474	0.4362	0.0848
Total wage differentials			WE		WU	BE	BU
0.4569			0.0660 (14.45%)		0.2581 (56.48%)	0.1112 (24.34%)	0.0216 (4.73%)

Table 12. Wage decompositions for industry segregation alone with selectivity correction

Industry	Observed distribution		Predicted distribution		Observed difference	Explained difference	Residual difference
Group	p^u	p^r	$\hat{p}^u$	$\hat{p}^r$	$p^u - p^r$	$p^u - \hat{p}^r$	$\hat{p}^r - p^r$
	1	2	3	4	5	6	7
Manufacturing	0.4256	0.7776	0.6241	0.4818	-0.3520	-0.0562	-0.2958
Service	0.5744	0.2224	0.3759	0.5182	0.3520	0.0562	0.2958
	$\ln\overline{w}^u - \ln\overline{w}^r$	$\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$p^r\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$p^r\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$\ln\overline{w}^u(p^u - \hat{p}^r)$	$\ln\overline{w}^u(\hat{p}^r - p^r)$
	8	9	10	11	12	13	14
Manufacturing	0.2404	0.4110	-0.0782	0.3196	-0.0608	-0.0778	-0.4056
Service	0.4553	0.6314	-0.1763	0.1404	-0.0392	0.0934	0.4870
Total wage differentials			WE		WU	BE	BU
0.4570			0.4600 (100.67%)		-0.1000 (-21.89%)	0.0156 (3.41%)	0.0814 (17.81%)

Table 13. Industry-occupation specific wage functions with multinomial selection

Variable	Blue collar in M industry		White collar in M industry		Blue collar in S industry		White collar in S industry	
	Migrants	Residents	Migrant	Residents	Migrants	Residents	Migrants	Residents
Male	0.17517	0.33939	0.23810	0.32416	0.06399	0.09101	0.30560	0.21389
	(0.000)	(0.000)	(0.047)	(0.000)	(0.364)	(0.129)	(0.101)	(0.000)
Schooling	0.03459	0.03639	0.03432	0.05232	0.05849	0.04666	0.09631	0.02591
	(0.000)	(0.005)	(0.034)	(0.001)	(0.008)	(0.000)	(0.145)	(0.020)
Experience	0.03697	0.01844	0.01670	0.01278	0.00793	0.01099	0.02916	0.02022
	(0.000)	(0.015)	(0.159)	(0.085)	(0.645)	(0.228)	(0.300)	(0.002)
Experience^2	-0.00098	-0.00038	-0.00042	-0.00044	0.00015	-0.00024	-0.00063	-0.00063
	(0.000)	(0.057)	(0.238)	(0.004)	(0.741)	(0.238)	(0.438)	(0.000)
Cadre	0.15283	-0.15737	0.22745	0.65197	-0.03058	0.29053	0.42381	-0.10420
	(0.398)	(0.530)	(0.306)	(0.001)	(0.880)	(0.020)	(0.144)	(0.405)
Stateown	0.14467	0.09196	0.04804	0.18833	-0.00300	-0.12899	-0.21184	-0.00677
	(0.001)	(0.032)	(0.579)	(0.000)	(0.983)	(0.193)	(0.345)	(0.914)
Beijing	-0.19902	-0.25386	0.04732	-0.42993	0.17703	-0.34362	-0.40044	-0.52194
	(0.001)	(0.007)	(0.858)	(0.000)	(0.208)	(0.000)	(0.060)	(0.000)
Wuxi	-0.07946	-0.27195	-0.02017	-0.41594	0.10625	-0.63386	-0.59968	-0.64820
	(0.037)	(0.067)	(0.915)	(0.000)	(0.498)	(0.000)	(0.057)	(0.000)
Constant	0.34421	0.44021	0.36841	1.23666	0.99848	1.05377	0.19488	2.08109
	(0.000)	(0.083)	(0.489)	(0.000)	(0.100)	(0.019)	(0.905)	(0.000)
λ	0.26304	0.27781	0.12178	-0.38924	-0.26926	0.11188	0.08111	-0.37632
	(0.080)	(0.206)	(0.726)	(0.124)	(0.259)	(0.598)	(0.853)	(0.028)
Adjusted R^2	0.1451	0.2025	0.0622	0.2932	0.2122	0.2592	0.2805	0.3535
N	1080	634	309	537	228	304	65	729

Figures in parentheses indicate *p*-values. M denotes for industrial sector, and S for service sector.

Table 14. Wage decompositions with multinomial selection

Occupation-industry group	Observed distribution		Predicted distribution		Observed difference	Explained difference	Residual difference
	p^u	p^r	$\hat{p}^u$	$\hat{p}^r$	$p^u - p^r$	$p^u - \hat{p}^r$	$\hat{p}^r - p^r$
	1	2	3	4	5	6	7
B-M	0.2877	0.6421	0.4026	0.3739	-0.3544	-0.0862	-0.2682
W-M	0.2436	0.1837	0.2130	0.3904	0.0599	-0.1468	0.2067
B-S	0.1379	0.1356	0.2224	0.0915	0.0023	0.0464	-0.0441
W-S	0.3308	0.0386	0.1621	0.1442	0.2922	0.1866	0.1056
	$\ln\overline{w}^u - \ln\overline{w}^r$	$\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$p^r\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$p^r\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$\ln\overline{w}^u(p^u - \hat{p}^r)$	$\ln\overline{w}^u(\hat{p}^r - p^r)$
	8	9	10	11	12	13	14
B-M	0.1753	0.1131	0.0621	0.0726	0.0399	-0.10702	-0.3331
W-M	0.3166	0.2126	0.1040	0.0391	0.0191	-0.2067	0.2910
B-S	0.2057	-0.1115	0.3172	-0.0151	0.0430	0.0761	-0.0723
W-S	0.1562	0.1972	-0.0410	0.0076	-0.0016	0.3401	0.1924
Total wage differentials			WE		WU	BE	BU
0.3851			0.1042 (27.05%)		0.1004 (26.08%)	0.1025 (26.61%)	0.0780 (20.25%)

Note: B-M denotes for blue-collar in industrial sector, W-M for white-collar in industrial sector. B-S for blue-collar in service sector, and W-S for white-collar in service sector.

Table 15. Wage decompositions with multinomial selection for male

Occupation-industry group	Observed distribution		Predicted distribution		Observed difference	Explained difference	Residual difference
	p^u	p^r	$\hat{p}^u$	$\hat{p}^r$	$p^u - p^r$	$p^u - \hat{p}^r$	$\hat{p}^r - p^r$
	1	2	3	4	5	6	7
B-M	0.3183	0.6438	0.4827	0.4344	-0.3255	-0.1161	-0.2094
W-M	0.2470	0.1694	0.1371	0.3614	0.0776	-0.1144	0.1920
B-S	0.1435	0.1404	0.2122	0.0738	0.0031	0.0697	-0.0666
W-S	0.2912	0.0465	0.1680	0.1305	0.2447	0.1607	0.0840
	$\ln \overline{w}^u - \ln \overline{w}^r$	$\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$p^r \hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$p^r \overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$\ln \overline{w}^u(p^u - \hat{p}^r)$	$\ln \overline{w}^u(\hat{p}^r - p^r)$
	8	9	10	11	12	13	14
B-M	0.2107	0.0947	0.1160	0.0610	0.0747	-0.1591	-0.2871
W-M	0.3535	0.3869	-0.0335	0.0655	-0.0057	-0.1799	0.3019
B-S	0.2154	-0.0413	0.2567	-0.0058	0.0360	0.1171	-0.1119
W-S	0.1652	0.3169	-0.1517	0.0147	-0.0071	0.3073	0.1605
Total wage differentials			WE		WU	BE	BU
0.3824			0.1355 (35.43%)		0.0980 (25.63%)	0.0854 (22.35%)	0.0635 (16.60%)

Note: B-M denotes for blue-collar in industrial sector, W-M for white-collar in industrial sector. B-S for blue-collar in service sector, and W-S for white-collar in service sector.

Table 16. Wage decompositions with multinomial selection for industry and ownership

Occupation-industry group	Observed distribution		Predicted distribution		Observed difference	Explained difference	Residual difference
	p^u	p^r	$\hat{p}^u$	$\hat{p}^r$	$p^u - p^r$	$p^u - \hat{p}^r$	$\hat{p}^r - p^r$
	1	2	3	4	5	6	7
N-M	0.1942	0.6159	0.3944	0.3058	-0.4217	-0.1116	-0.3101
S-M	0.2309	0.1617	0.2308	0.1651	0.0692	0.0658	0.0034
N-S	0.1883	0.1474	0.1859	0.2947	0.0409	-0.1064	0.1473
S-S	0.3866	0.0749	0.1889	0.2344	0.3117	0.1522	0.1595
	$\ln\overline{w}^u - \ln\overline{w}^r$	$\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$p^r\hat{\beta}^u(\overline{X}^u - \overline{X}^r)$	$p^r\overline{X}^r(\hat{\beta}^u - \hat{\beta}^r)$	$\ln\overline{w}^u(p^u - \hat{p}^r)$	$\ln\overline{w}^u(\hat{p}^r - p^r)$
	8	9	10	11	12	13	14
N-M	0.2275	-0.1987	0.4262	-0.1224	0.2625	-0.1493	-0.4151
S-M	0.1916	0.1614	0.0302	0.0261	0.0049	0.0920	0.0048
N-S	0.2825	0.0245	0.2580	0.0036	0.0380	-0.1550	0.2146
S-S	0.5144	0.4880	0.0264	0.0366	0.0020	0.2646	0.2773
Total wage differentials			WE		WU	BE	BU
0.3852			-0.0561 (-14.56%)		0.3074 (79.81%)	0.0523 (13.58%)	0.0816 (21.18%)

Note: N-M denotes for non-state-owned enterprises in industrial sector, S-M for state-owned in industrial sector. N-S for non-state-owned in service sector, and S-S for state-owned in service sector.

Table 17. Percentage distributions of resident and migrant workers by occupation-industry and ownership groups

Occupation-industry and ownership	Migrants	Residents
Blue collar in manufacture industry	64.21% (0.4795)	28.77% (0.4528)
Mean log hourly wage (total)	1.0667 (0.5040)	1.2420 (0.5580)
State-owned enterprises	14.63% (0.0086)	15.56% (0.0077)
Mean log hourly wage	1.1722 (0.4263)	1.3011 (0.4960)
Non-state-owned enterprises	49.58% (0.0122)	13.20% (0.0072)
Mean log hourly wage	1.0355 (0.5210)	1.1720 (0.6169)
White collar in manufacture industry	18.37% (0.3874)	24.36% (0.4294)
Mean log hourly wage (total)	1.0971 (0.6514)	1.4078 (0.6769)
State-owned enterprises	5.77% (0.0057)	13.29% (0.0072)
Mean log hourly wage	1.1171 (0.5485)	1.4910 (0.6241)
Non-state-owned enterprises	12.60% (0.0081)	11.07% (0.0067)
Mean log hourly wage	1.0794 (0.6944)	1.3079 (0.7240)
Blue collar in service sector industry	13.56% (0.3424)	13.79% (0.3449)
Mean log hourly wage	1.4357 (0.5475)	1.6414 (0.5851)
State-owned enterprises	1.55% (0.0030)	7.58% (0.0056)
Mean log hourly wage	1.5358 (0.6614)	1.5998 (0.4731)
Non-state-owned enterprises	12.01% (0.0079)	6.22% (0.0051)
Mean log hourly wage	1.4228 (0.5316)	1.6921 (0.6963)
White collar in service sector industry	3.86% (0.1928)	33.08% (0.4706)
Mean log hourly wage	1.6666 (0.8136)	1.8222 (0.6623)
State-owned enterprises	1.72% (0.0032)	25.32% (0.0093)
Mean log hourly wage	1.5829 (0.5416)	1.8692 (0.5732)
Non-state-owned enterprises	2.14% (0.0035)	7.76% (0.0057)
Mean log hourly wage	1.7330 (0.9826)	1.6691 (0.8780)
Total	100%	100%

Note: numbers in the brackets are standard deviations.

Appendix 1.

(Source: Figure 1.1 of Drury and Arneburg, 2001)

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