SELF-SELECTION AND WAGE DIFFERENTIALS IN URBAN CHINA:

A POLYCHOTOMOUS MODEL WITH SELECTIVITY

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Hongliang Zhang

Department of Urban Studies and Planning
Massachusetts Institute of Technology
Cambridge, Massachusetts

Abstract I (250 words)

Most existing studies on the wage determination in China's urban labor market are based on the assumption of exogenous sector choices and are therefore subject to estimation errors when sector selections are endogenous. **One important source for such endogeneity is the unmeasured workers' productive abilities, which affect both workers' sector choices and wage levels, but are not captured by individual data set and therefore not included in the estimations.** This study reconciles the problem by treating sector selections endogenously in the wage determination model. Lee's (1983) generalized selection-correction technique (mlogit-OLS estimate) is used to correct selection biases in a four-alternative choice set by distinguishing urban employment in China by ownership into four sectors: government (GOV), state-owned enterprises (SOE), urban collective enterprises (UCE), and private/individual enterprises (PIE). The estimation results indicate that there exists unmeasured worker heterogeneity across labor market sectors in urban China. With respect to their unmeasured productivity, workers adversely choose the state sector (GOV and SOE), but positively select into the non-state sector (UCE and PIE). The extents of the selectivity in the four sectors can be ranked in a continuum as PIE, UCE, SOE, and GOV, with PIE having the largest positive selection and GOV having the largest negative selection. The study further examines and contrasts three conceptually distinct measurements of the pairwise sectoral wage differential: the conditional differential, the unconditional differential, and the discrimination differential, with the discrimination differential measuring the premium received by workers participating in one sector versus the other due to the sectoral difference in their rewards to workers' observed human capital. The results suggest that the wage settings in China

are discriminatory against the non-state sectors, with state sector workers receiving a substantial premium over non-state sector workers.

I. Introduction

Employment sector choices and wage differentials across ownership sectors have attracted a great deal of attention of labor market studies in developing countries recently. A substantial body of empirical studies has investigated the issue of labor allocation and wage differentials across ownership sectors (e.g., Rutkowski, 1996 and Adamchik & Bedi, 2000 on Portland; Assaad, 1997 on Egypt; Tansel, 1999 on Turkey; Zhao, 2002 and Dong & Bowles, 2002 on China). The issue is particularly important for transitional economies like China where the state sector used to comprise the majority of wage employment but is now undergoing a substantial transformation. While this transition is occurring, the pre-reform administrative system continues to influence labor allocation and wage determination in both the state sector and the rest of the labor market. The existing administrative forces and the emerging market forces, together, result in a dualistic urban labor market, which is characterized by the existence of labor market that are segremented by

and result in a dualistic urban labor market. the system of labor allocation and the determination of rewards for work, especially for the state sector. in both the state sector and the rest of the labor market. The coexistence of the the existing both the structure of the existing economic system and the ongoing transformation process would have significant influence on labor allocation and wage setting in the rest of the labor market.

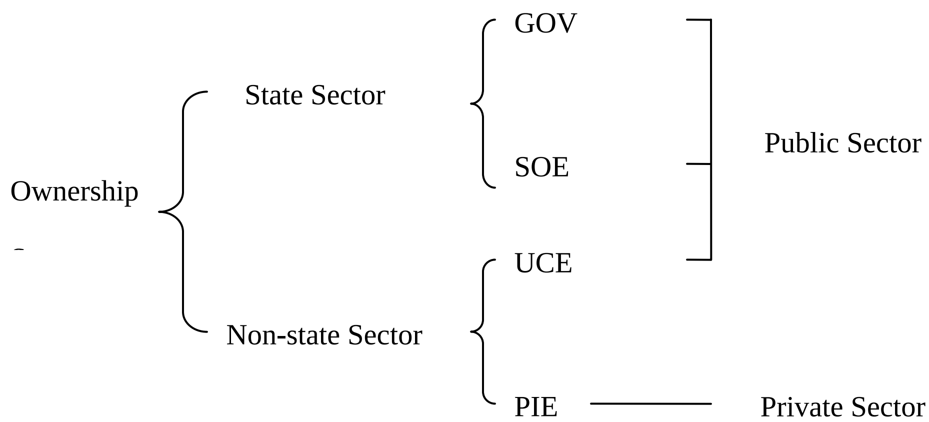
elements of the pre-reform administrative system continue to influence the allocation of resources in the economy Therefore, a comprehensive examination of labor allocation across ownership sectors and the wage determination for each sector is essential to understand the urban labor market in China.

However, most existing studies on

Answering the above question requires a comprehensive examination of labor allocation across sectors and sectoral wage determinations. An important potential empirical problem in such an examination is the sample selection bias. More specifically, the sample used to estimate the wage equation for each sector consists only of workers who self-select into that sector from the relative universe which in our study is all full-time urban employees in China. The possibility of sample selection biases arises when the sector selection is non-random and the unobserved worker characteristics affecting the sector choice also influence the wage level (Heckman, 1976, 1979). Examples for such variables include intelligence quotient (IQ), entrepreneurial ability, creativity, and "talent" at providing low effort, which are not observed in labor surveys but can impact both sector choice behaviors and wage levels. When self-selection bias exists, simple OLS wage regressions, which treat sector choices exogenously, are biased and provide inconsistent estimates of the wage coefficients. In that situation, workers' sector choices have to be treated endogenously to get consistent estimates of the wage equation coefficients. Although wage determinations have been intensively explored for China in the last two decades (e.g., Jamison & Van Der Gaag 1987; Byron and Manaloto, 1990; Johnson & Chow, 1997; Maurer-Fazio 1999; Zhang *et al.* 2002; Li, 2003; Fleisher & Wang, 2004), most of these studies are OLS estimates based on the assumption of exogenous sector choices and are subject to measurement errors when sector selection exists. To our knowledge, only two recently published papers (Zhao, 2002; Dong & Bowles, 2002) attempt to analyze the issue of the endogenous sector selection behavior. Zhao (2002) applies Heckman's two-step approach to examine pairwise selection between state-owned enterprises (SOE) and each of the following three alternative non-SOE sectors: urban collective enterprises (UCE), domestic private enterprises (DPE), and foreign-invested enterprises (PIE). Based on the 1996 urban household survey data, Zhao finds that there is no significant sample selection bias for any of the three selection models. However, applying the similar approach to a labor survey on China's light consumer goods industry in 1998, Dong and Bowles (2002) find that self-selection bias does exist between *"foreign-invested firms"* (FIF) and *"administered firms"* (AF). However, a common drawback in the two studies is that they are both restricted by the limitation of Heckman's (1976, 1979) two-step model that it is only applicable to binary choice situations. To fit into Heckman's framework, both Zhao (2002) and Dong and Bowles (2002) reformulate their analyses to examine sector selection in a binary choice case. Zhao uses a pairwise method to examine the selection between SOE and each of the three alternative non-SOE sectors, respectively. Dong and Bowles reformulate their analysis into a binary selection between FIF and AF by aggregating state-owned enterprises (SOE), township and village enterprises (TVE) and joint ventures (JV) together into the AF category. However, both of their reformulation strategies are subject to criticisms. Zhao's approach lacks theoretical grounds for the pariwise correction for only a partial of available sector choices instead of a full correction for all simultaneous choices. Dong and Bowles's approach may have potential problem due to the significant within-group heterogeneity in AF, given that SOE, TVE, and JV in China differ very substantially in their operation objectives and wage determination mechanisms, and they are subject to varying degrees of market pressure and administrative influence.

Our study reconciles the problems in the previous researches by applying a general selection-correction technique proposed by Lee (1983) to correct selection biases in a polychotomous choice case, i.e. individuals have more than two alternative choices. In his classical paper, Lee extends the classical Heckman's probit-OLS two-step estimate to a multinomial logit-OLS (mlogit-OLS) two-step estimate to allow selection correction for polychotomous choices. For its ability to correct selection in polychotomous choices and computational ease, Lee's mlogit-OLS two-step model is then widely applied in empirical studies on sample selection in polychotomous choice models (e.g, Trost & Lee, 1984; Gyourko & Tracy, 1988; Cohen & House, 1996; Tansel, 1999; Brewer et al., 1999; Hilmer, 2001). However, to our knowledge, this paper is the first application of such type of generalized selection model to China. In this paper, we distinguish urban employment in China by ownership into four sectors, government (GOV), state-owned enterprises (SOE), urban collective enterprises (UCE), and private/individual enterprises (PIE). Figure 1 shows the relationship among the terminologies on ownership sectors we used in remainder of the paper. The state sector includes SOE and GOV, and the non-state sector includes UCE and PIE. The private sector stands for PIE only, while the public sector includes all the other three publicly-owned sectors (GOV, SOE, and UCE).

Figure 1 Relationship among Terminologies on Ownership Sectors



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The sample frame is restricted to full-time employees only. Therefore, labor market participation is assumed as a priori in our study. Individuals in the sample frame face a four-alternative choice given their preference and sector need. In our first stage of estimation, we estimate a four-choice multinomial logit model for sector selection. We then use the multinomial logit estimation results to construct the selection-correction terms. In the second stage, we estimate Mincerian (1974) sectoral wage equations by OLS regressions with the selection-correction terms added to control for sample selections.

A review of the literature on earning differentials in China shows that most studies focus on three types of earning differentials: regional differentials(e.g., Chen & Fleisher, 1996; Morduch & Sicular, 2002), male-female differentials (e.g., Hughes & Maurer-Fazio, 2002; Shu & Bian, 2003), and urban-rural disparities (Knight & Song, 1999). As far as we know, Zhao's (2002) study mentioned earlier is the only published paper focusing on earning differentials across ownership sectors. However, no decomposition strategy is used in Zhao's paper to examine the sources of the differentials. We intend to fill this research gap in this paper by applying the Oaxaca-Blinder (Oaxaca, 1973; Blinder, 1973) decomposition in our analysis of sectoral wage differentials. The results we present on wage differentials are interesting for a variety of reasons. First, we use an extension of Oaxaca-Blinder method to decompose the wage differentials from the selection model into three components: (1) the endowment effect, (2) the remuneration effect, and (3) the selection effect. Second, we emphasize and contrast three conceptually distinct measurements of wage differentials from selection models: (1) conditional wage differentials, (2) unconditional wage differentials, and (3) discrimination differentials. The conditional wage differential measures the observed (realized) wage gap across sectors when selection effects are already taken into account. In contrast, the unconditional wage differential is the expected wage gap across sectors in the absence of sample selection (i.e., the selection effects are "zeroed out"). The discrimination differential measures the offered wage gap across sectors for the same individual in the absence of sample selection. Finally, the discrimination differential is interpreted as the premium received by workers participating in one sector versus the other due to the sectoral difference in their rewards to workers' observed human capital.

The estimation in this paper is derived primarily from a 1995 urban household survey data. The rest of the paper is organized as follows. Section II provides a brief overview of China's urban labor market. Section III discusses the conceptual framework for the mlgoit-OLS two-step model. Section IV describes the data and provides descriptive statistics for the key variables used in the analysis. Section V contains a discussion on the empirical results for the sector selection and sectoral wage equations. Section VI decomposes the estimated sectoral wage differentials based on the results in Section V. Finally, Section VII summarizes and concludes.

II. Overview of China's Urban Labor Market

China's pre-reform urban labor allocation system was one of the world's most highly centralized and tightly controlled. Almost all non-agricultural employment was in the public sector. The state played the key role in shaping labor market outcomes by assigning urban labors with the "iron rice bowl"—lifelong employment in the public sector, including both the state sector and the urban collective sector. There was very little labor mobility and wages were determined institutionally. The state-administered grade wage system failed to reward performance and provided little incentive to improve productivity. The chronic problems in labor allocation and wage structure helped to create a situation of economic stagnation, low productivity, lack of incentives, immobility, and pervasive overstaffing and underemployment in the public sector (Knight & Song, 1995).

In part as a response to these problems, China launched its economic reform in the late 1970s to move toward a market economy. Among other changes, the labor allocation and reward system has been undergoing a transition from an administrative system toward a market system. The state started the labor and wage reform in the early 1980s by providing workers a bonus to reward productivity. The labor contract system followed in the late 1980s to replace the "iron rice bowl" (Sabin, 1999). In the early 1990s, the voluntary severance program was introduced into SOE to solve the problem of overstaffing and underemployment. Among all the changes in the public sector, the most striking and influential is the mandatory labor retrenchment in public enterprises *(xigang)* started in 1994. By the end of 1999, the official figure of the accumulated laid-off workers exceeded 24.4 million, representing 13.2 percent of the urban labor force (Appleton, *et al.,* 2002).

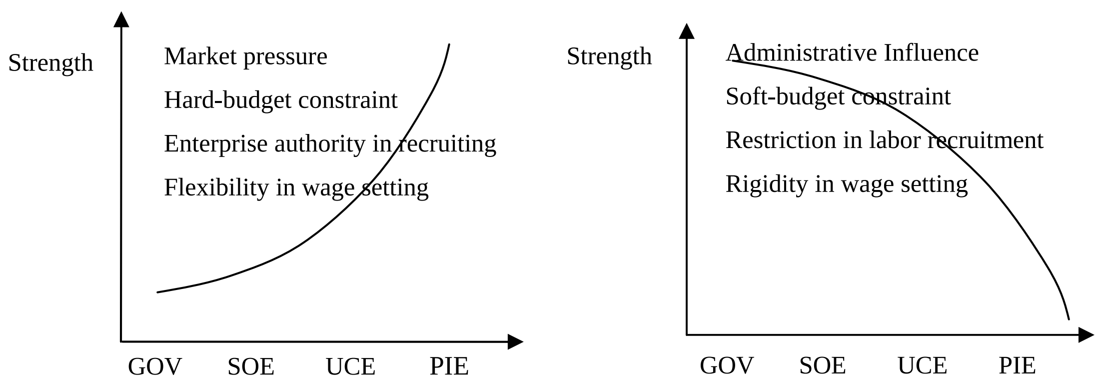
At the beginning of China's economic reform, private firms were virtually non-existent in urban China. In 1980, 76.2 percent of urban employment was in the state sector, 23.0 percent in the urban collective sector, and only 0.8 percent in the private sector (Zhao, 2002). During the reform period, the urban employment structure changed significantly in China. By 2002, the state sector's share of overall urban employment declined to 28.9 percent, while the urban collective sector's share dropped to 4.5 percent (NSB, 2003).[1] All the gradual reforms in the public sector, together with the significant change in the employment structure, have dramatically reshaped China's urban labor market, leading to

[1] The percentages are derived by dividing the total employed persons in each ownership sector by the overall urban employment. However, after 1990, the sum of employment by ownership sectors is less than the total urban employment since they are from different sources. The total urban employment is based on urban labor force survey, while the employment data by ownership are based on the enterprise self-reported data from all the independent accounting units covered by the Comprehensive Labor Statistics Reporting System (CLSRS) (NBS, 2003, p. 116). The gap between the sum of employment by ownership from CLSRS and the total urban employment is mainly due to two reasons: (1) the underreporting on employment for some enterprises covered by the CLSRS and (2) the informal employment not included by the CLSRS. The published statistics show that the gap is getting larger over the time. By 2002, 39% of the nation's urban employment is not included in the CLSRS, compared to only 9% in 1995 (NBS, 1996, 2003). However, since most of the state sector and urban collective sector employment is covered by the CLSRS and intentional misreporting would be rare in both sectors, the gap is dominated by the underreporting and informal employment in the private sector. There might still be downward biases in the percentages we derived for the state sector and the urban collective sector, but the magnitude of the biases should be trivial.

greater labor mobility and a more market-determined labor allocation and reward system. However, by comparison with other market reforms in China, the labor market reform is tardy and limited. China has not proceeded far enough to achieve an integrated and properly functioning urban labor market (Knight & Song, 1995). The urban labor market is still largely segmented by ownership sectors because of sectoral differences in the strengths of market/administration influence, hard/soft-budget constraint, the degrees of enterprise autonomy in labor recruitment, and the mechanism of wage settings (Dong & Bowles, 2002).

Figure 2 Characteristics Comparison for the Four Ownership Sectors

Figure 2.1 Figure 2.2



Source: Author's explanation.

Figure 2 summarizes the comparison on sectoral characteristics among the four ownership sectors. GOV is under strict control of the administrative system and least exposed to market pressure. It has the most rigorous administratively-determined recruitment system and wage setting among all the four ownership sectors. SOE is under a transformation from the previous central planning system to the market system. Some reforms have been made to remove the obstacles of the old system for the market-oriented transformation. However, SOE are still largely under the control of the state administrative agencies and are subject to administrative labor regulation in terms of job allocation, wage settings, and welfare provisions. The labor recruitment and reward system in SOE is expected to be a little more flexible than GOV, but still much more rigorous than the non-state sectors. UCE are typically small-scale capital-scarce enterprises. They are subject to harder budget constraints and are more loosely controlled by administrative agencies and regulations compared to SOE, which makes their labor allocation and wage settings more flexible. The PIE sector includes hard-budget-constrained, profit-oriented private or individual enterprises. They operate under a much looser regulatory regime and have more enterprise autonomy in labor recruitment and reward than the other sectors Thus, the four ownership sectors—GOV, SOE, UCE, and PIE—examined in this study can be located on a continuum with GOV representing the most "administered" sector and PIE the most "market-operated" sector.

III. A mlogit-OLS Model with Selection-Correction

As we have mentioned in Section I, a potential empirical problem in most existing studies on the wage determination in China is the sample selection bias due to the assumption of exogenous sector selections. To reconcile this problem, we treat the sector selection behavior endogenously in this study to control for the potential sample selection problem. Given that we have formulated the sector selection as a four-alternative choice, we adopt Lee's (1983) mlogit-OLS two-step estimation framework for modeling polychotomous choice problems with mixed continuous and discrete dependent variables. According to the rational choice theory, we assume individuals can rank mutually exclusive alternatives in order of utility and will choose to work in the sector with the maximum expected utility given their tastes and relevant resource constraints. The model can be characterized by the following equations:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = z_i^{'}\gamma_j + \varepsilon_{ij} \qquad (1)$$

$$y_{ij} = x_i^{'}\beta_j + u_{ij} \qquad (2)$$

where

i = *1, 2,…, N;*
j = *1, 2,… , M;*
U_{ij} = the utility individual *i* receives from working in sector *j*;
$z_i^{'}$ = a vector of exogenous individual characteristics affecting the sector selection;
γ_j = a vector of unknown utility parameters for sector *j;*
ε_{ij} = a disturbance term with zero population mean and constant variance;
y_{ij} = natural logarithm of hourly wage;
$x_{i_i}^{'}$ = a vector of exogenous individual characteristics determining the wage rate;
β_j = a vector of unknown sector-specific wage parameters to be estimated;
u_{ij} = a disturbance term with zero population mean and constant variance.

The two error terms ε_{ij} and u_{ij} represent the impact of unobserved variables on utilities and wages, respectively. Let us define the indicator function

$$I_i = j \quad \text{IFF} \quad \text{individual } i \text{ chooses sector } j, \quad j=1,\dots, M \qquad (3)$$

The sampling rule is that y_{ij} is observed if and only if $I_i=j$. The polychotomous choice model is formulated by utility maximization (McFadden, 1973).

$$I_i = j \qquad IFF \qquad U_{ij} > \max_{\substack{k=1,\dots,M \\ k\neq j}} U_{ik} \qquad (4)$$

Following the formulation in Lee (1983), we define the following residual for each individual and sector:

$$\eta_{ij} = \max_{\substack{k=1,2,\ldots,J \\ k \neq j}} U_{ik} - \varepsilon_{ij} \tag{5}$$

Substituting η_{ij} from (1) and (5) into (4) and rearranging, we obtain a reformulation of the sector choice indicator function:

$$I_i = j \qquad IFF \qquad \eta_{ij} < z_i^{'} \gamma_j \tag{6}$$

A very important note of Lee's formulation is that it relates the selection of the j^{th} alternative in a polychotomous choice situation as a binary decision, i.e., the j^{th} alternative will either be chosen or not, mutually exclusively (Trost & Lee, 1984). Assume now the disturbances $\eta_{ij} s$ are independently and identically Gumbel distributed. Thus, their cumulative and density functions are respectively (Bourguignon, Fournier & Gurgand 2001):

$$G(\eta_{ij}) = \exp(-\exp(-\eta_{ij})) \tag{7}$$

$$g(\eta_{ij}) = \exp(-\eta_{ij} - \exp(-\eta_{ij})) \tag{8}$$

As shown by McFadden (1973), the probability that alternative *j* will be chosen by individual *i* is:

$$\Pr(I_i = j) = \Pr(\eta_{ij} < z_i^{'} \gamma_j) = F(z_i^{'} \gamma_j) = \frac{\exp(z_i^{'} \gamma_j)}{\sum_{k=1}^{M} \exp(z_i^{'} \gamma_k)} \tag{9}$$

The worker's sector choice, then, is analyzed with a multinomial logit model. Using only observations who select into each sector, the conditional expected sectoral wage can be derived as:

$$\begin{aligned} E[y_{ij} \mid I_i = j] &= E[y_{ij} \mid \eta_{ij} < z_i^{'} \gamma_j] \\ &= x_i^{'} \beta_j + E[u_{ij} \mid \eta_{ij} < z_i^{'} \gamma_j] \end{aligned} \tag{10}$$

When $E[u_{ij} | \eta_{ij} < z_i^{'}\gamma_j] \neq 0$, the least squares estimation using the observed data produces inconsistent estimates of β_j. The case where u_{ij} and η_{ij} follow a bivariate normal distribution leads to the standard Heckman's two-step selection bias correction. A similar two-step correction procedure can be used to estimate (10) by transforming η_{ij} into a standard normal random variable (Gyourko & Tracy, 1988).

$$\eta_{ij}^{*} = \Phi^{-1}[(F(z_i^{'}\gamma_j)] \tag{11}$$

Where Φ denotes the cumulative distribution function (*cdf)* of the standard univariate normal distribution. Further, (6) can be transformed as:

$$I_i = j \qquad IFF \qquad \eta_{ij}^{*} < \Phi^{-1}[F(z_i^{'}\gamma_j)] \tag{12}$$

Substituting from (12) into the conditional term in Equation (10) yields that:

$$E[y_{ij} | I_i = j] = x_i^{'}\beta_j + E[u_{ij} | \eta_{ij}^{*} < \Phi^{-1}[F(z_i^{'}\gamma_j)]] \tag{13}$$

The conditional wage can be evaluated using the standard methods as:

$$\begin{aligned} E[y_{ij} | I_i = j] &= x_i^{'}\beta_j + \sigma_j\rho_j\left[-\frac{\phi\{\Phi^{-1}[(F(z_i^{'}\gamma_j)]\}}{\Phi\{\Phi^{-1}[F(z_i^{'}\gamma_j)]\}}\right] + v_{ij} \\ &= x_i^{'}\beta_j + \sigma_j\rho_j\left[-\frac{\phi\{\Phi^{-1}[(F(z_i^{'}\gamma_j)]\}}{F(z_i^{'}\gamma_j)}\right] + v_{ij} \end{aligned} \tag{14}$$

where ϕ and Φ denote the probability density function (*pdf)* and cumulative distribution function (*cdf)* of the standard univariate normal distribution, respectively. σ_j is the variance of the error term ε_{ij}, ρ_j is the correlation coefficient between u_{ij} and η_{ij}^{*}, and the error term v_{ij} has a zero mean and is uncorrelated with u_{ij}.

Equation (14) can be estimated in two stages. In the first stage, we estimate the polychotomous choice model by the logit maximum likelihood method. The multinomial logit model results will then be used to construct the selection-correction term (inverse Mills ratio) for individuals selecting into each sector (Greene, 2003, p. 759).

$$\hat{\lambda}_{ij} = -\frac{\phi\{\Phi^{-1}[(F(z_i'\gamma_j)]\}}{F(z_i'\gamma_j)}, \qquad where \;\; F(z_i'\gamma_j) = \frac{\exp(z_i'\gamma_j)}{\sum_{k=1}^{M}\exp(z_i'\gamma_k)} \tag{15}$$

In the second stage, the selection-correction term $\hat{\lambda}_{ij}$ will be included in the wage regression estimation and a simple OLS regression will yield a consistent estimate of β_j.

$$\begin{aligned} y_{ij} &= x_i'\beta_j + \rho_j\sigma_j\,\hat{\lambda}_{ij} + v_{ij} \\ &= x_i'\beta_j + \delta_j\hat{\lambda}_{ij} + v_{ij} \end{aligned} \tag{16}$$

The first term in Equation (16) is the offered or unconditional wage in sector *j*, while the second term captures the sector selection effect. Adding the two provides the conditional (or observed) wage in sector *j* (Bedi, 1998). A very important reference is that the interpretation of selection is counterintuitive as it runs against the estimated sign of δ_j (Gyourko & Tracy, 1988; Hilmer, 2001). The product $\delta_j\hat{\lambda}_{ij}$ can be interpreted as the estimate of the difference between the conditional wage and the unconditional wage in sector *j*, i.e., the received wage difference between individual *i* who self-selects into sector *j* ($\hat{\lambda}_{ij} \neq 0$) and another individual *k* with the same observed characteristics ($x_i = x_k$) but selected at random and assigned to sector *j* ($\hat{\lambda}_{kj}$ =0). The formulation of

$\hat{\lambda}_{ij}$ in Equation (15) shows that $\hat{\lambda}_{ij}$ is always negative for individuals self-selecting into sector j. Therefore, a significant estimate of δ_j with a negative sign means a positive selection effect ($\delta_j \hat{\lambda}_{ij}$ >0), indicating a positive selection for sector j in terms of workers' productivity[2], while a significant positive estimate of δ_j indicates an adverse selection in sector j.[3]

A major concern in using the Heckman-type two-step estimate is related to the identification of the selection equation and the wage equation. The underlying economic model often imposes the same variables to appear in both steps of estimation ($x_i = z_i$). Although the inverse Mills ratio is a nonlinear transformation of z_i, depending on the nonlinearity in the inverse Mills ratio alone to solve the identification problem always results in inflated second-step standard errors and unreliable estimates of β in the wage

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[2] When $\hat{\delta}_j$ is significant and negative, the product $\hat{\delta}_j \hat{\lambda}_{ij}$ is positive, indicating that given the observed individual characteristics (x_i), workers self-selecting into sector j in general receive higher wages than those randomly assigned individuals. Since wage is the pecuniary reward to productivity, it implies that workers self-selecting into sector j has higher unobserved productivity—productivity net of observed individual characteristics—than those random selected individuals from the sample frame. Therefore, sector j has a positive selection in terms of workers' (unobserved) productivity.

[3] Another perspective to interpret the selection is from the correlation between u_{ij} and ε_{ij}, the two error terms in Equation (1) and (2). A positive correlation coefficient (ξ_j) between u_{ij} and ε_{ij} means that the unobserved variables leading an individual to select into sector j will also increase his/her received wage in sector j. This implies that workers self-selecting into sector j have above-average productivity controlling for observed worker characteristics and sector j has a positive selection in workers' quality. However, the definition of η_{ij} (Equation (5)) shows that η_{ij} is negatively correlated with ε_{ij}, ξ_j should have the opposite sign as the correlation coefficient between u_{ij} and η_{ij}. Since δ_j in Equation (16) has the same sign as ρ_j (for σ_j >0), which is the correlation coefficient between u_{ij} and η^*_{ij} (the standardized transformation of η_{ij}), ξ_j has the opposite sign as δ_j. Therefore, a significant negative estimate of δ_j implies a positive selection in sector j. Similarly, a significant positive estimate of δ_j implies an adverse selection in sector j.

equation (Vella, 1998). To achieve identification, we need to add at least one variable in the selection equation which is excluded from the wage equation (i.e., the identification variable only impacts individual's sector choice but not the wage level). In this study, we choose "nature-of-recruitment" as the identification variable for the selection equation. The rationale is that individuals' job entry types can whose current jobs are assigned by the government or inherited from their parents have greater access to state sector jobs (i.e., SOE and GOV), while individuals whose current jobs are self-found are more likely to work in the non-state sectors (i.e., UCE and PIE). However, once the sector choice is known, the way of job entry is unlikely to impact the wage rate. In addition, the use of educational dummies and age as opposed to schooling and experience in the selection equation also helps to solve the identification problem.

IV. Data Description

For our study, we use the urban sample in Chinese Household Income Project 1995 (CHIP-95)[4] as the primary data set for analysis. The survey was conducted in 1996 by Institute of Economics, Chinese Academy of Social Sciences (CASS). It includes both an urban sample and a rural sample. Given the focus of this paper is on China's urban labor market, we use only the urban survey data in our analysis. The CHIP-95 urban sample was drawn from a larger nationally representative urban sample from the National Statistics Bureau (NSB) through a multistage sampling process. First, the following 11

[4] Riskin, Carl, Renwei Zhao and Shi Li. CHINESE HOUSEHOLD INCOME PROJECT, 1995 [Computer file], ICPSR version. Amherst, MA: University of Massachusetts, Political Economy Research Institute [producer], 2000. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2000.

provinces were selected out of a total of 31 provinces: Anhui, Beijing, Gansu, Guangdong, Henan, Hubei, Jiangsu, Liaoning, Shanxi, Sichuan and Yunnan. Second, 69 cities were chosen from these 11 provinces. The CHIP-95 urban sample finally includes 21,698 individuals from 6,931 urban households. For this study, we restrict the valid sample frame to full-time workers aged between 18 and 65 who provide information on their earnings and personal and job characteristics.[5] Given that our primary focus in this paper is to examine sector selection and sectoral wage determination, we need to measure workers' wages and employment sectors correctly. As the wage variable, we use the hourly wage in 1995. To be consistent across sectors, we use a very inclusive definition of wage income, which includes all sources of workplace-related income, including subsidies for public sector workers and private/individual enterprise profits. Non-work-related incomes, including property income, transfer income, and income from household sideline production, are excluded. Hourly wage is calculated by dividing annual wage by the estimated working hours per year[6]. The valid sample frame includes 9,914 observations, which we classify into the following four categories according to the ownership of their primary workplaces: SOE (52.9 percent), GOV (29.7 percent), UCE (13.9 percent), and PIE (3.4 percent)[7,8]. The "other" category (47 observations) is excluded to avoid ambiguity.

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[5]The valid sample frame only includes workers who were employed throughout year 1995 and worked on average no less than 30 hours per week.

[6] We exclude Individuals (53 observations) whose estimated hourly wage is less than 0.30RMB (0.04 USD) from the sample frame as the wage rates are too low to be realistic in urban China and can be regarded as reporting errors.

[7] Note that the employment share by ownership in the valid CHIP-95 urban sample differs significantly from the national labor statistics published by NBS. The share of private sector employment is much lower than national statistics, while the share of public sector employment is much higher. The discrepancy

Variable definitions and descriptive statistics by ownership sectors are provided in Table 1. We can see apparent differences in mean statistics for worker profiles of the four sectors. PIE tends to hire younger workers, with private sector employees about 4.0(/3.2/3.0) years younger than those in GOV (/SOE/UCE). The age gap is mirrored, and even blown up, in the average experience difference. The average labor market experience for PIE workers is 5.8 (/5.4/4.3) years less than GOV (/SOE/UCE) workers. A potential explanation of the amplification of the sectoral difference in experience is the delayed entry into the labor market for PIE employees. A further examination shows that the average labor market entry age is 18.7 for SOE, 19.2 for GOV, 19.7 for UCE, and 21.0 for PIE, which confirms our hypothesis of the delayed labor market entry for both UCE and PIE workers. UCE has a much higher female-male ratio (3:2) than the other three sectors. More than a quarter of the private sector employees have never married, compared to about one-tenth of the employees in the other three sectors. The state

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between published national labor statistics and household survey results is not unique to our data. Knight and Song (1991, 1995) using the 1986 and 1988 urban household surveys and Zhao (2002) using the 1996 urban household survey both report a much higher share of public sector employment than the published official labor statistics. The published national labor statistics are not based on urban household surveys; but the enterprise self-reported data from all the independent accounting units covered by the Comprehensive Labor Statistics Reporting System (CLSRS) (NBS, 2003, p. 116). One possibility is that the CHIP-95 urban household survey under-samples households with private sector employees. Migrant workers, who are generally employed in the private sector or informal sectors, are not included in the CHIP-95 urban household survey. However, some of them are counted in the CLSRS enterprise self-reported data. Another explanation is misreporting. Household survey participants may tend to identify themselves as state sector employees even though they worked in the private sector during the year. The Chinese urban labor market situation in the 1990s is that the majority of the private sector workers originally held positions in SOE or UCE. Even though they had left their original work units, a lot of them were still associated to their original work units and may still receive stipends and benefits from their original work units. Therefore, when asked about the ownership of their primary workplace, they may either intentionally or unintentionally give answers about their original work units as they may not think their current occupation is a kind of formal job.

[8] PIE includes the following five categories of ownership: private enterprise, self-employed individual enterprise, sino-foreign joint venture, foreign-owned enterprise, and township and village enterprise (TVE). 65 observations who identified themselves as “owner/manager of individual or private enterprises”, reported the ownership of their primary workplace as SOE, GOV, UCE, or other. For reasons discussed in footnote 9, we reclassify them as private sector employees.

sectors have much higher shares of party members among their employees, with party members accounting for 40.7 percent and 22.3 percent of GOV and SOE workforces, respectively. The “nature-of-recruitment” variable provides the information on whether the individual’s current job is self-found. 82.0 percent of the employees in the sample frame indicated that their jobs were assigned by the government or inherited from parents, which left only 18.0 percent who reported that their jobs were self-found. However, significantly higher portions of workers in PIE (67.0 percent) and UCE (29.3 percent)

Table 1 Variable Definitions and Mean Statistics by Ownership Sector

		All workers	SOE	GOV	UCE	PIE
Hourly wage	Hourly wage (in RMB)	3.160	3.094	3.586	2.490	3.212
		(2.142)	(1.978)	(2.410)	(1.788)	(2.593)
Log hourly wage	logarithm of hourly wage	0.986	0.975	1.137	0.726	0.919
		(0.578)	(0.562)	(0.526)	(0.610)	(0.706)
Weekly working hours	Average working hours per week (hours/week)	43.031	43.090	41.415	44.163	51.543
		(7.243)	(6.457)	(6.100)	(8.015)	(14.278)
Age	Age (years)	38.759	38.643	39.469	38.495	35.484
		(9.539)	(9.338)	(9.883)	(9.069)	(10.627)
Experience	Experience (years)	19.653	19.895	20.244	18.750	14.472
		(9.608)	(9.435)	(9.989)	(8.842)	(10.154)
Schoolinga	Years of schooling (years)	11.638	11.324	12.978	10.153	10.917
		(2.669)	(2.524)	(2.433)	(2.400)	(2.869)
Primaryb	Completed primary school (6 years)	0.049	0.049	0.017	0.108	0.109
		(0.217)	(0.215)	(0.128)	(0.310)	(0.312)
Lower secondary	Completed lower secondary school (9 years)	0.289	0.327	0.130	0.467	0.339
		(0.453)	(0.469)	(0.337)	(0.499)	(0.474)
General secondary	Completed general secondary school (12 years)	0.243	0.277	0.166	0.274	0.274
		(0.429)	(0.447)	(0.372)	(0.446)	(0.447)
Vocational secondary	Completed vocational secondary school (12 years)	0.175	0.162	0.252	0.080	0.100
		(0.380)	(0.368)	(0.434)	(0.272)	(0.301)
Professional school	Completed professional school (15 years)	0.164	0.136	0.270	0.059	0.100
		(0.370)	(0.343)	(0.444)	(0.235)	(0.301)
University	Completed university or above (16 years)	0.079	0.049	0.165	0.012	0.077
		(0.271)	(0.217)	(0.371)	(0.110)	(0.267)
Female	1 for female, 0 for male	0.463	0.437	0.443	0.598	0.490
		(0.499)	(0.496)	(0.497)	(0.490)	(0.501)
Married	1 for ever married (married, divorced, and widowed), 0 for never married	0.889	0.879	0.917	0.905	0.735
		(0.314)	(0.326)	(0.276)	(0.294)	(0.442)
Party membership	1 for partymembers, 0 for non-partymembers	0.262	0.223	0.407	0.137	0.124
		(0.440)	(0.416)	(0.491)	(0.344)	(0.330)
Nature of recruitment	1 for self-found, 0 for government assigned or inherited from parents	0.180	0.157	0.112	0.293	0.670
		(0.384)	(0.363)	(0.316)	(0.455)	(0.471)
N	Sample size	9,914	5,249	2,943	1,383	339

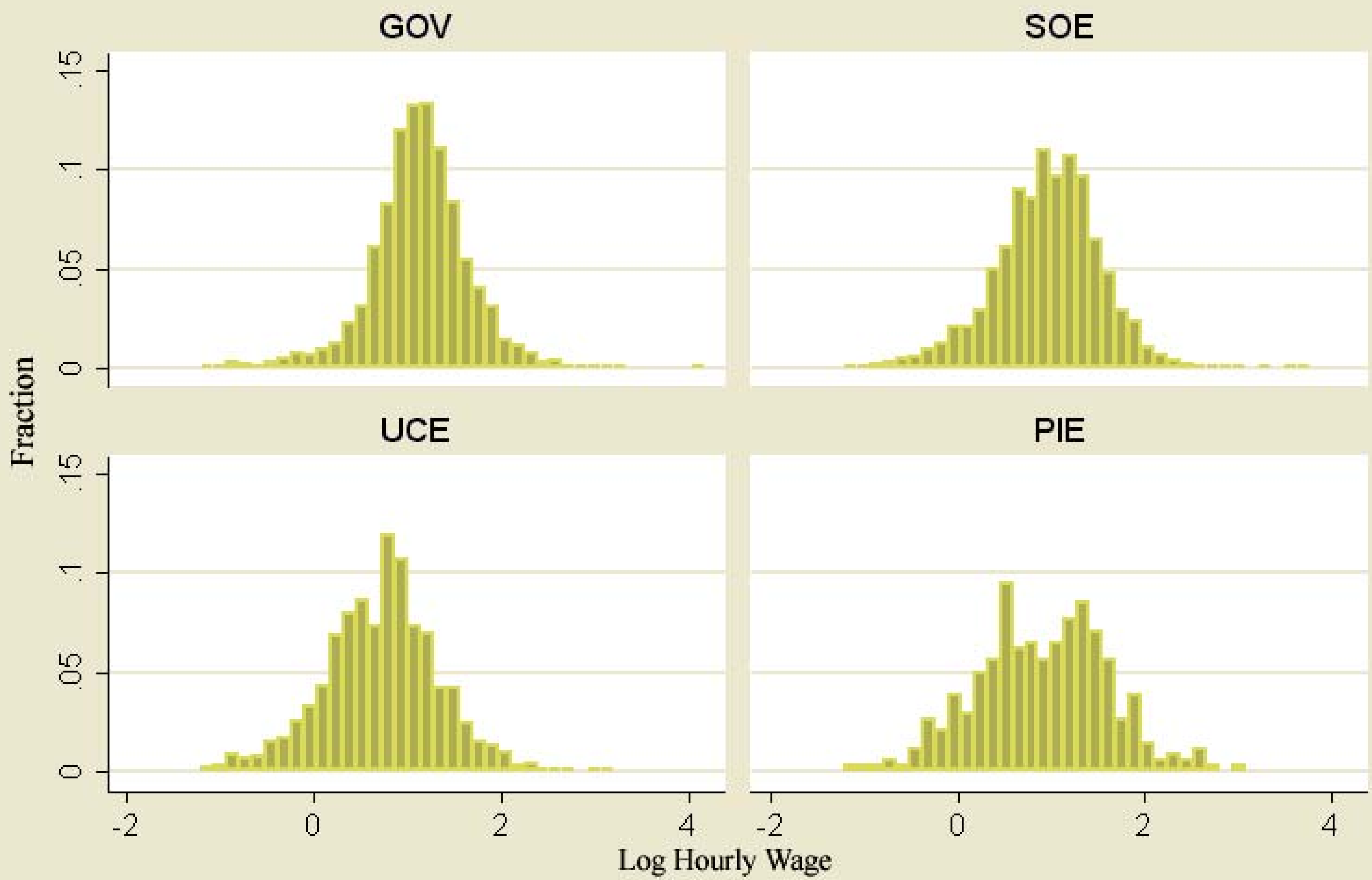
Note: Stardard deviations are in parentheses. Summary statistics for the provinceial dummies used in the analysis are not reported here.

Source: Author's calculation based on CHIP-95.

found their current positions through self-searching, compared to 15.7 percent in SOE and 11.2 percent in GOV.

The education measurement in the survey includes seven categories based on observations' highest completed education. Because it is actually the highest educational achievement as opposed to the years staying in school that impacts individuals' sector choices and wage levels, we transform the categorical education variable into a continuous "years-of-schooling" variable to replace the self-reported schooling variable. Following Li (2003) and others, the value of the "years-of-schooling" variable is assigned as follows: university and above (16 years), professional school (three-year college, 15 years), vocational secondary school (12 years), general secondary school (12 years), lower secondary school (9 years), primary school (6 years), and below primary school (2 years). Because of the small number of observations is in the "below-primary-school" category in the sample frame (29 observations in total, 2 in GOV and 2 in PIE), we combine the last two categories when assigning educational dummies. The urban labor force in China is concentrated in four educational categories: lower secondary (28.9 percent), general secondary (24.3 percent), vocational secondary (17.5 percent), and professional school (16.4 percent). Comparing the human capital for the four sectors, GOV has the best educated workforce, while UCE workers are least educated. The average years of schooling for GOV workers are 13.0 years, about 2.8 years more than UCE workers. The difference is even more obvious if we compare the educational dummies for the two sectors. 43.7 percent of the GOV workforce has professional education or above, while only 7.1 percent in UCE. However, 57.5 percent of UCE

Figure 3 Histogram of Log Hourly Wage by Ownership Sectors



Source: Author's calculation based on CHIP-95.

workers are at or below lower secondary, while this number is only 14.7 percent in GOV. Compared to PIE, SOE workers have slightly higher average years of schooling, and concentrate more on the upper middle level and professional education. But the distribution of PIE workers' education has big tails on both ends: at or below lower secondary and university or above.

Summary statistics on the hourly wage for each sector provides a picture of wage differentials at the outset. The average hourly wage is highest for GOV but lowest for UCE. The wage in PIE is slightly higher than SOE, but the wage variation in PIE is much larger, which results in the fact the average log wage in PIE is even lower than SOE. To better understand the within-sector wage distributions, we plot the histogram of the log hourly wage for each sector in Figure 3. It is obvious that the GOV wage is most compressed while the PIE wage is more dispersed. The results are consistent to our expectation as the GOV wage is strictly influenced by the administrative scale-wage system while the PIE wage is most flexible to reward workers' productivity difference. Another important observation is that workers in each sector differ significantly in their weekly working time. On average, private sector employees work 7 to 10 hours longer each week than their public sector counterparts.

V. Empirical Results

5.1 Multinomial Logit Sector Choice Equation Estimates

In estimating the polychotomous choice model given by Equation (9), we include variables in the *z* vector that we believe to be important for individuals' long-term decision in sector participation. In additional to age and age squared/100, the sector choice equation contains a set of dummy variables capturing individuals' gender, marital status, party membership, nature of recruitment, and educational achievement. The inclusion of the recruitment variable, as well as the use of age (instead of experience) and educational dummies (instead of "years-of-schooling") help us to identify the sector choice equation from the wage equation we will estimate in the second step. The benchmark of the respective set of dummies is a single (never-married) non-party-member male worker with primary education, whose job is assigned by the government.

Estimates of the multinomial logit coefficients and marginal effects are presented in Table 2. Provincial dummies are used to control regional differences in their employment structures by ownership sectors. However, as the focus of this paper is to generalize our results at the national level as opposed to examine regional disparities, coefficients on those provincial dummies are not reported. SOE is chosen as the base category and all the coefficients on SOE are set to zero. The marginal effects are evaluated using the sample means for age, age squared /100, and provincial dummies, but 0 for all other dummy variables.[9] An important feature is that the sum of the marginal effects of any variable on all the four sectors should be zero by definition. A one year increase in age is predicted to raise the probability of being in SOE, but reduce the chances of being in all the other three sectors. However, the effect is only significant for GOV. Females are predicted have a 5.8 percent higher probability than males of being in

[9] The sample means for age and age squared/100 are 38.76 and 15.94, respectively. The sample means of the provincial dummies instead of a default province are used so that the marginal effects of all other variables are evaluated at the national average.

Table 2 Multinomial Logit Estimates of the Sector Choice Equation

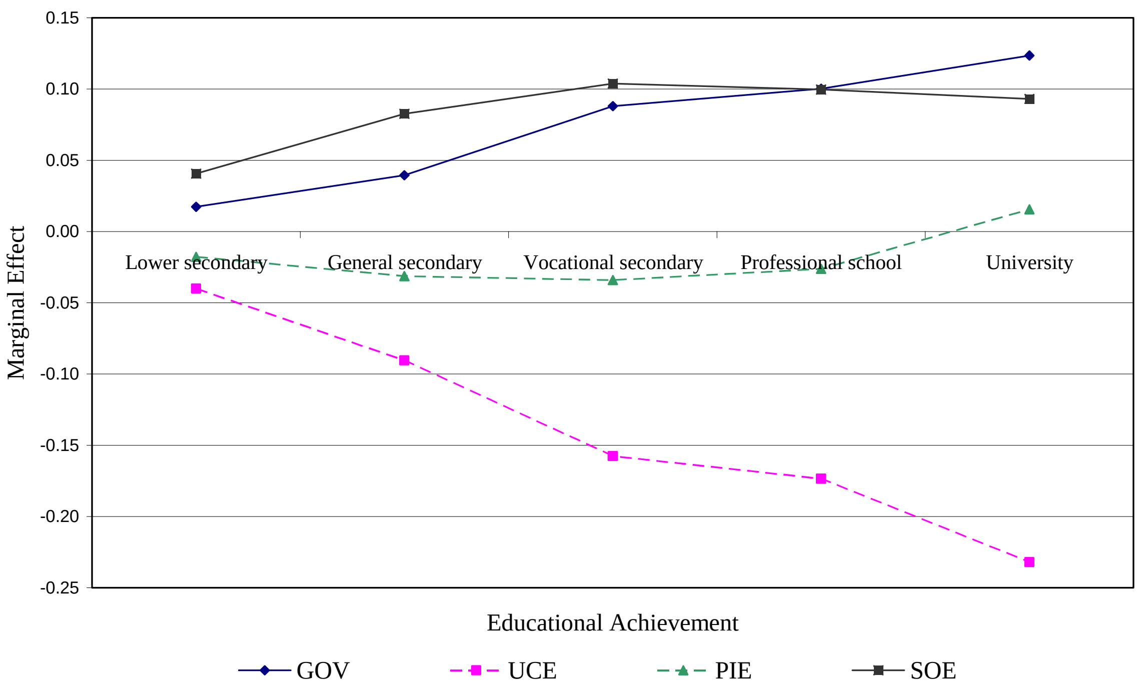
	Mlogit Coefficient Estimates			Marginal Effects			
	GOV	UCE	PIE	GOV	UCE	PIE	SOE
Intercept	-0.393	-1.004 *	-1.279	-	-	-	-
	(0.453)	(0.556)	(0.927)	-	-	-	-
Age	-0.136 ***	-0.039	-0.096 *	-0.006	-0.003	-0.003	0.013
	(0.024)	(0.031)	(0.051)				
Age squared/100	0.165 ***	0.039	0.102 *	0.007	0.003	0.004	-0.014
	(0.029)	(0.038)	(0.062)				
Female	0.306 ***	0.518 ***	0.067	0.011	0.058	-0.001	-0.068
	(0.052)	(0.066)	(0.121)				
Married	0.812 ***	0.497 ***	-0.028	0.036	0.053	-0.006	-0.083
	(0.123)	(0.156)	(0.236)				
Party membership	0.623 ***	-0.204 **	-0.184	0.032	-0.027	-0.008	0.003
	(0.059)	(0.093)	(0.186)				
Nature of recruitment	-0.060	0.723 ***	2.207 ***	-0.013	0.072	0.086	-0.146
	(0.077)	(0.077)	(0.132)				
Lower secondary	0.288 *	-0.349 ***	-0.470 **	0.017	-0.040	-0.018	0.041
	(0.170)	(0.122)	(0.224)				
General secondary	0.668 ***	-0.775 ***	-0.843 ***	0.039	-0.091	-0.031	0.082
	(0.170)	(0.131)	(0.238)				
Vocational secondary	1.595 ***	-1.299 ***	-0.935 ***	0.088	-0.158	-0.034	0.104
	(0.169)	(0.154)	(0.280)				
Professional school	1.839 ***	-1.409 ***	-0.743 ***	0.100	-0.173	-0.026	0.100
	(0.172)	(0.168)	(0.282)				
University	2.305 ***	-1.833 ***	0.245	0.123	-0.232	0.016	0.093
	(0.180)	(0.277)	(0.302)				
Provincial dummies		yes			-		
Log-likelihood		-9,319.750			-		

*Significant at 10% level
**Significant at 5% level
***significant at 1% level
Note: The dependent variable is the worker's sector of enployment: y=1 for SOE, y=2 for GOV, y=3 for UCE, y=4 for PIE. SOE is used as the base category and the parameters of the SOE equation are normalized to zero. Coefficients and marginal effects of provincial dummies are not reported. Standard deviations are in parentheses.

Source: Author's calcualtion based on CHIP-95.

UCE, but their chances of being in SOE are 6.8 percent lower. The effect of being married is predicted to raise the probability of selecting GOV (UCE) by 3.6 percent (5.3 percent), but reduce the probability of selecting SOE by 8.3 percent. As expected, party membership is predicted to increase the probability of being in the state sector but reduces the probability of being in the non-state sector. Using the “nature-of-recruitment” variable as the identification variable for the sector choice equation proves to be very successful as it has significant and substantial effect on individuals' sector choices. Getting the current job by self-searching is predicted to substantially increase the probability of being in the non-state sector (8.6 percent for PIE and 7.2 percent for UCE), but decrease the probability of being in SOE (by 14.6 percent).

Figure 4 Marginal Effect of Education on Sector Participation



Source: Author's calculation based on CHIP-95.

Figure 4 plots the marginal effect of each educational achievement on the sector participation for each ownership sector. For all levels of educational achievement except university education on PIE, we find a significant and negative education effect on non-state sector (UCE and PIE) participation. The marginal effects of all these educational dummies on UCE are much larger than those on PIE in absolute values, indicating that UCE has the most serious adverse selection in workers' education. Although statistically insignificant, the impact of university education on PIE participation is positive. A possible explanation is the dichotomy of the private sector employment. On the one hand, it is represented by those well-educated entrepreneurial owners and managers; on the other, it is concentrated in the labor-intensive, blue-collar, informal jobs. The marginal effects of the educational dummies on selecting GOV increase monotonously with levels of education, indicating that education has strictly positive incremental effect on GOV participation. However, the pattern in SOE takes an inversed "V" shape: the probability of selecting SOE peaks for vocational secondary education, but drops slightly for professional and university educations.

5.2 Wage Equation Estimates

Following Mincer (1974), we use years of schooling[10], experience, experience squared/100, and a set of dummy variables on gender, martial status, and party membership to control for workers' characteristics in the wage equation. A set of provincial dummies is also included to control for regional effects on wage levels. It is widely discussed in labor studies that returns to education may be non-linear and using educational dummies in the wage equation estimation can somewhat capture the nonlinearity effect (e.g. Willis, 1986). We acknowledge that possibility, but still use a continuous schooling variable for the following reasons. First, the sample size in our study, especially the number of observations in a certain sector with a certain educational level, may not be larger enough to provide reliable sector-degree-specific returns to

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[10] The most important merit of Mincer equation is that the coefficient on the years of schooling, which is the derivative of log earnings with respects to years of schooling $\partial \ln w / \partial s$, equals the marginal internal rate of return to additional schooling under a set of assumptions (see Bjorklund and Kjellstrom (2002) for detailed discussion).

Table 3 Sectoral Wage Equation Estimates: OLS and mlogit-OLS

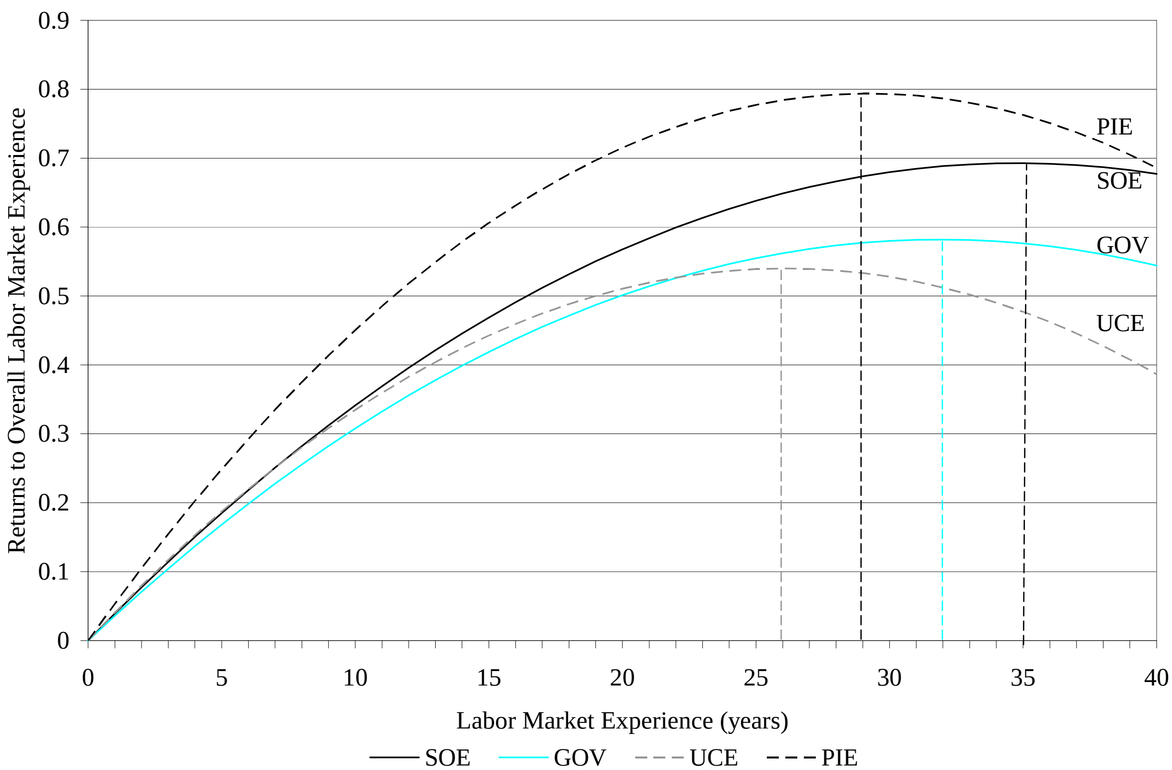
	SOE		GOV		UCE		PIE	
	OLS	mlogit-OLS	OLS	mlogit-OLS	OLS	mlogit-OLS	OLS	mlogit-OLS
Intercept	-0.032	-0.028	0.065	0.469	-0.320	-0.544	-0.155	-0.406
	(0.046)	(0.046)	(0.060)	(0.144)	(0.094)	(0.114)	(0.218)	(0.239)
Exp	0.041 ***	0.040 ***	0.033 ***	0.037 ***	0.043 ***	0.041 ***	0.059 ***	0.054 ***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.007)	(0.007)	(0.015)	(0.015)
Exp squared/100	-0.059 ***	-0.057 ***	-0.049 ***	-0.057 ***	-0.079 ***	-0.079 ***	-0.094 **	-0.093 **
	(0.007)	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)	(0.038)	(0.038)
Years of schooling	0.036 ***	0.037 ***	0.043 ***	0.026 ***	0.049 ***	0.024 **	0.053 ***	0.043 ***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.009)	(0.013)	(0.013)
Female	-0.097 ***	-0.092 ***	-0.052 ***	-0.067 ***	-0.126 ***	-0.066 **	-0.131 *	-0.149 **
	(0.013)	(0.015)	(0.016)	(0.017)	(0.027)	(0.032)	(0.068)	(0.068)
Married[a]	0.099 ***	0.106 ***	0.180 ***	0.145 ***	0.143 **	0.174 ***	-0.240 **	-0.279 **
	(0.029)	(0.030)	(0.035)	(0.037)	(0.060)	(0.060)	(0.114)	(0.114)
Party membership	0.080 ***	0.086 ***	-0.009	-0.047 **	0.083 **	0.024	0.102	0.044
	(0.017)	(0.018)	(0.017)	(0.021)	(0.039)	(0.043)	(0.114)	(0.115)
Selection		0.039		0.143 ***		-0.282 ***		-0.239 **
		(0.048)		(0.046)		(0.083)		(0.096)
Provincial dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.324	0.324	0.411	0.413	0.399	0.404	0.320	0.333
N	5,249		2,943		1,383		341	

*Significant at 10% level
**Significant at 5% level
***significant at 1% level
Note: The dependent variable is log hourly wage. Coefficients on provincial dummies are not reported. Standard deviations are in parentheses.

Source: Author's calcualtion based on CHIP-95.

education. Second, the nonlinearity in returns to different education levels—as some authors (e.g., Maurer-Fazio, 1999; Li, 2003) have investigated in the Chinese labor market context—is not the major focus of this study. Third, a continuous schooling variable, though not able to take into account the possible nonlinear education effects, can provide us reliable and straightforward estimates on sectoral returns to education for our purpose of sectoral comparisons.

Figure 5 Returns to Overall Experience by Employment Ownership Category



Source: Author's calculation based on CHIP-95

Sector-specific OLS and mlogit-OLS estimates of the wage equations are presented in Table 3. The dependent variable is log hourly wage and the coefficients on provincial dummies are not reported for the same reason discussed in Section 5.1. Our discussion in this section, if not explicitly specified, is based on the mlogit-OLS results. Following the classical Mincerian wage model, we include both experience and experience square/100 in the wage equation. The coefficients on experience square/100 are negative and significant for all the four sectors, indicating that the patterns of diminishing returns to additional years of experience exist for all sectors. Figure 5 plots the returns to overall experience by employment ownership sectors based on the mlogit-OLS coefficients. Although the quadratic experience function complicates the comparison, we can still see apparently that returns to overall experience are highest in PIE for all lengths of experience. Figure 5 also plots the number of years of experience needed for each sector to reach its peak return to experience. The wage peaks at 26 years of experience for UCE, 29 years of experience for PIE, 32 years for SOE, and 35 years for GOV. Peak returns to overall experience are reached later for SOE and GOV because returns to experience decelerate much more slowly in the state sectors. To explain these findings, we assume that the observed returns to experience can be divided into two components: the returns to productivity-augmenting associated with experience and the returns to seniority (tenure) independent of productivity. PIE has the highest returns to overall experience as the private sector wage is more productivity-based and provides higher rewards to productivity-augmenting attributable to experience than the other sectors. The explanation of the diminishing returns to additional years of experience for all sectors is that productivity rises at a decreasing rate with experience and the link between productivity and experience can even become negative (Mincer, 1974, p.65). The seniority effects are positive and more substantial in the state sectors, which help to slow down the diminishing rate in returns to additional years of experience in SOE and GOV.

Concentrating on the mlogit-OLS results, we note that male workers enjoy a wage advantage in all sectors. The male-female wage gap is largest in PIE, with PIE female workers earning on average 13.8 percent less than males (with coefficient -0.149).[11] This finding suggests that gender discrimination is larger in the private sector. Assaad (1997) for Egypt and Maurer-Fazio (1999) for China also find that the male-female differential is larger in the private sector than in the public sector. Married workers earn substantial premiums in the public sectors (SOE, GOV, and UCE) than single workers. But in the private sector, single workers earn more than married workers.[12] The reason is that the wage definition includes social benefits and subsidies workers received from their work units. In the public sectors, social benefits and subsidies account for a substantial portion of workers' wages and are related to workers' family structures[13], which results in the fact that married public sector workers, particularly those with children, receive higher wages than single workers controlling for other factors. For urban China in 1995, a lot of private sector jobs are intensive manual labor jobs in individual or small enterprises. There are almost no social benefits and subsidies in the private sector. The work intensity is relatively high—the average working hours per week is 51.5 hours (see Table 1). For their productivity advantage in manual labor jobs, single workers may be more suitable to private sector jobs and are better rewarded. The coefficients on party

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[11] See Halvorsen and Palmquist (1980) for the interpretation of dummy variables in semi-logarithmic equations. The precise percentage change $d_i = e^{\beta} - 1$, where β is the regression coefficient. In this case the coefficient on the female dummy for PIE is -0.149. The percentage wage effect of being a female in PIE $= e^{-0.149} - 1 = -0.138$.

[12] The dummy variable "married" takes value 0 for those who are never married and 1 otherwise, which leaves 105 observations who are either divorced or widowed grouped with the "married" group. However, it only accounts for 1.1% of the valid sample frame.

[13] One example is that married workers can get reimbursed from their work units for their children's educational and medical expenses.

membership are insignificant for UCE and PIE, indicating that party membership has no significant impact in wage settings in the non-state sectors. Party members in SOE earn a premium of 9.0 percent. However, unexpectedly, the coefficient on party membership in GOV is negative, indicating that party members in GOV earn 4.6 percent less than non-party-member workers. The earning disadvantage for party members in GOV is very surprising to us and we do not have a good explanation of the unexpected sign yet. However, the negative correlation between party membership and wage in GOV is not very strong as the mlogit-OLS coefficient is only marginally significant at 5% level and the OLS coefficient is insignificant.

The estimated rates of return to education in the mlogit-OLS model vary from 2.4 percent in UCE to 4.3 percent in PIE for an additional year of schooling. These rates are considerably lower than the 10.1% world average and the 9.6% Asia average (Psacharopoulos, 1994). However, low rates of returns to education are reported in most studies on wage determination in China (Fleisher & Wang, 2004)[14]. For instance, using the same data set as we use here, Li (2003) estimates the overall rate of return to schooling to be 5.4 percent without controlling for sample selections. Li's result is relatively close to our OLS estimates for sectoral wage equations. The correction for sample selection bias substantially reduces the estimated returns to education for all sectors except SOE. Psacharopoulos (1983) in an early study on public and private returns to schooling report that rates of returns to education tend to be lower in the noncompetitive public sector than in the competitive private sector because the

[14] See footnote 2 in Fleisher & Wang (2004) for an extensive list.

compression of pay scales in the public sector flattens mean wage differentials and hence depresses the returns to education. Our findings are consistent with those of Psacharopoulos as both the unadjusted (OLS) and the adjusted (mlogit-OLS) rates of return to schooling are highest in PIE.

The extent of the worker self-selection in each ownership sector is indicated by the estimated coefficients on the $-\varphi / F$ variables. The coefficients of the selectivity variables are statistically significant for all sectors expect SOE. As mentioned in Section III, the statistically significant and positive estimate of the selectivity coefficient in GOV implies an adverse selection in workers' quality, i.e., workers who self-select into GOV, in general, receive lower wages than a randomly selected individual with identical observable characteristics would be expected to earn in GOV. Thus, the unobserved worker characteristics increasing the probability of selecting GOV has a negative impact on wage, implying that workers selecting GOV have below-average productivity. Similarly, the statistically significant and negative estimates of the selectivity coefficients in UCE and PIE indicate that the selection effects in the two non-state sectors are positive. Thus, workers who self-select into UCE (PIE) receive higher wages than the expected wage for an individual selected at random from the labor force and assign to UCE (PIE). The coefficient of the selectivity variable for SOE has the expected sign but statistically insignificant. Because the wages in SOE are still largely administratively determined, we expect there is an adverse selection (positive coefficient on λ). However, the estimation results do not provide statistical evidence of the self-selection in SOE. Part of the reason is that when testing the existence of the self-selection in SOE, we use the entire full-time employed labor force as the base reference. The positive selection effects in UCE and PIE are largely canceled out by the adverse selection effect in GOV. Therefore, even if SOE has a significant adverse selection compared to the non-state sectors, the statistical evidence may not be powerful enough to give us significant coefficient estimate on the selectivity variable when we compare SOE to the entire full-time employed labor force. The chances to get significant coefficients on the selectivity variable are even less when SOE per se accounts for the majority (53 percent) of the relative universe to which we are comparing.

As known through the literature, a potential shortcoming of the mlogit model is its reliance on the assumption of the independence of irrelevant alternatives (IIA) (Hausman & McFadden, 1984; Small & Hsiao, 1985). The IIA property states that the ratio of the probabilities of choosing any two alternatives is independent of the attributes of any other alternative in the choice set. In other words, the IIA property assumes that the relative probability of two existing outcomes is unrelated to the addition or drop of a third outcome. We conduct the Small-Hsiao test (Small & Hsiao, 1985) and find that the IIA assumption is rejected. However, we are not surprising with the results for two reasons. First, it is widely acknowledged that the IIA property is a very restrictive assumption. Second, and more importantly, in China's urban labor market, the four sectors differ significantly in their relative relevance. More specifically, if we assume that there is no GOV option for a person who worked previously for the government, he/she is more likely to switch to SOE rather than UCE (PIE) as the labor recruitment mechanisms in the two state sectors are similar. Therefore, the ratio of the probabilities of choosing SOE and UCE (PIE) is dependent of the availability the GOV alternative in the choice set, thereby violating the IIA assumption.

Although the IIA assumption is very restrictive, the mlogit model remains widely used in empirical studies estimating polychotomous discrete variables due to its computational ease, i.e., the probability of choosing each potential outcome can be easily expressed and the resulting log-likelihood function can be maximized in a straightforward fashion (Hilmer, 2001). For our study, we believe that it is critical to have the four ownership sectors in the choice set (as opposed to a set of binary choices) in order to shed the clearest light on the issues of China's urban labor market that have not been examined in previous studies. For that reason, we decide that we should maintain the mlogit-OLS model even though the IIA property does not hold. However, in order to ascertain the sensitivity of our results to the selection of the choice model in the first stage, as well as the validity of the IIA assumption, we estimate a pairwise Heckman's two-step selection model by reformulating individuals' sector choice set into a set of binary choices: the state sector (SOE and GOV) vs. the non-state sector (UCE and PIE). Consistent to a priori expectation, the coefficients of the selectivity variables are significant and of the expected signs in both wage equations: workers adversely select into the state sector but positively select into the non-state sector (see Table A1 in the Appendix).[15]

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[15] Zhao (2002) applies the same pairwise two-step estimate strategy in her study on the earning differentials between state and non-state enterprises. However, using another data set (urban household survey 1996), she concludes that sector selection bias does not exist.

To further assess the selection effects for SOE versus the other two non-state sectors, we also estimate two pairwise Heckman-type two-step selection models for SOE vs. UCE and SOE vs. PIE, respectively. The selection effects in SOE are negative and significant for both models, indicating that SOE has a significant negative selection in workers' unobserved productivity compared to either UCE or PIE. The results for the three pairwise selection models presented in Table A1 provide supplementary evidence for our findings on the selectivity and reinforce our argument of the adverse selections in the state sectors and the positive selections in the non-state sectors.

VI. Wage Differentials

With the mlogit-OLS estimates of the wage equations, we estimate the projected wages in each of the four ownership sectors at its sample means of the independent variables ($\overline{\ln W_j} = \bar{x}_j^{'}\beta_j + \delta_j \bar{\hat{\lambda}}_j$). We then proceed to examine the pairwise sectoral wage differentials for any two targeted sectors. The classical method for such an examination on wage differentials is the Oaxaca-Blinder decomposition, which is developed by Oaxaca (1973) and Blinder (1973) independently and is now widely used in studies of wage discrimination. To handle the selection-correction terms in the wage equations, we adopt an extension of the Oaxaca-Blinder method, which decomposes the conditional (observed) sectoral wage gap into three components: (1) the endowment effect explained by the sectoral difference in the observed workers' productivity-related characteristics (Δx); (2) the remuneration effect due to the price discrimination to the observed worker characteristics ($\Delta\beta$); and (3) the selection effect due to the sample selection ($\Delta\sigma\lambda$)

(Oglobin, 1999). The consequences of the introduction of the selection-correction term are twofold. First, the estimated price vectors differ due to the correction of the sample selection bias. Second, the selection-correction term per se is a mixed measure of two effects—the endowment effect due to the sectoral difference in workers' *unobserved* productivity-related characteristics and the remuneration effect due to the sectoral difference in their returns to these unobserved characteristics. However, we cannot disaggregate the two effects as the selection-correction term introduced in the wage equation is instrument to the combination of the two effects.

For the ease of demonstration, we will present the framework of the method by decomposing the wage differentials between SOE and PIE. Subscriptions "S" and "P" are used to stand for SOE and PIE, respectively. The estimated log wages at the sample means of the two sectors take the following form:

$$\overline{\ln W_S} = \bar{x}_S^{'}\beta_S + \delta_S \bar{\hat{\lambda}}_S \tag{18}$$

$$\overline{\ln W_P} = \bar{x}_P^{'}\beta_P + \delta_P \bar{\hat{\lambda}}_P \tag{19}$$

To decompose the conditional sectoral wage gap, it is further necessary to make assumptions on a competitive price vector which operates as standard in valuing the different observed characteristics[16]. This price vector should reflect the remuneration of human capital characteristics in the absence of discrimination. In a SOE-PIE comparison in Chinese urban labor market context, we assume that the price vector in the private sector should reflect the market returns to workers' observed characteristics in the

[16] The decomposition results differ slightly with the selection of the standard price vector (see Beblo *et al*. (2003) for detailed discussion).

absence of discrimination. Therefore, the PIE price vector is used to value the endowment effect. The decomposition of the conditional sectoral log wage differential takes the following form:

$$\begin{aligned}\overline{\ln W_S} - \overline{\ln W_P} &= (\bar{x}_S^{'}\beta_S - \bar{x}_P^{'}\beta_P) + (\delta_S\,\bar{\hat{\lambda}}_S - \delta_P\,\bar{\hat{\lambda}}_P) \\ &= (\bar{x}_S^{'} - \bar{x}_P^{'})\beta_P + \bar{x}_S^{'}(\beta_S - \beta_P) + (\delta_S\,\bar{\hat{\lambda}}_S - \delta_P\,\bar{\hat{\lambda}}_P) \qquad (20)\end{aligned}$$

where the first term measures the endowment effect due to the sectoral difference in workers' observed characteristics (valued at the PIE price vector); the second term measures the remuneration effect due to the sectoral difference in their returns to the workers' observed characteristics (valued at the means of SOE workers' observed characteristics); and the third term measures the selection effect, which is a mixed measure of the sectoral difference in workers' unobservables related to productivity and the sectoral difference in their returns to those unobservables.

To further analyze wage differentials, we proceed to compare the unconditional wage gap between the two sectors. While the conditional wage is the wage obtained by an individual working in a particular sector, the unconditional wage is the expected or offered wage for an individual to work in that particular sector before he/she decides to join that sector. Since the unconditional wage is offered to the entire labor force and there is no sample selection, we can assume a random selection effect and set the selection-correction term to zero. Equations (21) and (22) show the unconditional log wages for SOE and PIE, respectively, at the sample means of each sector in the absence of sample selection.

$$\overline{\ln W_S^*} = \bar{x}_S^{'} \beta_S = \overline{\ln W_S} - \delta_S \,\bar{\hat{\lambda}}_S \tag{21}$$

$$\overline{\ln W_P^*} = \bar{x}_P^{'} \beta_P = \overline{\ln W_P} - \delta_P \,\bar{\hat{\lambda}}_P \tag{22}$$

Subtracting (22) from (21) gives the unconditional log wage differentials between SOE and PIE. For reasons discussed above, we then decompose the SOE-PIE log wage differentials by valuing the observed worker differences with the PIE price vector:

$$\begin{aligned} \overline{\ln W_S^*} - \overline{\ln W_P^*} &= (\overline{\ln W_S} - \delta_S \,\bar{\hat{\lambda}}_S) - (\overline{\ln W_P} - \delta_P \,\bar{\hat{\lambda}}_P) \\ &= (\bar{x}_S^{'} - \bar{x}_P^{'})\beta_P + (\beta_S - \beta_P)\bar{x}_S^{'} \end{aligned} \tag{23}$$

In the absence of sample selection, the decomposition of the "offered" wage gap has the same formulation as the original Oaxaca-Blinder decomposition, consisting of the endowment effect and the remuneration effect only. The last term in Equation (23)—the remuneration/discrimination effect—measures the gap between the offered SOE wage and the offered PIE wage for the same individual in the absence of sample selection. The SOE-PIE wage discrimination can be also interpreted as the net rent received by SOE workers compared to their PIE counterparts for SOE's higher aggregate returns to workers' observed characteristics.

Table 4 Pairwise Sectoral Wage Differentials

	(1) SOE vs. PIE	(2) GOV vs. PIE	(3) UCE vs. PIE	(4) SOE vs. UCE	(5) GOV vs. UCE	(6) GOV vs. SOE
Endowment effect (a)	11.1%	18.4%	0.5%	4.8%	10.1%	8.7%
Remuneration effect (b)	54.5%	83.4%	-6.7%	67.0%	97.9%	27.5%
Selection effect (c)	-46.8%	-58.1%	-4.6%	-42.2%	-53.5%	-11.3%
Discrimination differential (b)	54.5%	83.4%	-6.7%	67.0%	97.9%	27.5%
Unconditional wage differential (a) +(b)	65.6%	101.8%	-6.2%	71.8%	108.0%	36.2%
Conditonal wage differential(a) +(b)+(c)	18.7%	43.7%	-10.8%	29.6%	54.5%	24.9%

Source: Author's calcualtion based on CHIP-95.

Table 4 presents the decomposition results of the six pairwise sectoral wage gaps estimated at the sample means of the worker characteristics for each sector. By ranking the selection-correction terms ($\delta_j \bar{\hat{\lambda}}_j$), we can rank the four ownership sectors in a continuum by their selectivity as PIE, UCE, SOE, and GOV (consistent to Figure 2.1), with PIE having the largest positive selection and GOV having the largest negative selection.[17] As mentioned earlier in this section, we choose the price vector of the more competitive sector in valuing the endowment effect. According to Figure 2.1, we use the PIE price vector as the standard in valuing the endowment effects in column (1) to (3), the UCE price vector in column (4) and (5), and the SOE price vector in column (6).

[17] The selection effect is calculated by multiplying the selection coefficient (δ_j) and the mean value of the selection variable ($\bar{\hat{\lambda}}_j$) for workers in that sector. The calculated selection effect results are 0.441 for PIE, 0.395 for UCE, -0.027 for SOE and -0.140 for GOV.

Concentrating on the SOE-PIE wage differential, the conditional wage gap is 18.7 percent, i.e., the average SOE worker who self-selects SOE earn a wage 18.7 percent higher than an average PIE worker who self-selects PIE. Excluding the selection effect due to workers' difference in their unobserved characteristics, the unconditional (or offered) wage differential between SOE and PIE is 65.6 percent. The opposing selections detected in the two sectors result in a substantial negative selection effect due to sample selection (-46.8 percent), which causes the unconditional wage differential to be much greater than the conditional wage differential. Only a fairly small portion of the unconditional wage differential can be explained by the sectoral difference in their endowments in the observed human capitals (11.1 percent). The majority of the unconditional wage differential is due to the remuneration/discrimination effect (54.5 percent) —the sectoral difference in their rewards to workers' observed human capital. The positive SOE-PIE remuneration effect can be interpreted as a wage discrimination against PIE workers, or the net rent SOE workers receive due to the sectoral difference in wage settings[18].

A careful examination of the endowment effects for the six comparison groups shows that the four sectors can be sorted by the aggregate human capital endowment as GOV, SOE, UCE, and PIE, with GOV having the best human capital endowment. A similar examination of the remuneration or discrimination effect shows that GOV workers receive a wage premium of 27.5 percent over SOE, SOE workers receive a premium of

[18] The difference in the coefficients of the intercepts for the wage equations of the two sectors (Table 4), which is 37.8% in the SOE-PIE comparison, can be interpreted as the net rent received by SOE workers regardless of their human capital endowment.

54.5 percent over PIE, and PIE workers receive a premium of 6.7 percent over UCE. The largest selection effect (-58.1 percent) exists in the GOV-PIE wage differential, which is consistent to our finding that GOV has the largest adverse selection, while PIE has the largest positive selection in terms of workers' unobserved productivity. The largest conditional and unconditional wage gaps are both between GOV and UCE. The numbers can be interpreted as that the realized GOV wage (at the sample means) is 54.5 percent higher than the realized UCE wage, while the offered GOV wage (at the sample means) is 108.0 percent higher than the offered UCE wage. The difference between the two numbers—negative 53.5 percent—is the selection effect due to GOV's adverse selection and UCE's positive selection on workers' unobserved quality.

VII. Conclusion

In this paper, we examine the employment sector choices and the wage differentials among different ownership sectors in urban China in 1995. Most existing studies on wage determination in China are based on the assumption of the exogenous sector choices. Instead, we use a generalized selection model to take into consideration the endogenous sector choices and test the existence of sample selections in a polychotomous choice situation. The estimation results of the generalized selection model and supplementary evidences from pairwise examinations indicate that there is unobserved worker heterogeneity across labor market sectors in urban China. With respect to their unobserved productivity, workers adversely select into the state sector (GOV and SOE), but positively select into the non-state sector (UCE and PIE). The extent of the self-selection into each sector is consistent with the competitiveness of that sector, with the largest adverse selection found in GOV and the largest positive selection found in PIE.

Having provided statistical supports for the existence of self-selections, we further examine the selection-corrected sectoral wage determinations. Our results indicate that the competitive private sector tends to have higher rewards to workers' productivity-related characteristics than the public sector. Returns to overall labor market experience is highest in the private sector for all lengths of experience. Although returns to education in all the four sectors are low by international standards, the private returns to education are considerably higher than the public returns. The institutionally administered scale wages in the public sector result in flattened within-sector wage differentials and depress rewards to workers' productivity-related characteristics such as labor market experience and education. However, married workers earn a substantial premium in the public sectors as non-wage benefits account for an important portion of public wages and are related to family structures. With respect to the gender wage gap, male workers in all the four sectors have a significant wage premium over females, indicating that wage discrimination against women is a common feature in wage settings of all ownership sectors in China. However, the extent of such discrimination varies across ownership sectors, with the private sector having the highest discrimination against women.

Using the mlogit-OLS wage equation results, we estimate the conditional wage for each sector at the sample means of workers' characteristics and selection-correction term for that sector. An extension of the Oaxaca-Blinder decomposition method is used to decompose the conditional pairwise sectoral wage differentials. We further examine and contrast two other conceptually distinct measurements of the wage differential: unconditional differential and discrimination differential. Our primary findings on wage differentials across sectors can shed light on some labor market problems in China. First, the endowment effects indicate that the state sectors have better endowments in workers' observed human capital than the non-state sectors, with GOV having the highest endowment and PIE having the lowest endowment. However, comparing the three components—the endowment effect, the remuneration effect, and the selection effect—of the observed wage differentials, we find that the endowment effect only accounts for a relatively small portion of sectoral wage differentials. Second, the results of the wage discrimination differential across sectors indicate that the wage settings in China are discriminatory against the non-state sectors. Workers in both GOV and SOE receive a substantial rent compared to UCE and PIE, with the largest discrimination differential found between GOV and UCE. The wage discrimination against the non-state sectors helps to explain the immobility of the sate sector workers until the recently launched large-scale labor retrenchment in the state sector. However, since the study is based on the 1995 labor survey, the effect of the labor retrenchment is not reflected in our results. Third, the unconditional wage differentials are larger than the conditional wage differentials for both the SOE-PIE and SOE-UCE comparisons due to the negative selection effects. Although other reasons contribute to SOE's loss of competitiveness in the market, the results on the selection effects shed light on the issue in terms of workers' quality. The administratively determined wage setting in SOE depress rewards to workers' productivity difference, which results in the adverse selection on workers' unobserved productivity and workers' effort-shirking behavior in SOE.

In conclusion, empirical evidence from this study indicates that the labor market reforms in China are lagging behind its transition toward the market-oriented economy. The wage settings in the state sector are still largely administratively determined and fail to reward workers' productivity. The distorted wage structures in the state sector result in a segmented and inefficient urban labor market. A much wider and in-depth reform in the labor system and wage settings in the state sector is required to achieve an integrated and properly functioning labor market.

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Appendix

Table A1 Pairwise Heckman's Two-step Wage Equation Estimates

	SOE vs UCE		SOE vs PIE		State vs Non-state	
	SOE	UCE	SOE	PIE	State	Non-state
Sector Choice Equations:						
Intercept	0.997 **	-0.997 **	0.607 *	-0.607 *	0.627 **	-0.627 **
	(0.500)	(0.500)	(0.324)	(0.324)	(0.277)	(0.277)
Age	0.038	-0.038	0.022	-0.022	0.004	-0.004
	(0.027)	(0.027)	(0.018)	(0.018)	(0.015) ***	(0.015) ***
Age squared/100	-0.045	0.045	-0.024	0.024	0.000	0.000
	(0.033)	(0.033)	(0.022)	(0.022)	(0.019)	(0.019)
Female	-0.066	0.066	-0.296 ***	0.296 ***	-0.196 ***	0.196 ***
	(0.063)	(0.063)	(0.038)	(0.038)	(0.033)	(0.033)
Married	0.092	-0.092	-0.271 ***	0.271 ***	-0.042	0.042
	(0.129)	(0.129)	(0.090)	(0.090)	(0.076)	(0.076)
Party membership	0.061	-0.061	0.109 **	-0.109 **	0.213 ***	-0.213 ***
	(0.088)	(0.088)	(0.052)	(0.052)	(0.044)	(0.044)
Nature of recruitment	-1.107 ***	1.107 ***	-0.446 ***	0.446 ***	-0.620 ***	0.620 ***
	(0.066)	(0.066)	(0.046)	(0.046)	(0.039)	(0.039)
Lower secondary	0.211 *	-0.211 *	0.212 ***	-0.212 ***	0.255 ***	-0.255 ***
	(0.125)	(0.125)	(0.074)	(0.074)	(0.067)	(0.067)
General secondary	0.388 ***	-0.388 ***	0.466 ***	-0.466 ***	0.543 ***	-0.543 ***
	(0.131)	(0.131)	(0.078)	(0.078)	(0.071)	(0.071)
Vocational secondary	0.410 ***	-0.410 ***	0.726 ***	-0.726 ***	0.937 ***	-0.937 ***
	(0.146)	(0.146)	(0.088)	(0.088)	(0.078)	(0.078)
Professional school	0.332 **	-0.332 **	0.799 ***	-0.799 ***	1.026 ***	-1.026 ***
	(0.150)	(0.150)	(0.095)	(0.095)	(0.082)	(0.082)
University	-0.138	0.138	1.023 ***	-1.023 ***	1.063 ***	-1.063 ***
	(0.163)	(0.163)	(0.142)	(0.142)	(0.100)	(0.100)
Provincial dummies	Yes	Yes	Yes	Yes	Yes	Yes
Wage Equations:						
Intercept	0.036	-0.369	0.299 ***	-0.542 ***	0.230 ***	-0.346 ***
	(0.049)	(0.228)	(0.076)	(0.119)	(0.053)	(0.090)
Exp	0.038 ***	0.053 ***	0.037 ***	0.038 ***	0.035 ***	0.041 ***
	(0.003)	(0.015)	(0.004)	(0.007)	(0.003)	(0.006)
Exp squared/100	-0.055 ***	-0.089 **	-0.054 ***	-0.072 ***	-0.052 ***	-0.074 ***
	(0.007)	(0.037)	(0.008)	(0.016)	(0.006)	(0.015)
Years of schooling	0.035 ***	0.045 ***	0.016 ***	0.029 ***	0.027 ***	0.038 ***
	(0.003)	(0.013)	(0.004)	(0.008)	(0.003)	(0.007)
Female	-0.094 ***	-0.125 *	-0.037 **	-0.059 *	-0.053 ***	-0.099 ***
	(0.014)	(0.067)	(0.018)	(0.035)	(0.012)	(0.027)
Married	0.090 ***	-0.252 **	0.147 ***	0.184 ***	0.146 ***	0.023
	(0.029)	(0.111)	(0.033)	(0.062)	(0.023)	(0.053)
Party membership	0.076 ***	0.068	0.057 ***	0.050	0.025 *	0.052
	(0.017)	(0.111)	(0.020)	(0.042)	(0.013)	(0.041)
Provincial dummies	Yes	Yes	Yes	Yes	Yes	Yes
Selectivity variable	-0.275 ***	0.219 ***	-0.511 ***	0.274 ***	-0.379 ***	0.183 ***
	(0.061)	(0.083)	(0.085)	(0.086)	(0.047)	(0.056)
Uncensored observations	5,249	1,383	5,249	339	8,192	1,722

*Significant at 10% level
**Significant at 5% level
***significant at 1% level
Note: The dependent variable is log hourly wage. Coefficients on provincial dummies are not reported. Standard deviations are in parentheses.

Source: Author's calcualtion based on CHIP-95.

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