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Gender Labor Market Outcome Differentials in Korea: How Does the Horizontal Mismatch Play?

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Abstract

This study investigates the gender differentials in wages and job satisfaction using the Graduates Occupational Mobility Survey in Korea. Wage regressions estimate the impact of horizontal mismatch on wage differentials and overall job satisfaction differentials between workers with matched jobs and non-matched jobs. To deal with unobservable heterogeneity, we utilize Heckman's two-step method. The findings imply that male workers have higher wages and job satisfaction than female workers for both horizontally matched and not-matched groups. Moreover, gender wage and job satisfaction differentials are consistently larger in matched job workers than in non-matched job workers in recent periods.

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1 Introduction

Declining job quality and wage levels for college graduates in Korea have been significant problems, although the younger generation has dramatically decreased. There are many reasons for challenges that college graduates have for finding a suitable occupation after graduation. One example is that new jobs have yet to be created because of aging in the labor market and low economic growth rates. Another explanation may be the discrepancy between the labor force and the job market, which distorts supply and demand in the labor market in Korea (Ahn and Lee, 2022). The high educational mismatch rate in the younger generations has been considered one of the main reasons for the inability to provide skilled workers with the current labor market needs.

The education and job mismatch is measured by two distinct aspects of education and job match in terms of quantity (education levels) and quality (field of study). A mismatch between the level of schooling and job is referred to as a vertical mismatch, while a horizontal mismatch is referred to as a mismatch induced by a field of study. The discrepancies between education and job requirements would be negatively associated with the return of education in terms of labor productivity for college graduates.

The substantial literature on the vertical mismatch, especially the effects of over-education and underemployment has been well-documented. It points out that the over-education is associated with substantial wage penalties and lower job satisfaction (Hartog, 2000; Groot and Van Den Brink, 2000; Bauer, 2002; Chevalier, 2003; McGuinness, 2006; Fleming and Kler, 2008; Budría and Moro-Egido, 2008; Green and Henseke, 2016). Additionally, some previous studies identify the effects of over-education on job turnover rate (Groeneveld and Hartog, 2004; Verhaest and Omey, 2006). Groeneveld and Hartog (2004) and Verhaest and Omey (2006) point out that overqualified workers are more likely to leave and contribute to higher rates of job turnover than well-matched workers because of fewer opportunities in career development, such as promotion in a firm.

Although there has been considerable research regarding the vertical mismatch, fewer studies on the horizontal mismatch effects have been conducted, possibly because the effects of horizontal mismatch on labor market outcomes may be less substantial than vertical mismatch, which is likely negatively associated with earnings. The interest in the horizontal mismatch effects on labor market outcomes has recently grown across countries.

Two theories explain the relationship between horizontal mismatch and labor market outcomes. The first is Becker's human capital theory; Becker (1994) indicates that an individual's human capital determines the difference in labor market outcomes, especially wages. Additionally, the assignment problem model suggests that the assignment problem accounts for the difference in wages and productivity because of matching between workers and jobs, depending on heterogeneous characteristics (Tinbergen, 1956; Hartog, 1981, 1985;

Sattinger, 1993). According to both theories, mismatched graduates are more likely to have lower wages because of human capital characteristics and the assignment problem. Based on some theories Hur et al. (2019) indicate that those with horizontally mismatched jobs will likely face lower wages and job satisfaction levels because they are not utilizing their accumulated human capital for their tasks.

Some studies find that horizontal mismatch also reduces labor market productivity. Discrepancies between the field of study in college and job are likely to have wage penalties as much as over-education (Robst, 2007a,b; Boudarbat and Chernoff, 2012; Choi and Hur, 2020). Also, Robst (2008) and Ge et al. (2019) indicate that field-job mismatched workers are more likely to experience less job satisfaction or job-related well-being. Furthermore, Choi and Hur (2020) mention that lower wages and job satisfaction can play a significant role in having a greater chance of job turnover for mismatched workers than for workers whose college major is closely related to the job.

According to an Organisation for Economic Co-operation and Development(OECD) study regarding the mismatch between field and jobs, the proportion of discrepancies between education and job in Korea has been relatively higher than in other OECD countries (Montt (2015)). More than 70% of young people in Korea pursue tertiary education. There would be a greater probability of having a substantial proportion of over-educated people employed unless new jobs in the labor market are provided for them. Montt (2015) and Han (2020) point out that Korea has the highest rate of horizontal mismatch among OECD countries with about 50% of employed workers horizontally mismatched in Korea, while the average in other OECD countries is below 40%.

Some studies in Korea have focused on analyzing the effects of the discrepancy between the academic field and job, presenting that the horizontal mismatch is negatively associated with wages (Han, 2018; Hwang, 2018; Han, 2020). Han (2018) presents the horizontal mismatch of each college major. Those who studied a humanities field in a college are less likely to have a job related to the field than other majors because of a lack of demand for graduates in the market. Hwang (2018) indicates a negative effect on wages of about 2.3% if the field and job are horizontally mismatched. Han (2020) finds that the reason for the high horizontal mismatch rate in Korea is the stickiness of field choice in college.[1] He attributes the horizontal mismatch to the stickiness of the college system regarding field selection. Once students decide on a major when they are admitted to college, changing their major college is considerably challenging.

In addition to the horizontal mismatch effect on wages, a few studies analyze how the horizontal mismatch accounts for the gender wage gap (Choi and Hur, 2020; Ahn and Lee, 2022). Choi and Hur (2020) provide the gender differential on wages and job turnover rate in the U.S. using the Heckman-Lee and probit regression models. The wage penalty on female workers with a horizontally mismatched job is much greater than those

[1]Students choose a detailed field when they submit applications for a college. However, high school students have decided already on their academic path (liberal arts or natural sciences and engineering).

with a matched job. This penalty could be a reason for the motivation of the female workers' job movement. Ahn and Lee (2022) also find that female college graduates with mismatched jobs have lower wages than male graduates with mismatched jobs. They confirm that the horizontal mismatch contributes to the gender wage gap and that female graduates having an educationally matched job have even substantially lower wages than male graduates with a mismatched job. However, the results may not represent causal effects because their analyses are based on simple saturated models that may not consider unobservable characteristics, causing endogenous problems. This study tries to account for unobservable characteristics by controlling for selection bias.

This study contributes to the literature in a twofold way. First, we estimate the effects of the horizontal mismatch on wages and job satisfaction for college graduates in Korea to fill the gap in the literature. If graduates have a mismatched job unrelated to their field of study in college, they would be associated with a greater chance of wage penalty and less job satisfaction than those with a closely matched job. To that end, this study focuses particular attention on different patterns in the gender of the effects of the mismatch between the field of study and job. To estimate the gender-related effects of the horizontal mismatch on labor market outcomes, we use the Graduates Occupational Mobility Survey from 2008 to 2018, applying the Heckman two-step selection method to account for unobservables. We find that female employees in the mismatched group suffer a more significant wage penalty and less job satisfaction than male employees. However, male employees are more likely to switch jobs than female employees are.

The remainder of this study is organized as follows: Section 2 presents the Graduates Occupational Mobility Survey dataset used in this study. Section 3 discusses the base OLS results. Then, we discuss the results from the Heckman-Lee model. Section 5 summarizes and concludes.

2 Data: Graduates Occupational Mobility Survey

The empirical analyses use the Graduates Occupational Mobility Survey (hereafter GOMS) to identify the effects of the horizontal mismatch on post-secondary education graduates' labor productivity: wages, and overall job satisfaction.[2] GOMS provides extensive information on college graduates' job mobility, including other labor market outcomes such as educational attainment and wages in Korea. Although GOMS data have been constructed from longitudinal surveys of college graduates, it was changed to a cross-sectional structure in the 2012 version of the survey. This study uses only the first year of each longitudinal survey to have a consistent sample given this structural change. Ultimately, we utilize the data from 2008 to 2018.

This study estimates the gender differentials of wages and job satisfaction in horizontally matched and

[2]Data are available on the website the Korea Employment Information Service: https://survey.keis.or.kr/goms

Table 1: Summary Statistics

Variables	Mean	Std. Dev.	Variables	Mean	Std. Dev.
Field-Job Mismatch:			***Industry Type:***		
Matched	0.496	0.499	Business / Finance	0.325	0.462
Not Matched	0.504	0.499	Research Related	0.195	0.396
Job Satisfaction:			Education	0.157	0.364
Satisfied	0.567	0.495	Health / Medical	0.084	0.281
Unsatisfied	0.433	0.495	Arts / Design / Broadcast	0.068	0.261
			Tourism	0.032	0.174
Gender (male = 1)	0.558	0.496	Sales / Transportation	0.069	0.254
Age	27.01	4.526	Construction	0.003	0.056
Real Monthly Wages*	2,240.65	898.319	Manufacture	0.064	0.245
College Type (4-year College=1)	0.716	0.451	Agriculture / Fishery	0.002	0.045
Employer Type (Public Work = 1)	0.213	0.409			
Married	0.080	0.271	***Employer Size:***		
College Major:			Less than 10	0.175	0.341
Social Science	0.097	0.296	Between 10 and 29	0.138	0.345
Humanities	0.234	0.423	Between 30 and 49	0.073	0.259
Education	0.078	0.268	Between 50 and 99	0.100	0.299
Engineering	0.296	0.456	Between 100 and 299	0.117	0.321
Natural Science	0.117	0.322	Between 300 and 499	0.056	0.229
Medical	0.081	0.273	Between 500 and 999	0.062	0.241
Arts and Physical	0.097	0.296	Over 1000	0.279	0.448
Number of Observations = 123,208					

Note: Graduates Occupational Mobility Survey (2008 - 2018).
* 1000 KRW = 1 USD. Numbers about are in US dollar.

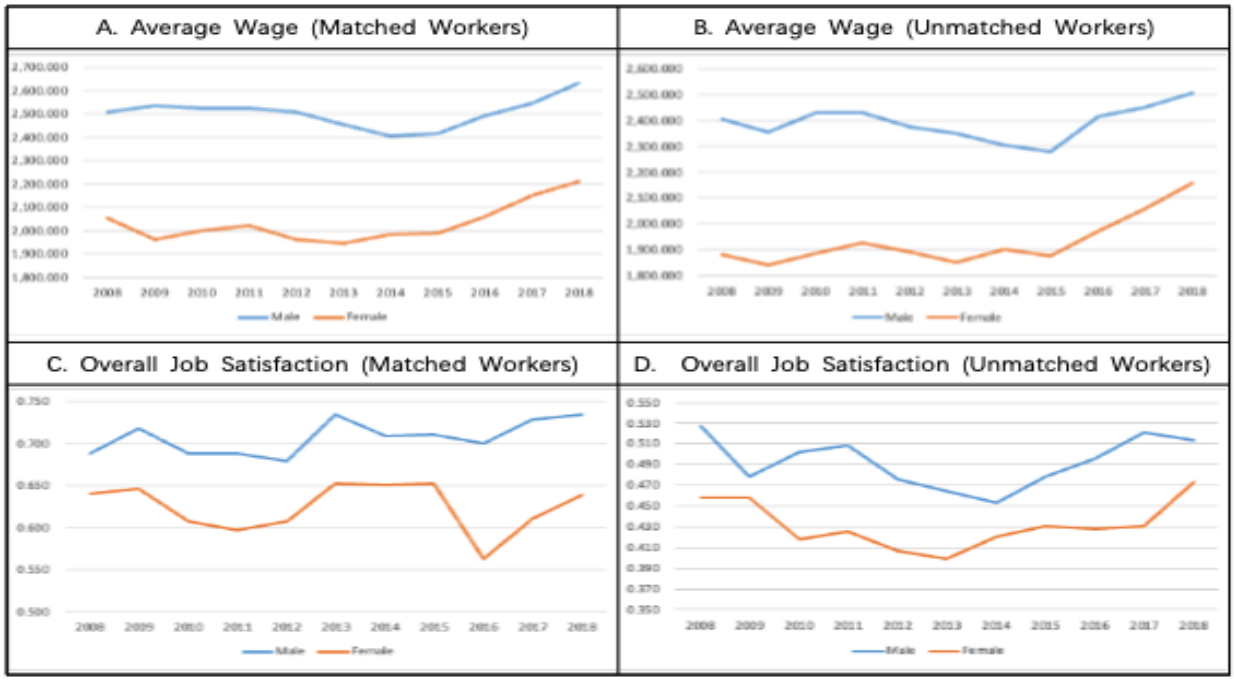
unmatched groups. The analyses consider only full-time employees who work more than 35 hours per week. In other words, we do not include self-employed and part-time workers in the sample. If we include self-employed and part-time workers in the analyses, they are more likely to be counted in the unmatched group because their tasks are relatively unrelated to what they have learned in college. It may create sample bias.

There are two ways to measure the horizontal mismatch: subjective and objective. Han (2018) uses the objective method, directly mapping between a major and a job. The method would be advantageous to compare the degree of the horizontal mismatch across countries. However, categorizing college majors is hardly achievable in Korea. Because it is too vague to distinguish the major in Korea, researchers' arbitrary selection is inevitable to categorize majors.[3]

Another measure of the horizontal mismatch is to use self-reported information, which is subjective. Han (2018) also discusses that the self-reported measure would be more accurate and reduce measurement errors if

[3]We can find names of college majors that provide an example of ambiguity, such as international studies, international economics, and international business administration. The international studies major is not only an interdisciplinary major, but it is less likely to be categorized as an academic field by being combined with another major, such as economics or business administration. Because students in international studies take various courses related to international issues, such as international trade, international politics, finance, and official development assistance, we can hardly infer the category from the course of a major. 'Facial business management' at Won-Kwang Digital University is another unique example of the case. It is difficult to categorize this major into a specific group without the arbitrary choice of authors

Figure 1: Gender Differentials in Subgroups



the horizontal mismatch defines a disparity between the major and task (not job) than the objective method. Therefore, this study considers the self-reported measure of the horizontal mismatch to be appropriate to analyze the horizontal mismatch roles in differentials of gender labor market outcomes.

A variable of interest is the degree of relevancy between the college fields (majors) and job tasks. In GOMS, there is a direct question on the horizontal mismatch: How well is your college major related to your workplace tasks? The Horizontal mismatch question consists of five categories: 1. completely unrelated, 2. unrelated, 3. somewhat related, 4. related, and 5. closely related.[4] We consider persons who responded 1, 2, and 3 in the question as those who hold an unmatched job and 4 and 5 as a matched job.

Two dependent variables are log-transformed monthly averaged wages and overall job satisfaction. GOMS asks many detailed questions on job satisfaction, such as overall wages (earnings) and the firm's benefits. Among many satisfaction questions, we consider self-reported overall job satisfaction as one of the dependent variables because the survey consistently asks about overall satisfaction, and this variable aligns with other satisfaction-related variables. The overall satisfaction consists of five categories: 1. seriously dissatisfied, 2. dissatisfied, 3. average 4, satisfied, and 5. very satisfied. We consider those who responded 4 and 5 as those who were overall satisfied with their jobs.

[4]The exact question is: how is your college major related to your job tasks? (if you have multiple majors (i.e. double major), please only consider your main major to answer.)

Table 2: Detailed Summary of Key Variables in Subgroups, Year-by-Year

Panel A: Detailed Summary of Key Variables on Female in Subgroups

	Wages		Overall Satisfaction		4-Yr College		Major: Humanities		Major: Social Science	
Year	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched
2008	2,056.085	1,884.621	0.641	0.458	0.685	0.694	0.092	0.192	0.181	0.292
2009	1,961.861	1,843.183	0.647	0.458	0.619	0.599	0.082	0.161	0.233	0.337
2010	2,000.493	1,887.485	0.608	0.418	0.639	0.649	0.083	0.158	0.261	0.391
2011	2,023.944	1,927.720	0.597	0.426	0.649	0.668	0.080	0.171	0.264	0.354
2012	1,960.642	1,891.499	0.608	0.407	0.658	0.694	0.096	0.182	0.236	0.290
2013	1,947.362	1,850.425	0.653	0.399	0.687	0.664	0.080	0.194	0.178	0.262
2014	1,984.457	1,904.324	0.651	0.421	0.686	0.668	0.064	0.176	0.193	0.293
2015	1,988.041	1,877.967	0.652	0.431	0.698	0.721	0.073	0.186	0.192	0.301
2016	2,062.140	1,973.534	0.563	0.428	0.704	0.766	0.083	0.215	0.192	0.283
2017	2,150.349	2,059.675	0.611	0.431	0.777	0.801	0.078	0.221	0.205	0.278
2018	2,210.875	2,159.128	0.639	0.473	0.770	0.831	0.083	0.226	0.189	0.255
	Major: Education		Major: Engineering		Major: Natural Science		Major: Medical/Health		Major: Arts & Physical	
Year	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched
2008	0.234	0.067	0.109	0.115	0.117	0.164	0.157	0.049	0.109	0.120
2009	0.214	0.701	0.088	0.107	0.104	0.135	0.159	0.054	0.119	0.135
2010	0.166	0.051	0.081	0.096	0.109	0.133	0.198	0.056	0.102	0.135
2011	0.173	0.048	0.089	0.116	0.109	0.132	0.165	0.059	0.118	0.120
2012	0.193	0.058	0.095	0.110	0.094	0.145	0.159	0.057	0.128	0.157
2013	0.215	0.073	0.097	0.115	0.124	0.122	0.165	0.060	0.139	0.174
2014	0.207	0.069	0.094	0.113	0.129	0.129	0.171	0.072	0.142	0.147
2015	0.200	0.055	0.098	0.122	0.127	0.143	0.191	0.059	0.118	0.134
2016	0.130	0.046	0.116	0.123	0.138	0.138	0.206	0.064	0.135	0.131
2017	0.163	0.053	0.133	0.125	0.117	0.141	0.179	0.065	0.124	0.118
2018	0.156	0.052	0.146	0.138	0.131	0.135	0.166	0.062	0.128	0.132

Panel B: Detailed Summary of Key Variables on Male in Subgroups

	Wages		Overall Satisfaction		4-Yr College		Major: Humanities		Major: Social Science	
Year	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched
2008	2,510.758	2,406.533	0.689	0.527	0.755	0.704	0.047	0.094	0.166	0.231
2009	2,534.980	2,355.673	0.718	0.478	0.708	0.623	0.041	0.079	0.208	0.270
2010	2,528.241	2,432.599	0.689	0.502	0.741	0.689	0.043	0.075	0.228	0.305
2011	2,523.846	2,430.845	0.689	0.508	0.760	0.695	0.046	0.091	0.238	0.292
2012	2,507.482	2,373.373	0.679	0.476	0.720	0.701	0.041	0.094	0.188	0.264
2013	2,453.944	2,350.667	0.735	0.464	0.728	0.694	0.047	0.092	0.155	0.216
2014	2,407.966	2,305.012	0.709	0.453	0.758	0.704	0.044	0.087	0.151	0.213
2015	2,416.054	2,278.974	0.710	0.478	0.755	0.729	0.035	0.092	0.157	0.227
2016	2,495.230	2,415.806	0.700	0.496	0.759	0.760	0.037	0.107	0.159	0.229
2017	2,548.648	2,452.595	0.728	0.521	0.812	0.804	0.036	0.111	0.164	0.221
2018	2,635.574	2,507.453	0.734	0.514	0.815	0.791	0.042	0.122	0.161	0.223
	Major: Education		Major: Engineering		Major: Natural Science		Major: Medical/Health		Major: Arts & Physical	
Year	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched	Matched	Not Matched
2008	0.057	0.024	0.459	0.430	0.109	0.123	0.076	0.022	0.086	0.076
2009	0.057	0.019	0.445	0.415	0.089	0.102	0.073	0.032	0.085	0.082
2010	0.051	0.020	0.427	0.386	0.100	0.105	0.078	0.028	0.073	0.081
2011	0.064	0.028	0.401	0.380	0.092	0.103	0.079	0.027	0.079	0.079
2012	0.061	0.026	0.464	0.409	0.097	0.105	0.078	0.026	0.070	0.076
2013	0.064	0.030	0.500	0.444	0.092	0.119	0.073	0.028	0.069	0.069
2014	0.061	0.027	0.485	0.453	0.125	0.105	0.064	0.035	0.071	0.080
2015	0.060	0.027	0.507	0.441	0.106	0.114	0.077	0.028	0.057	0.070
2016	0.053	0.019	0.498	0.438	0.112	0.116	0.085	0.026	0.056	0.063
2017	0.056	0.025	0.483	0.440	0.122	0.129	0.085	0.025	0.055	0.049
2018	0.056	0.027	0.490	0.421	0.119	0.117	0.079	0.029	0.051	0.060

Note: Wages indicate real monthly averaged wages of a given year in US dollars.

Table 1 provides descriptive statistics for the analyses of the horizontal field-job mismatch. Interestingly, we find that the proportion of the horizontal mismatch is 49.6%, and the mismatched portion is 50.4%. Based on sample statistics, half of the college graduates accepted a job offer, although the job was unrelated to their college field. The mean monthly wage for college graduates is approximately $2,241 USD. [5] The proportion of overall job satisfaction is also like the mismatch pattern: those who answered 'satisfied' are 56.7%. In contrast, 43.3% are not satisfied with their job in general.

Additionally, we control for persons' other characteristics in our empirical analyses, such as age, gender, college type (2- or 3-year college / 4-year college), college location, college major, industry type, and company size. Omitted groups are an engineering field for college majors, business/finance for the industry type, and fewer than 10 workers for the employer size, respectively. This study uses 123,208 college graduates over more than ten years (2008-2018) to analyze the effects of horizontal mismatch between education and job.

Table 2 summarizes the mean values of crucial variables for females and males for both horizontally matched and mismatched groups over time. According to panel A in Table 2, the average wages of females have generally increased in both groups by about the same amount. Female graduates' overall job satisfaction for both groups remained relatively consistent. Panel B in Table 2 also shows that the average wages of males also increased about the same amount over time for both groups. We can find substantial gender wage gaps, such that a male's average wages in the horizontally mismatched group are even greater than horizontally matched females' wages for whole periods. Overall job satisfaction in the horizontally matched group of males has slightly increased from 0.689 to 0.734 in 2018, as shown in Table 2. On the other hand, it has remained relatively the same for the mismatched group.

In addition, we offer the statistics from Table 2. We find that the gender gap in wages and job satisfaction is substantial in both groups over the sample period. As shown in Figure 1, male workers are more likely to receive higher wages and to be satisfied with their jobs than female workers. Overall, gender wage and job satisfaction gaps are similar for both groups. In contrast, the mean of real wages and job satisfaction in the non-matched group are significantly less than in the matched group.

3 Basic OLS Model

This study employs a descriptive OLS model to estimate the effects of horizontal mismatch on wage and job satisfaction differentials. We estimate two separate equations, one with the matched group and another

[5] We transformed the real wages from Korean Won to US Dollar with exchange rates, 1000KRW = 1 USD.

with not-matched group workers. The descriptive regression equation is,

$$Y_{it} = \alpha + \beta Gender_{it} + X_{it}\Gamma + \epsilon_{it}, \quad d_{it} = 0 \text{ or } 1, \ t = 2008, \ldots, 2018, \tag{1}$$

where Y_i includes either *log monthly averaged wages* or *Overall job satisfaction* at a given year t. *Log monthly averaged wages* is log transformed monthly averaged wages of college graduates. *Overall job satisfaction* is a dummy variable: 1 indicates that a college graduate i is satisfied with a current job. *Gender* is a dummy variable, indicating 1 for males and 0 for females. Since we focus on the effect of gender in the labor market, the baseline models separately control gender from other characteristics. X_i includes other detailed socioeconomic and demographic information such as age, college types and location, industry types, and contract types. ϵ_i is an error term. d_{it} indicates whether a college graduate i in year t is horizontally mismatched, so if $d_{it} = 1$, it denotes the graduate has a matched job between the educational field and job in year t and 0 otherwise. Omitted groups are engineering for college majors, business/finance for industry, and fewer than 10 workers for employer size.

In addition, we have another baseline OLS model to estimate the gender effect on wages and job satisfaction, year-by-year, for both 'matched' and 'not-matched' groups. OLS models for the comparison are,

$$\begin{aligned} Y_{it}^g =& \alpha_t^g + X_{it}^g \beta^g + \varepsilon_{it}^g, \ if \ g = \text{male or female}, \ and \\ & d_{it} = 0 \text{ or } 1, \ where \ t = 2008, \ldots, 2018. \end{aligned} \tag{2}$$

The term X_{it} is the same as equation (1).

Table 3 presents the results of descriptive regressions. We find significant differences in labor market outcomes between genders across education-job mismatch groups.[6] Columns (1) to (2) show that gender accounts for their wages. Gender differential patterns in wages are similar across the subgroups, with male graduates receiving 10.4 percent (Matched) and 8.4 percent (Not Matched) higher salaries than female graduates. Specifically, the gender wage gap in the horizontally mismatched group is somewhat greater than the gap in the matched group, about 2 percent. College graduates who studied humanities, social science, natural science, or arts and physical education are likely to have lower wages than those who studied engineering in college, regardless of the mismatch of fields.

Columns (3) and (4) in Table 3 show gender differences in job satisfaction and that male graduates are

[6]This study additionally estimates the average effects of horizontal mismatch and gender differentials of earnings and job satisfaction with the pooled sample. Compared with the results of Table 3, an estimate of gender earnings differential is 0.09, between 0.104 from column (1) and 0.084 from column (2). Also, an estimate of gender differential of job satisfaction is 0.068, between 0.054 and 0.078 from columns (3) and (4). The results also indicate that male college graduates are more likely to have greater wages and be satisfied with their jobs than female graduates in the early stages of their careers. Further estimation results are available upon request

Table 3: Descriptive OLS Results of Gender Differential and Horizontal Mismatch

Dependent Variable:	Log Earnings		Job Satisfaction	
Horizontal Mismatch:	Matched	Not Matched	Matched	Not Matched
	(1)	(2)	(3)	(4)
Gender	0.104***	0.084***	0.054***	0.078***
	(0.003)	(0.003)	(0.005)	(0.005)
Age	0.057***	0.051***	0.003*	0.003*
	(0.003)	(0.003)	(0.002)	(0.002)
4-Yr University	0.075***	0.105***	0.008	0.017***
	(0.003)	(0.003)	(0.005)	(0.005)
Major:				
Humanities	-0.046***	-0.088***	0.022***	0.028***
	(0.004)	(0.007)	(0.007)	(0.009)
Social Science	-0.030***	-0.036***	0.002	0.012*
	(0.003)	(0.005)	(0.006)	(0.007)
Education	0.066***	0.182***	0.068***	0.123***
	(0.008)	(0.007)	(0.011)	(0.009)
Natural Science	-0.033***	-0.077***	0.022***	0.011
	(0.004)	(0.006)	(0.007)	(0.007)
Medical / Health	0.029***	0.087***	-0.019	-0.005
	(0.007)	(0.007)	(0.013)	(0.011)
Arts and Physical Education	-0.083***	-0.099***	-0.021**	-0.013
	(0.005)	(0.006)	(0.008)	(0.010)
Occupation:				
Research	0.020***	-0.037***	-0.023***	-0.024***
	(0.004)	(0.005)	(0.007)	(0.007)
Education / Law	-0.059***	-0.120***	-0.014**	0.007
	(0.005)	(0.007)	(0.007)	(0.007)
Health / Medical	0.014**	-0.024***	-0.077***	-0.099***
	(0.007)	(0.007)	(0.013)	(0.011)
Arts / Design / Broadcast	-0.048***	-0.063***	-0.069***	-0.052***
	(0.006)	(0.006)	(0.009)	(0.010)
Tourism / Food	-0.115***	-0.096***	-0.049***	-0.049***
	(0.007)	(0.008)	(0.011)	(0.013)
Sales / Transportation	0.007*	0.032***	-0.006	0.019*
	(0.004)	(0.007)	(0.007)	(0.010)
Construction	0.055***	0.021	-0.064**	-0.003
	(0.021)	(0.034)	(0.030)	(0.044)
Manufacture	0.017***	0.015**	-0.031***	0.003
	(0.005)	(0.006)	(0.008)	(0.010)
Agricultrue / Fishery	-0.066**	-0.031	0.005	0.016
	(0.032)	(0.026)	(0.005)	(0.040)
Employer Size:				
Between 10 and 29	0.044***	0.064***	-0.023***	-0.003
	(0.004)	(0.004)	(0.007)	(0.007)
Between 30 and 49	0.079***	0.117***	-0.041***	0.016**
	(0.004)	(0.006)	(0.009)	(0.008)
Between 50 and 99	0.102***	0.145***	-0.023***	0.024***
	(0.005)	(0.005)	(0.008)	(0.007)
Between 100 and 299	0.127***	0.148***	-0.043***	-0.003
	(0.004)	(0.005)	(0.007)	(0.008)
Between 300 and 499	0.173***	0.181***	-0.007	-0.004
	(0.005)	(0.006)	(0.010)	(0.010)
Between 500 and 999	0.195***	0.203***	-0.007	0.005
	(0.005)	(0.006)	(0.009)	(0.009)
Over 1,000	0.294***	0.300***	0.071***	0.080***
	(0.004)	(0.004)	(0.006)	(0.006)
Constant	3.840***	4.006***	0.433***	0.622***
	(0.041)	(0.047)	(0.051)	(0.046)
Obs.	62,046	61,162	62,046	61,162
R^2	0.371	0.362	0.029	0.052
Other Controls:				
Year Dummies	x	x	x	x
Age^2	x	x	x	x
School Location	x	x	x	x
Public vs. Private Job	x	x	x	x
Employment Contract Type	x	x	x	x

Note: Omitted groups are engineering for the major category, business / Finance for the industry category, and less than 10 workers for the employer size. Standard errors in parenthesis are robust, and $^{*}p < .10$,$^{**}p < .05$, and $^{***}p < .01$.

Table 4: OLS Results, Year-by-Year

	Wage Differential		Job Satisfaction	
	Matched (1)	Not Matched (2)	Matched (3)	Not Matched (4)
2008	0.094***	0.098***	0.074***	0.070***
	(0.016)	(0.010)	(0.023)	(0.013)
2009	0.139***	0.121***	0.104***	0.061***
	(0.015)	(0.010)	(0.020)	(0.014)
2010	0.150***	0.139***	0.080***	0.069***
	(0.014)	(0.009)	(0.020)	(0.012)
2011	0.124***	0.095***	0.068***	0.071***
	(0.015)	(0.009)	(0.022)	(0.012)
2012	0.109***	0.093***	0.086***	0.070***
	(0.015)	(0.009)	(0.025)	(0.013)
2013	0.102***	0.091***	0.048***	0.077***
	(0.015)	(0.009)	(0.024)	(0.014)
2014	0.061***	0.048***	0.005	0.046***
	(0.016)	(0.011)	(0.024)	(0.014)
2015	0.061***	0.071***	0.014	0.051***
	(0.014)	(0.008)	(0.025)	(0.013)
2016	0.079***	0.087***	0.075***	0.096***
	(0.016)	(0.008)	(0.025)	(0.013)
2017	0.063***	0.075***	0.075***	0.103***
	(0.013)	(0.008)	(0.026)	(0.013)
2018	0.057***	0.066***	0.003	0.063***
	(0.014)	(0.008)	(0.025)	(0.013)
All	0.107***	0.097***	0.063***	0.071***
	(0.007)	(0.003)	(0.007)	(0.004)

Note: Occupational Mobility Survey (2008-2018). Robust standard errors in parentheses: $^{*}p < .10$,$^{**}p < .05$, $and^{***}p < .01$.

satisfied more with their jobs than female graduates regardless of horizontal mismatch status. However, the gender difference in job satisfaction in the mismatched group is lower than in the horizontally matched group, unlikely gender differences in wages. Among the college majors, those who studied humanities and education fields in a college have significantly higher satisfaction with their jobs than engineering-field graduates in both matched and mismatched groups.

Table 4 shows the estimated wage and job satisfaction gap of gender, year by year, using equation (2). Columns (1) and (2) of Table 4 indicate that male graduates might receive significantly higher wages than female graduates, 6% to 15% in both groups. The mean of wage differentials is 10.7% in the matched group and 9.7% in the mismatched group.

Columns (3) and (4) in Table 4 present the job satisfaction differentials by gender. Gender differences in job satisfaction are substantial in most years in the matched group, while there is no difference between genders in some years, such as 2014, 2015, and 2018. Gender differences in job satisfaction are substantial in most years in both matched and not-matched groups. The magnitudes for insignificant years remain positive. Male graduates in the mismatched group are also more likely to be satisfied with their jobs than female graduates, and all of these differences are statistically significant at a 1% level.

4 Accounting for Unobservables

The OLS model assumes that the 'mismatch' variable is uncorrelated with the disturbance term, implying that mismatch status differences in unobserved characteristics do not affect the estimated wage and job satisfaction. However, if unobservable characteristics are related to both mismatch status and the error term, then our previous OLS findings could be biased. Here, we relax this assumption. Controlling for selection bias from unobservable characteristics, we utilize the Heckman two-step correction model, the most traditional approach for self-selection bias.[7] Suppose that unobservable factors matter to workers' selection of matched and mismatched jobs. A conventional example of this unobservable characteristic is workers' innate 'ability.' Workers with higher abilities can earn higher wages in matched and mismatched jobs. In addition, those workers with higher searching abilities have an absolute advantage in finding better-matched jobs for them and receive higher wages and job satisfaction. As a result, within one distribution, there can be selection bias through unobservable ability with a higher fraction of workers in matched jobs with higher searching ability and a higher fraction of workers in mismatched jobs with lower searching ability workers. These unobservable characteristics, such as 'reservation wage,' also affect workers' self-selection. Workers with lower wages are more likely to accept the mismatched job offer. These are as in a Roy model.

Suppose that workers are categorized in two different horizontal mismatch statuses (1= matched and 0=not matched) on the basis of the probit selection rule:

$$
\begin{aligned}
d_i^* &= V_i\psi + \epsilon_2 \\
d_i &= \begin{cases} 1 & if\ \epsilon_2 > -V_i\psi \\ 0 & if\ \epsilon_2 \leq -V_i\psi. \end{cases}
\end{aligned} \tag{3}
$$

We assume that $V_i = f(X_i, Z_i, Male)$. Mismatched status (d_i) is observable for workers, however, the potential selection variable d_i^* is unobservable. We added the vector Z_i variable to capture the difference in probability of choosing mismatched jobs among workers given other observable characteristics. This variable is marital status. Married workers need time to participate in family in-laws' events such as birthdays, memorial ceremonies, national holidays (Lunar New Year's Day and Thanksgiving Day), and so on. These married workers already have two jobs, and neither is easy. Thus, these additional roles for married workers potentially restrict their career choices and make them more likely to accept a job with more flexible working

[7] We also consider using the Fixed Effect model and analyzed it. However, due to the nature of the Fixed effect model, our key control variables, which are time-invariant, have been removed from the model. These variables include gender, education, college major, occupation, and employer size. Some of those variables change during the period if an individual switches the value of the above variables. For example, an individual gains more education after college graduation or moves to a larger/smaller firm size employer. However, there needs to be a larger number of individuals who change to estimate the wage and job satisfaction differentials. Since the cost of using the Fixed effect model in this study is higher than its benefit, we believe that applying the Heckman model is appropriate to control for unobservable characteristics in this study.

hours by lowering the reservation wage, even though it is a mismatched job. Based on this selection rule, wage equations can be re-written as:

$$ln(Y_{it}^{m}) = \beta_0^m + \beta_{1it}^m Male_{1t} + \beta_{2it}^m X_{it} + \epsilon_1 \quad if \quad d_{it} = 1 \tag{4}$$

$$ln(Y_{it}^{nm}) = \beta_0^{nm} + \beta_{1it}^{nm} Male_{1t} + \beta_{2it}^{nm} X_{it} + \epsilon_0 \quad if \quad d_{it} = 0. \tag{5}$$

Since we relax the uncorrelated assumption, ϵ_2 from equation (3) and error terms from the above equations (ϵ_0, ϵ_1) are not independent and identically distributed (iid) across our sample workers. Therefore, without iid assumption, $\mathrm{E}[\epsilon_2 \mid d_i V_i] \neq 0$, our OLS findings lead us to biased conclusions. However, according to Heckman (1979), this selection bias from unobservable characteristics can be solved by adding the inverse Mills ratio (IMR) to the equation. Under the joint normality assumption of the Heckman-Lee model, sample selection and self-selection can be considered as a form of the omitted-variable problem (Antonakis et al., 2010; Clougherty et al., 2016). The Heckman procedure, adding IMR, is an effective method to control for selection bias (Shaver, 1998).

We follow the standard Heckman two-step procedure to estimate the wage and job satisfaction equation. We first estimate equation (3) using the probit model (matched =1, mismatched =0). For this procedure, we add Z_i variable to capture the difference in the probability of choosing mismatched jobs. Then, the equations (4) and (5) can be re-written as:

$$ln(Y_{it}^{m}) = \beta_0^m + \beta_{1it}^m Male_{1t} + \beta_{2it}^m X_{it} + \frac{\sigma_{12}}{\sigma_2}\left[\frac{f(V_i\psi)}{1 - F(V_i\psi)}\right] + \nu_1 \quad if \quad d_{it} = 1, \tag{6}$$

$$ln(Y_{it}^{nm}) = \beta_0^{nm} + \beta_{1it}^{nm} Male_{1t} + \beta_{2it}^{nm} X_{it} + \frac{\sigma_{02}}{\sigma_2}\left[\frac{f(V_i\psi)}{1 - F(V_i\psi)}\right] + \nu_0 \quad if \quad d_{it} = 0, \tag{7}$$

where σ_{12} is the covariance of ϵ_1 and ϵ_2, σ_{02} is the covariance of ϵ_0 and ϵ_2, f is the standard normal density function, and F is the cumulative normal density function. The estimated value of the selectivity terms from the probit are substituted in the above equations, and ν_1 and ν_0 are the applicable error terms.

Table 5 shows the summary of coefficients on the selectivity coefficients, with one table for wage equation and another table for job satisfaction. Most of the IMR coefficients are statistically significant. Especially for female workers, IMR has positive and statistical significance for both matched and unmatched workers. The statistically significant coefficient of IMRs suggests that the original equations' error terms correlate with the probability of choosing mis/matched jobs. In other words, unobservable characteristics matter for estimating wage and job satisfaction. Thus, we re-estimate the gender wage and job satisfaction differentials using the Heckman model.

Table 6 shows the result from the wage equations using the Heckman model. We find that the wage

differential between male and female workers is consistently positive for overall sample periods, most of which are statistically significant. Females received lower wages for matched and mismatched workers than comparable males in the Korean labor market. The wage penalty for female workers is between 3.3% (in 2014) and 15.1% (in 2009) for matched workers and between 6.1% (in 2010) and 15.1% (in 2009) for mismatched workers.

Wage differentials peaked in 2009 due to the impact of the 2008 Crises in the Republic of Korea. Patterson and Benuyenah (2021) indicate that the Great Recession in 2008-2009 caused job polarization in Korea. The female wage penalty was increased in the 2008-2009 global financial crisis as the polarization favorably worked for males to protect their jobs. However, it forces females into occupations in poor conditions. Similarly, Biasi and Sarsons (2022) point out that wage differentials are likely to increase during the recession since female workers are more acclimated to flexible wages than male workers, which means they have less power to negotiate their wages proactively.

Regarding gender wage differential, Figure 2 plots the coefficients of Table 6. The gender wage gap has fluctuated more for matched workers than for mismatched workers. The results from recent years show that workers with matched jobs have a higher wage gap between male and female workers than those with mismatched jobs. This wage differential pattern differs from what we find using the OLS wage equation. The wage differentials from the OLS model suggest that female workers with mismatched jobs have more wage discrimination than those from matched jobs.

Table 6 summarizes the overall job satisfaction differentials between genders in Korea. The estimated coefficients from matched workers are relatively more significant statistically than those from mismatched workers. These findings show that all the statistically significant estimations are positive for matched and mismatched workers. That is, a higher proportion of male workers are satisfied with their jobs than female workers. There are three estimations with negative coefficients, however, these are statistically insignificant. We compare the estimations from matched and mismatched workers in Figure 3. Job satisfaction differentials between genders decreased until 2012 and then increased for matched workers that have a higher job-

Table 5: Statistics for The Inverse Mills Ratio

Dependent Variable:	Log Monthly Wages		Overall Job Satisfaction	
Horizontal Mismatch:	Matched	Not Matched	Matched	Not Matched
	(1)	(2)	(3)	(4)
Male	0.224	1.302***	-0.361	0.557**
	(0.157)	(0.384)	(0.228)	(0.221)
Female	0.891***	0.872***	0.527***	0.577***
	(0.199)	(0.180)	(0.160)	(0.157)

Note: Robust standard errors in parenthesis are robust, and $^{*}p < .10$,$^{**}p < .05$, *and*$^{***}p < .01$.

Table 6: Heckman Selection Model Results, Year-by-year

	Wage Differential		Overall Job Satisfaction	
	Matched (1)	Not Matched (2)	Matched (3)	Not Matched (4)
2008	0.143***	0.088***	0.095*	0.075*
	(0.048)	(0.028)	(0.057)	(0.041)
2009	0.151**	0.152***	0.273***	-0.001
	(0.068)	(0.054)	(0.072)	(0.061)
2010	0.057	0.061	0.025	-0.091
	(0.063)	(0.051)	(0.067)	(0.059)
2011	0.106***	0.087***	0.112***	0.028
	(0.031)	(0.018)	(0.043)	(0.031)
2012	0.132***	0.074***	-0.010	0.073***
	(0.033)	(0.032)	(0.043)	(0.027)
2013	0.083	0.099**	0.025	0.082*
	(0.056)	(0.039)	(0.050)	(0.042)
2014	0.033	0.064***	0.023	0.021
	(0.049)	(0.021)	(0.038)	(0.028)
2015	0.098***	0.080***	0.098***	0.006
	(0.019)	(0.022)	(0.026)	(0.031)
2016	0.081***	0.080***	0.105***	0.057**
	(0.020)	(0.016)	(0.029)	(0.026)
2017	0.093***	0.081***	0.138***	0.055**
	(0.019)	(0.017)	(0.030)	(0.027)
2018	0.070***	0.073***	0.053***	0.025
	(0.015)	(0.015)	(0.020)	(0.025)
All	0.168***	0.098***	0.127***	0.037
	(0.027)	(0.025)	(0.030)	(0.025)

Note: Occupational Mobility Survey (2008-2018). Robust standard errors in parentheses:$*p < .10, **p < .05$, and $***p < .01$.
Robust Standard Error: To estimate standard error between two separate equations, we employ the bootstrap method.

satisfaction differential between male and female workers than mismatched workers. In addition, we compare the results from the OLS and Heckman models. Regarding wage differentials, we find that both OLS and Heckman estimations are positive, and the majority are statistically significant.

Figure 4.1 and Figure 4.2 plot OLS and Heckman wage differentials for matched and mismatched workers, respectively. Overall trends of wage differentials have decreased since 2012. However, Heckman estimations fluctuate more after controlling selection biases than before controlling for them. Comparing results from OLS and Heckman reveals more intriguing findings. First, our OLS estimations are all positive and statistically significant. However, after controlling for selection bias, job satisfaction differentials become less significant and have a mixed magnitude between negative and positive. Thus, we can conclude that selection bias significantly matters in estimating job satisfaction differentials. In Figure 4.3 and Figure 4.4, OLS and Heckman's estimations move similarly, however, Heckman estimations change more dynamically.

Figure 2: Wage Differentials in Subgroups Controlling for Selection

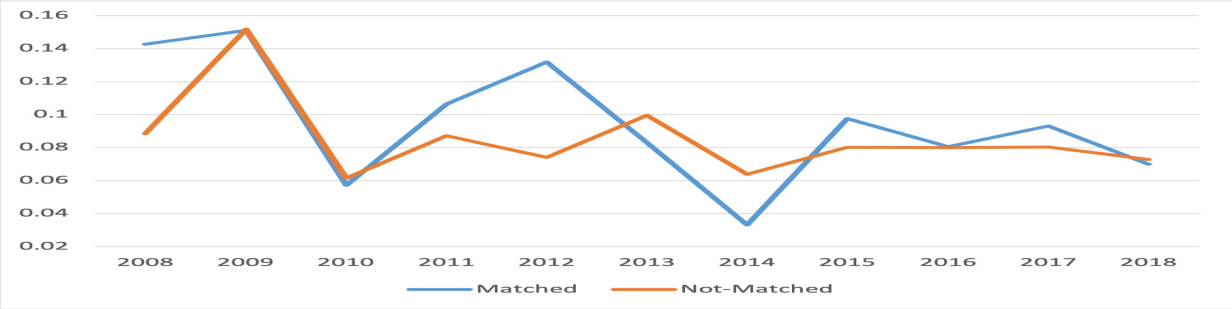


Figure 3: Job Satisfaction Differentials in Subgroups Controlling for Selection

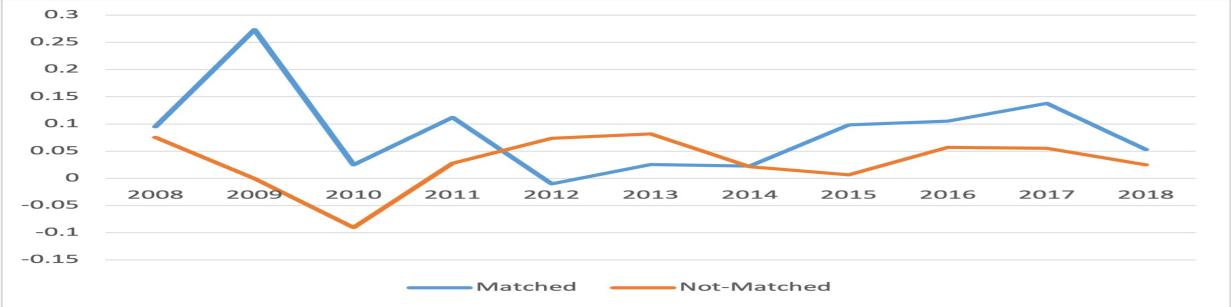
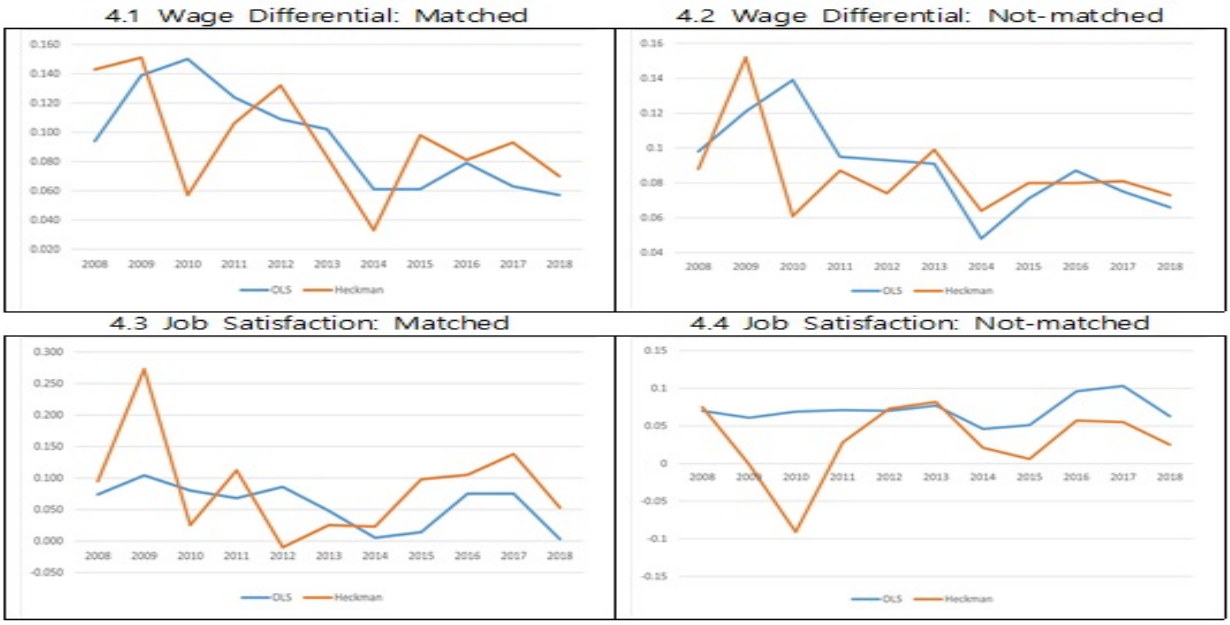


Figure 4: Comparison of Gender Differentials in Subgroups: OLS vs. Heckman



5 Conclusion

Gender discrimination in the labor market continues to be a severe problem in Korea, impacting wages and job satisfaction. The educational mismatch can take into account gender differences, and both vertical and horizontal mismatch are the socially prevailing issues in Korea. More than 50% of college graduates in Korea have horizontally mismatched jobs. This feature is the highest among OECD countries. Our study investigates the effects of the horizontal mismatch on wage and job satisfaction differentials by gender using Korean college graduates' occupation data.

This study finds that male workers in the early career stage are more likely to earn higher wages than female workers in both the horizontally matched and the not-matched groups. Findings from this research suggest that the pattern of the gender effect on wages is similar in both groups. According to Table 3, male workers are likely to have 10.4% (8.4%) greater wages than female workers in the Matched (Not Matched) group. The impact on job satisfaction shows a similar pattern. Male graduates are more likely to be satisfied with their jobs in both groups.

Also, we estimate the gender differentials in wages and job satisfaction year by year from 2008 to 2018. The pattern of the gender wage gap has been reduced for 11 years in both groups. The gender wage gap in the matched group was greater than the not-matched group before 2015. In contrast, the gender wage gap in the non-matched group was greater since 2015. Regarding job satisfaction, male graduates are more likely to be satisfied with their tasks whether they are mismatched with the field of study or not. In addition, we try to obtain the causal relationship between the horizontal mismatch and gender wage and job satisfaction differentials by applying the Heckman selection model. After dealing with unobservable characteristics, we find a similar pattern of the gender wage differentials to the OLS results in both groups. However, the results for job satisfaction are different. We maintain that male workers were more satisfied with their jobs than female workers, but the estimations in some years are not statistically significant. This means there was no job satisfaction penalty for those years.

While this study provides a meaningful snapshot of wage and job satisfaction differentials, this study has some limitations. First, the dataset is only available to before the COVID-19 period, which is a 2018 answer, the survey of 2019. With more recent data, a study would have provided updated patterns of gender income and job satisfaction differentials. Thus, we leave COVID-19 effects on gender differentials and the horizontal mismatch for future study. Also, this study only covers the labor market outcomes in the early stage of college graduates' careers. It does not allow us to investigate the pattern of gender differentials long term. Additionally, we consider many variables that affect the selection between matched and unmatched jobs, such as whether a household has children and the number of children. However, without observations related to children, we cannot use them as instruments in this research. As the survey focuses on labor market

outcomes in the early career stage, survey participants are less likely to have children, though they may have a greater chance of marriage. Finally, the workforce variables we utilize in this research are a horizontal mismatch, wage, and job satisfaction. Although these are helpful measures of the labor market, multiple measures can be added to evaluate these outcome variables fully, such as job turnover, labor productivity, and performance. Therefore, further studies should consider how this double discrimination affects labor market outcomes. Despite limitations, this study demonstrates the role of the horizontal mismatch in a variation of gender differentials in the Korean labor market.

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