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ABSTRACT

A new gender wage gap decomposition methodology is introduced that does not suffer from the identification problem caused by unobserved non-discriminatory wage structure. The methodology is used to measure the relative size of Korean gender wage gaps from 1994 to 2000 across industries, differentiated by industrial *knowledge intensity*, where knowledge intensity is the extent to which industries produce or employ high-technology products. Korea represents an important case study, since it possesses one of the fastest growing knowledge-intensive economies, among industrialized countries. Empirical results indicate that over this period, discrimination (the unexplained portion of the gender wage gaps) in Korea was statistically smaller in knowledge-intensive industries than in industries with low knowledge intensity. Also, discrimination was declining on average over the period. This suggests that continued growth in knowledge-intensive industries in Korea may lead to further declines in the overall gender gap.

JEL Codes: C12, J31, J71

Keywords: discrimination, labor markets, wage differential, compensation.

I. INTRODUCTION

Although there is an extensive body of literature on the decomposition of gender wage differentials, based on a single cross-section of data, there have been relatively few studies that analyze how these components evolve over time. For example, see Blau and Kahn (1999). In the last few years, many developing countries have undergone substantial changes in their industrial compositions and market structures, due to development strategies, shifting trade policies, and sectoral shifts in the global economy (Freeman, 2004). Therefore, a dynamic analysis of the evolution of the gender wage gap in a developing country seems particularly relevant. In particular, developing countries in Asia experienced a substantial shift towards knowledge-intensive industries at the end of the last decade (OECD, 2000), where knowledge-intensity is measured as the extent to which industries utilize a skilled or educated workforce or the extent to which technologically advanced processes are used in the production of output.

An interesting question is then, "are these 'knowledge based' industries more or less prone to gender discrimination than 'non-knowledge based' industries?" A second interesting question is, "to what extent has this shift towards knowledge based industries been accompanied with a change in the prevalence of gender discrimination in Asian economies?" In this study, we analyze inter-industry gender wage gaps by knowledge intensity in Korea, using a cross sectional occupational wage survey between the years 1994 and 2000. The Korean economy provides a good test case, as the transition towards knowledge based industries in this country was substantial (OECD, 2000). Also, Korea experienced a steady decrease in the overall female-male wage differentials.[1] We find that in each year considered, Korean knowledge based industries were less discriminatory than non-knowledge based

[1] For non-agricultural industries, the average female-to-male earnings ratio was 44.2% in 1980 but was 63.2% in 2000 (Korean Labor Institute, Labor Statistics, 2004).

industries in terms of pay differentials. We also find that the decrease the in the overall wage gap was accompanied by a decrease in the discriminatory (unexplained) portion of the gap.

To analyze inter-industry wage differentials by knowledge intensity, we identify a new decomposition methodology that allows us to make relative comparisons across industries and across time. Conventional decomposition techniques (Oaxaca 1972, and Blinder, 1973) are not identified in the sense that the investigator must decide *a priori* on an appropriate measure of the unobserved non-discriminatory wage structure (Neumark, 1988). Our method identifies *relative* inter-industry gender wage gaps and does not require an *ad hoc* proxy for the non-discriminatory wage structure, because the estimation is designed to eliminate this structure, when it can be assumed to be fixed across industries and across time. Our estimates reveal that gender discrimination in "knowledge based" industries was significantly lower than in "non-knowledge based" industries in Korea in all years considered. The results hold for knowledge based industries within both the manufacturing and service sectors of the Korean economy, as well as for the economy as a whole. Our analysis reveals that dynamic fluctuations of discrimination in the manufacturing sector at the end of the millennium were consistent with the timing of the Asian financial crisis, and it may be possible that gender discrimination improved during a period of intense industrial competition. While this is not formally investigated or tested, it is consistent with the arguments of Becker (1971).

The paper is organized as follows. The next section summarizes theories that link industrial composition and knowledge intensity to the magnitude of the unexplained gender wage gap. In Section III, we develop a *relative* estimation strategy to estimate inter-industry "non-discriminatory percentages", our normalized measure of gender discrimination. Our strategy does not suffer from the lack of identification described by Neumark (1988). Section IV describes the survey data used in this study, as well as the classification of industries into "knowledge based" and "non-knowledge based" categories. Section V presents the empirical results and compares the components of inter-industry wage differentials in knowledge based industries with non-knowledge based industries. We repeat the analysis at a more disaggregated level and compare the manufacturing sector and service sector by their knowledge intensity. The final section summarizes and concludes.

II. INDUSTRIAL COMPOSITION AND GENDER WAGE GAPS

Krueger and Summers (1988) refueled an empirical and theoretical debate about the causes of gender wage differentials. They found that the structure of the wage in the United States was not compatible with a neoclassical model (Edin and Zetteberg, 1992), showing that inter-industry gender wage disparities persisted between workers with identical individual characteristics and working conditions. Several other studies, using standard wage regressions, also support the existence of inter-industry gender wage differentials for apparently equally skilled workers; many of these studies conclude that gender discrimination cannot be refuted. See Gibbons and Katz (1992), Helwege (1992), Fields and Wolff (1995), and Abowd, Karamarz, Margolis (1999).[2] In the last decade, many developing countries experienced changes in industrial composition due to development strategies, trade liberalization, and global economic shifts (OECD, 2000). If the level of gender discrimination is different (lower) in industries that are experiencing higher growth rates relative to other industries, then a change (decrease) in the economies overall gender gap may accompany these changes in the industrial composition (ceteris paribus).

There are several reasons why we might expect different levels of gender discrimination in different industries. First, productivity of labor in some industries is an increasing function of physical power for which the female labor force has comparative and

[2] It is not our intent to argue the validity of wage regression for decomposing wage differentials, because they clearly have their drawbacks. However, they have been and continue to be a fairly standard tool in the literature.

absolute disadvantage. Other things being equal, it is natural to expect higher gender wage disparities in these industries relative to the industries that do not require physical strength. Clearly, this is an argument for a marginal product differential, but these differences may push employers in these industries towards discriminatory tastes. Second, there are substantial differences in the degree of competition in different industries due to differences in product and labor markets, government regulations, and trade policies. Becker (1971) claims that increasing competition results in lower levels of discrimination, which would cause inter-industry differences in the wage gaps. Finally, given today's globalization of markets, industries that are export-oriented (and not global monopolies) may be less likely to discriminate in their long-run labor practices, as competition in international market precludes survival of firms with inefficient (discriminatory) labor market practices.

Melitz (2003) develops a dynamic model to analyze the intra-industry effects of international trade. In this model, exposure to trade causes only the most productive firms to survive within an industry. There is also a large empirical literature showing that exposure to trade increases the overall level of productivity in an industry through the mechanism described above. In the classic Becker (1971) model, a firm (employer) that has tastes for discrimination will employ fewer than the profit maximizing number of female employees, and consequently will achieve suboptimal profits. We expect that market mechanism would force firms with tastes for discrimination to exit the market, causing the overall level of discrimination to be lower in export-oriented industries relative to industries that trade domestically. Hellerstein, Neumark, and Troske (2002) test whether competitive market forces reduce or eliminate discrimination using plant level longitudinal data. They find a positive relationship between firm-level profitability and the proportion of female labor force. They also find evidence that among plants with high market power, those that employ a relatively large female labor force are more profitable, whereas no such relationship exist for plants with low market power. The results are consistent with the short-run implications of Becker’s model of employer discrimination.

There is also a class of models that posit differential employment search costs as support for the existence of employer discrimination. Black (1995) constructs a model that supports employer discrimination when sequential search costs are considered. In this model, prejudiced employers only hire majority workers, whereas unprejudiced employers hire both majority and minority workers. Since job search costs are higher for minority workers, they lower their reservation wage, creating a wage differential between majority and minority workers. Black's model also predicts that as the fraction of unprejudiced firms increases, the wage differential vanishes, because search cost are effectively reduced for minority workers. Therefore, if discrimination is different (lower) on average in developed counties than in developing countries (for a variety of reasons that will not be discussed here), then a shift towards trade liberalization and a global economy would (change) decrease wage differentials in developing economies on average (ceteris paribus).

If there are differences between industries in terms of discriminatory practices, then the evolution of gender wage gaps may be partially correlated with the changes in the industrial structure of the countries, holding worker characteristics constant. Insofar as knowledge based industries are less capital intensive and more human capital intensive, they may exhibit smaller (physical) capital barriers to entry and higher potential long-run competition than non-knowledge based industries. Assuming the existence of discrimination, as an economy shifts towards more knowledge based and (potentially) more competitive industries, the overall level of gender wage gaps should decrease even when male-female characteristics are unchanged. In this study, we identify and estimate a decomposition of inter-industry gender wage gaps by knowledge intensity in Korea, a country that experienced a large transition to knowledge based industries in the last three decades.[3] Korea is also an extreme example of rapid improvement in the overall gender wage gaps, although gender wage gaps in Korea are still larger than most OECD countries. Figure 1 shows the evolution of female-to-male ratio of earnings between 1980 and 2000. For non-agricultural industries, the female-to-male earnings ratio in Korea had increased monotonically and fast, from 44.2% in 1980 and 63.7% in 1998, and leveled off between 1998 and 2000. This continuous improvement in the earnings ratio is associated with an improvement in discrimination (or the unexplained portion of the usual average wage gap). Our results indicate that there appears to be a strong correlation between a transition towards knowledge based industries and a decrease in gender discrimination in Korea at the end of the millennium.

III. DECOMPOSITION FRAMEWORK

The classic Oaxaca-Blinder wage decomposition attempts to quantify gender discrimination in a highly stylized Becker (1971) model (See Oaxaca, 1973 or Blinder, 1973). This decomposition hinges on perfectly competitive labor markets where workers with the same skills earn the same wage everywhere. That is, there exists some non-discriminatory wage structure vector, θ, that maps the demographic attributes (including education, age, and experience) of a worker into a wage, regardless of industry, occupation, or human capital investment.[4] Empirical implementations posit that if worker i possess demographic characteristic vector, x_i, then the worker should be paid a non-discriminatory wage, $y_i = x_i\theta$, where the wage is typically in logarithmic form. Then, gender discrimination can be quantified, in part, as deviations of observed male and female wage structures from the unobserved or hypothetical standard, θ.

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[3] For years from 1990 to 2000, for instance, the growth of real value-added of the Korean economy was mainly led by knowledge based manufacturing, while employment growth mainly led by knowledge based services. For details, see Jung and Choi (2006).

[4] In what follows, we effectively assume that this non-discriminatory structure is constant over time, as well.

While much has been written on the estimation of the male and female wage structures using regression, little has been written on the estimation of θ to which the estimated structures are to be compared, in order to quantify discrimination. The Oaxaca-Blinder procedure proceeds by substituting either the estimated male wage structure or the estimated female wage structure for θ to calculate discrimination. According to Neumark (1988), substituting the estimated male wage structure implies the additional assumption that males are paid their marginal product, while substituting the estimated female wage structure implies that females are paid their marginal product. The choice of which estimate structure to use for the unobserved non-discriminatory structure, θ, has implications for the measurement of discrimination. An extreme example of this range is Ferber and Greene (1982), where wage discrimination for a sample of university professors was 2 percent, based on the male non-discriminatory wage structure, and was 70 percent, based on the female non-discriminatory wage structure. It is in this sense that these estimates are not identified. Neumark suggests an alternative estimator for θ based on a regression that pools male and female observations in the sample. The technique presented here use differences in counterfactual wage estimates to produce measures of *relative* discrimination that are no longer a function of θ, so no arbitrary decision on which structure to choose is eliminated. It is in this sense that our estimates are identified.

The goals here are: a) to partition a Korean labor market data set by year and industry, where industries can be categorized as either "knowledge based" or non-knowledge based" and b) to estimate gender wage gaps over time and industry type to determine if gender wage gaps have been statistically declining over time, and if their decline is in anyway related to knowledge intensity. These estimates are calculated at various levels of aggregation in the data. The next subsection details estimation strategies at each level of aggregation considered.

A. Estimation of wage gaps

Let $k = 1,...,K$ index industries at different levels of aggregation (e.g., knowledge based and non-knowledge based, or hi-tech, medium hi-tech, medium lo-tech, and lo-tech manufacturing). Let $t = 1,...,T$ index time in years. Consider the $2 \times T$ log-wage regressions.

$$y_{ft} = x_{ft}\theta_{ft} + \sum_{k=2}^{K} \beta_{ftk} d_{ftk} + \varepsilon_{ft} \qquad (1)$$

$$y_{mt} = x_{mt}\theta_{mt} + \sum_{k=2}^{K} \beta_{mtk} d_{mtk} + \varepsilon_{mt} \qquad (2)$$

where y_{ft} and y_{mt} are F_t- and M_t-dimensional column vectors, respectively, representing the log wage for female and males, respectively; x_{ft} and x_{mt} are $(F_t \times g)$ and $(M_t \times g)$ dimensional matrices, respectively, of observable explanatory variables; θ_{ft} and θ_{mt} are g-dimensional parameter vectors; β_{ftk} and β_{mtk} are scalar parameters; d_{ftk} and d_{mtk} are F_t- and M_t-dimensional vectors (respectively) of observable dummy variables for industry; and ε_{ft} and ε_{mt} are F_t- and M_t-dimensional error vectors, respectively, satisfying the usual set of regression assumptions. Define the following averages:

$$\bar{x}_{ft} = \frac{1}{F_t}\iota'_{F_t} x_{ft} \ \ (1\times g) \ \text{and} \ \bar{x}_{mt} = \frac{1}{M_t}\iota'_{M_t} x_{mt} \ \ (1\times g)$$

where ι_{F_t} and ι_{M_t} are F_t- and M_t-dimensional column vectors of ones, respectively. These are average demographic characteristics in each year for females and males, respectively. Ordinary least squares yields $2 \times T \times K$ predicted counterfactuals in each industry:

$$\hat{y}_{ftk} = \bar{x}_{ft}\hat{\theta}_{ft} + \hat{\beta}_{ftk}, \qquad (3)$$

$$\hat{y}_{mtk} = \bar{x}_{mt}\hat{\theta}_{mt} + \hat{\beta}_{mtk}, \qquad (4)$$

where $\hat{\beta}_{ft1} = \hat{\beta}_{mt1} = 0$.

These are counterfactuals in the sense that we use $\bar{x}_{ft}$ average female characteristics in year *t* for all industries (instead of average female characteristics in year *t* in industry *k*) to calculate $\hat{y}_{ftk}$. This produces the predicted wage that an average female in year *t* would make if they were randomly placed in industry *k*. The procedure is similar for calculating $\hat{y}_{mtk}$. This difference is essentially how identification is achieved. Then, $T \times K$ decompositions of counterfactual male-female wage differences are:

$$\hat{y}_{ftk} - \hat{y}_{mtk} = \{(\hat{\beta}_{ftk} - \hat{\beta}_{mtk}) + \bar{x}_{ft}(\hat{\theta}_{ft} - \theta) - \bar{x}_{mt}(\hat{\theta}_{mt} - \theta)\} + (\bar{x}_{ft} - \bar{x}_{mt})\theta \qquad (5)$$

where θ is some unobserved, non-discriminatory wage structure; it is the product of labor associated with a labor market that does not have tastes for discrimination. This is similar to the Oaxaca-Blinder decomposition with one minor difference: the *counterfactual* male-female differential is decomposed and not the *average* male-female differential (say, $\bar{y}_{ft} - \bar{y}_{mt}$). Using the counterfactual seems reasonable, because the Oaxaca-Blinder decomposition implicitly assumes that labor markets are competitive, and in this highly stylized world, labor should be readily substitutable across industries, particularly when it is the average laborer being substituted. In what follows, we cannot solve or account for this particular shortcoming of the model.[5]

A particularly appealing feature of this formulation of the decomposition is that equation (5) highlights the fact that the explained portion of the gap, $(\bar{x}_{ft} - \bar{x}_{mt})\theta$, is not identified. Therefore, the extent to which changes in the overall gap over *t* due to changes in average male-female characteristic differential, $(\bar{x}_{ft} - \bar{x}_{mt})$, is not estimable without *knowing* θ. Therefore, even gender wage differences based on *worker productivity differences* are not measurable in the context of the Oaxaca-Blinder decomposition. This is important, because the

[5] That is, we still must assume that θ is constant over industries, and also over time.

decomposition is usually dichotomized into an "explained" and an "unexplained" portion, but without knowledge of θ, NOTHING is truly "explained."

This may seem like a somewhat grim view of the Oaxaca-Blinder decomposition, but the decomposition is salvageable (in some sense). The problem is that the decomposition seeks to identify a dichotomy based on some "gold standard", θ, which assigns weights (or importance) to average worker characteristics. However, if the gold standard is the same across industries (as these models typically assume), then we can use the variability over *k* to identify a relative measure of discrimination that is based on some male and female worker of average characteristics working in any industry *k* and being paid some economy-wide gold standard, θ. (This is the essence of the identifying assumption.) Based on equation (5), discrimination (the bracketed potion of the counterfactual wage decomposition in the equation) is:

$$\hat{\delta}_{tk}(\theta, \bar{x}_{ft}, \bar{x}_{mt}) = \{(\hat{\beta}_{ftk} - \hat{\beta}_{mtk}) + \bar{x}_{ft}(\hat{\theta}_{ft} - \theta) - \bar{x}_{mt}(\hat{\theta}_{mt} - \theta)\} \qquad (6)$$

which is also not identified, since θ is not identified. Let $\hat{\delta}_{t[k]}(\theta, \bar{x}_{ft}, \bar{x}_{mt}) = \max_k \hat{\delta}_{tk}(\theta, \bar{x}_{ft}, \bar{x}_{mt})$. Notice that because of the linearity (monotonicity) of the decomposition, it doesn't matter what we use for θ to find the index of the maximum, $[k]$. The magnitude of $\hat{\delta}_{t[k]}(\theta, \bar{x}_{ft}, \bar{x}_{mt})$ is a function if θ, but the index of the maximum, $[k]$, is the same regardless of what is selected for θ, because it is mapping into a set of characteristics, $\bar{x}_{ft}$ or $\bar{x}_{m}$ that doesn't vary over *k*. Therefore, selecting $\theta = 0$ is fine for finding $[k]$, but $\theta = \hat{\theta}_{mt}$ is what is normally used (men are paid the non-discriminatory standard, and women are paid below it). Then differencing across *k*:

$$\hat{\gamma}_{tk}(\bar{x}_{ft}, \bar{x}_{mt}) = \hat{\delta}_{t[k]}(\theta, \bar{x}_{ft}, \bar{x}_{mt}) - \hat{\delta}_{tk}(\theta, \bar{x}_{ft}, \bar{x}_{mt}) \qquad (7)$$

$$\hat{\gamma}_{tk}(\bar{x}_{ft}, \bar{x}_{mt}) = (\hat{\beta}_{ft[k]} - \hat{\beta}_{mt[k]}) - (\hat{\beta}_{ftk} - \hat{\beta}_{mtk}) \qquad (8)$$

These are comparisons within years but between industries, and they sweep out the non-discriminatory wage structure, θ, and are therefore identified. Relative estimators of this type were first considered by Horrace and Oaxaca (2001). Horrace (2005) explains that these measures are "relative to a within sample standard," and argues that the differencing may reduce estimation biases associated with non-zero means for ε_{ft} and ε_{mt}.

The measure in (8) identifies relative comparisons between industries while sweeping out θ but (unfortunately) not between *years*, because the averages $\bar{x}_{ft}$ and $\bar{x}_{mt}$ are a function of *t*. To make comparisons between years *and* occupations, define the averages male and female characteristics across industries and years as $\bar{x}_f$ and $\bar{x}_m$. Let

$$F = \sum_{t=1}^{T} F_t \text{ and } M = \sum_{t=1}^{T} M_t$$

then *grand means* over all years and industries are

$$\bar{x}_f = \frac{1}{F}\sum_{t=1}^{T} F_t \bar{x}_{ft} \quad (1\times g) \text{ and } \bar{x}_m = \frac{1}{M}\sum_{t=1}^{T} M_t \bar{x}_{mt} \quad (1\times g)$$

Plugging these values in for $\bar{x}_{ft}$ and $\bar{x}_{mt}$ in the previous analysis, we can difference across *k* and *t*. Let

$$\hat{\delta}_{tk}(\theta,\bar{x}_f,\bar{x}_m) = \{(\hat{\beta}_{ftk} - \hat{\beta}_{mtk}) + \bar{x}_f(\hat{\theta}_{ft} - \theta) - \bar{x}_m(\hat{\theta}_{mt} - \theta)\} \tag{9}$$

Let $\hat{\delta}_{[tk]}(\theta,\bar{x}_f,\bar{x}_m) = \max_{t,k} \hat{\delta}_{tk}(\theta,\bar{x}_f,\bar{x}_m)$, so that

$$\hat{\gamma}_{tk}(\bar{x}_f,\bar{x}_m) = \hat{\delta}_{[tk]}(\theta,\bar{x}_f,\bar{x}_m) - \hat{\delta}_{tk}(\theta,\bar{x}_f,\bar{x}_m) \tag{10}$$

and,

$$\hat{\gamma}_{tk}(\bar{x}_f,\bar{x}_m) = (\hat{\beta}_{f[tk]} - \hat{\beta}_{m[tk]}) - (\hat{\beta}_{ftk} - \hat{\beta}_{mtk}) + \bar{x}_f(\hat{\theta}_{f[t]} - \hat{\theta}_{ft}) - \bar{x}_m(\hat{\theta}_{m[t]} - \hat{\theta}_{mt}) \tag{11}$$

where $[tk]$ corresponds to the index of the maximal $\hat{\delta}_{tk}$ for $\theta = 0$ over both k and t, and where $[t]$ corresponds to index of the same year associated with $[tk]$. These are comparisons between years and industries, that sweep out θ, because the averages $\bar{x}_f$ and $\bar{x}_m$ are no longer a function of t.

There is some industry in some year, $[tk]$, that possesses that maximal value of the unexplained counterfactual wage gap (discrimination): $\hat{\delta}_{[tk]}$. Then the difference, $\hat{\gamma}_{tk} \geq 0$, captures the (relative) extent to which industry k in year t is discriminatory. A convenient normalization is the "non-discriminatory percentage" $\exp\{-\tilde{\gamma}_{tk}\} \in (0,1]$, $k = 1,..., K$, $t = 1,..., T$. The normalization can be interpreted as follows: "in a labor market where skill and the non-discriminatory wage structure are constant over industry and time (save for the differentials β_{ftk} and β_{mtk}), industry-year $[tk]$ is 100 percent non-discriminatory relative to all industry-years in the sample tk, and all other industry-years are some fraction (of 100 percent) non-discriminatory." Clearly, certain problems inherent in the classical Oaxaca-Blinder decomposition remain here. For example, *actual* labor markets are marked with some level of heterogeneity across industries in terms of worker characteristics and (presumably) in terms of their non-discriminatory wage structures. However, our measure does not suffer from the lack of identification embodied in an arbitrary selection of, say $\theta = \hat{\theta}_{mt}$. Also, there is truly no sense in which we have identified the "unexplained portion" of some observed wage gap, $\bar{y}_{ft} - \bar{y}_{mt}$. In fact we are decomposing the estimate $\hat{y}_{ftk} - \hat{y}_{mtk}$, which is technically "not observed," so there is no way to relate our measure back to the overall gap, $\bar{y}_{ft} - \bar{y}_{mt}$. However, this is the cost of the identification: everything is relative to the unidentified difference $\hat{\delta}_{[tk]}(\theta, \bar{x}_f, \bar{x}_m)$, not the "identified" difference $\bar{y}_{ft} - \bar{y}_{mt}$.

The estimates in equation (11) are used in the empirical analyses that follow. First, we partition the data into "knowledge-based industries" and "other industries", so that K = 2 (one dummy variable in each regression). This produces two estimate of $\hat{\gamma}_{kt}(\bar{x}_f, \bar{x}_m)$ in each of seven years, $t = 1994,...,2000$. Then, we partition the data into four industries: knowledge-based manufacturing, knowledge-based services, other manufacturing, and other services, so that K = 4 (three dummy variables in each regression). This produces four estimates of $\hat{\gamma}_{kt}(\bar{x}_f, \bar{x}_m)$ in each of seven years, $t = 1994,...,2000$. We now discuss variance estimation for the estimates in equation (11).

B. Variance-covariance estimation

Since θ will ultimately be eliminated by differencing, we set $\theta = 0$ in what follows. Hence, the estimator of interest is:

$$\hat{\delta}_{tk}(0, \bar{x}_f, \bar{x}_m) = (\bar{x}_f \hat{\theta}_{ft} + \hat{\beta}_{ftk}) - (\bar{x}_m \hat{\theta}_{mt} + \hat{\beta}_{mtk}) \tag{12}$$

Let $\hat{\theta}^*_{ft} = [\hat{\theta}_{ft}, \hat{\beta}_{ft2},..., \hat{\beta}_{ftK}]'$ and $\hat{\theta}^*_{mt} = [\hat{\theta}_{mt}, \hat{\beta}_{mt2},..., \hat{\beta}_{mtK}]'$ be $(g + K - 1)$ column vectors, so that $\hat{\theta}^*_f = [\hat{\theta}^*_{f1},..., \hat{\theta}^*_{fT}]'$ and $\hat{\theta}^*_m = [\hat{\theta}^*_{m1},..., \hat{\theta}^*_{mT}]'$ are $T(g + K - 1)$ column vectors. Let Q be a $K - 1$ identity matrix bordered above by a $K - 1$ row vector of zeros. Therefore Q is a $K \times (K - 1)$ matrix. Therefore, $C_f = I_T \otimes [\iota_K \otimes \bar{x}_f, Q]$ and $C_m = I_T \otimes [\iota_K \otimes \bar{x}_m, Q]$ are $TK \times T(g + K - 1)$ matrices. Then,

$$\underset{(TK \times 1)}{\hat{\Delta}(0, \bar{x}_f, \bar{x}_m)} = C_f \hat{\theta}^*_f - C_m \hat{\theta}^*_m \tag{13}$$

is a TK column vector, and is the vector representation of the estimates in equation (12), with typical element $\hat{\delta}_{tk}$. Let D be constructed from a $(TK - 1)$ negative identity matrix with a column vector of ones inserted in $[tk]$ column position from the left and then a column of zeroes inserted in the $[tk]$ row position from the top. For example if $[tk]$ is the second element of $\hat{\Delta}$, then

$$\underset{(TK\times TX)}{D} = \begin{bmatrix} -1 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 1 & -1 & 0 & \cdots & 0 \\ 0 & 1 & 0 & -1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 1 & 0 & 0 & \cdots & -1 \end{bmatrix}$$

Then,

$$\underset{TK\times 1}{\hat{\Gamma}}(\bar{x}_f, \bar{x}_m) = [\hat{\gamma}_{11}(\bar{x}_f, \bar{x}_m)...\hat{\gamma}_{TK}(\bar{x}_f, \bar{x}_m)]' = D\hat{\Delta}(0, \bar{x}_f, \bar{x}_m) \tag{14}$$

is the vector representation of the $\hat{\gamma}_{tk}(\bar{x}_f, \bar{x}_m)$ in equation (10). Since the male and female samples are independent,

$$Var\{\underset{TK\times TK}{\hat{\Gamma}}(\bar{x}_f, \bar{x}_m)\} = D[C_f Var(\hat{\theta}^*_f)C_f' + C_m Var(\hat{\theta}^*_m)C_m']D' \tag{15}$$

Treating the samples in each of the T regressions are independent,

$$Var(\hat{\theta}^*_f) = \begin{bmatrix} Var(\hat{\theta}^*_{f1}) & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & Var(\hat{\theta}^*_{f2}) & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & Var(\hat{\theta}^*_{fT}) \end{bmatrix},$$

a $T(g+K-1)$ square matrix, where $Var(\hat{\theta}^*_{ft})$ is a $(g+K-1)$ square matrix returned by any regression software package. It follows similarly for $Var(\hat{\theta}^*_{mt})$. Also notice that θ is a constant, so it is true that

$$Var\{\underset{(TK\times TK)}{\hat{\Delta}}(\theta, \bar{x}_f, \bar{x}_m)\} = Var\{\hat{\Delta}(0, \bar{x}_f, \bar{x}_m)\} \tag{16}$$

Therefore,

$$Var\{\hat{\Delta}(\theta, \bar{x}_f, \bar{x}_m)\} = C_f Var(\hat{\theta}^*_f)C_f' + C_m Var(\hat{\theta}^*_m)C_m' \tag{17}$$

IV. DATA

The data used for the empirical analysis are from the 1994 to 2000 Wage Structure Survey of the Ministry of Labor of Korea. The Survey provides information on personal characteristics and earnings data for workers employed in firms with 10 or more employees in all industries, except the public administration sector.[6] For the empirical analysis, the agricultural and mining industries, as well as agricultural occupation, were excluded. The final data set includes about 0.4 million workers for years 1994-1998, and about 0.5 million workers for 1999 and 2000.

The industrial classification for the empirical analysis is presented in Table 1. Knowledge based manufacturing sectors are classified based on their R&D intensity and knowledge-based service sectors are classified based on the ratio of college graduates. Knowledge-based manufacturing refers to high-technology manufacturing in areas such as electronics and communication equipment, and also to medium-high-technology manufacturing in areas such as computers and motor vehicles. Other manufacturing includes medium-low-technology manufacturing covering chemicals, rubber and plastic products, metals, and also low-technology manufacturing ranging from food and textiles to paper products. Knowledge-based services include communications, finance, business services, health, education, and cultural services. Non-knowledge based services or "other services" include the industries like utilities, construction, wholesale and retail trade, hotels and restaurants, and transport and storage. These industrial groupings were made based upon the two-digit Korean Standard Industrial Classification (KSIC).

V. RESULTS

In order to estimate non-discriminatory percentages for industry groups, wage regressions for male and female groups were estimated for years 1994 to 2000. The first set of regressions

[6] The Survey was extended to newly include small firms with 5-9 employees since 1999, but workers employed in firms with 5-9 employees were excluded from the final data set for consistency.

included dummy variables for whether an individual was employed in a knowledge based industry or not. Estimation results of these regressions are presented in Table 3. As an estimator of equation (11), we report two values ($k = 1,\ 2$; knowledge and non-knowledge based) of the "non-discriminatory percentages," $\exp\{-\hat{\gamma}_{tk}\}$, for seven years $t = 1,...,7$. The top section of Table 5 contains these values and the standard errors of the estimators.[7] Here, the largest value of $\hat{\hat{\delta}}_{[tk]} = -0.4445$ corresponds to the knowledge based industries in 1999.[8] Thus, for knowledge based industries in 1999, $\hat{\gamma}_{tk} = 0$ and $\exp\{-\hat{\gamma}_{tk}\} = 1$, so in 1999 knowledge based industries were "100 percent non-discriminatory," meaning that, relatively speaking, knowledge based industries in 1999 were the least discriminatory industry-year in the sample. All other industry-years are evaluated relative to this standard.

Table 5 shows that, in 1994 knowledge based industries were 93.8 percent non-discriminatory and non-knowledge based industries were 90.7 percent non-discriminatory. In 2000, knowledge based industries were 98.4 percent nondiscriminatory and non-knowledge based industries were 96.2 percent non-discriminatory. Figure 2 shows the values of non-discriminatory percentages as well as 95 percent confidence intervals based on the standard errors in equation (17). According to our estimation, knowledge based industries had significantly higher non-discriminatory percentages in all years considered. Although in 1996 the two estimates were relatively close, the difference was still significant based on the 95 percent confidence intervals. The non-discriminatory percentages in two groups of industries follow a different trend between 1994 and 2000. Non-knowledge based industries or "other industries" (the solid line) show a relatively fast improvement between 1994 and 1996,

---

[7] Note that the standard errors are for $\hat{\gamma}_{tk}$ not the normalization $\exp\{-\hat{\gamma}_{tk}\}$, but they can be used to calculate confidence intervals on the $\exp\{-\hat{\gamma}_{tk}\}$, since it is a monotonic transformation of $\hat{\gamma}_{tk}$. We do this in the sequel.

[8] Note that $\hat{\hat{\delta}}_{[tk]} = -0.4445$ is not readily interpretable as a measure of discrimination, because it is evaluated at $\theta = 0$.

followed by a relatively steady three years and a significant improvement in 2000. Knowledge based industries (the dashed line), however, follow a different pattern. Between 1994 and 1996 non-discrimination improved very slightly, followed by a large improvement in 1997 and an insignificant decline in 1998. In 1999, knowledge based industries have the largest non-discriminatory percentage (100 percent), but it decreased to 98.4 percent in 2000.

There is a strong possibility that we are picking up the effects of the Asian Financial Crisis that occurred between 1997 and 1998. This may be particularly true for knowledge based *manufacturing* industries in Korea, which experienced very strong growth immediately before the financial crisis. The OECD (2000) report characterizes Asian economies before the financial crisis as “industrial over-capacity due to excessive investment in manufacturing”. The rapid increase in the non-discriminatory percentages for knowledge based industries between 1996 and 1997 may be correlated with this over-capitalization in Asian manufacturing and the subsequent steep decline in Asian currencies after the crisis. It is not clear what mechanism produced this apparent correlation, nor are we willing to speculate on it, since it is beyond the scope of this research. However, the coincidence of the decrease in the unexplained portion in the gender wage in Korean knowledge based industries and the Asian financial crisis is too pronounced in Figure 2 to be ignored. In the next analysis, we will show that the changes in discrimination for knowledge based industries were, in fact, substantial in the manufacturing sector, but weak or non-existent in the service sector.

To disaggregate the industry effects, we re-estimated the regressions with three industry dummies representing the knowledge based manufacturing, knowledge based services, non-knowledge based manufacturing (other manufacturing), and the non-knowledge based services (other services) as the omitted category. The regression results are tabulated in Table 4. Normalized estimates of equation (11) can be found in Table 5. Figures 3 and 4 show the evolution of non-discriminatory percentages for these four industry classifications. Lower and upper limits of confidence intervals (based on standard errors reported in Table 5) show that the non-discriminatory percentages were significantly higher in knowledge based industries for both manufacturing and services.

The empirical finding that non-discriminatory percentages are significantly higher in knowledge based industries is consistent with the hypothesis that non-productivity related discrimination in knowledge based industries is more costly than in non-knowledge based industries. That is, non-productivity related discrimination is perhaps more detrimental to the competitiveness of knowledge based industries than non-knowledge based industries, where the former is heavily dependent upon knowledge inputs, and perhaps subject to higher degree of competition. Notice, also, that non-discriminatory percentages are higher in services than in manufacturing. Non-discriminatory percentages in non-knowledge based services are lower than those in knowledge based services and are higher than those in both knowledge based and non-knowledge based manufacturing. These differences, perhaps, reinforce the argument that gender discrimination is likely to be larger in sectors that require more physical power, where female workers have a comparative disadvantage. Also, the difference in non-discriminatory percentages between knowledge based sectors and non-knowledge based sectors is smaller for manufacturing than for services.

Again, there seems to be some (unexplained) correlation between the steep increases in the non-discriminatory percentages in the manufacturing sector (Figure 4) and the Asian Financial Crisis that occurred between 1997 and 1998. In Figure 4, we see a significant drop in 1999 knowledge based manufacturing industries, as well as in non-knowledge based industries. Although it is beyond the scope of this paper to analyze effects of the Asian crisis on Korean labor markets, it is interesting to see that the improvements in non-discriminatory percentages between 1994 and 1998 were partially reversed in knowledge based manufacturing industries and completely reversed in non-knowledge based manufacturing industries as the financial crisis was mitigated. In 2000, there was a significant improvement in non-knowledge based industries and a slight decrease in knowledge based industries. Figure 3 shows that, in the service sector, the correlation between the financial crisis and gender discrimination was so clear as in the manufacturing sector. In 1998, there was a slight decrease in non-discriminatory percentages in non-knowledge based services, followed by a significant improvement. In knowledge based service industries, however, there was a slight decrease in the trend, followed by a significant improvement. In 2000, both knowledge and non-knowledge based service industries experienced a fall in terms of non-discriminatory percentages.

VI. CONCLUSIONS

If one accepts the validity of Oaxaca-Blinder decompositions from linear wage regressions then the counterfactual decomposition presented herein is identified, while the usual decomposition is not. Our technique also readily lends itself to comparisons across separate regression periods and to a convenient normalization of discrimination to percentages on the unit interval. We have also provided an explanation of how to calculate standard errors for our estimates. Our technique could be applied to any partition of the data (not just a partition based on knowledge intensity) and to other forms of discrimination (e.g., discrimination by race), as well.

Our application suggests that discrimination was smaller in knowledge intensive industries in Korea than in non-knowledge intensive industries at the end of the last decade, and this difference seems to have been most pronounced in the manufacturing sector. In absolute terms we do not know the difference and by how much it changed over time; this is the cost of the relative estimation procedure. There was some volatility in the level of discrimination around the time of the Asian Financial Crisis, particularly in the manufacturing sector. Despite this volatility, discrimination declined on average over the seven-year period.

It would be interesting to explore the nature of the causality (if any) between the overall decline in discrimination and the events surrounding the Asian Financial crisis, but this is left for future research.

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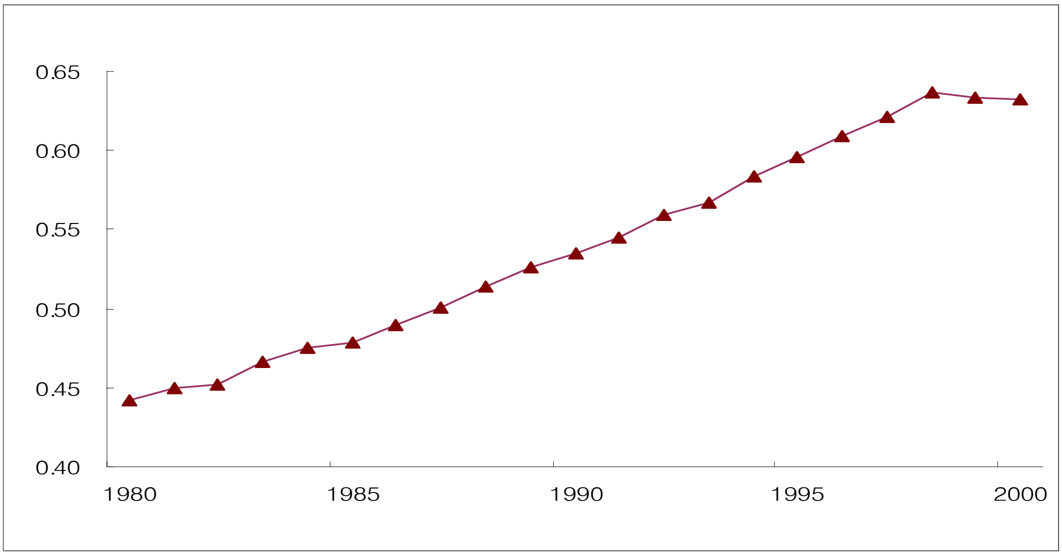
FIGURES

Figure 1: Female-to-Male Ratio of Average Earnings



Source: *Korean Labor Institute, Labor Statistics* (2004).

Figure 2: Non-Discriminatory Percentages, Knowledge Based Industries and Other Industries

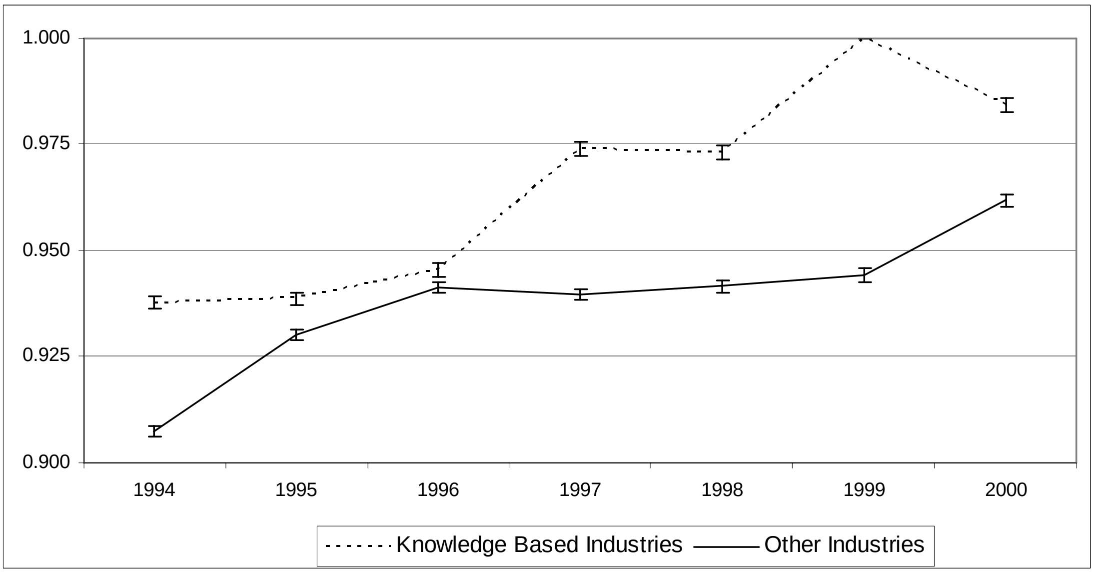


Figure plots $\exp\{-\hat{\gamma}_{tk}\}$ where $\hat{\gamma}_{tk}$ is based on equation (11).
[*tk*] = [Knowledge Based Industries, 1999]. 95% confidence bounds.
Other Industries = Non-Knowledge Based Industries.

Figure 3: Non-Discriminatory Percentages, Knowledge Based *Services* and Other *Service*

Figure plots $\exp\{-\hat{\gamma}_{tk}\}$ where $\hat{\gamma}_{tk}$ is based on equation (11).
[*tk*] = [Knowledge Based Services, 1999]. 95% confidence bounds.
Other Services = Non-Knowledge Based Services.

Figure 4: Non-Discriminatory Percentages, Knowledge Based *Manufacturing* and Other *Manufacturing*

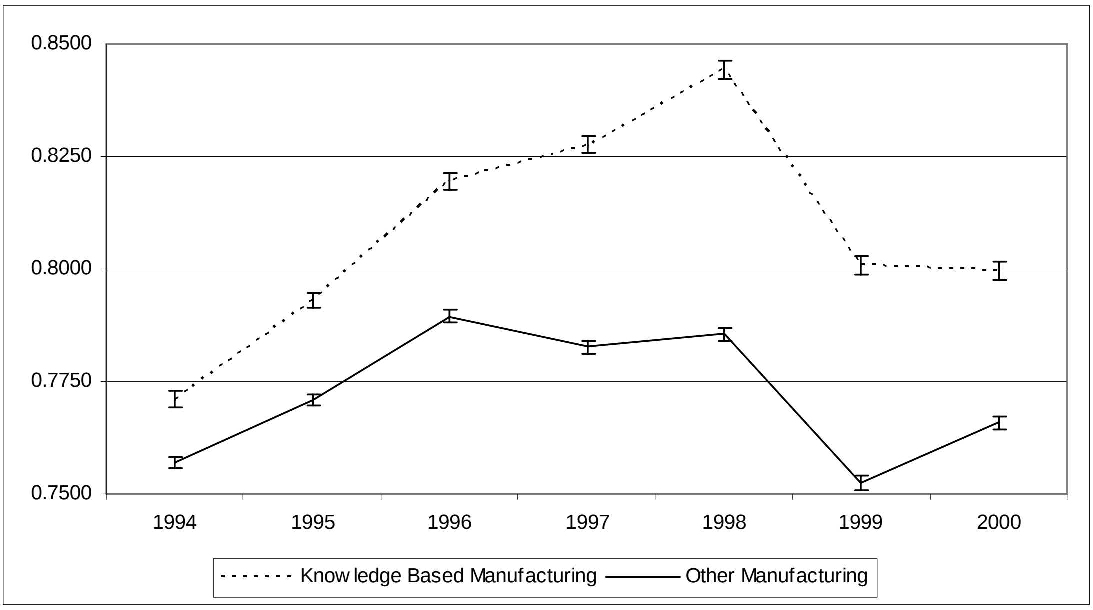


Figure plots $\exp\{-\hat{\gamma}_{tk}\}$ where $\hat{\gamma}_{tk}$ is based on equation (11).
[*tk*] = [Knowledge Based Services, 1999]. 95% confidence bounds.
Other Manufacturing = Non-Knowledge Based Manufacturing.

Table 1: Classification of Knowledge Based Industries

			R&D Intensity[1] (1999)	College Graduates[2] (2001)
Knowledge-based Manufacturing (KBM)	High-tech	Electronical machinery	10.6	16.8
		Communication equipment	17.9	19.8
	Medium-high-tech	Office/accounting/computing machinery	7.0	17.0
		Motor vehicles	8.9	11.8
Other Manufacturing (OM)	Medium-low-tech	Chemicals	3.6	29.6
		Rubber/plastic products	3.5	12.1
		Non-metallic mineral products	1.9	11.5
		Metals	1.0	13.6
		Fabricated metal products	1.0	8.9
		Non-electrical machinery	3.6	11.5
		Precision instruments	4.1	8.9
		Other transport equipment	1.1	26.5
		Furniture, and Manufacturing n.e.c.	1.6	10.2
	Low-tech	Food, beverages, tobacco	0.7	10.0
		Textiles, apparel, leather	0.9	6.7
		Wood and paper products	0.5 [3]	14.1
		Printing	-	29.0
		Petroleum refineries/products	0.5	44.7
		Recycling	-	3.8
Knowledge-based Services (KBS)	Communications		-	29.2
	Financial services		-	31.0
	Business services		-	35.2
	Education services		-	59.5
	Health services/social work		-	31.2
	Culture/recreation		-	23.3
Other Services (OS)	Electricity, gas, water supply		-	30.7
	Construction		-	13.2
	Wholesale/retail trade		-	15.4
	Hotels and restaurants		-	4.7
	Transport and storage		-	10.9
	Real estate activities		-	15.0
	Other services		-	18.7
All Industries			1.8	19.0

Notes: 1) R&D expenditures as a percentage of value added in each industry.
2) The ratio of 4-year college graduates to the total employed(%).
3) Includes printing industry.

Sources: OECD(2002), *Science, Technology and Industry Outlook*,
NSO, Korea(2002), *The Economically Active Population Survey*.

Table 2: Descriptive Statistics*

	1994		1995		1996		1997		1998		1999		2000	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Logarithm of Hourly Wage (Won)	8.00	8.55	8.16	8.68	8.34	8.84	8.44	8.92	8.45	8.93	8.46	8.90	8.59	9.02
	(0.44)	(0.49)	(0.45)	(0.49)	(0.46)	(0.52)	(0.47)	(0.51)	(0.48)	(0.52)	(0.52)	(0.54)	(0.52)	(0.55)
Age	30.72	36.39	30.92	36.67	31.39	36.69	31.96	37.21	32.12	37.61	32.14	37.48	32.68	37.82
	(11.57)	(9.95)	(11.67)	(10.06)	(11.69)	(10.27)	(11.70)	(10.33)	(11.46)	(10.03)	(11.09)	(9.87)	(11.06)	(10.00)
Married	0.43	0.76	0.43	0.76	0.44	0.74	0.47	0.76	0.47	0.78	0.49	0.76	0.49	0.75
	(0.49)	(0.43)	(0.50)	(0.43)	(0.50)	(0.44)	(0.50)	(0.43)	(0.50)	(0.42)	(0.50)	(0.43)	(0.50)	(0.43)
Tenure	3.48	5.94	3.79	6.33	3.66	5.99	3.92	6.25	4.27	6.74	4.33	6.64	4.22	6.68
	(3.67)	(5.73)	(3.89)	(6.02)	(4.03)	(6.06)	(4.21)	(6.13)	(4.35)	(6.29)	(4.34)	(6.24)	(4.47)	(6.45)
Education:														
Less Than High School	0.32	0.21	0.30	0.19	0.28	0.17	0.26	0.16	0.23	0.14	0.21	0.14	0.20	0.14
	(0.47)	(0.41)	(0.46)	(0.39)	(0.45)	(0.37)	(0.44)	(0.37)	(0.42)	(0.35)	(0.41)	(0.35)	(0.40)	(0.35)
High School	0.54	0.48	0.54	0.48	0.53	0.48	0.52	0.48	0.51	0.46	0.51	0.45	0.48	0.45
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Two-Year College	0.07	0.08	0.09	0.09	0.10	0.09	0.12	0.10	0.14	0.11	0.14	0.11	0.16	0.12
	(0.26)	(0.28)	(0.28)	(0.28)	(0.30)	(0.29)	(0.32)	(0.30)	(0.35)	(0.31)	(0.35)	(0.32)	(0.37)	(0.32)
Four-Year College or above	0.06	0.23	0.07	0.24	0.09	0.26	0.10	0.26	0.12	0.28	0.14	0.30	0.15	0.29
	(0.24)	(0.42)	(0.26)	(0.43)	(0.29)	(0.44)	(0.30)	(0.44)	(0.32)	(0.45)	(0.35)	(0.46)	(0.36)	(0.45)

Table 2: Descriptive Statistics, con't *

	1994		1995		1996		1997		1998		1999		2000	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Establishment Size:														
10-29 Employees	0.22	0.21	0.23	0.22	0.24	0.22	0.25	0.24	0.26	0.24	0.30	0.25	0.30	0.27
	(0.42)	(0.41)	(0.42)	(0.41)	(0.43)	(0.42)	(0.44)	(0.42)	(0.44)	(0.42)	(0.46)	(0.43)	(0.46)	(0.45)
30-99 Employees	0.30	0.28	0.28	0.27	0.28	0.26	0.28	0.26	0.27	0.26	0.29	0.25	0.31	0.27
	(0.46)	(0.45)	(0.45)	(0.44)	(0.45)	(0.44)	(0.45)	(0.44)	(0.45)	(0.44)	(0.45)	(0.43)	(0.46)	(0.44)
100-299 Employees	0.19	0.21	0.19	0.20	0.19	0.20	0.20	0.21	0.20	0.21	0.19	0.22	0.18	0.21
	(0.40)	(0.41)	(0.39)	(0.40)	(0.40)	(0.40)	(0.40)	(0.41)	(0.40)	(0.41)	(0.39)	(0.41)	(0.38)	(0.40)
300-499 Employees	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.05	0.06	0.06	0.06
	(0.25)	(0.26)	(0.25)	(0.26)	(0.25)	(0.26)	(0.26)	(0.25)	(0.25)	(0.25)	(0.22)	(0.23)	(0.23)	(0.24)
500+ Employees	0.21	0.23	0.23	0.24	0.22	0.24	0.20	0.22	0.20	0.23	0.17	0.22	0.15	0.19
	(0.41)	(0.42)	(0.42)	(0.43)	(0.41)	(0.43)	(0.40)	(0.42)	(0.40)	(0.42)	(0.38)	(0.42)	(0.36)	(0.39)
Industries**:														
Knowledge Based Industries	0.37	0.28	0.40	0.30	0.43	0.32	0.45	0.33	0.48	0.36	0.47	0.34	0.48	0.33
	(0.48)	(0.45)	(0.49)	(0.46)	(0.49)	(0.47)	(0.50)	(0.47)	(0.50)	(0.48)	(0.50)	(0.47)	(0.50)	(0.47)
Knowledge Based Manufacturing	0.12	0.10	0.14	0.11	0.13	0.12	0.13	0.12	0.12	0.11	0.11	0.11	0.12	0.12
	(0.33)	(0.30)	(0.35)	(0.31)	(0.34)	(0.32)	(0.34)	(0.32)	(0.33)	(0.32)	(0.32)	(0.32)	(0.33)	(0.32)
Knowledge Based Services	0.25	0.18	0.26	0.19	0.29	0.21	0.32	0.22	0.36	0.24	0.36	0.23	0.36	0.21
	(0.43)	(0.39)	(0.44)	(0.39)	(0.46)	(0.41)	(0.46)	(0.41)	(0.48)	(0.43)	(0.48)	(0.42)	(0.48)	(0.41)

* The values in parenthesis correspond to standard deviations of the variables.

** Refer to Table 1 for classification of the industries.

Table 3: Regression Results – Two Industry Dummies, Dependent Variable: Logarithm of hourly wage in Korean Won. *

	1994		1995		1996		1997		1998		1999		2000	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
(Constant)	7.14	6.92	7.34	6.98	7.39	7.12	7.51	7.23	7.53	7.13	7.51	6.74	7.65	6.80
	[2337.02]	[2476.09]	[2412.69]	[2583.62]	[2348.87]	[2571.38]	[2335.75]	[2603.06]	[2138.41]	[2364.39]	[1935.69]	[2086.14]	[2033.06]	[2120.42]
Age	0.02	0.05	0.02	0.05	0.02	0.05	0.02	0.05	0.02	0.05	0.02	0.07	0.02	0.07
	[121.12]	[347.97]	[99.56]	[367.00]	[132.90]	[353.28]	[116.15]	[348.16]	[103.75]	[336.23]	[69.86]	[434.96]	[75.26]	[432.26]
Age-squared	-0.03	-0.06	-0.03	-0.06	-0.03	-0.06	-0.03	-0.05	-0.03	-0.06	-0.02	-0.08	-0.02	-0.08
	[-135.54]	[-334.08]	[-117.69]	[-347.82]	[-153.49]	[-337.90]	[-137.62]	[-329.02]	[-130.46]	[-314.91]	[-83.03]	[-421.37]	[-94.49]	[-405.52]
High School	0.24	0.17	0.26	0.19	0.26	0.21	0.27	0.21	0.24	0.20	0.32	0.19	0.28	0.21
	[320.95]	[334.23]	[342.83]	[378.20]	[322.84]	[379.19]	[324.32]	[367.50]	[249.69]	[320.51]	[303.29]	[280.44]	[280.49]	[308.73]
2-year college	0.39	0.29	0.41	0.32	0.40	0.35	0.42	0.36	0.37	0.35	0.44	0.32	0.42	0.35
	[339.77]	[374.53]	[384.21]	[437.54]	[367.68]	[450.72]	[380.86]	[468.73]	[318.14]	[428.95]	[340.62]	[363.31]	[345.92]	[404.66]
4-year college +	0.66	0.53	0.66	0.56	0.69	0.59	0.70	0.60	0.65	0.57	0.71	0.58	0.70	0.61
	[554.29]	[908.09]	[604.69]	[992.26]	[633.73]	[963.95]	[632.70]	[960.08]	[553.95]	[865.10]	[567.89]	[797.49]	[583.15]	[846.72]
30-99 employees	-0.02	-0.04	-0.04	-0.05	0.00	-0.04	0.00	-0.06	-0.03	-0.05	0.01	0.00	0.00	-0.01
	[-26.63]	[-86.35]	[-54.55]	[-92.55]	[-5.97]	[-82.03]	[-3.27]	[-108.32]	[-38.33]	[-96.54]	[14.02]	[-5.71]	[-6.38]	[-16.12]
100-299 employees	-0.01	-0.06	0.00	-0.05	0.00	-0.06	0.02	-0.07	0.01	-0.05	0.03	0.04	0.03	0.04
	[-6.65]	[-104.14]	[3.06]	[-99.46]	[5.18]	[-116.19]	[27.98]	[-127.19]	[12.08]	[-85.59]	[30.09]	[62.81]	[39.15]	[58.90]
300-499 employees	0.03	-0.04	0.06	0.01	0.05	0.02	0.06	-0.01	0.06	0.03	0.05	0.08	0.10	0.14
	[28.49]	[-46.74]	[53.67]	[11.02]	[46.73]	[21.18]	[53.95]	[-7.37]	[49.82]	[34.29]	[31.73]	[83.25]	[70.45]	[146.73]
500+ employees	0.08	0.04	0.07	0.06	0.12	0.08	0.14	0.10	0.13	0.13	0.13	0.19	0.12	0.13
	[100.26]	[78.66]	[100.51]	[106.18]	[161.89]	[147.85]	[180.53]	[179.74]	[154.85]	[226.08]	[135.32]	[294.45]	[122.82]	[200.32]

Table 3: Regression Results – Two Industry Dummies, con't

	1994		1995		1996		1997		1998		1999		2000	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Married	-0.01	0.09	0.00	0.09	-0.01	0.10	-0.02	0.08	-0.01	0.08	0.01	0.07	0.00	0.08
	[-8.59]	[147.93]	[0.02]	[170.04]	[-12.29]	[170.22]	[-26.71]	[138.96]	[-11.23]	[125.39]	[10.35]	[114.26]	[5.32]	[123.49]
Tenure-square	-0.21	-0.11	-0.21	-0.10	-0.18	-0.10	-0.18	-0.09	-0.15	-0.09	-0.13	-0.06	-0.19	-0.11
	[-241.88]	[-260.47]	[-258.77]	[-284.97]	[-226.39]	[-276.53]	[-238.63]	[-253.33]	[-185.61]	[-244.43]	[-153.27]	[-148.77]	[-214.62]	[-258.30]
Tenure	0.09	0.06	0.09	0.06	0.09	0.06	0.09	0.05	0.08	0.05	0.08	0.04	0.09	0.05
	[573.86]	[603.72]	[616.85]	[645.92]	[564.96]	[631.49]	[575.51]	[595.35]	[514.08]	[587.41]	[462.27]	[436.81]	[540.87]	[550.69]
Knowledge-Based Industry	0.12	0.08	0.10	0.09	0.10	0.10	0.12	0.09	0.14	0.11	0.16	0.10	0.14	0.11
	[216.71]	[201.87]	[186.69]	[225.33]	[193.65]	[247.74]	[224.18]	[215.06]	[235.26]	[256.37]	[247.97]	[229.08]	[219.94]	[252.61]

* t-values of the coefficients are presented in the brackets.

Table 4: Regression Results – Four Industry Dummies, Dependent Variable: Logarithm of hourly wage in Korean Won.*

	1994		1995		1996		1997		1998		1999		2000	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
(Constant)	7.18	6.98	7.39	7.04	7.44	7.15	7.55	7.27	7.56	7.20	7.57	6.83	7.68	6.92
	[2359.04]	[2472.80]	[2428.99]	[2592.81]	[2366.75]	[2558.74]	[2363.52]	[2597.50]	[2151.97]	[2369.76]	[1985.76]	[2103.02]	[2068.51]	[2160.12]
Age	0.02	0.05	0.02	0.05	0.03	0.05	0.02	0.05	0.02	0.05	0.02	0.07	0.02	0.07
	[130.75]	[336.08]	[110.38]	[352.87]	[144.59]	[345.43]	[129.82]	[337.59]	[115.09]	[319.83]	[85.32]	[420.34]	[92.70]	[413.64]
Age-squared	-0.03	-0.06	-0.03	-0.06	-0.04	-0.06	-0.03	-0.05	-0.03	-0.05	-0.03	-0.08	-0.03	-0.07
	[-147.29]	[-324.80]	[-130.76]	[-336.52]	[-167.90]	[-331.95]	[-153.95]	[-321.26]	[-143.48]	[-302.21]	[-99.80]	[-411.73]	[-112.51]	[-392.97]
High School	0.21	0.17	0.23	0.19	0.23	0.21	0.25	0.21	0.22	0.20	0.28	0.19	0.25	0.21
	[286.39]	[332.96]	[303.14]	[375.70]	[288.32]	[380.05]	[294.25]	[369.88]	[230.90]	[324.30]	[271.33]	[284.03]	[256.16]	[310.73]
2-year college	0.32	0.28	0.35	0.31	0.34	0.35	0.35	0.36	0.33	0.34	0.36	0.31	0.36	0.34
	[275.43]	[367.87]	[312.48]	[430.88]	[302.13]	[444.88]	[315.22]	[460.95]	[271.85]	[421.19]	[276.77]	[355.63]	[287.07]	[389.20]
4-year college +	0.60	0.52	0.60	0.54	0.63	0.58	0.63	0.58	0.60	0.56	0.62	0.56	0.62	0.58
	[490.39]	[881.14]	[530.88]	[960.91]	[560.28]	[938.41]	[560.71]	[931.09]	[498.86]	[838.14]	[490.95]	[767.28]	[510.69]	[804.39]
30-99 employees	-0.01	-0.04	-0.03	-0.04	0.01	-0.04	0.01	-0.05	-0.02	-0.05	0.03	0.00	0.01	0.00
	[-17.66]	[-85.18]	[-42.55]	[-90.08]	[7.38]	[-79.98]	[10.65]	[-104.05]	[-25.25]	[-90.12]	[35.53]	[6.93]	[14.15]	[5.27]
100-299 employees	0.01	-0.06	0.02	-0.05	0.02	-0.06	0.03	-0.07	0.02	-0.04	0.06	0.05	0.06	0.05
	[14.54]	[-99.19]	[22.37]	[-91.52]	[24.62]	[-110.97]	[45.26]	[-119.94]	[25.97]	[-76.92]	[62.77]	[74.67]	[69.58]	[79.59]
300-499 employees	0.05	-0.03	0.07	0.02	0.07	0.02	0.08	0.00	0.08	0.04	0.08	0.09	0.13	0.16
	[41.67]	[-42.21]	[69.48]	[20.30]	[59.94]	[26.24]	[68.65]	[0.07]	[63.33]	[47.27]	[53.82]	[99.20]	[98.10]	[173.67]
500+ employees	0.11	0.06	0.11	0.08	0.16	0.10	0.18	0.12	0.16	0.16	0.19	0.22	0.16	0.17
	[146.02]	[107.57]	[147.25]	[148.92]	[204.34]	[167.07]	[220.27]	[209.81]	[186.34]	[266.18]	[192.80]	[332.29]	[170.72]	[266.82]

Table 4: Regression Results – Four Industry Dummies, con't *

	1994		1995		1996		1997		1998		1999		2000	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Married	0.00	0.09	0.00	0.09	-0.01	0.10	-0.02	0.08	-0.01	0.08	0.02	0.07	0.01	0.07
	[-3.97]	[147.67]	[-2.46]	[169.13]	[-8.01]	[170.98]	[-21.75]	[139.94]	[-14.23]	[125.74]	[16.60]	[114.44]	[10.10]	[121.34]
Tenure-square	-0.20	-0.11	-0.21	-0.11	-0.18	-0.11	-0.18	-0.10	-0.15	-0.10	-0.13	-0.07	-0.19	-0.11
	[-242.42]	[-270.47]	[-264.70]	[-297.14]	[-227.00]	[-282.28]	[-242.73]	[-263.69]	[-188.02]	[-259.72]	[-151.54]	[-161.47]	[-212.36]	[-271.52]
Tenure	0.09	0.06	0.09	0.06	0.08	0.06	0.08	0.05	0.08	0.05	0.07	0.05	0.09	0.06
	[560.45]	[611.48]	[613.28]	[655.48]	[556.93]	[634.35]	[574.00]	[603.66]	[511.48]	[600.96]	[451.92]	[452.57]	[528.48]	[568.12]
Knowledge Based Manufacturing	-0.05	0.00	-0.06	-0.01	-0.05	0.05	-0.04	0.01	0.00	0.00	-0.08	-0.01	-0.08	-0.05
	[-51.60]	[3.16]	[-66.49]	[-13.33]	[-50.66]	[70.60]	[-37.89]	[13.77]	[-1.77]	[-3.45]	[-69.14]	[-16.05]	[-68.41]	[-65.19]
Knowledge Based Services	0.14	0.10	0.10	0.12	0.10	0.12	0.12	0.11	0.13	0.13	0.14	0.11	0.13	0.14
	[179.05]	[189.50]	[130.31]	[225.26]	[135.48]	[229.55]	[155.10]	[217.10]	[168.98]	[255.96]	[165.78]	[190.42]	[156.28]	[234.62]
Other Manufacturing	-0.07	-0.03	-0.09	-0.03	-0.08	-0.01	-0.09	-0.02	-0.07	-0.03	-0.14	-0.06	-0.12	-0.08
	[-92.74]	[-64.86]	[-124.97]	[-73.34]	[-114.49]	[-21.20]	[-121.97]	[-39.65]	[-89.84]	[-59.68]	[-160.91]	[-122.59]	[-137.01]	[-161.57]

* t-values of the coefficients are presented in the brackets.

Table 5: Non-Discriminatory Percentages

	1994	1995	1996	1997	1998	1999	2000
Two Industry Dummies:							
Knowledge Based Industries	0.938	0.939	0.945	0.974	0.973	*1.000*	0.984
	(0.00081)	(0.00079)	(0.00079)	(0.00079)	(0.00080)	(0.00000)	(0.00084)
Non – Knowledge Based Industries	0.907	0.930	0.941	0.940	0.942	0.944	0.962
	(0.00073)	(0.00072)	(0.00073)	(0.00074)	(0.00076)	(0.00080)	(0.00078)
Four Industry Dummies:							
Knowledge Based Manufacturing	0.771	0.793	0.820	0.828	0.844	0.801	0.800
	(0.00119)	(0.00113)	(0.00116)	(0.00117)	(0.00123)	(0.00136)	(0.00127)
Non-Knowledge Based Manufacturing	0.757	0.771	0.790	0.783	0.786	0.752	0.766
	(0.00088)	(0.00087)	(0.00090)	(0.00091)	(0.00095)	(0.00100)	(0.00097)
Knowledge Based Services	0.933	0.928	0.952	0.964	0.966	*1.000*	0.982
	(0.00098)	(0.00095)	(0.00096)	(0.00096)	(0.00096)	(0.00000)	(0.00102)
Non-Knowledge Based Services	0.811	0.842	0.860	0.859	0.847	0.869	0.863
	(0.00100)	(0.00097)	(0.00098)	(0.00098)	(0.00101)	(0.00104)	(0.00105)

Values are $\exp\{-\hat{\gamma}_{tk}\}$,. where $\hat{\gamma}_{tk}$ is based on equation (11). Values in parentheses are t-states for $\hat{\gamma}_{tk}$, which are used to construct confidence intervals in Figures 3 – 5.