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Tromp, Nikolas

Kyungpook National University

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Nikolas Tromp
Kyungpook National University
nikolas.tromp@gmail.com

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Abstract

I analyze the gender wage gap in South Korea across the wage distribution in 2003 vs. 2013. Gaps are decomposed into composition and structural effects using a semi-parametric framework. I find a "glass ceiling" effect in both years with larger wage gaps at the upper end of the wage distribution. Decompositions show that the structural effect decreases, and composition effect increases, in importance as we move up the distribution. Between 2003 and 2013, a fall in the composition effect drives the narrowing of the wage gap across the entire distribution. While a fall in the structural effect augments the narrowing at the lower end of the distribution, a rise in the structural effect curtails it at the upper end, maintaining the glass ceiling. Lastly, controlling for occupational choice causes minor increases in the composition effect at the lower end and structural effect at the upper end of the distribution.

JEL Classification: C14, J31, J71

Key Words: Gender wage gaps, Decomposition methods, Wage Distributions

1 Introduction

Differences between male and female wages in South Korea (henceforth Korea) tend to be large and exceed those of other industrialized countries (Amsden, 1990; Cho, Cho and Song, 2010). Over the last few decades, however, relative improvements in female productivity characteristics (such as educational attainment, experience and job tenure) and anti-discrimination legislation led to reductions in the gender wage gap (Berger, Groothuis and Jeon, 1997; Cho, 2007; Cho, Cho and Song, 2010; Monk-Turner and Turner, 2004). While previous research provides valuable insights into what factors explain wage gaps at the mean or median, it overlooks potentially important differences across the wage distribution. This paper, therefore, supplements the existing literature by analyzing the gender wage gap in Korea across the entire wage distribution and how it has changed between 2003 and 2013. I adopt an approach developed by DiNardo, Fortin, and Lemieux (1996) to decompose wage gaps into parts ascribed to differences in productivity characteristics (composition effects) and parts ascribed to differences in returns to productivity characteristics (structural effects) at various quantiles across the wage distribution. In addition, I investigate the role of occupational choice on the gender wage gap in an auxiliary analysis.

Briefly, the results reveal a "glass ceiling" effect where the gender wage gap widens as we move up the wage distribution. Decompositions show that this is mostly attributed to large composition effects at the upper end of the wage distribution which contrast large structural effects seen in the Netherlands and Colombia. Between 2003 and 2013, the wage gap falls across the entire distribution by between 0.05 to 0.09 log wage points. A fall in the composition effect drives the narrowing of the wage gap across the entire distribution. While a fall in the structural effect augments the narrowing at the lower end of the distribution, a rise in the structural effect curtails it at the upper end, maintaining the glass ceiling. I conjecture that relative improvements in productivity characteristics of woman may not have been fully realised at the upper end of the distribution due to "wage discrimination." The inclusion of occupational choice tends to increase the composition effect at the lower end and increase the structural effect at the upper end of the wage distribution.

2 Method and Data

2.1 Decompositions

I use a decomposition method developed by DiNardo, Fortin, and Lemieux (1996)(henceforth DFL) to analyze gender wage gaps at various quantiles across the wage distribution. This technique estimates counterfactual wage densities by using reweighting functions. These counterfactual wage densities are assumed to be those that female workers would face (holding productivity characteristics constant) if they were paid like male workers. Thus, the difference between the counterfactual and actual female wage densities is the structural effect, i.e., the part of the wage gap ascribed to differences in returns to productivity characteristics. The remaining part of the wage gap is the composition effect, i.e., the part of the wage gap ascribed to differences in productivity characteristics.[1]

DFL start by noting a wage density, $f_{s|c}(w)$, is defined as the integral of a density of wages conditional on productivity characteristics, $f_s(w|x)$, over a distribution of productivity characteristics, $f_c(x)$. The subscripts s and c define the wage structure and distribution of covariates for males and females (i.e., $s = m$ or f and $c = m$ or f). Thus a wage density is written as:

$$f_{s|c}(w) = \int f_s(w|x) f_c(x) dx. \tag{1}$$

The actual wage densities for males and females are $f_{m|m}$ and $f_{f|f}$. Thus, the gender wage gap is written as $f_{m|m} - f_{f|f}$. The gender wage gap can be decomposed by subtracting and adding the counterfactual wage density $f_{m|w}$ as follows:

$$f_{m|m} - f_{f|f} = \underbrace{(f_{m|m} - f_{m|f})}_{\text{Composition Effect}} + \underbrace{(f_{m|f} - f_{f|f})}_{\text{Structural Effect}}. \tag{2}$$

[1]Decompositions can be written by switching the reference group for structural and composition effects. In other words, the counterfactual wage density could be that which male workers would face (holding productivity characteristics constant) if they were paid like female workers. The choice ultimately comes down to the assumption regarding whether the male or female wage would exist in the absence of discrimination. I assume the male wage structure would prevail as is common in this line of research.

DFL note that the counterfactual wage density can be written as:

$$f_{m|f}(w) = \int f_m(w|x) f_f(x) dx \tag{3}$$

$$= \int f_m(w|x) \frac{f_f(x)}{f_m(x)} f_m(x) dx \tag{4}$$

$$\equiv \int f_m(w|x) \psi(x) f_m(x) dx, \tag{5}$$

where the "reweighting" function $\psi(x)$ is

$$\psi(x) \equiv \frac{f_f(x)}{f_m(x)} \equiv \frac{f(x|f)}{f(x|m)}.^2 \tag{6}$$

Using Bayes' rule, this ratio can be rewritten as:

$$\psi(x) \equiv \frac{Pr(f|x)}{Pr(m|x)} \cdot \frac{Pr(m)}{Pr(f)}. \tag{7}$$

$Pr(m)$ and $Pr(f)$ can be estimated with simple sample proportions and $Pr(f|x)$ and $Pr(m|x)$ with a probit model. Equation (5) shows that the counterfactual wage density is identical to the male wage density "reweighted" by the function $\psi(x)$. Thus, after estimating the weights, $\psi(x)$, we can obtain the counterfactual wage density and quantile estimates using weighted quantile functions.

In order to identify meaningful structural and composition effects the following assumption must hold.

Ignorability Assumption: *Let D_g denote gender for $g = m$ or f and ϵ denote unobservables that affect wages conditional on X. Also let (D_g, X, ϵ) have a joint distribution. For all x in X: ϵ is independent of D_g given $X = x$ (Fortin, Lemieux and Firpo, 2010).*

In other words, the unobservables, ϵ, conditional on x are independent of gender; $\epsilon \perp D_g | x$. As Fortin et. al. (2010) explain, the correlation between unobserved ability and measured education likely produces inaccurate estimates for the return to education and thus invalidates *detailed* decompositions. This clearly applies to my analysis as education is one of the major covariates. However, as long as the distribution of unobserved ability conditional on observed characteristics is the same across genders, *aggregate* decompositions are valid. I therefore restrict analysis and interpretations to aggregate decompositions focusing on the total structural and composition effects rather than those for each individual covariate.[3]

[2] I denote $f_f(x)$ as $f(x|f)$ in order to make the conditionality explicit.
[3] See Fortin et. al. (2010) for a discussion of other technical assumptions for decompositions to be valid.

2.2 Data

The data for this analysis come from the 2003 and 2013 cohorts of the Economically Active Population Survey (EAPS) in Korea. The EAPS covers a wide range of work-related questions for people aged 16 or older while excluding armed forces and foreigners. Although it has been conducted since 1963, questions regarding wages have only been included in the August supplementary survey since 2001. Table 1 provides summary statistics.

The sample is restricted to workers between the age of 16 and 65 years of age with hourly wages between 1,000 to 100,000 Won. Wages are measured as log hourly wages in 2003 Won for both cohorts and adjusted to thousands of Won. The independent variables include educational attainment, experience, experience squared, tenure, tenure squared, age, marriage status, firm size, regular or non-regular worker status, and union status. These variables are also fully interacted in the model.

Educational attainment is measured using 5 dummy variables for the highest level of education attained which include middle school (or less), high school, technical college (2 or 3 year courses), university and graduate school.[4] Experience is measured in years of potential experience by subtracting years of schooling and 6 from respondents' age. Tenure and tenure squared are reported in years of work for the respondent's current firm. Regular/non-regular worker status, union membership and firm size are all coded with binary indicators with firm size being split above and below 300 workers.[5]

A potential issue when conducting wage gap decompositions is whether differences in occupations between males and females are the result of personal choice or discrimination. By including occupations we assume that occupational differences are a matter of choice. Thus discrimination is measured as different returns to occupations but discrimination in entering an occupation (or the effect of the expectation of future discrimination in certain occupations) may be incorrectly attributed to the composition effect. As a result, I conduct an auxiliary analysis to investigate the sensitivity of the results to occupational choice. The occupation dummy variables include managers, professionals, office workers, services, retailers, agriculture and fishing, technicians, machine operators, and laborers as the reference group. Table 2 shows summary statistics for male and female occupations.

[4] Middle school is adopted as the reference group.
[5] Non-regular workers include temporary and daily workers.

3 RESULTS

3.1 Main Decompositions

The baseline wage gaps and decomposition results are presented in Table 3. In 2003, the log wage gap widens as we move up the distribution from 0.37 at the 10^{th} quantile to 0.59 at the 75^{th} and then narrows to 0.51 at the 90^{th} quantile. This trend can be seen in Figure 1(a). The larger wage gap at higher quantiles is commonly referred to as the "glass ceiling" effect in the wage gap literature (Badel and Peña, 2010). Next, I use the DFL method to decompose the wage gap into structural and composition effects. Row 2 shows that the structural effect at the 10^{th}, 25^{th} and 50^{th} quantiles explains between 50% to 60% of the gender wage gap. As we move up to the 75^{th} and 90^{th} quantiles, however, the structural effect accounts for only 33% and 12% of the wage gap respectively. This contrasts research conducted by Albrecht, van Vuuren and Vroman (2009) on the Dutch gender wage gap and Badel and Peña (2010) on the Colombian gender wage gap who find that the structural effect explains the lion's share of the wage gap at the upper end of the distribution. Row 3 shows that the composition effect increases in importance as we move up the distribution, from roughly 43% of the wage gap at the 10^{th} quantile to 88% at the 90^{th} quantile. Figure 1(a) provides a visual representation of the above trends and shows where the composition effect overtakes the structural effect at approximately the 60^{th} quantile. Overall, the results highlight that differences in returns to productivity characteristics are relatively more important in explaining the gender wage gap at the lower end and middle of the wage distribution, while differences in productivity characteristics themselves become more important at the upper end of the wage distribution.

Row 4 presents the log wage gap in 2013. Analogous to 2003, the log wage gap exhibits a glass ceiling effect, widening as we move up the wage distribution from 0.29 at the 10^{th} quantile to 0.54 at 75^{th} quantile and then narrowing to 0.45 at the 90^{th} quantile. Decompositions show that the structural effect accounts for between 60% to 70% of the wage gap at the 10^{th} and 25^{th} quantiles. In contrast to 2003, the structural effect does not fall as sharply as we move up the distribution, continuing to explain approximately 38% of the wage gap at the 90^{th} quantile. This difference is made clear by comparing Figures 1(a) and 1(b). The composition effect, on the other hand, exhibits a flatter rise as we move up the wage distribution than in 2003, increasing from 38% of the wage gap at the 10^{th} quantile to 62% at the 90^{th}. Overall, despite small differences between 2003 and 2013 the structural and composition effect trends remain fairly similar.

Rows 7, 8, and 9 present the changes in the baseline wage gap, structural effect, and composition effect between 2003 and 2013. During this period, the wage gap fell across the entire distribution by between 0.05 to 0.09 log wage points. The structural effect decreased by 0.03 and 0.06 at the 10^{th} and 50^{th} quantiles but increased by 0.04 and 0.11 at the 75^{th} and 90^{th} quantiles. The composition effect fell across the entire distribution, most notably by 0.09 and 0.17 log wage points at the 75^{th} and 90^{th} quantiles. To sum up, a decrease in composition and structural effects drives the fall in the wage gap at the lower end and middle of the wage distribution. At the upper end of the distribution, a rise in the structural effect partially offsets a fall in the composition effect. These results suggest relative improvements in female productivity characteristics reduced the wage gap across the entire wage distribution. While a fall in wage discrimination at the lower end and middle of the wage distribution may have augmented this effect, a rise at the upper end may have curtailed it. One possible scenario is that females were unable to fully realise their gains from relative improvements in productivity characteristics as a result of an increase in wage discrimination at the upper end of the wage distribution. I conjecture that as females enter more professional occupations they may find themselves in relatively higher paying jobs where there is greater room for wage discrimination. I address this in the following subsection.

3.2 Decompositions with Occupations

The decomposition results with the inclusion of occupation dummy variables are presented in Table 4. In 2003, adding these variables leads to small decreases in the structural effect (increases in the composition effect) at the 10^{th} and 25^{th} quantiles of 0.04 and 0.02. At the 50^{th}, 75^{th} and 90^{th} quantiles there are small increases in the structural effect (decreases in the composition effect) of 0.02, 0.03 and 0.06. These changes can be seen by comparing Figures 1(a) and 2(a). One possible explanation is that differences in occupations between males and females may have played a minor role in explaining the wage gap at the lower end of the distribution. On the other hand, differences in returns to occupations may have been more important at the upper end of the distribution. Nevertheless, the changes are minimal and the main findings of a fall in the relative importance of the structural effect and a rise in the relative importance of the composition effect as we move up the distribution remains unchanged.

In 2013, the inclusion of occupation dummy variables once again leads to decreases in the structural effect (increases in the composition effect) at the 10^{th} and 25^{th} quantiles of 0.02 and 0.03. At the 50^{th}, 75^{th} and 90^{th} quantiles we see increases in the structural effect (decrease in the composition effect) of 0.02, 0.06 and

0.03. These changes can be seen by comparing Figures 1(b) and 2(b). These changes lend themselves to the same explanation as in 2003. Also, the rise in the structural effect at the 75^{th} and 90^{th} quantiles as a result of the inclusion of occupation dummy variables provides some evidence that there may be greater room for wage discrimination as females find themselves in higher paying jobs.

Lastly, concerning the changes between 2003 and 2013, the inclusion of occupation dummy variables leads to heterogenous and minimal changes across the distribution. Therefore the main findings remain unchanged that a fall in the composition effect narrows the wage gap across the entire distribution, while a fall in the structural effect augments the narrowing at the lower end of the distribution, and a rise in the structural effect curtails it at the upper end.

4 CONCLUSION

Using EAPS data from two cohorts and DFL decompositions, I analyzed the gender wage gap in Korea across the entire wage distribution between 2003 and 2013. This involved exploring the relative importance of differences in productivity characteristics (composition effects) and differences in returns to productivity characteristics (structural effects) among males and females.

The results reveal a glass ceiling effect where the gender wage gap widens as we move up the wage distribution. Decompositions show that in both 2003 and 2013, the relative importance of the structural effect increases and composition effect decreases as we move up the distribution. This contrasts what is seen in the Netherlands and Colombia. Between 2003 and 2013, the wage gap fell across the entire distribution by between 0.05 to 0.09 log wage points. A decrease in composition and structural effects drives the fall in the wage gap at the lower end and middle of the wage distribution. At the upper end of the distribution, a rise in the structural effect partially offsets a fall in the composition effect. These results suggest relative improvements in female productivity characteristics reduced the wage gap across the entire wage distribution. While a fall in wage discrimination at the lower end and middle of the wage distribution may have augmented this effect, a rise at the upper end may have curtailed it. Lastly, the inclusion of occupations tends to increase the composition effect at the lower end and structural effect at the upper end of the wage distribution in both 2003 and 2013.

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Table 1: Summary Statistics for Males and Females

	EAPS - 2003		EAPS - 2013	
	Males	Females	Males	Females
Mean Log Wage	2.18	1.67	2.41	1.97
	(0.64)	(0.61)	(0.64)	(0.60)
Median Log Wage	2.14	1.58	2.38	1.91
Age	39.5	37.8	43.0	42.3
	(10.2)	(11.2)	(10.4)	(11.2)
Married	0.74	0.60	0.73	0.66
Experience in yrs.	20.5	20.0	23.1	23.6
	(11.7)	(13.6)	(11.8)	(13.3)
Tenure in yrs.	5.85	2.54	7.28	4.09
	(7.34)	(4.26)	(8.50)	(5.84)
Education Levels				
Middle School	0.15	0.28	0.09	0.18
High School	0.42	0.41	0.35	0.38
Technical College	0.12	0.14	0.17	0.18
University	0.26	0.16	0.33	0.23
Graduate School	0.05	0.02	0.06	0.03
Large Firm (300+)	0.17	0.07	0.16	0.07
Regular Worker	0.63	0.35	0.75	0.56
Union	0.16	0.06	0.18	0.08
Sample Size	14039	9786	12948	9791

Note: Standard deviations are in parenthesis. Wages are in 2003 Korean Won and are in thousands.

Table 2: Occupational Composition for Males and Females

	EAPS - 2003		EAPS - 2013	
	Males	Females	Males	Females
Managers	0.03	0.00	0.03	0.00
Professionals	0.19	0.18	0.19	0.23
Office workers	0.19	0.22	0.21	0.23
Services	0.05	0.18	0.05	0.15
Retailers	0.04	0.13	0.06	0.12
Agriculture/Fishing	0.01	0.00	0.01	0.00
Technicians	0.18	0.05	0.15	0.03
Machine Operators	0.19	0.06	0.19	0.05
Laborers	0.13	0.18	0.12	0.19

Note: Laborers are chosen as the reference group.

Table 3: Main Decomposition Results

		Mean	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
	Wage Gap	0.51***	0.37***	0.48***	0.56***	0.59***	0.51***
		(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)
EAPS 2003	Structural Effect	0.23***	0.22***	0.29***	0.30***	0.19***	0.06***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
	Composition Effect	0.28***	0.16***	0.19***	0.26***	0.40***	0.45***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Wage Gap	0.44***	0.29***	0.41***	0.47***	0.54***	0.45***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
EAPS 2013	Structural Effect	0.21***	0.19***	0.29***	0.24***	0.23***	0.17***
		(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
	Composition Effect	0.22***	0.11***	0.13***	0.23***	0.31***	0.28***
		(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
	Wage Gap	-0.07***	-0.08***	-0.07***	-0.09***	-0.05**	-0.06
		(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.04)
Difference 2013-2003	Structural Effect	-0.02**	-0.03	0.00	-0.06***	0.04**	0.11**
		(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)
	Composition Effect	-0.06***	-0.05	-0.06***	-0.03	-0.09***	-0.17***
		(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)

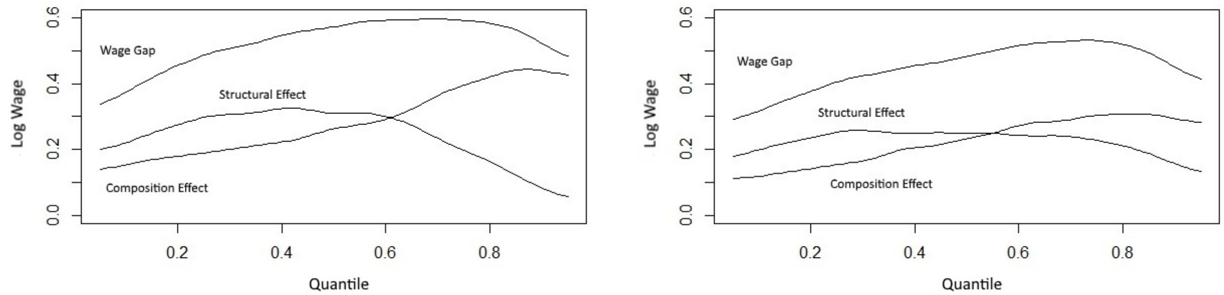
Note: Bootstrapped standard errors (based on 1,000 replications) are reported in parentheses. Statistical significance is denoted by *** for the 1% level, ** for the 5% level, and * for the 10% level.

Table 4: Decomposition Results with Occupations

		Mean	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
	Wage Gap	0.51***	0.37***	0.48***	0.56***	0.59***	0.51***
		(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)
EAPS 2003	Structural Effect	0.23***	0.18***	0.27***	0.32***	0.22***	0.12***
		(0.01)	(0.03)	(0.02)	(0.02)	(0.01)	(0.03)
	Composition Effect	0.27***	0.19***	0.22***	0.24***	0.37***	0.39***
		(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	Wage Gap	0.44***	0.29***	0.41***	0.47***	0.54***	0.45***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
EAPS 2013	Structural Effect	0.23***	0.17***	0.26***	0.26***	0.29***	0.20***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Composition Effect	0.21***	0.12***	0.15***	0.21***	0.25***	0.25***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Wage Gap	-0.07***	-0.08***	-0.07***	-0.09***	-0.05**	-0.06
		(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.04)
Difference 2013-2003	Structural Effect	0.00	-0.01	-0.01	-0.06**	0.07**	0.08**
		(0.01)	(0.04)	(0.03)	(0.03)	(0.02)	(0.04)
	Composition Effect	-0.06***	-0.07*	-0.07**	-0.03	-0.12***	-0.14***
		(0.01)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)

Note: Bootstrapped standard errors (based on 1,000 replications) are reported in parentheses. Statistical significance is denoted by *** for the 1% level, ** for the 5% level, and * for the 10% level.

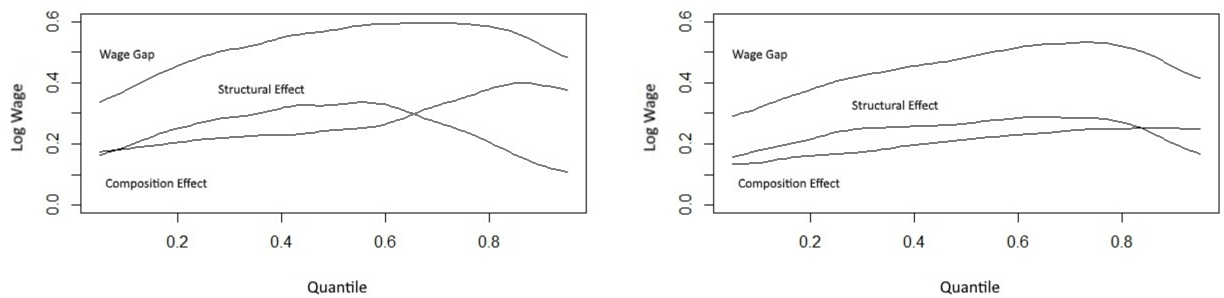
Figure 1: Gender Wage Gap Decompositions



(a) 2003

(b) 2013

Figure 2: Gender Wage Gap Decompositions with Occupations



(a) 2003

(b) 2013