Impact of Vertical and Horizontal Mismatches on Earnings Among Highly-Educated Employees in Japan

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The IAFOR International Conference on Education in Hawaii 2023
Official Conference Proceedings

Abstract

This study investigates the vertical and horizontal mismatches among highly-educated employees in Japan. The critical point of view on the effects of job-education mismatches on graduate earnings is that job-education mismatches leads to the waste of human capital accumulated during graduates' study years and brings negative consequences-earnings penalties. Our analysis reveals that vertical mismatch is more likely to significantly lower annual earnings compared with horizontal mismatch for both men and women. We also find that this mainly applies to university graduates and there is no significant penalty of vertical or horizontal mismatch among employees with a master's or a doctoral degree. Our results also suggest that the horizontal mismatch is more common among female employees and that the penalty for overeducation is more severely pronounced in the fields of natural sciences or medicine and pharmacy.

Keywords: Vertical Mismatch, Horizontal Mismatch, Higher Education

Introduction

Educational mismatch among university graduates is well known in two forms: vertical and horizontal mismatch. Vertical mismatch is defined as the situation where the degree level held by a worker does not match the required degree level for their job. Overeducation exists when a worker is employed in a job that requires a lower level of degree than that possessed by the worker. Under-education exists when a worker has a lower level of degree than that required for the job. Meanwhile, horizontal mismatch occurs when the type of the worker's specified field is not appropriate for the job (Park 2018).

Regarding vertical mismatch, two different measures can be derived from the objective analyses. The first measure, based on Verdugo and Verdugo (1989), defines required schooling as one standard-deviation range around the mean level of schooling within an occupation. The second measure, suggested by Kiker *et al.* (1997), defines the modal value instead of the mean level of education within a given occupation to measure required schooling. Meanwhile, to determine the required field of study as the objective viewpoint, Nieto *et al.* (2015) used the actual distribution of educational fields within the different occupations. They measured horizontal mismatch in terms of the percentage mode of fields within an occupation.

Mahuteau *et al.* (2015) pointed out that both horizontal and vertical mismatch can lead to the largest wage penalty for men. Tao and Hung (2014) described that the impact of vertical educational mismatch is greater compared with horizontal educational mismatch. Carroll and Tani (2013) found that the effect of overeducation on wages varies among fields of study. Verhaest *et al.* (2017) also investigated vertical and horizontal mismatches simultaneously and reported that graduates with an arts and humanities degree are more likely to experience any type of mismatch. Robst (2007) explained the interaction effects between being mismatched and college major: the wage penalties to being mismatched are higher in degree fields where there is less risk of being mismatched, such as health professions, engineering, and computer science. Furthermore, Frenette (2004) found that the magnitudes of vertical mismatch are different across degrees; there is a strong negative earnings effect for the bachelor's degree and little or no earnings effect for the master's or doctoral degrees.

In Japan, some researchers have investigated vertical mismatch (ex. Ichikawa 2016, Hirao 2016, Hirao 2020). However, no study has explored the effect of horizontal mismatch. Our contribution is to investigate vertical and horizontal mismatch using recent Japanese panel data. The rest of this paper is organized as follows. Section 2 explains the data and estimation model. Section 3 presents the results, and Section 4 concludes.

Data and estimation model

We used panel data from the "Japanese Panel Study of Employment Dynamics" conducted by Recruit Works Research Institute, a Japanese think tank, for the years 2016–2020. The survey is conducted every January and is a follow-up survey. Although samples are added every year, there are some non-response years in the continuous samples, thus making for unbalanced panel data.

The targets of our analysis were highly educated persons (college graduates and above) under the age of 60 years who were employed in December of the previous year at the time of the survey. Those who had been with their company for less than one year were excluded in consideration of annual income declines.

The dependent variable is the logarithm of the annual income of the subjects in the previous year. Values that exceeded the mean annual earnings ± standard deviation×3 were excluded as outliers and logarithmically transformed. The analysis method used the random-effect model.

We used 44 classifications of occupations, excluding “unclassifiable occupations.” Regarding the number of years of education used to determine vertical mismatch, we set the following: 9 years for junior high school graduates; 12 years for high school graduates; 14 years for vocational, junior college, and technical college graduates; 16 years for university graduates; and 18 years for medical and pharmaceutical school graduates. In addition, we set 18 years for those who completed a master’s course in a graduate school, and 21 years for those who completed a doctoral course in a graduate school. We used eight categories of majors to determine horizontal mismatch: Humanities (base), Social Sciences, Natural Sciences, Medicine and Pharmacy, Architecture, Arts (Music and Fine Arts), Welfare, and Other.

We used the deviation and mode methods to create vertical mismatch variables. According to the deviation method, those in the range of ±1 standard deviation years of education from the average number of years of education for each occupation possess the required education; those with more years of education are overeducated; and those with fewer years of education are undereducated. According to the mode method, in each occupation, those with the most common number of years of education are deemed as having the required education; those with more years of education are overeducated; and those with fewer years of education are undereducated.

We used two methods to create the horizontal mismatch variables: number of people and distribution. The number of people is a method in which the majors with the largest number of persons in each occupation are deemed as “horizontal match” and the rest as “horizontal mismatch.” Distribution is a method in which, given the bias in the number of people in each major, the number of students in all majors is standardized at 100, and how they are distributed in each occupation is ascertained. Those that comprise the highest percentage of majors in each occupation are deemed as “horizontal match,” and the others as “horizontal mismatch.”

Based on the above, employees who belong to any of the 44 occupational categories can be classified into three categories in terms of mismatch in years of education: overeducation, required education, and undereducation. Mismatch in terms of major can be classified into two categories, horizontal match and horizontal mismatch. As such, each employee can be classified into any one of 3×2, or a total of 6 categories.

The most common mismatch was overeducation × horizontal mismatch at 29.3% for men and 47.2% for women in the case of vertical mismatch measured by the deviation method and horizontal mismatch measured by the number of persons. This indicates that although university graduates tend to be overeducated, horizontal matching is more pronounced in women.

Other explanatory variables included years of experience, years of experience squared, years of service, dropout dummy, four-level junior high school performance dummy, job title dummy, company size and civil service dummy, regular employee dummy, married and unmarried dummy (base), with children dummy, youngest child is aged 0–3 years dummy, industry 16 classification dummy, 2019 survey dummy, on-the-job training experience dummy, off-the-job training experience dummy, and self-development dummy.

We used required education × horizontal mismatch as the base category. We measured the wage penalty for those falling under the other five categories. In addition, we estimated the wage penalty by education and major.

Analysis results

Table 1 shows the analysis results for men. The "omitted" variable was the one for which the number of relevant samples was small and the estimation results omitted. Being overeducated implied a reduction in annual earnings of about 4.9% to 7.7% even in the horizontal match. The results also showed that the overlap of overeducation and horizontal mismatch could reduce wages by about 5.9% to 7.0%. The mismatch between the two was not very large. In other words, being overeducated could reduce wages more than the effect of mismatch in major. Indeed, the horizontal mismatch was not significant in the two estimates for those meeting the required education.

Vertical classification method	Deviation	Mode	Deviation	Mode
Horizontal classification method	Mode of employees		Mode of distribution	
Overeducation×horizontal match	-0.049 ***	-0.058 ***	-0.051 ***	-0.077 ***
	(0.010)	(0.012)	(0.012)	(0.014)
Undereducation×horizontal match	(omitted)	-0.015	(omitted)	-0.021
		(0.045)		(0.045)
Education required×horizontal mismatch	-0.015	-0.020 *	-0.012	-0.028 ***
	(0.012)	(0.011)	(0.011)	(0.009)
Overeducation×horizontal mismatch	-0.067 ***	-0.070 ***	-0.059 ***	-0.069 ***
	(0.011)	(0.012)	(0.010)	(0.011)
Undereducation×horizontal mismatch	0.128	-0.001	0.130	-0.008
	(0.088)	(0.070)	(0.088)	(0.070)
Other explanatory variables	✓	✓	✓	✓
R squared	0.390	0.390	0.390	0.390
Number of observations	20,112	20,112	20,112	20,112

Notes: robust standard errors in parentheses. ***P < 0.01, **P < 0.05, *P < 0.1

Table1: Effects of vertical and horizontal mismatch for male employees

Table 2 shows the analysis results for women. For women, overeducation × horizontal match reduced annual earnings by about 5.5% to 10.1%, whereas overeducation × horizontal mismatch reduced annual earnings by about 7.1% to 11.1%, indicating that horizontal mismatch was also a wage penalty. Even for women with the required education, annual earnings were reduced by about 5.6% to 7.7% for horizontal mismatch.

Regarding annual earnings, men reported high values in the fields of medicine, pharmacy, and natural sciences (Table 1). For women, the major dummies were almost insignificant, and the difference in annual earnings by major could hardly be confirmed.

Vertical classification method	Deviation	Mode	Deviation	Mode
Horizontal classification method	Mode of employees		Mode of distribution	
Overeducation×horizontal match	-0.055 **	-0.101 ***	-0.060 **	-0.095 ***
	(0.025)	(0.029)	(0.025)	(0.031)
Undereducation×horizontal match	(omitted)	0.002	(omitted)	0.006
		(0.101)		(0.100)
Education required×horizontal mismatch	-0.059 **	-0.062 **	-0.077 ***	-0.056 ***
	(0.026)	(0.025)	(0.023)	(0.017)
Overeducation×horizontal mismatch	-0.071 ***	-0.111 ***	-0.096 ***	-0.100 ***
	(0.023)	(0.026)	(0.022)	(0.022)
Undereducation×horizontal mismatch	0.187	0.223 *	0.157	0.224 *
	(0.176)	(0.135)	(0.176)	(0.135)
Other explanatory variables	✓	✓	✓	✓
R squared	0.469	0.470	0.469	0.470
Number of observations	8,429	8,429	8,429	8,429

Notes: robust standard errors in parentheses. ***P < 0.01, **P < 0.05, *P < 0.1

Table 2: Effects of vertical and horizontal mismatch for female employees

Conclusion

We examined the effects of vertical and horizontal mismatch on annual earnings using Japanese data. The results showed that for both men and women, vertical mismatch is more likely to lower annual earnings significantly compared with horizontal mismatch. Our results also indicated that the negative effect of horizontal mismatch might be significantly larger for women than for men.

Some of our findings are consistent with the results of previous researches. However, the detailed reasons for the wage penalties could not be clarified in the present analysis and shall be left as an issue for future research.

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