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On the standard errors of Oaxaca-type decompositions for inter-industry gender wage differentials

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Abstract

Horrace and Oaxaca (2001) treat the regressors in gender wage gap by industry measures as non-stochastic when computing the corresponding standard errors. However, the non-stochastic regressors assumption is thought to be inappropriate in modern econometrics. In this paper, we derive the correct standard errors for the measures proposed by Horrace and Oaxaca (2001). We then empirically apply the derived correct standard errors in regard to the March 1998 Current Population Survey data adopted in Horrace and Oaxaca (2001), as well as the Manpower Utilization Survey in the Taiwan area conducted by the Census Bureau over the years from 1978 to 2003. The empirical results suggest that the researchers would be better to use the correct standard errors derived in this paper, accompanied by the White correction, to arrive at a more accurate statistical inference.

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1 Introduction

Since the influential work of Blinder (1973) and Oaxaca (1973), economists (especially labor economists) have been able to decompose the mean sample differences between female and male workers into explained and unexplained differences. The decomposition techniques can also be applied to any two categories of samples, such as union versus nonunion workers, skilled versus unskilled labors, and private versus public sector workers. However, the hypothesis testing associated with the coefficient and characteristic effects will suffer from the incorrect standard errors problem because the underlying regressors are assumed to be non-stochastic. Jann (2005) first pays attention to this issue of estimating the asymptotic variances of the decomposition components. He proposes the consistent estimation of the asymptotic variances under the assumption of stochastic regressors.

In many cases, adding sets of categorical variables can shed light on the gender wage differentials. For instance, one might want to investigate the pattern of inter-industry wage differentials separately for females and males by incorporating the industry dummies in the (log) wage equations. Fields and Wolff (1995) propose a measure ($\hat{g}_j$, where j denotes the jth industry) for gender wage gaps by industry. As documented in Horrace and Oaxaca (2001), the measure proposed by Fields and Wolff (1995) is not immune to the identification problem[1] addressed by Oaxaca and Ransom (1999) in detailed decomposition. Horrace and Oaxaca (2001) consider three alternative measures ($\hat{\phi}_j$, $\hat{\delta}_j$, and $\hat{\gamma}_j$) to estimate gender wage gaps by industry that are not vulnerable to the invariance problem.

When inspecting the measures $\hat{\phi}_j$ and $\hat{\delta}_j$, we are aware that the two measures are dependent upon the mean individual characteristics. Horrace and Oaxaca (2001) treat the regressors as non-stochastic and derive the corresponding standard errors for the measures $\hat{\phi}_j$ and $\hat{\delta}_j$. In modern econometrics, however, the non-stochastic regressors assumption is considered to be inappropriate. If we allow for stochastic regressors, the asymptotic covariance matrices for the measures $\hat{\phi}_j$ and $\hat{\delta}_j$ in Horrace and Oaxaca (2001) will be inconsistent. The statistical inference based on the inconsistent standard errors will be misleading. In this paper, we will try to obtain the right standard errors for $\hat{\phi}_j$ and $\hat{\delta}_j$ along the lines of Jann (2005). In addition, since heteroskedasticity is common in cross sectional data sets, we also provide the White correction for different versions of the standard errors. The empirical results not only confirm the theory that the introduction of extra variation in the stochastic regressors will inflate the asymptotic variances, but also suggest that the robust standard errors should be taken into account when we compute the inter-industry gender wage gap measures, $\hat{\phi}_j$ and $\hat{\delta}_j$, proposed by Horrace and Oaxaca (2001).

In the next section, we will briefly review the existing gender wage gap estimators by industry. We derive the right standard errors of the gender wage gap estimators by industry under the stochastic regressors assumption in Section 3. Section 4 illustrates the implementation of the proposed standard error estimator to the gender wage differentials in industry using the March 1998 Current Population Survey (CPS) data adopted in Horrace and Oaxaca (2001) as well as the Manpower Utilization Survey (MUS) in the Taiwan area by the

[1] The identification problem means that the coefficients of the constant term and dummy variables are not invariant to the choice of the left-out reference group.

Census Bureau for the years 1978 to 2003. The final section concludes the paper.

2 Gender Wage Gap by Industry Estimators

Fields and Wolff (1995) consider a standard log-wage model to estimate the gender wage gap by industry:

$$y_i^f = \alpha^f + \sum_{j=2}^{J} \beta_j^f d_{ij}^f + x_i^f \theta^f + \varepsilon_i^f; \tag{2.1}$$

$$i = 1, ..., F;\ j = 1, ..., J$$

$$y_i^m = \alpha^m + \sum_{j=2}^{J} \beta_j^m d_{ij}^f + x_i^m \theta^m + \varepsilon_i^m; \tag{2.2}$$

$$i = 1, ..., M;\ j = 1, ..., J,$$

where (2.1) and (2.2) represent the log-wage regressions for F female and M male workers, respectively. Superscript f denotes female and m denotes male. y_i is the logarithm of the hourly wage and x_i is a $1 \times p$ vector of characteristic regressors, which may contain continuous or binary variables. d_{ij} is a dummy variable that equals one if the ith worker is employed in the jth industry and equals zero otherwise. Without loss of generality, the first category is set as the left-out reference group in J classifications, i.e., $d_{i1} = 0$. α, β, and θ are parameters to be estimated. ε_i is the disturbance term which is assumed to satisfy the classical assumptions such as i.i.d. and homoskedasticity.[2]

We can compute the log-wage for a representative male and for a representative female worker in industry j by averaging the fitted values in (2.1) and (2.2) for all persons in industry j:

$$\hat{y}_j^f = \hat{\alpha}^f + \hat{\beta}_j^f + \bar{x}_j^f \hat{\theta}^f$$

$$\hat{y}_j^m = \hat{\alpha}^m + \hat{\beta}_j^m + \bar{x}_j^m \hat{\theta}^m,$$

where $\bar{x}_j^f$ and $\bar{x}_j^m$ are the mean characteristics of a representative female and male worker in the jth industry, respectively. In addition, the "hat" denotes the estimated counterpart of the true parameter throughout this paper. Using the strategy introduced in Oaxaca (1973), one can decompose the gender wage gap in industry j into unexplained (coefficients effects) and explained components (characteristics effects) as follows:

$$\hat{y}_j^f - \hat{y}_j^m = (\hat{\alpha}^f - \hat{\alpha}^m) + (\hat{\beta}_j^f - \hat{\beta}_j^m) + \bar{x}_j^f(\hat{\theta}^f - \hat{\theta}^m) + (\bar{x}_j^f - \bar{x}_j^m)\hat{\theta}^m, \tag{2.3}$$

where the first three terms on the right-hand side of (2.3) are the unexplained components, while the last term corresponds to the explained wage gap in industry j. Fields and Wolff (1995) define the gender wage gap for industry j as:

$$\hat{g}_j = (\hat{\alpha}^f - \hat{\alpha}^m) + (\hat{\beta}_j^f - \hat{\beta}_j^m). \tag{2.4}$$

[2] Of course, one can allow the error terms to be heteroskedastic and adopt robust standard errors.

Since $\hat{g}_j$ is not identified, Horrace and Oaxaca (2001) propose three alternatives:

$$\hat{\phi}_j = (\hat{\alpha}^f - \hat{\alpha}^m) + (\hat{\beta}^f_j - \hat{\beta}^m_j) + \bar{x}^f_j(\hat{\theta}^f - \hat{\theta}^m) \tag{2.5}$$

$$\hat{\delta}_j = (\hat{\alpha}^f - \hat{\alpha}^m) + (\hat{\beta}^f_j - \hat{\beta}^m_j) + \bar{x}^f(\hat{\theta}^f - \hat{\theta}^m) \tag{2.6}$$

$$\hat{\gamma}_j = \max_{n=1...J} \hat{g}_n - \hat{g}_j = \max_{n=1...J} \hat{\delta}_n - \hat{\delta}_j \tag{2.7}$$

Horrace and Oaxaca (2001) also derive the asymptotic variances for $\hat{\phi}_j$, $\hat{\delta}_j$ and $\hat{\gamma}_j$ based on the assumption of the non-randomness of $\bar{x}^f_j$ and $\bar{x}^f$. If we allow for a more plausible assumption of the stochastic regressors, the variance matrices derived in Horrace and Oaxaca (2001) are no longer correct. Note that the standard errors for the measures $\hat{g}_j$ and $\hat{\gamma}_j$ do not depend on the mean individual characteristics $\bar{x}^f_j$ or $\bar{x}^f$, so that the assumption regarding the regressors has nothing to do with the standard errors. Hence, this paper aims at the standard errors for the measures $\hat{\phi}_j$ and $\hat{\delta}_j$.

3 Standard Errors of the Gender Wage Gap by Industry Estimators

We follow the notation used in Horrace and Oaxaca (2001) and let $\hat{\xi}^{f\prime} = [\hat{\alpha}^f, \hat{\beta}^f_2, ..., \hat{\beta}^f_J]$, $\hat{\xi}^{m\prime} = [\hat{\alpha}^m, \hat{\beta}^m_2, ..., \hat{\beta}^m_J]$, $\hat{\kappa}^f = [\hat{\theta}^{f\prime}, \hat{\xi}^{f\prime}]'$, $\hat{\kappa}^m = [\hat{\theta}^{m\prime}, \hat{\xi}^{m\prime}]'$, $C = [[\bar{x}^{f\prime}_1, ..., \bar{x}^{f\prime}_J]', L]$, and $C^* = [\iota_J \otimes \bar{x}^f, L]$, where

$$L = \begin{bmatrix} 1 & 0 & 0 & ... & 0 \\ 1 & 1 & 0 & ... & 0 \\ 1 & 0 & 1 & ... & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & ... & 0 & 1 \end{bmatrix}$$

is a $J \times J$ matrix, ι_J is a J dimensional column vector of ones, and $\otimes$ denotes the Kronecker product. We also let C'_j and $C^{*\prime}_j$ be the jth row vector of matrix C and C^*, respectively.[3] We immediately have $\hat{\phi}_j = C'_j(\hat{\kappa}^f - \hat{\kappa}^m)$ and $\hat{\delta}_j = C^{*\prime}_j(\hat{\kappa}^f - \hat{\kappa}^m)$. If the regressors are assumed to be non-stochastic, we have the following proposition associated with the variances for $\hat{\phi}_j$ and $\hat{\delta}_j$:

Proposition 3.1. *If the regressors in (2.1) and (2.2) are non-stochastic, the estimated variances for $\hat{\phi}_j$ and $\hat{\delta}_j$ $(j = 1, ..., J)$ are given by:*

$$\widehat{Var}[\hat{\phi}_j] = C'_j[\widehat{Var}[\hat{\kappa}^f] + \widehat{Var}[\hat{\kappa}^m]]C_j \tag{3.1}$$

$$\widehat{Var}[\hat{\delta}_j] = C^{*\prime}_j[\widehat{Var}[\hat{\kappa}^f] + \widehat{Var}[\hat{\kappa}^m]]C^*_j. \tag{3.2}$$

Proof. See the Appendix for variance estimation in Horrace and Oaxaca (2001). □

[3] For instance, $C_1 = [\bar{x}^f_1 \ 1 \ \iota'_{(J-1)} \otimes 0]'$, which is a $(p + J) \times 1$ column vector.

However, if the assumption regarding the design matrix is relaxed to be stochastic, the variation of the stochastic regressors should be taken into consideration to yield the correct variances for $\hat{\phi}_j$ and $\hat{\delta}_j$. The result is summarized in the proposition below:

Proposition 3.2. *If the regressors in (2.1) and (2.2) are stochastic, the estimated variances for* $\hat{\phi}_j$ *and* $\hat{\delta}_j$ *($j = 1, ..., J$) are given by:*

$$\widehat{Var}[\hat{\phi}_j] = C_j'[\widehat{Var}[\hat{\kappa}^f] + \widehat{Var}[\hat{\kappa}^m]]C_j + (\hat{\kappa}^f - \hat{\kappa}^m)'\widehat{Var}[C_j](\hat{\kappa}^f - \hat{\kappa}^m) + tr\{\widehat{Var}[C_j](\widehat{Var}[\hat{\kappa}^f] + \widehat{Var}[\hat{\kappa}^m])\} \tag{3.3}$$

$$\widehat{Var}[\hat{\delta}_j] = C_j^{*\prime}[\widehat{Var}[\hat{\kappa}^f] + \widehat{Var}[\hat{\kappa}^m]]C_j^* + (\hat{\kappa}^f - \hat{\kappa}^m)'\widehat{Var}[C_j^*](\hat{\kappa}^f - \hat{\kappa}^m) + tr\{\widehat{Var}[C_j^*](\widehat{Var}[\hat{\kappa}^f] + \widehat{Var}[\hat{\kappa}^m])\} \tag{3.4}$$

Proof. Let $C_j = u_1$ and $(\hat{\kappa}^f - \hat{\kappa}^m) = u_2$. It is easy to see that u_1 and u_2 are uncorrelated under mild classical assumptions for linear regressions. Then, by Lemma A.1 in the Appendix, the population variance of $\hat{\phi}_j$ is given by:

$$\begin{aligned} Var[\hat{\phi}_j] &= E[C_j]'[Var[\hat{\kappa}^f - \hat{\kappa}^m]]E[C_j] + E[\hat{\kappa}^f - \hat{\kappa}^m]'Var[C_j]E[\hat{\kappa}^f - \hat{\kappa}^m] \\ &\quad + tr\{Var[C_j](Var[\hat{\kappa}^f - \hat{\kappa}^m])\} \\ &= E[C_j]'[Var[\hat{\kappa}^f] + Var[\hat{\kappa}^m]]E[C_j] + E[\hat{\kappa}^f - \hat{\kappa}^m]'Var[C_j]E[\hat{\kappa}^f - \hat{\kappa}^m] \\ &\quad + tr\{Var[C_j](Var[\hat{\kappa}^f] + Var[\hat{\kappa}^m])\}, \end{aligned}$$

where the second equality follows based on the fact that there is no correlation between the female and male samples. Now, replacing the expected values and variances with their sample counterparts leads to the estimated variance of $\hat{\phi}_j$:

$$\begin{aligned} \widehat{Var}[\hat{\phi}_j] &= C_j'[\widehat{Var}[\hat{\kappa}^f] + \widehat{Var}[\hat{\kappa}^m]]C_j + (\hat{\kappa}^f - \hat{\kappa}^m)'\widehat{Var}[C_j](\hat{\kappa}^f - \hat{\kappa}^m) \\ &\quad + tr\{\widehat{Var}[C_j](\widehat{Var}[\hat{\kappa}^f] + \widehat{Var}[\hat{\kappa}^m])\} \end{aligned}$$

The desired result for $\widehat{Var}[\hat{\delta}_j]$ can be obtained similarly. □

By inspecting equations (3.1), (3.2) and (3.4), (3.3), we can see that the variances for $\hat{\phi}_j$ and $\hat{\delta}_j$ based on the stochastic regressors assumption are higher than those based on the non-stochastic assumption. This fact suggests that ignoring the possible stochastic properties of the regressors will result in under-estimation of the standard errors, and will tend to over-reject the null hypothesis.

As far as the estimation of $\widehat{Var}[C_j]$ is concerned, the analogy principle yields the estimated variance of C_j by means of the following:

$$\widehat{Var}[C_j] = \frac{\mathcal{X}'\mathcal{X}}{n_j(n_j - 1)},$$

where

$$\mathcal{X} = \begin{bmatrix} x^f_{11_j} - \bar{x}^f_{1_j} & ... & x^f_{p1_j} - \bar{x}^f_{p_j} & 0 & ... & 0 \\ ... & ... & ... & ... & ... & ... \\ x^f_{1n_j} - \bar{x}^f_{1_j} & ... & x^f_{pn_j} - \bar{x}^f_{p_j} & 0 & ... & 0 \end{bmatrix},$$

is a $n_j \times (p + J)$ matrix of the deviation from the mean, $x^f_{pn_j}$ is the n_jth observation of the pth regressor for females in industry j, $\bar{x}^f_{p_j}$ is the mean of the pth characteristic for females in industry j, and n_j is the number of observations in industry j. The estimation of $\widehat{Var}[C^*_j]$ can be similarly computed.

4 Empirical Illustration

4.1 March 1998 CPS Data

To apply the proposed estimator empirically, we first use the March 1998 CPS data set employed in Horrace and Oaxaca (2001). By using the sample selecting criterion stated in Horrace and Oaxaca (2001), we have a sample of 27,426 males and 25,444 females. The regression model sets out to explain the log-hourly wage based on covariates which include an intercept, education, potential experience, squared potential experience, size of population of residence, a binary variable for urban residence, three dummy variables for region of residence, a binary variable for marital status, a binary variable for race, twelve dummy variables for occupation, and thirteen dummy variables for industry.

One can see that the t-ratios of $\hat{\delta}_j$ and $\hat{\phi}_j$ become lower if stochastic regressors are taken into consideration. See Table 1. This confirms the theoretical result that stochastic regressors inflate the variances of $\hat{\delta}_j$ and $\hat{\phi}_j$. In this particular data set, we do not see any dramatic change in the significance of the t-ratios among all industries when correct standard errors are utilized.[4] However, if we compute the White robust standard errors for the cases of fixed and stochastic regressors, we can observe that the impact of both measures of $\hat{\delta}_j$ and $\hat{\phi}_j$ on Wholesale Trade are no longer insignificant, but instead are significant at the 10% level.

4.2 1978-2003 Taiwan's MUS Data

We now turn to the data set from the Census Bureau in Taiwan for the Manpower Utilization Survey (MUS), which has been conducted annually since 1978 with a view to gaining an understanding of manpower utilization in the Taiwan Area. The MUS data set includes the wages for females and males as well as control variables such as education, potential experience, squared potential experience, job tenure, squared job tenure, a binary variable for marital status, a binary variable for living in an urban area, six dummy variables for occupations, three dummy variables for region of place of work, and seven dummy variables for industries. Note that, unlike fourteen categories for industries in the CPS data set, the

[4]Even though the stochastic regressors assumption does not play an important role in the CPS data set, we do find that the randomness assumption matters in other data sets such as the MUS data set in Taiwan.

industries in the MUS data set are classified into eight categories, which consist of Mining, Agri., Forestry, & Fisheries, Durables Manufacturing, Construction, Business, Transp. & Communication, Finance, Insurance & Real Estate, and Personal Services. Since the MUS data sets are available from 2003 back to 1978, we will try to estimate the gender wage gap by industry every year in Taiwan. The numbers of observations for females and males in each year are summarized in Table 2. To save space, we do not list the detailed t-ratios of $\hat{\delta}_j$ and $\hat{\phi}_j$ for all industries in each year. Instead, the selected years and industries are reported for illustration purposes.[5]

There are several findings with respect to the empirical results derived from using the MUS data. First, Table 3 once again tells us that imposing stochastic regressors in fact increases the standard errors and in turn lowers the t-ratio in all industries and years. Secondly, the randomness or non-randomness of the covariates may affect the significance of the t-ratio. For instance, in 1988 the t-ratio of $\hat{\phi}_j$ for Mining changed from -2.6662 to -2.5522, which implies that $\hat{\phi}_j$ is significant at the 1% level under the fixed regressors assumption but only significant at the 5% level under the stochastic regressors assumption. The t-ratio of $\hat{\phi}_j$ in 1984 also indicates that the correct standard error should be used, otherwise, the statistical test will be distorted. Third, we observe that robust standard errors need to be computed in order to make correct inferences. In many cases, the decisions based on t-ratios have been drastically overturned under fixed covariates with White correction. For example, the t-ratio of $\hat{\delta}_j$ for Agri., Forestry, & Fisheries in 1986 is insignificant at all three common levels, but with a robust standard error it is strongly significant at the 5% level. In 2001, the t-ratio of $\hat{\phi}_j$ for Mining reverses from insignificant at all levels to significant at the 1% level. Finally, one can see that the impact on the significance of the t-ratios by adopting the White correction is larger than that of using correct standard errors. The t-ratios of $\hat{\delta}_j$ and $\hat{\phi}_j$ are obviously different under fixed and stochastic regressors, although they do not make much difference except in several cases. If we use the White correction, the t-ratios under two scenarios of regressors almost reach the same conclusion, except for the t-ratio of $\hat{\phi}_j$ for Mining in 1999. It is also worth noting that our proposed correction matters more for the $\hat{\phi}_j$ parameters than for the $\hat{\delta}_j$ parameters.[6] One can see that the t-ratios in columns 1 and 3 are uniformly within 0.0003 in the top panel of Table 3, but as different as 0.183 in the bottom panel. This is because $\hat{\phi}_j$ parameters in (2.5) involve the industry-specific sample means, which naturally contain more sampling errors. To sum up, we recommend that the researchers use the correct standard error derived in this paper as well as the White correction to obtain a more accurate statistical inference.

5 Conclusion

We are concerned with the standard errors of the gender wage differential in industry estimators. Since the estimators, $\hat{\delta}_j$ and $\hat{\phi}_j$, considered in Horrace and Oaxaca (2001) do not

[5]The complete set of empirical results encompassing 1978-2003 for all industries is available upon request from the author.

[6]I owe this observation and the following discussions to a referee.

incorporate the randomness of the covariates, the resulting asymptotic variances will be incorrect in general, and the statistical inference will be invalid. In this paper, we contribute to the literature by deriving the correct standard errors under the assumption of stochastic regressors.

A large number of t-ratios for $\hat{\delta}_j$ and $\hat{\phi}_j$ using the 1998 CPS and 1978-2003 MUS data sets are computed to demonstrate the importance of having the correct standard errors. The results show that the impact of the stochastic regressor on standard errors should not be neglected because in some cases the significance of the t-ratio will be reversed. We also find that adopting robust standard errors usually changes the results dramatically. As researchers employ the estimators $\hat{\delta}_j$ and $\hat{\phi}_j$ in Horrace and Oaxaca (2001), combining the correct standard errors derived in this paper with the White correction would be better for reaching a more accurate conclusion.

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A Appendix

Lemma A.1. *The variance of the product of two uncorrelated random vectors* u_1 *and* u_2 *could be written as*

$$Var[u_1' u_2] = \mu_1' \Sigma_2 \mu_1 + \mu_2' \Sigma_1 \mu_2 + tr[\Sigma_1 \Sigma_2],$$

where μ_l, $l = 1, 2$, *is the vector of the expected values of the random variables in* u_l *and* Σ_l *is the matrix of the variances and covariances, that is* $\Sigma_l = E[(u_l - \mu_l)(u_l - \mu_l)']$.

Proof. See the Appendix in Jann (2005). □

Table 1: Gender Wage Gap by Industry Estimators with Various Standard Errors for CPS 1998 data

	t-ratio of $\hat{\delta}_j$							
Industries	Fix[a]		Fix-R		Sto		Sto-R	
Agric., Forestry, & Fisheries	-1.284		-1.175		-1.284		-1.175	
Wholesale Trade	-1.286		-1.713[b]	*	-1.285		-1.713	*
Mining	-5.007	***	-4.877	***	-5.006	***	-4.876	***
Durables Manufacturing	-7.463	***	-8.139	***	-7.458	***	-8.133	***
Transp. & Communication	-9.678	***	-10.572	***	-9.672	***	-10.565	***
Personal Services	-7.537	***	-7.652	***	-7.532	***	-7.647	***
Business & Repair Services	-3.888	***	-4.165	***	-3.886	***	-4.163	***
Prof. & Related Services	-13.415	***	-13.087	***	-13.398	***	-13.071	***
Construction	-12.632	***	-11.812	***	-12.623	***	-11.805	***
Public Adminstration	-7.961	***	-7.544	***	-7.956	***	-7.540	***
Retail Trade	-5.056	***	-4.660	***	-5.054	***	-4.659	***
Non-Durables Manufacturing	-5.733	***	-5.027	***	-5.732	***	-5.026	***
Entertainment	-14.130	***	-13.63	***	-14.106	***	-13.608	***
Finance, Insurance & Real Estate	-7.342	***	-8.105	***	-7.338	***	-8.101	***
Industries	t-ratio of $\hat{\phi}_j$							
Agric., Forestry, & Fisheries	-1.248		-1.065		-1.233		-1.052	
Wholesale Trade	-1.586		-2.118	**	-1.566		-2.071	**
Mining	-5.222	***	-5.094	***	-5.152	***	-5.025	***
Durables Manufacturing	-11.419	***	-12.867	***	-11.273	***	-12.660	***
Transp. & Communication	-13.490	***	-14.996	***	-13.355	***	-14.811	***
Personal Services	-6.823	***	-6.989	***	-6.747	***	-6.907	***
Business & Repair Services	-5.084	***	-5.474	***	-5.017	***	-5.391	***
Prof. & Related Services	-15.975	***	-15.291	***	-15.842	***	-15.173	***
Construction	-12.516	***	-11.78	***	-12.404	***	-11.686	***
Public Adminstration	-7.088	***	-6.720	***	-7.013	***	-6.657	***
Retail Trade	-2.498	**	-2.472	**	-2.493	**	-2.467	**
Non-Durables Manufacturing	-4.865	***	-4.248	***	-4.817	***	-4.216	***
Entertainment	-15.023	***	-14.228	***	-14.934	***	-14.152	***
Finance, Insurance & Real Estate	-7.515	***	-8.370	***	-7.437	***	-8.263	***

[a] Fix, Fix-R, Sto, and Sto-R stand for the method of computing standard errors using fixed regressors, fixed regressors with the White correction, stochastic regressors, and stochastic regressors with the White correction, respectively.

[b] *, **, and *** denote statistically significant at the 10%, 5%, and 1% significance levels, respectively.

Table 2: Number of Observations for Females and Males in the MUS 1978-2003

Year	Female	Male
1978	4291	8028
1979	4748	8627
1980	4910	8828
1981	5151	9523
1982	5229	9257
1983	5422	9031
1984	6025	9524
1985	6069	9673
1986	6363	9641
1987	7191	10258
1988	7016	10320
1989	6935	10361
1990	6725	10197
1991	6703	9887
1992	6571	9926
1993	7027	10932
1994	7301	11157
1995	7424	11158
1996	7341	10453
1997	7329	10539
1998	7681	10996
1999	7484	10825
2000	7626	10908
2001	7635	10405
2002	7981	10841
2003	7816	10624

Table 3: Selected Gender Wage Gap by Industry Estimators with Various Standard Errors for Taiwan's MUS Data

		t-ratio of $\hat{\delta}_j$							
Year	Industry	Fix[a]		Fix-R		Sto		Sto-R	
1979	Mining	-1.6242		-2.9380[b]	***	-1.6240		-2.9369	***
1981	Mining	-1.4346		-1.8890	*	-1.4344		-1.8887	*
1983	Agric., Forestry, & Fisheries	-2.0081	**	-2.7027	***	-2.0080	**	-2.7024	***
1984	Agric., Forestry, & Fisheries	-1.8160	*	-1.9994	**	-1.8158	*	-1.9992	**
1986	Agric., Forestry, & Fisheries	-1.6151		-2.1752	**	-1.6150		-2.1750	**
1988	Agric., Forestry, & Fisheries	-2.1465	**	-1.8366	*	-2.1463	**	-1.8365	*
1994	Agric., Forestry, & Fisheries	-2.2095	**	-3.5901	***	-2.2093	**	-3.5894	***
1997	Agric., Forestry, & Fisheries	-3.0437	***	-2.5448	**	-3.0434	***	-2.5446	**
2000	Agric., Forestry, & Fisheries	-3.0772	***	-2.3230	**	-3.0769	***	-2.3229	**
2001	Agric., Forestry, & Fisheries	-3.3421	***	-2.2649	**	-3.3420	***	-2.2649	**
2002	Mining	-1.3978		-2.1360	**	-1.3978		-2.1359	**
2003	Mining	-2.1423	**	-4.1005	***	-2.1422	**	-4.1000	***

		t-ratio of $\hat{\phi}_j$							
Year	Industry	Fix		Fix-R		Sto		Sto-R	
1984	Mining	-2.6671	***	-5.1124	***	-2.4834	**	-4.0858	***
1988	Mining	-2.6662	***	-2.3608	**	-2.5522	**	-2.2799	**
1999	Mining	-1.9104	*	-1.6512	*	-1.8885	*	-1.6369	
2001	Mining	-1.0178		-2.7083	***	-1.0114		-2.5928	***
2003	Mining	-1.8219	*	-3.4892	***	-1.7643	*	-3.1279	***

[a] Fix, Fix-R, Sto, and Sto-R stand for the method of computing standard errors using fixed regressors, fixed regressors with the White correction, stochastic regressors, and stochastic regressors with the White correction, respectively.

[b] *, **, and *** denote statistically significant at the 10%, 5%, and 1% significance levels, respectively.