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Bootstrapping Statistical Inferences of Decomposition Methods for Gender Earnings Differentials[*]

Yue Ma[+] and Ying Chu Ng[++]

Abstract

Applying the standard bootstrapping technique with corrections for heteroskedasticity for a sample of the 1997 Urban Household Survey in China, the present paper attempts to test (1) whether the commonly used decomposition methods for gender earnings differentials give significantly different results, and (2) whether the explained component is significantly different from the unexplained component (which is commonly referred to as discrimination) within each decomposition method. Based on a national data set, the empirical results indicated some significant differences in both tests. The implication of the results is that the proposed bootstrapping technique can be regarded as a guideline on applying which approach to decompose gender earnings differentials among different methods without losing important information, and on evaluating the relative importance of the decomposition components for any chosen method.

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I. Introduction

The theoretical framework of gender discrimination analysis was developed by Becker (1957). Blinder (1973) and Oaxaca (1973) outlined the measurement for gender discrimination by introducing the decomposition method of the wage (earnings) differentials. Alternative decomposition methods were further developed and proposed by others, for example, Cotton (1988), Neumark (1988) and Oaxaca and Ransom (1994). Within the Blinder-Oaxaca decomposition framework, one will obtain a range of estimates for the discrimination (Cotton 1988). Based on the discriminatory behavior of employers, the method proposed by Neumark (1988) produces a lower estimate for the discrimination than those proposed by Oaxaca in a study by Neumark (1988, p.293) and is confirmed also in our study (cf. Table 3). Up until now, there is no common consensus on which decomposition method is better than the others. Moreover, there is little concern about the statistical significance of the estimated explained and unexplained (commonly referred as the discrimination) components derived from the decomposition across various decomposition methods. These issues, indeed, are of equal importance in the sense that policy implications are generally put forward according to the estimated results.

Using a sample of individuals drawn from the 1997 Urban Household Survey in China, the present paper attempts to answer the following two questions: (1) Did the commonly used decomposition methods give significantly different results? and (2) Is the explained component significantly different from the unexplained component within each decomposition method? In this paper, we propose a new procedure to implement a standard bootstrapping technique, with corrections for heteroskedasticity, to investigate these two questions on one specification[1] of the Mincerian earnings function. Our results indicated that there are significant differences in the estimated

[1] We note that the estimated unexplained component may be dependent upon the chosen reference group of the dummy variables, as discussed in Jones (1983). However, this is not the focus of the present paper.

explained component and thus the unexplained component (discrimination) across selected decomposition methods. Furthermore, it was found that there are significant differences between the explained and the unexplained components within each decomposition method. Our bootstrapping procedure may be regarded as a guideline on how to choose different decomposition methods without losing important information, and on evaluating the relative importance of the explained versus the unexplained components for any chosen method.

The remaining part of the paper is organized as follows. The next section outlines the decomposition methods commonly used to measure gender earnings discrimination in the literature and the bootstrap technique for making statistical inferences. Section 3 briefly discusses the data and the specification for the gender earnings function adapted in the present study. A summary of the estimations of the earnings function is also included. The statistical tests on the significance of the decomposition components across different methods and within each method are presented in Section 4. The final section concludes the paper.

II. The Decomposition of Gender Earnings Differentials and the Bootstrap Technique

A. Decomposition Methods

To address the issues of gender earnings differentials and thus the gender discrimination issue requires estimation of the earnings functions by gender. The logarithmic male (lnE^M) and female (lnE^F) earnings functions take the following forms.

$$\ln E^M = \alpha^M + \sum \beta_i^M X_i^M + \varepsilon_M \tag{1}$$

$$\ln E^F = \alpha^F + \sum \beta_i^F X_i^F + \varepsilon_F \tag{2}$$

where X_i^M and X_i^F represent two vectors of earnings determinants including personal characteristics (education, working experience, and place of residence) and job-related information (occupation, sector of employment, and the type of enterprise ownership), for male and female respectively. β_i^M and β_i^F are the corresponding estimated coefficients, while α^M and α^F are constant terms. ε_M and ε_F are random error terms.

The male versus female average earnings differential is

$$\overline{\ln E}^M - \overline{\ln E}^F = (\alpha^M + \sum \beta_i^M \overline{X}_i^M) - (\alpha^F + \sum \beta_{\mathrm{i}}^{\mathrm{F}} \overline{X}_i^F) \qquad (3)$$

where $\overline{\ln E}^M$ and $\overline{\ln E}^F$ are the average male and female earnings in logarithm, respectively. $\overline{X}_i^M$ and $\overline{X}_i^F$ are the average earnings-determining characteristics of the male and female samples, respectively. This differential can be decomposed into two main components, namely the explained and the unexplained (commonly referred as discrimination) component. Among the various decomposition methods, the method introduced by Oaxaca (1973) and the one proposed by Neumark (1988) are commonly used in the literature. Accordingly, the present paper is focused on these two methods for illustration purpose. The applications of both methods in the literature are abundant. The work of Ashraf (1996), Finnie and Wannell (2004), Hayfron (2002), Hinks (2002), Prescott and Wandschneider (1999), and Silber and Weber (1999) are among the examples. For studies of China, see Chen, Démurger and Fournier (2005), Gustafsson and Li (2000), Liu, et al (2000), and Maurer-Fazio and Hughes (2002).

The decomposition procedure developed by Oaxaca (1973) splits the total gender earnings differentials (the left-hand side of Equation (3)) into two components. That is,

$$\overline{\ln E}^M - \overline{\ln E}^F = \sum \beta_i^M (\overline{X}_i^M - \overline{X}_i^F) + [\sum \overline{X}_i^F (\beta_i^M - \beta_i^F) + (\alpha^M - \alpha^F)]. \qquad (4)$$

The first component (the first term on the right-hand side of the equality) is the differential attributable to gender differences in the observable productive characteristics *themselves*, while the second component (the terms in the square bracket) is the earnings gap due to differences in the male and female *returns* to these productive characteristics. It is this second component (the unexplained component) which is generally attributed to “discrimination”.

An issue associated with Equation (4) is that the differences in male and female productive characteristics are valued according to the male returns. In other words, it assumes that the male earnings structure is the earnings structure that would prevail in the absence of discrimination. It could be argued that the female earnings structure would prevail instead in the absence of discrimination (Oaxaca 1973). In other words, Equation (4) can be rewritten as

$$\overline{\ln E}^{M} - \overline{\ln E}^{F} = \sum \beta_i^{F} (\overline{X}_i^{M} - \overline{X}_i^{F}) + [\sum \overline{X}_i^{M} (\beta_i^{M} - \beta_i^{F}) + (\alpha^{M} - \alpha^{F})]. \qquad (5)$$

Although functionally equivalent, these two decompositions generally yield different estimates for the earnings differential components. As a result, Oaxaca (1973), in discussing the final result, suggested to taking the average of the two decomposition estimates.

Neumark (1988) proposed an alternative decomposition method, which decomposes the average gender earnings differential into three components[2]. That is,

$$\overline{\ln E}^{M} - \overline{\ln E}^{F} = \sum \beta_i^{p} (\overline{X}_i^{M} - \overline{X}_i^{F}) + [\sum \overline{X}_i^{M} (\beta_i^{M} - \beta_i^{p}) + (\alpha^{M} - \alpha^{p})] + [\sum \overline{X}_i^{F} (\beta_i^{p} - \beta_i^{F}) + (\alpha^{p} - \alpha^{F})] \qquad (6)$$

where the β_i^ps are the estimated coefficients for the pooled sample of male and female individuals, representing the nondiscriminatory earnings structure, and α^p is the constant term of the pooled sample regression. The first term on the right-hand side of Equation (6) is the difference in the male and female average productive

[2] The idea is explicitly outlined in Cotton (1988).

characteristics evaluated as the market would be in the absence of "discrimination". The last two terms in the square bracket contribute to the treatment (unexplained) component. The first term in the square bracket measures the male "pure" treatment advantage if it is positive. Similarly, the second term in the square bracket, if positive in value, represents the female's "pure" treatment disadvantage. Thus, these last two terms represent the amount by which male productive characteristics are overvalued and the amount by which female productive characteristics are undervalued. For the sake of comparison across methods, the last two terms would be combined into one in the following analysis.

B. Corrections for Heteroskedasticity

If the variance of the residual is not constant across observations, the regression is heteroskedastic. This could happen in our study due to a well-known phenomenon that women rarely got top-paying jobs. This implies that the distributions of earnings among women are tighter than among men (Stock and Watson, 2003, p.128). Although heteroskedasticity does not cause bias or inconsistency for the ordinary least squares estimation of all the parameters in equations (1), (2) and their pooled specification (Wooldridge, 2003, p.257), it does cause severe problems for inferences.[3] As a result, we need to specify a general functional form for the variance to correct for the heteroskedasticity (White, 1980). A simplified functional form of heteroskedasticity is given by Wooldridge (2003, p.269). Taking the residual for the male earning function as an example, we have:

$$\ln\left(\hat{\varepsilon}_M^2\right) = \delta_0 + \delta_1 \hat{y}^M + \delta_2 \left(\hat{y}^M\right)^2 + \mu_\sigma^M \tag{7}$$

where $\hat{y}^M$ is the fitted value of lnE^M.

In Equation (7), we have taken the logarithm for the

[3] For example, if the heteroskedasticity is ignored, the estimator would be inefficient. This implies that the estimated variances are no long valid for constructing confidence intervals and t statistics (Wooldridge, 2003, p.258).

squared-residuals to make sure the fitted value of $\hat{\varepsilon}_M^2$ to be always positive.

Under the null hypothesis of homoskedasticity, we have:

H_0: $\delta_1 = \delta_2 = 0$.

If we reject H_0, then it indicates the presence of heteroskedasticity.

C. Bootstrapping Procedure

Existing literature provides strong evidence that the estimates of each component vary by decomposition methods. To test whether there are significant discrepancies of the two decomposition methods presented in Equations (4) to (6), the standard bootstrapping procedure is applied. The reason that we choose to apply a bootstrapping procedure instead of a traditional parametric test is due to the complexity of our problem. Take the decomposition Equation (4) as an example. Both the explained and the unexplained components in Equation (4) involve the product of two random variables, $\hat{\beta}_i$ and $\overline{X}_i$. Even under the standard normality assumption, the parametric statistical inference for these two components is complicated. The advantage of bootstrap is to allow the researcher to make inferences without imposing specific distributional assumptions and without the need for analytic formulas for the sampling distribution's parameters. In fact, the bootstrap has been widely applied in testing the occupation segregation index (Boisso, Hayes, Hirschberg and Silber 1994), poverty index (Osberg and Xu 2000), income inequality (Mills and Zandvakili 2004), and earnings difference by demographic groups using quantile regression (Fitzenberger and Kurz 2003). For a detailed discussion on the technique, please refer to Efron (1982) and Efron and Gong (1983).

In the present context, the procedure can be summarized by the following 11 steps.

Step 1. Estimate the male earnings function (1) on the actual data with sample size T^M, to obtain the parameters $\hat{\alpha}^M$, $\hat{\beta}_i^M$, and residuals $\hat{\varepsilon}_M$.

Step 2. Estimate the female earnings function (2) on the actual data with sample size T^F, obtain the parameters $\hat{\alpha}^F$, $\hat{\beta}_i^F$, and residuals $\hat{\varepsilon}_F$.

Step 3. Estimate the male-female pooled earnings function on the actual data with sample size $T=T^M+T^F$, obtain the parameters $\hat{\alpha}^P$, and $\hat{\beta}_i^P$.

Step 4. Calculate the explained and unexplained components for the two decomposition methods given by Equations (4) to (6), based on the parameters estimated from Steps 1 to 3.

Step 5. Estimate the variance equation (7) for male to get residual $\hat{\mu}_\sigma^M$, and parameters $\hat{\delta}_0^M, \hat{\delta}_1^M$ *and* $\hat{\delta}_2^M$. Similarly, estimate the variance equations for female to obtain ($\hat{\mu}_\sigma^F, \hat{\delta}_0^F, \hat{\delta}_1^F, \hat{\delta}_2^F$).

Step 6. Randomly draw a male sample of size T^M with replacement from the residuals $\hat{\mu}_\sigma^M$ estimated from Step 5, and call this new sample as $\hat{\mu}_\sigma^{M*}$. Then obtain $\ln\left(\hat{\varepsilon}_M^2\right)^*$ from equation:

$$\ln\left(\hat{\varepsilon}_M^2\right)^* = \hat{\delta}_0^M + \hat{\delta}_1^M \hat{y}^M + \hat{\delta}_2^M \left(\hat{y}^M\right)^2 + \hat{\mu}_\sigma^{M*},$$

where $\hat{y}^M$ =fitted value of lnE^M from Step 1.

Next construct $\hat{\varepsilon}_M^*$ from $\hat{\varepsilon}_M^* = sign(\hat{\varepsilon}_M)\exp\left[\frac{1}{2}\ln\left(\hat{\varepsilon}_M^2\right)^*\right]$. Finally generate a bootstrapped-dependent variable $\ln E^{M*}$ by Equation (1):

$$\ln E^{M*} = \hat{\alpha}^M + \sum \hat{\beta}_i^M X_i^M + \hat{\varepsilon}_M^*$$

Step 7. Estimate the male earnings function (1) on the bootstrapped data $\ln E^{M*}$ and actual X_i^M, obtain the parameters $\hat{\alpha}^{M*}$ and $\hat{\beta}_i^{M*}$.

Step 8. Apply Steps 6 and 7 to the female earnings function (2) with a sample of size T^F, to obtain the parameters $\hat{\alpha}^{F*}$ and $\hat{\beta}_i^{F*}$ based on bootstrapped data.

Step 9. Estimate the male/female pooled earnings function on the bootstrapped data $\ln E^{M*}, \ln E^{F*}$, generated from Step 6 and 8 respectively, as well as actual X_i^M and X_i^F, to obtain the parameters $\hat{\alpha}^{P*}$ and $\hat{\beta}_i^{P*}$.

Step 10. Calculate the explained and unexplained components for the two methods given by Equations (4) to (6), based on the parameters estimated on the bootstrapped data generated from Steps 6 to 8.

Step 11. Go back to Steps 6 to 10, and repeat a total of N times. A set of N explained and unexplained components for each of the two methods will thus be obtained. They are the bootstrapped distributions of these components.

Based on these bootstrapped distributions resulted from N repetitions, we can then make inferences about the relative size of the explained and thus the unexplained components across the two methods reviewed in this paper. Given the fact that the total differential is constant across both methods, that is, the total differential is always equal to $\overline{\ln E}^M - \overline{\ln E}^F$, testing on the explained component will suffice. Specifically, we construct the pair-wise distributions of the differential explained component of Equation (4) versus Equation (5), Equation (5) versus Equation (6), and Equation (4) versus Equation (6). In constructing the 95% confidence intervals, we adopt both the standard percentile approach and the percentile-t approach for comparison purpose, although the latter is found to outperform the former in other studies (e.g. Li and Maddala 1999).

The standard 95% percentile confidence interval is based on the 2.5% and 97.5% quantiles of the distributions of explained component differential. The 95% percentile-t confidence interval is given by $\Delta^{m}_{ij} \pm t_{2.5\%}\ \sigma_{\Delta ij}$, where Δ_{ij} is explained component differential between decomposition Equations (i) and (j) (i, j=4, 5, 6), the superscript '*m*' indicates that Δ^{m}_{ij} is the mean of bootstrapped estimations of Δ_{ij}, $t_{2.5\%}$ is the critical value from the *t*-distribution with N-1 degrees of freedom that is exceeded with probability 97.5%, N is the number of bootstrap repetitions (N=1,000 in our case)[4], $\sigma_{\Delta ij}$ is the standard error of the bootstrapped distribution of Δ_{ij}, and Δ_{ij} is bootstrapped explained component differential.

To test the relative size of the explained and unexplained components within each decomposition method, the pair-wise distributions of the difference between the explained and unexplained component for each method were constructed. Again, the bootstrapped 95% confidence intervals of both the percentile and the percentile-t approaches were applied.

Silber and Weber (1999) proposed a different bootstrap approach to test the significance of the two decompositions. However, their approach suffers from three limitations. Firstly, they did not consider the possibility of heteroskedasticity. Secondly, they did not test the significance between the explained and unexplained components of the estimations. Finally, they treated the alternative estimate as a fixed number in the null hypothesis when they compare two decomposition methods. In fact, since any of decomposition measure is a random variable estimated from a random sample, their tests may be biased by imposing an incorrect assumption.

III. Data and Earnings Function Estimations

The data employed in this study were extracted from the 1997

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[4] That is, $t_{2.5\%}$=1.96 with N=1,000 in our case.

Urban Household Survey conducted by the Urban Socio-Economic Survey Organization of the State Statistical Bureau of China[5]. The data sampled China's urban population of 10 provinces and municipalities. Individual information such as employment status, the highest level of education attained, age, gender, years of actual working experience, sector of employment, occupation, and annual labor income were collected. The annual labor income includes both salaries and other cash subsidies associated with the job. To account for the provincial price differences, the income variable was deflated by the provincial GDP deflator extracted from the *Comprehensive Statistical Data and Materials on 50 Years of New China* (1999). Among the 10,863 individuals under analysis, there were 5,717 males (52.6%) and 5,146 females (47.4%).

Table 1 presents the sample statistics by gender. The average earnings of the females was 82.3% that of the males.[6] Males attained a higher level of education, particular at the university level and above. Males were not only having more years of actual working experience, they also tended to be senior technicians or working in the government sector. Many more females were employed by collective enterprises, while the percentage of males and females working in private enterprises was fairly the same. With the opening up of the Chinese economy in the 1980s, it was not surprising that a high percentage of individuals (over 38% of the sample) worked in the manufacturing industry. A noticeable difference in the sectoral employment by gender was that males

[5] Although it is known that a survey has been done in 2002, it has not been released for public use. With no alternative choice, the present study has to adopt the latest Chinese data available to the authors. The survey data of 1997 was done after China has been undergoing economic transformation for two decades. The existence of discrimination (represented by the unexplained component) in transition economy like China is not generally as clear cut as that has been found in developed countries. Testing the significance between the explained and the unexplained components becomes an important issue. Accordingly, data from China is chosen for illustration purpose. With a representative national sample, the results derived from the data should be relatively reliable.

[6] The t-test showed that the difference in earnings by gender was statistically significant at the 5% significance level.

tended to be in the construction and communication industries while females were more likely to be working in the services industries. The overall sample distributions across provinces are quite similar between males and females.

As outlined in the previous section, the logarithmic earnings of an individual were regressed on a list of explanatory variables. With the available information, the explanatory variables include education level with primary education and below as the reference group, actual working experience and its square, occupation with services and other types of occupation as the omitted category, the type of enterprises with non-state-owned enterprises as the omitted group, industrial sector with agriculture, utility and other industries as the reference group, and the place of residence with Ganshu province as the reference group. The earnings function estimations for the pooled sample and the sample by gender were reported in Table 2. The performance of the OLS estimations was found to be satisfactory with R^2 ranging between 0.42 and 0.46. Most of the explanatory variables are significant with expected signs. Earnings of an individual increased with education level. The earnings profiles exhibited standard concave shape. Occupation, enterprise ownership type, industrial sector, and the place of residence were found to be significant in affecting the earnings of both males and females.

IV. Statistical Inference of the Gender Earnings Differentials

Based on our sample of individuals, the difference in the log earnings by gender was 0.2364. This differential was decomposed into the explained component and the unexplained component according to the two decomposition methods presented in Equations (4) to (6). Equation (4) is Oaxaca’s approach with male’s earnings structure as the non-discrimination earnings structure (Oaxaca-M hereafter). It produced the lowest value in the explained component but the highest value in the unexplained component (cf. Table 3). The results from the Oaxaca-F approach (treating the female’s earnings structure as the non-discrimination structure) fall within the range of the Oaxaca-M approach and the Neumark method (Equation (6), treating the pooled earnings structure as the non-discrimination structure). Clearly, our data set supports the argument that the Neumark method gives rise to a lower estimate for the unexplained component than that of the two Oaxaca approaches (Neumark, 1988, p.293).

However, the divergences of these results could not be confirmed in the absence of a statistical test. The bootstrap testing procedure discussed earlier is therefore applied. Given the fact that the gender earnings differential is significantly different and the total differential is constant across all two methods, testing on the explained component will suffice.

Before applying our bootstrapping procedure, we first conduct the heteroskedasticity test presented in Section II.B. The test statistic for the pooled sample is $F(2, 10860)=34.48$, which rejects the null of homoskedasticity at the 5% significance level. It indicates that the heteroskedasticity corrections of our proposed bootstrapping procedure outlined in Section II.C is necessary.

Based on 1,000 bootstrap repetitions, Table 4 presents the results of the pair-wise distributions of the difference in the explained component of the decomposition methods: (1) Oaxaca-M versus Oaxaca-F (Equation (4) versus Equation (5)), (2) Oaxaca-F versus Nuemark (Equation (5) versus Equation (6)), (3) Oaxaca-M versus Neumark (Equation (4) versus Equation (6)), and (4) Oaxaca's average of male and female estimates versus Neumark[7].

Regardless which type of confidence interval (CI) is adopted, the explained components estimated from the Oaxaca-M and the Oaxaca-F approaches were indifferent from each other at the 5% significance level. A similar conclusion can be drawn for the comparison between the Oaxaca-F approach and the Neumark method. However, the explained components estimated from the

[7] The last pair-wise comparison is based on the averaged estimates from Equation (4) and Equation (5) suggested in Oaxaca's (1973, p.704) original paper.

Oaxaca-M and average approaches are both significantly smaller than the Neumark method at the 5% level. Given the fact that the total earnings differential is constant across both methods, the results of Table 4 also imply that the unexplained component of the Neumark method is significantly smaller than that of the Oaxaca-M and average approaches.

The confirmation of the decomposition method is the first step in addressing the issue of gender discrimination. To complete the story, we also tested the significance of the contribution of the explained and unexplained component within each of the two methods. For each decomposition method, we construct the pair-wise distributions of the difference in the explained and unexplained component, utilizing the results of the same bootstrap procedure for the previous analysis. The results are given in Table 5. Again, bootstrapped 95% confidence intervals of both percentile and percentile-t approaches were applied.

As shown in Table 5, both the Oaxaca-M and average approaches (Equation (4)) gave a significantly smaller explained component than the unexplained component at the 5% level. In other words, discrimination played a more significant role in shaping the gender earnings differentials according to the Oaxaca-M and average approaches. The statistics presented in the last two columns of Table 5 revealed that equal contribution of both the explained and the unexplained components towards the total earnings differentials was found. To conclude, discrimination (the unexplained component) contributed at least 50% of the gender earnings differentials for our sample of Chinese workers.

V. Conclusion

To summarize, our testing procedure utilised to experiment with our Chinese data set suggests that although estimates from the Oaxaca (1973) approach based on female earnings structure (Oaxaca-F, Equation (5)) lie between the Oaxaca (1973) approach based on male earnings structure (Oaxaca-M, Equation (4)) and the Neumark (1988) method (Equation (6)), the estimates of Oaxaca-F approach are not significantly different from that of these two other methods. However, the Oaxaca-M and average approaches present the smallest explained component, which are significantly smaller than their unexplained counterparts, and are also significantly smaller than the explained component estimated by the Neumark method. These conclusions imply that the two decomposition methods we reviewed have quite significant statistical discrepancies.

For researchers who are interested in utilizing our data set for further investigation, there are two options for them. One is to apply the Oaxaca-F approach, since its results are insignificantly different from the other two approaches. Alternatively, one has to present the results from all of the Oaxaca-M and average approaches and the Neumark method, since their results are significantly different.

One may argue that our results may be case specific. Using a randomized national data set of a reasonable sample size, we believe that the issue of the significance test on the decomposition methods and the components within each method is warranted. We merely provide a guideline on how to choose different decomposition methods without losing important information, and on evaluating the relative importance of the explained versus the unexplained components for any chosen method. To ensure robust results, further application to other data sets or research areas should be encouraged.

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Table 1. Summary statistics for the male and female samples

	Males		Females	
	Mean	Standard Deviation	Mean	Standard Deviation
Earnings	2318.09	1540.67	1908.28	1368.68
Primary and Below	0.04	0.19	0.04	0.20
Lower Secondary	0.29	0.45	0.33	0.47
Upper Secondary	0.28	0.45	0.31	0.46
Diploma or Technical Institutions	0.13	0.33	0.15	0.35
University or Above	0.27	0.44	0.17	0.37
Experience	20.76	9.90	17.70	8.66
Senior Technical Staff	0.10	0.30	0.06	0.24
Junior Technical Staff	0.06	0.23	0.08	0.28
Technical Workers	0.05	0.21	0.08	0.27
Senior Government Officials or Managers	0.03	0.16	0.005	0.07
Junior Government Officials	0.09	0.29	0.03	0.18
Clerical Workers	0.22	0.41	0.21	0.41
Sales Workers	0.04	0.19	0.09	0.28
Manual Workers	0.40	0.49	0.37	0.48
Services Workers and Workers of Other Occupations	0.02	0.15	0.07	0.26
State-owned Enterprises	0.86	0.35	0.75	0.43
Collectives	0.11	0.31	0.22	0.41
Foreign-invested Enterprises	0.03	0.18	0.03	0.18
Manufacturing	0.40	0.49	0.38	0.49
Construction	0.05	0.21	0.03	0.17
Communication and Transportation	0.07	0.26	0.05	0.21
Wholesales and Retails	0.09	0.28	0.14	0.35
Finance and Insurance	0.02	0.15	0.02	0.16
Real Estate	0.04	0.20	0.06	0.24
Social Services and Public Health	0.04	0.19	0.06	0.23
Education	0.07	0.25	0.08	0.27
Technology	0.03	0.17	0.02	0.15
Public Administration	0.13	0.33	0.08	0.27
Agriculture, Utility and Other Industries	0.07	0.26	0.07	0.26
Beijing	0.07	0.25	0.07	0.26
Liaoning	0.16	0.37	0.16	0.37
Jiangsu	0.13	0.34	0.13	0.33
Guangdong	0.10	0.31	0.11	0.31
Shanxi	0.10	0.30	0.10	0.30
Anhui	0.08	0.27	0.08	0.27
Hubei	0.12	0.32	0.12	0.32
Sichuan	0.10	0.30	0.10	0.30
Chongqin	0.07	0.26	0.08	0.27
Gansu	0.06	0.24	0.06	0.23
Sample Size	5717		5146	

Table 2. Estimation results of the earnings functions

	Males	Females	Pooled Sample
Constant	7.0788*	6.6526*	6.8561*
	(0.0763)	(0.0816)	(0.0552)
Lower Secondary	0.0376*	0.1282*	0.0797*
	(0.0373)	(0.0426)	(0.0285)
Upper Secondary	0.0846*	0.2436*	0.1696*
	(0.0385)	(0.0436)	(0.0293)
Diploma or Technical Institutions	0.1021*	0.3258*	0.2166*
	(0.0419)	(0.0488)	(0.0323)
University or Above	0.1797*	0.4081*	0.3005*
	(0.0418)	(0.0501)	(0.0325)
Experience	0.0514*	0.0492*	0.0478*
	(0.0026)	(0.0036)	(0.0021)
Experience Square	-0.0009*	-0.0008*	-0.0008*
	(0.00006)	(0.0001)	(0.00005)
Senior Technical Staff	0.2415*	0.1927*	0.2389*
	(0.0533)	(0.0523)	(0.0355)
Junior Technical Staff	0.1639*	0.1522*	0.1744*
	(0.0552)	(0.0469)	(0.0348)
Technical Workers	0.1476*	0.1292*	0.1577*
	(0.0555)	(0.0464)	(0.0347)
Senior Government Officials or Managers	0.2897*	0.3660*	0.3213*
	(0.0638)	(0.1237)	(0.0517)
Junior Government Officials	0.2109*	0.2647*	0.2528*
	(0.0525)	(0.0596)	(0.0359)
Clerical Workers	0.1114*	0.0978*	0.1273*
	(0.0481)	(0.0389)	(0.0292)
Sales Workers	-0.0279	-0.0745	-0.0433
	(0.0581)	(0.0466)	(0.0356)
Manual Workers	0.0934*	-0.0065	0.0846*
	(0.0471)	(0.0375)	(0.0282)
State-owned Enterprises	-0.2948*	-0.1530*	-0.2289*
	(0.0392)	(0.0479)	(0.0310)
Collectives	-0.5256*	-0.4185*	-0.5168*
	(0.0435)	(0.0502)	(0.0331)
Manufacturing	-0.1816*	-0.1077*	-0.1495*
	(0.0273)	(0.0338)	(0.0217)
Construction	-0.2040*	-0.1051	-0.1432*
	(0.0407)	(0.0574)	(0.0341)

	Males	Females	Pooled Sample
Communication and Transportation	-0.0028	-0.0107	0.0168
	(0.0353)	(0.0484)	(0.0292)
Wholesales and Retails	-0.1829*	-0.0870*	-0.1367*
	(0.0371)	(0.0415)	(0.0280)
Finance and Insurance	0.1231*	0.1187	0.1185*
	(0.0509)	(0.0612)	(0.0399)
Real Estate	-0.0991*	-0.0193	-0.0604
	(0.0418)	(0.0469)	(0.0316)
Social Services and Public Health	-0.0292	0.0830	0.0279
	(0.0435)	(0.0479)	(0.0324)
Education	-0.0526	-0.0088	-0.0402
	(0.0377)	(0.0446)	(0.0292)
Technology	-0.0810	-0.0028	-0.0516
	(0.0471)	(0.0618)	(0.0384)
Public Administration	-0.0631	0.0113	-0.0293
	(0.0326)	(0.0442)	(0.0269)
Beijing	0.8269*	0.8670*	0.8416*
	(0.0382)	(0.0463)	(0.0301)
Liaoning	0.3058*	0.2160*	0.2642*
	(0.0330)	(0.0407)	(0.0262)
Jiangsu	0.1424*	0.2152*	0.1751*
	(0.0340)	(0.0417)	(0.0269)
Guangdong	0.3523*	0.4296*	0.3843*
	(0.0353)	(0.0432)	(0.0279)
Shanxi	-0.2068*	-0.2943*	-0.2476*
	(0.0349)	(0.0429)	(0.0277)
Anhui	-0.6315*	-0.6338*	-0.6343*
	(0.0367)	(0.0452)	(0.0291)
Hubei	-0.3983*	-0.3048*	-0.3595*
	(0.0345)	(0.0420)	(0.0272)
Sichuan	0.0515	0.1104*	0.0822*
	(0.0353)	(0.0430)	(0.0279)
Chongqin	0.0658	0.1404*	0.0949*
	(0.0377)	(0.0454)	(0.0296)
R-squared	0.4560	0.4241	0.4383

Notes: Standard errors are in parentheses. * indicates significant at the level of 5% or less.

Table 3. Explained and unexplained components by two decomposition methods

		Explained Component (1)	Unexplained Component (2)	Total Earnings Differential ($\ln \overline{E}^M - \ln \overline{E}^F$) (3)=(1)+(2)
Oaxaca method	by male equation (4)	0.0967	0.1397	0.2364
	by female equation (5)	0.1045	0.1319	0.2364
	Average of male and female estimates	0.1006	0.1358	0.2364
Neumark Method (Equation (6))		0.1140	0.1224	0.2364

Note: Estimates are based on Tables 1 and 2.

Table 4. A comparison of explained components across different decomposition estimates

Explained component differential		Δ_{45} Oaxaca-M vs. Oaxaca-F estimates	Δ_{56} Oaxaca-F vs. Neumark method	Δ_{46} Oaxaca-M vs. Neumark method	Δ_{a6} Oaxaca-average vs. Neumark method
Estimated from actual data		-0.007805	-0.009490	-0.01729	-0.01340
Of bootstrapped Δ_{ij}:	Mean	-0.008743	-0.006244	-0.01499	-0.01062
	Median	-0.008959	-0.006293	-0.01516	-0.01064
	Standard error	0.005646	0.003585	0.002665	0.001418
Bootstrapped 95% confidence interval (CI) (N=1,000 repetitions)	Percentile CI	[-0.01955, 0.002462]	[-0.01291, 0.001107]	[-0.01997, -0.009323]	[-0.01346, -0.007870]
	P-value for H_0: Δ_{ii} =0	0.112	0.070	0.000	0.000
	Percentile-t CI	[-0.1981, 0.002322]	[-0.02021, -0.00976]	[-0.01327, 0.00078]	[-0.02021, -0.00976]
	P-value for H_0: Δ_{ij} =0	0.1218	0.0819	0.0000	0.0000

Note: Δ_{ij} means that explained component of Equation (i) minus that of Equation (j), i, j=4, 5, 6. Δ_{a6}=(Δ_{56}+Δ_{46})/2.

Table 5. A comparison of explained and unexplained components within each decomposition estimation

Explained-unexplained differential:		Oaxaca method: Δ_4 by male equation	Oaxaca method: Δ_5 by female equation	Oaxaca method: Δ_a average of male & female estimates	Neumark method: Δ_6
Estimated from actual data		-0.04300	-0.02739	-0.0352	-0.008400
Of bootstrapped Δ_i:	Mean	-0.03055	-0.01306	-0.02180	-0.0005722
	Median	-0.03065	-0.01335	-0.02165	-0.0005841
	Standard error	0.009932	0.01130	0.009019	0.007168
Bootstrapped 95% confidence interval (CI) (N=1,000 repetitions)	Percentile CI	[-0.05016, 0.01034]	[-0.03402, 0.01058]	[-0.03976, -0.004533]	[-0.01467, 0.01362]
	P-value for H_0: Δ_i=0	0.002	0.240	0.000	0.938
	Percentile-t CI	[-0.05001, -0.01108]	[-0.03522, 0.009096]	[-0.04205, -0.001559]	[-0.01462, 0.01377]
	P-value for H_0: Δ_i=0	0.0022	0.2482	0.01580	0.9364

Note: Δ_i means that explained minus unexplained component based on Equation (i), i=4, 5, 6. Δ_a=(Δ_4+Δ_5)/2.