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THE INCOME PENALTY OF VERTICAL AND HORIZONTAL EDUCATION-JOB MISMATCHES IN THE KOREAN YOUTH LABOR MARKET: A QUANTILE REGRESSION APPROACH*

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Abstract

In this paper we estimate the income effects of over-education and horizontal education-job mismatch jointly by quantile regressions using a data set of Korean college graduates. We find that over-education and horizontal mismatch are positively correlated. Thus, the income loss by over-education (horizontal mismatch) is overestimated if it is estimated ignoring horizontal mismatch (over-education). This overestimation problem is particularly prevalent for workers at low and near-median deciles of the conditional income distribution. We also find that the income penalty on over-education is prevalent for most all quantiles, whereas the income penalty on horizontal mismatch is significant for lower quantiles.

Keywords: vertical and horizontal mismatches, income penalty, quantile regression.
JEL Classification Codes: I20, J20, J21, J23, J24

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I. *Introduction*

There are two types of education-job mismatches for college graduates: vertical and horizontal mismatches. *Vertical mismatch* refers to the mismatch between a worker's education level and the required education level for his/her job (e.g., over-education or under-education), whereas *horizontal mismatch* refers to the mismatch between a worker's field of study in college and his/her job. To date, studies on education-job mismatches have primarily focused on the estimation of income loss due to over-education. This research trend is related to the ongoing world-wide rapid expansion of higher education. Previous studies have found that the income penalty over-educated workers bear ranges from 13 to 27 percent of well-matched workers' earnings; see, for example, Bauer (2002), Chevalier (2003), Cohn and Ng (2000), Duncan and Hoffman (1981), Freeman (1976), Groot and Maassen (1995, 2000), Hartlog (1980, 2000), Rumberger (1981, 1987), Sicherman (1991), and Verdugo and Verdugo (1992).

Researchers have paid limited attention to horizontal education-job mismatch until recently. The income penalty on horizontal mismatch was first estimated by Robst (2007) and then by some follow-up studies, such as Kelly, O'Connell and Smyth (2010); Nordin, Persson and Rooth (2010); and McGuiness and Sloane (2011). The estimates of the income penalty on horizontal mismatch by these studies range from 10 to 32 percent of horizontally matched workers' earnings. However, most of these studies estimated the income effect of horizontal mismatch ignoring the effect of over-education.

The main purpose of this paper is to show that the income effects of over-education and horizontal mismatch should be estimated jointly, not separately. Regressions conducted ignoring the income effect of horizontal mismatch (over-education) may overestimate the income penalty associated with over-education (horizontal mismatch) if horizontal mismatch is positively correlated with over-education. Analyzing data from a cohort of Korean college graduates, we find that the incidences of the two mismatches are indeed positively correlated for both male and female workers.

We use quantile regressions analysis to estimate both the income effects of over-education and horizontal mismatch. Some previous studies of education-job mismatches have also used quantile regressions to estimate the income effect of over-education; see, for example, Hartlog, Pereira and Vieira (2001); Budria and Moro-Egido (2006); McGuinness and Bennett (2007). However, to our knowledge, this is the first paper to use quantile regressions to estimate the two income penalties of vertical mismatch and horizontal mismatch jointly.[1]

Our analysis is based on two assumptions. First, following most of the previous studies of education-job mismatches, we assume that workers' observable characteristics such as education, experience and education-job mismatches are uncorrelated with their unobservable abilities. Second, motivated by Arias, Hallock and Sosa-Escudero (2001) and McGuinness and Bennett (2007), our regressions allow workers' education-related characteristics to have different effects on labor earnings depending on workers' unobservable abilities. Specifically, we assume that the k^{th} conditional quantile of the wage distribution (conditional on a set of explanatory

[1] While Kelly, O'Connell and Smyth (2010) reported the income effects of over-education and field mismatch jointly estimated by ordinary least squares (OLS), their quantile regression analysis focused only on the economic returns of different fields of study.

variable) is the earnings of a representative worker whose ability level corresponds to the k^{th} quantile of the ability distribution. Under the two assumptions, quantile regressions allow us to identify the effects of education-job mismatches on different quantiles of conditional labor income distribution. By comparing the regression results from different quantiles of conditional labor income, we can find how the income effects of mismatches may vary over workers' different ability levels.

Estimating the income effects of over-education and horizontal mismatch jointly is particularly important for the analysis of the (South) Korean labor market. The Korean colleges offer excessively many different fields of study compared to the number of available job types in the labor market. For example, in the U.S., more than 30,000 different types of jobs are available while colleges offer about 150 distinct fields of study.[2] In contrast, in Korea, only about 10,000 different types of jobs are available while more than 1,000 fields of study are offered by colleges.[3] Nordin, Persson and Rooth (2010) demonstrated that income penalty on horizontal mismatch is greater in Sweden than in other European countries because the Swedish higher education system offers an excessively large number of fields of study. According to their study, horizontally mismatched male and female workers suffer from the income losses equivalent to 32 and 28 percent of well-matched male and female workers, respectively. Their results suggest that income penalty on horizontal mismatch would be also great in Korea. In addition, since a large percentage of high school graduates go to college compared to many other countries,[4] the costs of over-education are also expected to be very high in Korea.

Although our estimation results are from Korean data, they could be externally valid in other Asian countries such as Japan, China and Hong Kong, because these countries and Korea have very similar higher-education systems. Compared to Western countries, Asian countries offer excessively subdivided fields of study and have very high college attendance rates of high-school graduates.

Our major findings are the following. For both male and female workers, the estimated penalty on one type of mismatch (either horizontal or vertical) obtained ignoring the other type of mismatch is greater than the corresponding estimate obtained controlling for both types of mismatches. This result suggests that the estimated income penalties on mismatches by previous studies are likely to be the over-estimated ones because the studies estimated the two different income penalties separately. In particular, we find that the bias is larger for lower income (or ability) quantile groups. For both male and female workers, the income penalty on over-education is significantly negative for almost all different quartiles of conditional income distribution. In contrast, the income penalty on horizontal mismatch is significant for workers at lower quantiles of conditional labor income distribution. These results indicate that both talented and less talented workers can suffer from income loss by over-education, while income loss by horizontal mismatch is more likely to occur for less talented workers.

The rest of this paper is organized as follows. Section II introduces some theories related to education-job mismatches and their consequences. Section III explains our data. Section IV introduces the basic regression model we use to analyze our data. Regression results are reported and discussed in sections V and VI. Some concluding remarks follow in section VII.

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[2] See The 2003 National Follow-up Survey of College Graduates by the National Science Foundation of the U.S.

[3] See the 2005 Korean National Follow-up Survey of College and Graduate School Graduates on Economic Activity.

[4] For example, 83.4% of Korean high school graduates went to college in the year of 2008.

II. *Theory and Discussion*

McGuinness (2006), Budria & Moro-Egido (2006) and Robst (2007) provide some theoretical explanations of income penalty on over-education. Their explanations are based on three different theories: the Human Capital Theory (hereafter HCT), Career Mobility Theory (hereafter CMT) and Assignment Theory (hereafter AT). Some theories related to horizontal mismatch are discussed in Robst (2007). In this section we briefly summarize the three theories that can explain income loss by over-education and discuss how they can also explain penalty on horizontal education-job mismatch.

Both the HCT and CMT predict that individual workers' labor earnings are determined by their labor productivity, at least in the long run. The HCT predicts that a worker's wage may equal her/his labor productivity even in the short run. If the equality of wage and productivity holds even in the short run, there is only one way that the HCT can explain the persistent empirical finding of income penalty on over-education. That is, the empirical finding is a biased estimation result caused by the regressions with imperfect measures of human capital; see McGuiness (2006) and Budria and Moro-Egido (2006). The amount of human capital a worker possesses (that determines his/her labor productivity) may depend on many factors such as formal education, on-the job training and ability. If these factors are substitutable components of human capital, workers with different education levels could make the same earnings as long as they possess the same amount of human capital. Thus, if ability and other human capital components are not properly controlled for in regressions, the workers with higher education levels would falsely appear paid less than the workers on the same jobs with lower education levels.

Even if the negative income effect of over-education is real and not just a biased estimation result, it does not necessarily negate the relevance of the HCT. The negative income effect of over-education may be only a temporary phenomenon if firms need some time until they can fully utilize individual workers' human capital. For example, imagine the jobs for which a worker's maximum labor productivity level is determined by his/her education level, but a series of on-the-job trainings are required to reach the maximum productivity level. Workers having such jobs would appear paid insufficiently compared to their education levels, especially in their earlier career. This scenario is formally proposed by the CMT by Hersch (1991), Galor and Sicherman (1990) and Sicherman (1991). According to this theory, workers accept jobs for which they are initially over-educated. They do so in order to gain experience and on-the job training to enhance their future job prospects. The acquired skills or experience help them move towards higher (and better paying) occupation levels where they can make full use of their qualifications. Workers are over-educated in their earlier careers, and being temporarily over-educated is a part of their career paths. The CMT, as well as the HCT, predicts that over-education is a short run phenomenon and disappears gradually over time.

However, empirical evidence is not supportive for the notion that the negative income effect of over-education is only a short-run phenomenon or a biased estimation result. Many studies have found that estimated income penalty on over-education is still large and significant even if unobservable individual heterogeneity was controlled for; see Budria and Moro-Egido (2006) for the list of these studies.

An alternative view of over-education is provided by the AT; see Sattinger (1993).

According to this theory, labor earnings are determined not only by workers' human capital, but also by job-specific characteristics such as job requirements and productivity ceilings. Over-education can arise when a worker matches a job for which his/her human capital cannot be fully utilized. Jobs may have wage ceilings meaning workers can never earn more. If so, workers with higher education levels become over-educated when they match the jobs with low wage ceilings. This imperfect match can result from high job search costs or imperfect information on the job market. Under the AT, over-education is not just a short-run phenomenon. It could be rather a long-term economic problem that can arise in inefficient labor markets.

The income penalty on horizontal education-job mismatch can also be explained by the above three theories. Choosing a field of study in her college or graduate school, a student accumulates the knowledge or skills that are particularly productive to some specific jobs. According to the HCT, horizontally mismatched workers should earn less than horizontally well-matched workers because the former workers' specialized skills are not fully productive for their jobs. However, under the HCT, this horizontal mismatch is only a short-run phenomenon. In the long run, a worker's labor income is determined by the amount of total human capital he/she possesses. The CMT also predicts that the income loss by horizontal education-job mismatch is a short-run phenomenon. According to the CMT, young workers have incentives to take horizontally mismatching jobs if they can provide better job opportunities in the future than the jobs matching their fields of study. Thus, horizontal mismatch is the outcome of a young worker's voluntary choice to trade her current earnings for higher future earnings. In contrast, under the AT, horizontal education-job mismatch, as well as over-education, could be a long-run economic problem caused by high job-search costs or imperfect information about the labor market. Because of such frictions in the labor market, some workers can be unluckily allocated to the jobs for which they cannot fully utilize their human capital.

All of the three theories suggest that both over-education and horizontal education-job mismatch have negative income effects at least for young workers. However, over-education and horizontal education-job mismatch influence labor earnings in different ways. A worker's time in college is related to the amount of general human capital that he/she can use for any job, while his/her field of study is more to the amount of occupation-specific human capital that he/she can productively use only for some specific jobs. College graduates can find vertically matching employers from many different occupations. A worker's over-education problem is resolved as he/she finds a new job that pays the equivalence of the productivity of his/her general human capital. The new job does not have to match the worker's field of study in college. In contrast, horizontally matching jobs for a worker must be the ones that match her field of study in college. Furthermore, when students enter colleges, they have to decide on their fields not only considering their tastes and career preferences, but also comparing expected life-time earnings from many different alternative career paths. Thus, whether a student can have a horizontally matching job in the future crucially depend on the quality of the life-time earnings from different occupations at the time they choose their fields. Unless accurate forecasts of average incomes and job opportunities from many different occupations are available for comparison at earlier college years, many students are likely to end up being horizontally mismatched after their graduation. Vertical mismatch (over-education) is less likely to occur than horizontal mismatch because it is easier to compare expected earnings and employment opportunities related to different education levels than different occupations or jobs.

These differences between vertical and horizontal mismatches indicate the importance of estimating the income effects of vertical and horizontal mismatches jointly. First, the relative sizes of income losses by the two mismatches would depend on the relative importance of the general and job-specific human capital in determining labor earnings. For example, if the job-specific human capital is a much less (more) important determinant of labor earnings than the general human capital, the income loss by horizontal mismatch would be much smaller (greater) than that by over-education. Second, if the income losses by mismatches are real phenomena caused by inefficient labor markets, it is important to identify the income losses by vertical and horizontal mismatches separately. This is so because different polices are recommended for vertical and horizontal mismatches. For example, college students in Korea cannot easily change their fields of study. In most of the colleges in Korea, students choose their fields of study in the first year. No students or only a limited number of students are allowed to change their majors in later years. If the average income loss by horizontal mismatch is large in Korea, policies that can ease restrictions on transfer should be recommended. Such policies would help students make better choices of fields of study because they can have more time to gather and compare information from many different career alternatives. However, the same policies may have only limited effects on the income loss by vertical mismatch.

III. *Data and Sample Characteristics*

The data set analyzed by this study comes from the 2005 Korean National Follow-up Survey of College and Graduate School Graduates on Economic Activity (hereafter, the 2005 KCGEA). The data are corrected from a cohort of the individuals who graduated from two-year colleges or higher educational institutes in the year 2003 and who entered the labor market within the same year. The data set is a follow-up of the survey data obtained during the year 2005.

The number of observations we use for our analysis is 12,666, which amounts to 3% of the total number of graduates in 2003. Of the 12,666 individuals with complete observations, 51.28% were male and 48.73% were female; 47.80% were graduates from two-year colleges, 45.62% were from four-year colleges, and 6.58% were graduate degree earners. Our data set is much larger than those used by previous studies,[5] but it contains as rich information related to workers' economic statuses and individual characteristics as previously used data sets.

Table 1 provides a list of the variables that we use for our regressions along with their definitions. Whether a worker matches his/her job vertically or horizontally is determined by the worker's self-assessment. The over-education (under-education) group consists of the individuals who indicated that their final educational degrees were higher (lower) than what their jobs normally required. The vertically matched group includes those whose final degrees matched the levels their jobs normally required. Those who indicated their fields of study were completely and partially different from what their jobs normally required were categorized into

[5] None of the previous studies that used quantile regression have analyzed data covering more than 2,000 individuals. For example, McGuinness and Bennett (2007) analyzed data from 1,255 individuals.

TABLE 1. LIST OF VARIABLES AND THEIR DEFINITIONS

Variable name	Definition
Ln(W)	Ln (after-tax hourly income of a worker)
Age	A worker's age
Mar	Binary variable indicating being married: one for married and zero for non-married
Jobtype	Binary variable indicating jobtype: one for a regular job and zero for a temporary job
D_j	Binary variables indicating education level: 2-year college (j=1), 4-year college (j=2), and graduate schools (j=3).
HM_j	Binary variables indicating horizontal mismatch: match (j=1), complete mismatch (j=2), and partial mismatch (j=3).
VM_j	Binary variables indicating vertical mismatch: match (j=1), over-education (j=2), and under-education (j=3).
$Field_j$	Binary variable corresponding to the 17 classified fields of study

the "completely horizontally matched" and "partially horizontally mismatched" groups, respectively. The "horizontally matched" group consists of workers who indicate their fields of study match the normal requirements of their jobs.

Tables 2 and 3 report summary statistics for some selected variables. Tables 2 and 3 report the statistics from male and female workers, respectively. As presented in Table 2, the average age of male workers is 27.93 years and the average of their logarithmic yearly earnings, $Ln(W)$, is 7.71, which roughly amounts to $20, 000.[6] As expected, the average education level of horizontally or vertically matched graduates is higher than that of completely horizontally or vertically mismatched graduates. Furthermore, income penalty on complete horizontal mismatch is somewhat bigger than that on vertical mismatch. Specifically, while completely horizontally mismatched male workers earn 10% (roughly $1, 963) less than their horizontally matched coworkers (growth rate of yearly income = ΔLn(yearly income) = 0.1), over-educated male workers earn 8% less (roughly $1, 660) than their vertically matched coworkers (ΔLn(yearly income)= 0.08).

Table 3 shows that the average age of female workers is 24.69 years and the average of their logarithmic yearly income is 7.41.[7] Thus, female workers, on average, enter the labor market earlier while earning less than male workers. This discrepancy between males and females entering the workforce and pay is because Korean male workers have to complete the mandatory military service of 2 years before entering the labor market. However, firms count the service years as two-years of work experience in determining initial wages. Consequently, male workers' initial wages are higher than those of female workers.

Table 4 presents the distributions of vertical matches and mismatches, showing that 70.4% of all workers in our sample have jobs that match their education levels (vertical match), while 17.4% of the workers are over-educated. It appears that whether a worker is vertically matched or not depends on his/her education level. Workers with higher education degrees are more likely to be vertically matched and less likely to be over-educated. The frequency of vertical match is different for male and female workers on a small scale, while frequency varies on a

[6] The exchange rate used in this study is $1 = 1,100 won.

[7] It roughly amounts to $15,000.

Table 2. Summary Statistics for Male Workers

	Total	Horizontal Match			Vertical Match		
		complete mismatch	partial mismatch	match	over-education	under-education	match
Age	27.93 (4.42)*	27.43 (4.35)	28.01 (4.45)	28.08 (4.41)	27.90 (4.42)	27.40 (3.94)	28.04 (4.43)
Ln(*W*)	7.71 (0.37)	7.63 (0.41)	7.72 (0.34)	7.73 (0.36)	7.65 (0.40)	7.70 (0.36)	7.73 (0.36)
Years of Education	15.28 (1.22)	14.97 (1.11)	15.25 (1.17)	15.48 (1.31)	15.18 (1.22)	15.15 (1.22)	15.34 (1.22)
*Jobtype***	0.87 (0.34)	0.80 (0.40)	0.90 (0.30)	0.87 (0.33)	0.81 (0.39)	0.87 (0.34)	0.88 (0.32)

Notes: * The numbers in parentheses are standard deviations.
** *Jobtype* is a binary variable which equals one (zero) for a worker having a regular (temporary) job.

Table 3. Summary Statistics for Female Workers

	Total	Horizontal Match			Vertical Match		
		complete mismatch	partial mismatch	match	over-education	under-education	match
Age	24.69 (4.18)*	24.67 (4.43)	24.52 (3.97)	24.84 (4.25)	24.64 (4.18)	24.64 (4.24)	24.50 (3.80)
Ln(W)	7.41 (0.37)	7.35 (0.39)	7.41 (0.37)	7.45 (0.37)	7.33 (0.38)	7.42 (0.39)	7.44 (0.37)
Years of Education	15.05 (1.19)	14.82 (1.07)	14.99 (1.14)	15.22 (1.27)	15.00 (1.19)	15.00 (1.11)	15.07 (1.20)
Jobtype	0.77 (0.42)	0.71 (0.45)	0.75 (0.43)	0.82 (0.38)	0.70 (0.46)	0.78 (0.41)	0.79 (0.41)

Note: * The numbers in parentheses are standard deviations.

Table 4. Distribution of Vertical Mismatch (Unit = %)

	Under-Education			Matched Education			Over-Education		
	Male	Female	Total	Male	Female	Total	Male	Female	Total
Total	13.5	10.5	12.2	70.0	71.0	70.4	16.5	18.5	17.4
2-year College	15.0	9.0	11.8	65.0	70.3	67.8	20.0	20.7	20.4
4-year College	13.0	12.8	13.0	72.2	70.4	71.5	14.8	16.8	15.5
Graduate School	10.9	6.9	9.4	75.3	80.2	77.1	13.8	12.9	13.5

larger scale across different education levels. Among those with two-year college degrees or graduate school degrees, female workers are more likely to be vertically matched than male workers (70.3% vs. 65.0% for two-year college graduates, and 80.2% vs. 75.3% for those with graduate degrees).

Table 5 reports the distributions of horizontal matches and mismatches, which shows that 37.4%, 44.2% and 18.4% of all workers have jobs that match, partially mismatch, and

Table 5. Distribution of Horizontal Mismatch (Unit = %)

	Complete Match			Partial Mismatch			Complete Mismatch		
	Men	Women	Total	Men	Women	Total	Men	Women	Total
Total	35.6	39.8	37.4	46.6	41.1	44.2	17.8	19.1	18.4
2-year College	28.0	37.6	33.0	49.7	41.1	45.4	22.3	21.3	21.8
4-year College	36.2	39.2	37.4	47.1	42.8	45.5	16.7	18.0	17.1
Graduate School	61.5	62.4	61.8	31.0	28.7	30.2	7.5	8.9	8.0

Table 6. Distribution of Over-Education, Complete Horizontal Mismatch and Income

Income group	Male		Female	
	Over-education	Complete Horizontal Mismatch	Over-education	Complete Horizontal Mismatch
Lower income (income $\leq$ 3rd decile)	23.57%	24.93%	26.86%	24.17%
Middle income (3rd decile $<$ income $\leq$ 7th decile)	16.02%	17.60%	21.29%	19.12%
Higher income (income $>$ 7th decile)	15.22%	15.86%	15.46%	15.59%

completely mismatch their field of studies, respectively. The probability of a worker being horizontally mismatched depends on his/her gender and education level. For each educational group (2-year college, 4-year college or graduate school[8]), female workers are more likely to be horizontally matched. For example, among two-year college graduates, 37.4% of female workers have jobs matching their fields of study, whereas only 28% of males do. However, this gender gap becomes narrower as the education level increases. For both female and male workers, those with higher education degrees are more likely to be horizontally matched. More than 60% of workers with graduate degrees have jobs matching their fields of study.

It appears that Korean workers are much more likely to be horizontally mismatched than the U.S. workers. Studying the income effects of horizontal mismatch, Robst (2007) found that 54.8% of the U.S. workers in his sample have jobs matching their fields of study.[9] As discussed above, there are two possible reasons for this difference between Korea and the United States. The first is that colleges and graduate schools in Korea offer a much larger number of fields of study, perhaps too large a number of different fields relative to the number of job types. The second is that changing fields of study is much harder in Korea.

We now consider the relationships between earnings and education-job mismatches. Table 6 shows the percentages of education-job mismatches for three different earnings groups. Among the male workers with earnings in the bottom 30%, 24.57% of them are over-educated

[8] The graduate group consists of the workers with Master degrees.
[9] For more detail, see Table 1 of Robst (2007).

and 24.93% are completely horizontally mismatched. In contrast, among the male workers with earnings in the top 30%, 15.22% are over-educated and 15.86% are horizontally completely mismatched. It appears that the probabilities of being vertically or horizontally mismatched fall as income increases. Table 6 show that educational mismatches and earnings of female workers are also inversely related. For both genders, workers with higher earnings are generally less likely to have mismatched jobs. The results related to over-education are similar to what McGuinness and Bennett (2007) found from their Northern Ireland data.

IV. *Empirical Model*

The foundation of our empirical study is the following regression model:

$$Ln(W)=Z'\beta+(Z'\xi)\varepsilon, \tag{1}$$

where i indexes individual workers, $Ln(W)$ is logarithmic (after-tax) yearly income, Z is the vector of observable individual or job characteristics, ε is the unobservable ability, β denotes the vector of the coefficients of regressors in Z, and ξ denotes the vector of interaction effects of regressors and unobservable ability. Following most previous studies, we assume that the observable individual characteristics and unobservable ability are uncorrelated. However, model (1) allows each of the variables in Z to have an interaction effect with the unobservable ability on the logarithmic income. Thus, the effects of the variables in Z on the logarithmic income can differ across different ability levels. For example, for the ϕ^{th} conditional quantile of log earnings, $Quant_{\phi}(Ln(W)|Z)=Z'\beta_{\phi}$ $(\phi\in(0,1))$, $\beta_{\varphi}=\beta+\xi\times Quant_{\phi}(\varepsilon|Z)$.

Our empirical analysis mainly follows that of McGuinness and Bennett (2007), except that we concurrently estimate income penalties on over-education and horizontal mismatch. Specifically, the model we estimate is the following quantile version of the Mincer earnings equation:

$$Quant_{\phi}[Ln(W)|Z]=X'\pi+\sum_{j=2}^{3}\alpha_j D_j+\sum_{j=2}^{3}\gamma_j HM_j+\sum_{j=2}^{3}\delta_j VM_j+\sum_{j=2}^{17}\theta_j Field_j. \tag{2}$$

Here, X is a vector of a worker's socio-economic and job characteristics. Included in X are A*ge*, *Mar* and *Jobtype*.[10] The HM_j are binary variables indicating two different degrees of horizontal mismatch, and the VM_j are binary variables indicating two different degrees of vertical mismatch.[11] Finally, the $Field_j$ are the binary variables that classify fields of study; the D are binary variables indicating two different education levels; see Table 1 for more detailed descriptions of these variables.

A key assumption behind our use of quantile regressions is that the conditional incomes of

[10] *Jobtype* is the only variable used for job characteristics. In determining income, we use this variable because recently, *Jobtype* was found to be the most important factor in Korea's youth labor market among factors related to job characteristics. In addition to *Jobtype*, both firm size and firm type reflect whether the job is in the public or private sector, which also has been considered to reflect job characteristics in previous studies; see McGuinness and Bennett (2007), and Kelly, O'Connell and Smyth (2010). We do not use firm size and type, because we would lose too many observations if requiring these variables and because *Jobtype* is a much more important factor than the other two.

[11] The reference group at each binary variable of equation (2) is the variable corresponding to j = 1.

individual workers are sorted by their unobservable ability levels. Thus, correct inferences from our estimation results require that unobservable factors other than ability, such as on-the-job training, should have little effect on the conditional distribution of earnings. Our data consist of individuals with very similar education and experience levels. In addition, for all workers, years of experience are at most two years. Thus, unobservable factors other than ability are likely to be homogenous in the data, and ability is likely to be the main, if not sole, determinant of the conditional distribution of earnings.

Because our data are from young college graduates only, we are unable to examine whether the income losses by over-education and horizontal education-job mismatch are short-run phenomena that occur during workers' younger ages as suggested by the Human Capital Theory (HCT) or Career Mobility Theory (CMT). However, analyzing our data by quantile regressions, we can partially test for the relevance of the Human Capital Theory (HCT) and the Assignment Theory (AT) for the income penalties on vertical and horizontal education-job mismatches.

According to the omitted variable bias argument of the HCT, less able workers are more likely to be over-educated because they have incentives to compensate for their lower ability with higher education. However, among the workers with the same levels of ability and other unobservable human capital components, there is no reason why over-educated workers earn less. Thus, if the omitted variable bias argument is correct, quantile estimates of income penalty on over-education would be generally small and/or insignificant.

On the other hand, under the AT, over-education is an outcome of high job search costs or imperfect information on the job market. Thus, even the most talented workers can be over-educated for their jobs when they fail to find the jobs that match their education levels. Consequently, even for able workers, over-education could be negatively associated with labor earnings. In addition, the AT predicts that the income penalty for over-education is greater for female workers than for male workers. The public sector, which includes the Education section, is known to be a sector in which a large portion of jobs imposes wage ceilings that are lower than workers' true labor productivities. Because female workers are relatively more likely to be in the Public sector than male workers, female workers are generally more exposed to wage ceilings; see Burdia and Moro-Egido (2006) and McGuiness and Bennett (2007).

Related to horizontal education-job mismatch, the HCT predicts that young workers earn less when their jobs do not match their fields of study in college. As we discussed in section II, college graduates' fields of study are related to their occupation-specific human capital. Then, among the workers who possess the same level of ability and other human capital components, horizontally mismatched workers should earn less because their jobs require lower levels of occupation-specific human capital than do jobs of their well-matched coworkers. For any group of workers with the same level of ability, mismatched workers would earn less than well-matched workers.

The AT also predicts that horizontal education-job mismatch incurs income loss, but on a smaller scale than the HCT predicts. Under the AT, workers' wages are determined by either their human capital or their jobs' wage ceilings. Unless wages are completely bound to the ceilings, workers' earnings should be related to their human capital at least partly, and, therefore, horizontal mismatch must have some income effect. However, wage ceilings weaken the income effect of horizontal mismatch. To see why, consider the extreme case in which wages are determined solely by job characteristics and bound to wage ceilings. For this case, both horizontally matched and mismatched workers' earnings are bound to wage ceilings and they make the same earnings; that is, horizontal mismatch would not have any income effect. For the same reason, the negative income effect of horizontal education-job mismatch would be weaker for more able workers. Other things being equal, more able workers' wages are more likely to be bound to wage ceilings.

V. *Empirical Results*

We begin with the results from the OLS (ordinary least squares) regression of model (2). The results are reported in Table 7. As discussed in section 4, the OLS estimation results reveal the income penalties that mismatched workers with average ability levels may suffer from. Table 7 shows that income penalties on education-job mismatches are significant for both male and female workers. While the earnings of over-educated male workers are smaller than those of their vertically matched coworkers by 4.48% (see the estimated coefficient of VM_2), the earnings of completely horizontally mismatched male workers are smaller than those of their horizontally matched male coworkers by 2.88% (see the estimated coefficient of HM_2). For female workers, the penalty on over-education amounts to 7.24% of the earnings of vertically matched workers, while the penalty on complete horizontal mismatch is 2.14%.

The estimated effects of the socio-economic variables on income are generally consistent with our expectations. Age and income have expected quadratic relationships for both male and female workers. Married workers earn more than singles. *Jobtype* has significant positive effects on both male and female workers' incomes. Workers with regular jobs earn more than those with temporary jobs by around 24%. However, unexpectedly, four-year college graduates earn more than their coworkers with graduate degrees (see the estimated coefficients of D_2 and D_3). This is so for both male and female workers. This result is consistent with what McGuinness and Bennett (2007) found from their Northern Ireland data. One possible explanation for this counterintuitive finding is that individuals in our data are at earlier stages of their careers. As McGuinness and Bennett (2007) explained, such young workers are likely to be undergoing on-the-job training, while an educational degree is relatively a lesser important determinant of labor productivity.

Table 7 also reveals the income effects of different fields of study. Different fields of study have different income effects. Their effects are also different across different genders. Among male workers, those who majored in business and economics (Field4), engineering (Field7) or a health profession (Field9) earn more than those who specialized in computers and IT (reference group), whereas those who majored in architecture (Field2), liberal arts (Field12), natural sciences (Field13) or visual and performing arts (Field16) earn less. Among female workers,[12] only those who majored in business and economics make more earnings than those who majored in computers and IT. Those who studied education (Field6), home economics

[12] In our data, no female worker majored in a health profession field. Neither did female workers graduate from medical or dental schools. There are two reasons. First, a relatively smaller number of female Korean students go to medical or dental schools. Second, we lose a large number of sample observations in order to use *Jobtype* as a regressor. When *Jobtype* is not used, our sample contains a small number of female workers who graduated from health profession related schools.

TABLE 7. OLS REGRESSION RESULTS

	Male	Female
Age	0.0727 (0.0071)***	0.0787 (0.0071)***
Age^2	-0.0007 (0.0001)***	-0.0010 (0.0001)***
Mar	0.0640 (0.0109)***	0.0357 (0.0174)**
D_2	0.1097 (0.0090)***	0.1649 (0.0100)***
D_3	0.0613 (0.0162)***	0.1275 (0.0201)***
HM_2	-0.0288 (0.0114)**	-0.0214 (0.0123)*
HM_3	-0.0104 (0.0089)	-0.0017 (0.0102)
VM_2	-0.0448 (0.0102)***	-0.0724 (0.0104)***
VM_3	0.0014 (0.0114)	-0.0162 (0.0150)
Jobtype	0.2579 (0.0117)***	0.2429 (0.0101)***
Field2	-0.0203 (0.0444)	0.1216 (0.0207)***
Field3	-0.0438 (0.0190)**	-0.0149 (0.0296)
Field4	0.0202 (0.0380)	0.0117 (0.0433)
Field5	0.0636 (0.0158)***	0.0310 (0.0189)*
Field6	-0.0085 (0.0382)	0.0017 (0.0344)
Field7	-0.0256 (0.0291)	-0.0588 (0.0207)***
Field8	0.0460 (0.0136)***	0.0378 (0.0237)
Field9	0.0245 (0.0220)	0.0093 (0.0203)
Field10	0.0515 (0.0216)**	-
Field11	-0.0391 (0.0297)	-0.0573 (0.0236)**
Field12	0.0123 (0.0346)	0.0277 (0.0507)
Field13	-0.1547 (0.0282)***	-0.0538 (0.0262)**
Field14	-0.0563 (0.0277)**	0.0165 (0.0343)
Field15	-0.0218 (0.0213)	-0.0349 (0.0207)*
Field16	0.0370 (0.0236)	0.0212 (0.0338)
Field17	-0.0607 (0.0175)***	-0.0997 (0.0183)***
Const	5.978 (0.1211)***	5.8820 (0.1137)***
R^2	0.3016	0.2586
# of observation	6426	6240

Notes: Standard errors are in parentheses. All estimates and standard errors are multiplied by 100 so that the unit of all numbers is a percentage (%). The variables whose name contains "field" are binary index variables for 17 different fields of study: Field1 = Computers and IT, Field2 = Agriculture, Field3 = Architecture, Field4 = Biological sciences, Field5 = Business and Economics, Feld6 = Communication, Field7 = Education, Field8 = Engineering, Field9 = Languages, Field10 = Health profession, Field11 = Home economics, Field12 = Law, Field13 = Liberal arts, Field14 = Natural sciences, Field15 = Social sciences, Field16 = Park/Environment/Resources, Field17 = Visual and performing arts. Field10 is omitted from the regression for female workers because no females in our sample specialized in the fields related to health occupations. The superscripts "*", "**" and "***" indicate significance at the 10%, 5% and 1%, respectively.

(Field11), liberal arts (Field12), social sciences (Field14) or visual and performing arts (Field16) earn less than those who specialized in computers and IT. In general, the effect of the study field on earnings is weaker for female workers.

The income effects of education-job mismatches may depend on workers' ability levels. Thus, we re-estimate model (2) by QR for male and female workers, separately. We consider 9 different deciles of conditional distribution of earnings. The results are reported in Tables 8 and 9. Following McGuinness and Bennett (2007), we interpret the results under the assumption that workers' ability levels are proportional to the ranks of their conditional earnings (conditional on their observed characteristics).

TABLE 8. QUANTILE REGRESSION RESULTS FROM MALE WORKERS

	Deciles of yearly earnings								
	1th	*2nd*	*3rd*	*4th*	*5th*	*6th*	*7th*	*8th*	*9th*
ϕ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Age	0.085***	0.078***	0.065***	0.068***	0.067***	0.069***	0.062***	0.068***	0.054***
	(0.0107)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.006)	(0.012)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.0004***	-0.001***	-0.0003**
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
MAR	0.074***	0.060***	0.066***	0.074***	0.069***	0.064***	0.058***	0.060***	0.073***
	(0.0159)	(0.013)	(0.012)	(0.0128)	(0.012)	(0.013)	(0.013)	(0.010)	(0.019)
D_2	0.085***	0.091***	0.111***	0.112***	0.119***	0.125***	0.137***	0.130***	0.100***
	(0.0130)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.008)	(0.015)
D_3	-0.006	0.050***	0.094***	0.112***	0.137***	0.128***	0.146***	0.129***	0.083***
	(0.0214)	(0.011)	(0.017)	(0.018)	(0.017)	(0.019)	(0.020)	(0.015)	(0.029)
HM_2	-0.067***	-0.056***	-0.050***	-0.053***	-0.036***	-0.023*	-0.017	-0.007	0.019
	(0.067)	(0.014)	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)	(0.010)	(0.020)
HM_3	-0.010	-0.019*	-0.016*	-0.011	-0.009	-0.016	-0.015	-0.000	-0.000
	(0.013)	(0.011)	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)	(0.008)	(0.015)
VM_2	-0.026*	-0.035***	-0.036***	-0.038***	-0.039***	-0.050***	-0.048***	-0.048***	-0.000
	(0.014)	(-0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.009)	(0.018)
VM_3	-0.023	-2.1e-09	0.010	0.015	0.016	0.014	0.010	-1.15e08	0.009
	(0.016)	(0.014)	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)	(0.010)	(0.020)
Jobtype	0.449***	0.333***	0.258***	0.238	0.211***	0.185***	0.175***	0.168	0.137***
	(0.016)	(0.014)	(0.012)	(0.014)	(0.012)	(0.013)	(0.015)	(0.011)	(0.020)
Field2	0.072	0.033	0.006	0.010	0.001	-0.030	-0.082	-0.123***	-0.137*
	(0.063)	(0.052)	(0.047)	(0.051)	(0.047)	(0.051)	(0.055)	(0.038)	(0.076)
Field3	-0.030	-0.024	-0.057***	-0.045**	-0.034*	-0.040*	-0.041*	-0.056***	-0.048
	(0.027)	(0.023)	(0.020)	(0.022)	(0.020)	(0.022)	(0.023)	(0.017)	(0.031)
Field4	0.092*	0.087*	0.050	0.057	0.028	0.014	0.018	-0.025	0.033
	(0.054)	(0.044)	(0.040)	(0.044)	(0.040)	(0.044)	(0.047)	(0.034)	(0.061)
Field5	0.072***	0.088***	0.065***	0.067***	0.052***	0.069***	0.079***	0.055***	0.106***
	(0.022)	(0.019)	(0.017)	(0.018)	(0.017)	(0.018)	(0.020)	(0.014)	(0.027)
Field6	-0.026	0.017	-0.010	0.029	0.010	-0.014	-0.016	-0.009	0.088
	(0.055)	(0.045)	(0.040)	(0.044)	(0.040)	(0.044)	(0.047)	(0.034)	(0.066)
Field7	-0.047	-0.011	0.033	0.038	0.028	0.012	-0.003	-0.040	-0.048
	(0.041)	(0.034)	(0.031)	(0.034)	(0.031)	(0.034)	(0.036)	(0.026)	(0.047)
Field8	0.072***	0.075***	0.060***	0.055***	0.050***	0.052***	0.044***	0.013	0.033
	(0.020)	(0.016)	(0.015)	(0.016)	(0.014)	(0.016)	(0.017)	(0.012)	(0.023)
Field9	0.067**	0.052**	0.033	0.069***	0.056**	0.038	0.027	-0.001	0.071*
	(0.031)	(0.026)	(0.023)	(0.026)	(0.023)	(0.026)	(0.027)	(0.020)	(0.037)
Field10	0.019	0.036	0.038*	0.046*	0.047**	0.052**	0.054**	0.041**	0.079**
	(0.031)	(0.026)	(0.023)	(0.026)	(0.023)	(0.025)	(0.027)	(0.019)	(0.036)
Field11	0.053	0.019	-0.021	-0.057*	-0.068**	-0.058*	-0.063*	-0.058**	-0.055
	(0.042)	(0.035)	(0.032)	(0.034)	(0.031)	(0.034)	(0.036)	(0.027)	(0.050)
Field12	0.023	0.032	0.045	0.064	0.028	0.024	-0.015	-0.016	0.067
	(0.049)	(0.041)	(0.037)	(0.040)	(0.037)	(0.040)	(0.042)	(0.031)	(0.059)
Field13	-0.363***	-0.214***	-0.212***	-0.127***	-0.077***	-0.047	-0.063*	-0.061**	0.018
	(0.040)	(0.033)	(0.030)	(0.033)	(0.030)	(0.032)	(0.035)	(0.026)	(0.049)
Field14	-0.063	0.018	-0.046	-0.058*	-0.027	-0.021	-0.037	-0.047*	-0.032
	(0.039)	(0.033)	(0.029)	(0.032)	(0.029)	(0.032)	(0.034)	(0.025)	(0.047)
Field15	-0.023	-0.012	-0.040*	-0.031	-0.012	-0.030	-0.031	-0.018	-0.012
	(0.030)	(0.025)	(0.023)	(0.025)	(0.023)	(0.025)	(0.026)	(0.019)	(0.037)
Field16	0.072***	0.073***	0.026***	0.024	0.011	0.003	-0.002	-0.001	0.051
	(0.034)	(0.028)	(0.025)	(0.027)	(0.025)	(0.028)	(0.029)	(0.021)	(0.041)
Field17	-0.095***	-0.076***	-0.079***	-0.080***	-0.066***	-0.040**	-0.052**	-0.046***	0.030
	(0.025)	(0.021)	(0.019)	(0.020)	(0.019)	(0.020)	(0.022)	(0.016)	(0.030)
Const	5.35***	5.61***	5.97	6.00	6.09***	6.12***	6.29***	6.31***	6.67***
	(0.182)	(0.150)	(0.129)	(0.141)	(0.129)	(0.140)	(0.147)	(0.108)	(0.030)
Pseudo R2	0.1999	0.1735	0.1670	0.1659	0.1862	0.1790	0.1891	0.1709	0.1830

Table 9. Quantile Regression Results from Female Workers

	Deciles of yearly earnings								
	1th	*2nd*	*3rd*	*4th*	*5th*	*6th*	*7th*	*8th*	*9th*
ϕ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Age	0.128^{***} (0.011)	0.111^{***} (0.006)	0.118^{***} (0.007)	0.116^{***} (0.007)	0.0944^{***} (0.005)	0.083^{***} (0.008)	0.076^{***} (0.008)	0.070^{***} (0.007)	0.072^{***} (0.009)
Age^2	-0.002^{***} (0.0002)	-0.002^{***} (0.0001)	-0.002^{***} (0.0001)	-0.002^{***} (0.0001)	-0.001^{***} (0.0001)	-0.001^{***} (0.0001)	-0.001^{***} (0.0001)	-0.001^{***} (0.0001)	-0.001^{***} (0.0001)
MAR	-0.009 (0.030)	-0.006 (0.017)	0.003 (0.018)	0.053^{***} (0.018)	0.045^{***} (0.012)	0.053^{***} (0.018)	0.066^{***} (0.021)	0.068^{***} (0.018)	0.112^{***} (0.021)
D_2	0.128^{***} (0.017)	0.145^{***} (0.010)	0.168^{***} (0.010)	0.162^{***} (0.010)	0.173^{***} (0.007)	0.177^{***} (0.010)	0.184^{***} (0.012)	0.184^{***} (0.011)	0.205^{***} (0.012)
D_3	-0.015 (0.035)	0.032 (0.020)	0.103^{***} (0.021)	0.113^{***} (0.021)	0.170^{***} (0.014)	0.187^{***} (0.021)	0.200^{***} (0.012)	0.219^{***} (0.021)	0.235^{***} (0.025)
HM_2	-0.039^{*} (0.021)	-0.043^{***} (0.013)	-0.019 (0.013)	-0.022^{*} (0.013)	-0.028^{***} (0.009)	-0.039^{***} (0.125)	-0.015 (0.014)	-0.015 (0.013)	0.007 (0.015)
HM_3	0.000 (0.018)	-0.000 (0.010)	-0.001 (0.011)	-0.007 (0.011)	-0.016^{**} (0.007)	-0.017^{*} (0.010)	-0.009 (0.012)	-0.015 (0.011)	-0.000 (0.012)
VM_2	-0.084^{***} (0.017)	-0.069^{***} (0.010)	-0.050^{***} (0.010)	-0.065^{***} (0.011)	-0.065^{***} (0.007)	-0.069^{***} (0.011)	-0.080^{***} (0.012)	-0.058^{***} (0.011)	-0.045^{***} (0.013)
VM_3	0.000 (0.026)	-0.016 (0.015)	0.000 (0.016)	0.000 (0.016)	-0.000 (0.010)	-0.006 (0.015)	-0.034^{*} (0.017)	-0.028^{*} (0.016)	-0.008 (0.018)
Jobtype	0.347^{***} (0.168)	0.288^{***} (0.010)	0.247^{***} (0.011)	0.219^{***} (0.010)	0.195^{***} (0.007)	0.177 (0.010)	0.163^{***} (0.012)	0.154^{***} (0.011)	0.117^{***} (0.012)
Field2	0.147^{***} (0.036)	0.143^{***} (0.021)	0.152^{***} (0.022)	0.131^{***} (0.022)	0.121^{***} (0.014)	0.121^{***} (0.021)	0.155^{***} (0.022)	0.009^{***} (0.014)	0.098^{***} (0.023)
Field3	0.064 (0.050)	0.025 (0.030)	0.028 (0.031)	-0.015 (0.030)	-0.046 (0.021)	-0.074^{**} (0.030)	0.033^{*} (0.033)	-0.094^{***} (0.021)	-0.075^{**} (0.033)
Field4	-0.038 (0.072)	-0.046 (0.042)	-0.035 (0.046)	-0.025 (0.045)	0.008 (0.030)	0.054 (0.044)	-0.034 (0.047)	0.038 (0.029)	0.070 (0.048)
Field5	0.074^{**} (0.032)	0.041^{**} (0.019)	0.070^{***} (0.020)	0.051^{*} (0.020)	0.031^{**} (0.013)	0.017 (0.019)	0.049 (0.021)	-0.0001 (0.013)	0.004 (0.022)
Field6	0.030 (0.059)	0.043 (0.034)	0.046 (0.036)	0.021 (0.036)	0.003 (0.024)	-0.037 (0.035)	0.026 (0.039)	-0.021 (0.024)	-0.012 (0.040)
Field7	-0.130^{***} (0.036)	-0.091^{***} (0.021)	$-0.037^{*)}$ (0.022)	-0.010 (0.022)	-0.017 (0.014)	-0.017 (0.021)	-0.078 (0.022)	-0.035^{**} (0.014)	-0.087^{***} (0.023)
Field8	0.053 (0.041)	0.036 (0.024)	0.059^{**} (0.025)	0.028 (0.025)	0.016 (0.016)	0.017 (0.024)	0.033 (0.027)	0.016 (0.016)	0.029 (0.027)
Field10	0.016 (0.035)	0.025 (0.020)	0.033 (0.022)	0.020 (0.021)	0.015 (0.014)	0.018 (0.021)	0.033 (0.023)	-0.026 (0.014)	0.006 (0.023)
Field11	-0.013 (0.041)	-0.039^{*} (0.024)	-0.041 (0.025)	-0.028 (0.025)	-0.062^{***} (0.016)	-0.074^{***} (0.024)	-0.027^{***} (0.026)	-0.067^{***} (0.016)	-0.053^{*} (0.027)
Field12	0.080 (0.083)	0.038 (0.051)	0.0189 (0.053)	0.050 (0.053)	0.002 (0.035)	-0.010 (0.051)	0.011 (0.057)	-0.021 (0.035)	-0.021 (0.056)
Field13	-0.050 (0.044)	-0.039 (0.026)	-0.048^{*} (0.028)	-0.061^{**} (0.027)	-0.067^{***} (0.018)	-0.074^{***} (0.027)	-0.027^{**} (0.029)	-0.062^{**} (0.018)	-0.051 (0.030)
Field14	-0.045 (0.058)	0.025 (0.034)	0.043 (0.036)	0.044 (0.036)	0.015 (0.024)	0.005 (0.035)	0.033 (0.038)	0.006 (0.023)	0.052 (0.039)
Field15	-0.020 (0.036)	-0.039^{*} (0.021)	-0.033 (0.022)	-0.030 (0.022)	-0.034^{**} (0.014)	-0.033 (0.021)	-0.028^{*} (0.023)	-0.065^{***} (0.014)	-0.016 (0.024)
Field16	0.035 (0.057)	-0.048 (0.034)	0.034 (0.036)	0.025 (0.035)	0.015 (0.023)	0.004 (0.034)	0.033 (0.038)	-0.017 (0.024)	0.043 (0.038)
Field17	-0.149 (0.031)	-0.104^{***} (0.018)	-0.083^{***} (0.019)	-0.088^{***} (0.019)	-0.074^{***} (0.013)	-0.074^{***} (0.019)	-0.100 (0.020)	-0.067^{***} (0.013)	-0.059^{**} (0.021)
Const	4.79^{***} (0.177)	5.15^{***} (0.104)	5.13^{***} (0.113)	5.33^{***} (0.114)	5.69^{***} (0.079)	5.93^{***} (0.122)	6.13^{***} (0.125)	6.28^{***} (0.117)	6.39^{***} (0.022)
Pseudo-R^2	0.1430	0.1272	0.1471	0.1489	0.1683	0.1610	0.1655	0.1859	0.1828

Table 8 reports the QR results from male workers. There are two main findings from the table related to income penalty on horizontal education-job mismatch. First, the penalty on complete horizontal mismatch (coefficient of HM_2) is significant for the lower and middle segment of earnings distribution. The income penalty is significant for those at the 1st – 6th deciles of the conditional distribution of earnings, while it is not for those at the other top three deciles of the distribution. This result is consistent with the notion that workers with lower or middle abilities are more likely to suffer from horizontal mismatches. These findings are consistent with the prediction of the Assignment Theory (AT) as discussed in the end of section 4. Second, partial horizontal mismatch is generally insignificant. The penalty on partial mismatch is only marginally significant (at 10% significance level) for the 2nd (ϕ = 0.2) and 3rd (ϕ = 0.3) deciles of conditional earnings (or ability), but not even marginally so for all other deciles. The results related to partial horizontal mismatch are generally consistent with the OLS results reported in Table 7.

Table 8 also shows that the income penalty on over-education (coefficient of VM_2) is significant and relatively constant over different deciles of conditional earnings other than the 9th decile. This result is contradictive to the Human Capital Theory's (HCT's) explanation that the income penalty on over-education may be a biased result from regressions conducted omitting important human capital related variables such as ability and on-the-job training. Under this bias scenario, over-education should not have a significant income effect for workers with similar ability levels. However, our result implies that even for workers at the same quantile of ability level, over-education has a significant negative income effect. In addition, the size of the penalty does not change sensitively as ability level changes, except for the workers with the upper 10% of ability level. This result is in contrast to what McGuiness and Bennett (2007) found from their Northern Ireland data. They found significant income penalties on over-education only from the workers with low ability levels. Except for the workers with ability levels compatible with the 9th decile of ability, our result indicates that in Korea, over-educated workers with higher ability levels suffer from income losses as much as those with lower ability levels do. As discussed in the end of section 4, this result is more consistent with the prediction of the AT than with that of the Human Capital Theory (HCT).

Table 8 also shows that returns on attained education levels vary across different segments of the ability distribution. The returns for four-year college and graduate school education are greater for workers with average or higher abilities than for those with lower abilities. This finding is consistent with what Harmon, Oosterbeek and Walker (2003) found from their U.K. data. An additional notable observation from the table is that both the returns for four-year college and graduate school education vary widely over different deciles of ability. The finding is consistent with the notion that the worldwide rapid increase in the demand for higher education has also led to a substantial increase in heterogeneity in ability among workers.

The QR results for fields of study are roughly similar to the OLS results. Almost all of the QR results reported in Table 8 show that male graduates who majored in business & economics (Field5), engineering (Field8) or a health profession (Field10) earn more than those who specialized in computers and IT. For almost all cases, male graduates who majored in architecture (Field3), liberal arts (Field13) or visual and performing arts (Field17) earn less than those who specialized in computers and IT. For the group of workers with the top 10% highest ability (earnings) (the 9th decile), the graduates of business and economics and health professions, earn 11.18% and 8.22%, respectively, more earnings than those of computer and

IT. The result for a health profession is very similar to what Kelly, O'Connell and Smyth (2010) found from the Ireland data.[13] The fields of study other than business and economics and a health profession are not important determinants of income for the highest ability workers.

The QR results from female workers are presented in Table 9. The main results are as follows. First, similarly to the results from male workers, the income penalty on over-education is pervasive for all deciles of ability, while the income penalty on horizontal mismatch is concentrated in the low or near-median deciles of the conditional income distribution. That is, the significance and relative size of income loss by over-education are not sensitive to ability levels, while the income effect of horizontal mismatch is insignificant for workers at high deciles of the ability distribution. Once again, these results are more consistent with the prediction of the AT than that of the HCT.

Second, the income penalty associated with over-education is larger for female workers than for male workers. For example, compared to their well-matched counterparts with the same levels of ability, over-educated females with the lowest ability level (at the 1st decile) earn 8.4% less (efficient of VM_2), while those with the highest ability level (at the 9th decile) earn 4.6% less. In contrast, over-educated males with the lowest ability level (at the 1st decile) earn 2.6% less than their well-matched male coworkers, and those with the ability level at the 9th decile does not suffer from income loss. Burdia and Moro-Egido (2006) and McGuinness and Bennett (2007) also found that the income penalties on over-education are higher for female workers than for male workers. They explained this result under the AT: Job requirements, as proxied by over-education, may impose lower productivity/earning ceilings to female workers than to male workers.

Third, the estimation results for the return for attained education are very similar to the results from male workers. For example, both the returns for four-year college and graduate school education are also greater for workers with average or higher abilities than for those with lower abilities in female workers.

As discussed earlier, there is a strong positive correlation between vertical and horizontal mismatches in our data. Table 10 provides the correlation coefficients between over-education and complete horizontal mismatch at different deciles of the unconditional earnings distribution although the unconditional distribution is different from the conditional earnings distribution.[14]

TABLE 10. CORRELATION BETWEEN OVER-EDUCATION AND COMPLETE HORIZONTAL MISMATCH

	Deciles 1-3	Deciles 4-6	Deciles 7-9
Male	0.1506	0.1063	0.0637
Female	0.2037	0.1168	0.1098

[13] They found that medicine and veterinary graduates earn 28.9% more than arts and humanities graduates.

[14] We also calculated the sample correlation coefficients for two groups of workers whose earnings are below and above the unconditional median earnings. We calculated the coefficients for male and female workers separately. For both male and female workers, we found the correlation coefficients for the below-median earnings groups are greater than those for the above-median group. Specifically, the correlation coefficients are 0.16 and 0.19, respectively, for the male and female workers with below-median earnings, while the coefficients are 0.1 for both male and female workers with above-median earnings.

The correlation coefficient is generally higher for low earnings groups and for female workers. These results suggest that the estimation of the income penalty on over-education (horizontal mismatch) ignoring horizontal mismatch (over-education) may overstate the penalty, particularly for low-income and/or female workers.

In order to examine the extent of the overestimation, we re-estimate income penalties on horizontal and vertical matches separately by two different regressions and compare the results with those reported in Tables 8 and 9. The separate regression results from male and female workers are reported in Tables 11 and 12, respectively. Only the estimated income effects of education-job mismatches are reported to save space. For both male and female workers, the estimated penalty on one type of mismatch (either horizontal or vertical mismatch) obtained by ignoring the other type of mismatch is greater than the corresponding estimate reported in Tables 8 or 9, regardless of ability level. In particular, as expected, the biases are larger for the workers whose conditional earnings are at the 1st to 5stdeciles. For example, the quantile regression for ϕ = 0.1 without controlling for the income effect of horizontal mismatch shows that for male workers at the 1st decile of conditional earnings distribution, the income penalty on over-education amounts to 3.46% of well-matched workers' earnings. In contrast, the same regression with controlling for the income effect of horizontal mismatch shows that the income penalty would be 2.6% of well-matched workers. Thus, for the male workers at the 1st decile of the conditional earnings distribution, the (absolute) bias in the estimated income penalty by

Table 11. Estimated Effects of One Type of Mismatch with and without Controlling for the Other Type (Male Workers)

	Deciles of yearly earnings								
	1*th*	2*nd*	3*rd*	4*th*	5*th*	6*th*	7*th*	8*th*	9*th*
ϕ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
HM_2	-0.067***	-0.056***	-0.050***	-0.053***	-0.036***	-0.023*	-0.017	-0.007	0.019
(with VM_2 & VM_3)	(0.067)	(0.014)	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)	(0.010)	(0.020)
HM_2	-0.073***	-0.057***	-0.057***	-0.061***	-0.039***	-0.025**	-0.022	-0.011	0.019
(no VM_2 & VM_3)	(0.016)	(0.013)	(0.014)	(0.011)	(0.008)	(0.011)	(0.015)	(0.009)	(0.021)
VM_2	-0.026*	-0.035***	-0.036***	-0.038***	-0.039***	-0.050***	-0.048***	-0.048***	-0.000
(with HM_2 & HM_3)	(0.014)	(-0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.009)	(0.018)
VM_2	-0.034***	-0.041***	-0.040***	-0.046***	-0.041***	-0.053***	-0.048***	-0.047***	-0.009
(no HM_2 & HM_3)	(0.014)	(0.010)	(0.008)	(0.009)	(0.007)	(0.012)	(0.011)	(0.010)	(0.017)

Table 12. Estimated Effects of One Type of Mismatch with and without Controlling for the Other Type (Female Workers)

	Deciles of yearly earnings								
	1*th*	2*nd*	3*rd*	4*th*	5*th*	6*th*	7*th*	8*th*	9*th*
ϕ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
HM_2	-0.039*	-0.043***	-0.019	-0.022*	-0.028***	-0.039***	-0.015	-0.015	0.007
(with VM_2 & VM_3)	(0.021)	(0.013)	(0.013)	(0.013)	(0.009)	(0.125)	(0.014)	(0.013)	(0.015)
HM_2	-0.069***	-0.050***	-0.036***	-0.046***	-0.040***	-0.048***	-0.044***	-0.020	-0.000
(no VM_2 & VM_3)	(0.018)	(0.013)	(0.003)	(0.015)	(0.005)	(0.014)	(0.014)	(0.014)	(0.016)
VM_2	-0.084***	-0.069***	-0.050***	-0.065***	-0.065***	-0.069***	-0.080***	-0.058***	-0.045***
(with HM_2 & HM_3)	(0.017)	(0.010)	(0.010)	(0.011)	(0.007)	(0.011)	(0.012)	(0.011)	(0.013)
VM_2	-0.095***	-0.073***	-0.051***	-0.068***	-0.068***	-0.071***	-0.079***	-0.067***	-0.042
(no HM_2 & HM_3)	(0.016)	(0.011)	(0.007)	(0.009)	(0.002)	(0.004)	(0.010)	(0.007)	(0.012)

ignoring complete horizontal mismatch is about 0.8% (= 3.4%−2.6%) of well-matched workers' earnings, which amounts to the relative bias of 30.8% (= 100× (3.4−2.6) /2.6). Similarly, comparing the results from the quantile regressions for ϕ = 0.1 with and without controlling for the income effect of vertical mismatch, we can easily see that for female workers at the 1st decile of conditional earnings distribution, the absolute bias in the estimated income effect of horizontal mismatch is 3.0% (= 6.9%−3.9%), which is equivalent to the relative bias of 76.9% (= 100×(6.9−3.9)/3.9). For the workers whose conditional earnings are at the 1st to 5st deciles, the relative biases in the estimated penalties on horizontal mismatch are 1.8%−15.10% for males and 16.3%−109.0% for females when the penalty is estimated ignoring the effect of over-education. Related to over-education, the relative biases in estimated income penalties are 10.0%−30.8% for male workers and 2.0%−13.1% for female workers when the penalties are estimated ignoring the effect of horizontal education-job mismatch.

VI. *Sensitivity Analysis*

In this section, we address two estimation issues. First, we consider potential interaction effects of mismatches and education level. The sizes of income penalties on horizontal mismatch and over-education may be different across different education levels. In order to explore this possibility, we do additional regressions adding interaction terms between education levels and education-job mismatches as extra regressors for our quantile regression model:

$$Quant_{\phi}[Ln(W_i)|Z_i] = X'_i\pi + \sum_{j=2}^{3}\alpha_j D_{j,i} + \sum_{j=2}^{17}\theta_j Field_{j,i} + \sum_{j=2}^{3}\sum_{k=1}^{3}\xi_{kj}D_{k,i}HM_{j,i} + \sum_{j=2}^{3}\sum_{k=1}^{3}\mu_{kj}D_{k,i}VM_{j,i}, \quad (3)$$

Here in this equation, ξ_{1j} and μ_{1j} capture the interaction effects for 2-year college graduates; ξ_{2j} and , for 4-year college graduates; and ξ_{3j} and μ_{3j}, for graduate school graduates.

Table 13 reports the results from the quantile regressions of model (3) with male workers only. The income penalty on complete horizontal mismatch varies across different education levels. To be specific, the income effect of complete horizontal mismatch (HM_2) is significantly negative for 4-year college graduates except at the 9th decile of conditional earnings. For graduate school graduates, the effect is significantly negative for those at the 4th to 8th deciles of conditional earnings. For these earning groups, the income effect of horizontal mismatch is greater for graduate school graduates than for 4-year college graduates. In contrast, for the 2-year college graduates, horizontal mismatch has insignificant or significant but small negative effects for those at the 1st to 7th deciles of conditional income. However, for 2-year college graduates at the 8th and 9th deciles of conditional income, horizontal education-job mismatch has positive income effects. While it is an unexpected result, it is not without possible explanation. Consider talented students who are admitted to 2-year colleges and whose fields of study are related to low-paying occupations. Such students could rather earn higher incomes in the future by choosing the jobs that do not match their fields of study well. Their talents may allow them to acquire required skills for any jobs. This is more likely to happen for talented 2-

TABLE 13. THE EFFECT ON INCOME PENALTY BY EDUCATION LEVEL: MALE

		Deciles of yearly earnings								
		1th	*2nd*	*3rd*	*4th*	*5th*	*6th*	*7th*	*8th*	*9th*
2-year College	HM_2	-0.025	-0.045***	-0.022	-0.025*	-0.001	-0.001	0.003	0.029***	0.080***
		(0.021)	(0.017)	(0.015)	(0.014)	(0.010)	(0.013)	(0.016)	(0.011)	(0.027)
	VM_2	-0.004	-0.001	-0.010	-0.016	-0.023**	-0.009	-0.008	-0.019*	0.003
		(0.022)	(0.018)	(0.015)	(0.014)	(0.011)	(0.014)	(0.017)	(0.011)	(0.028)
4-year College	HM_2	-0.081***	-0.063***	-0.071***	-0.072***	-0.052***	-0.037***	-0.037**	-0.033***	-0.036
		(0.021)	(0.016)	(0.014)	(0.013)	(0.010)	(0.012)	(0.015)	(0.010)	(0.025)
	VM_2	-0.043**	-0.066***	-0.058***	-0.066***	-0.064***	-0.072***	-0.071***	-0.069***	-0.015
		(0.022)	(0.017)	(0.015)	(0.014)	(0.011)	(0.013)	(0.016)	(0.011)	(0.027)
Graduate School	HM_2	0.041	0.006	-0.059	-0.129***	-0.185***	-0.161***	-0.140***	-0.105***	-0.091
		(0.064)	(0.051)	(0.043)	(0.040)	(0.030)	(0.038)	(0.047)	(0.030)	(0.078)
	VM_2	-0.158***	-0.157***	-0.093**	-0.051	-0.072***	-0.096***	-0.109**	-0.083***	-0.046
		(0.059)	(0.047)	(0.040)	(0.037)	(0.028)	(0.035)	(0.044)	(0.029)	(0.068)

year college graduates than for talented 4-year college or graduate school graduates. Talented students could overcome the income loss by two years of investment in mismatched fields much easier than for those with four or more years of investment.

The income penalty on over-education (VM_2) also varies across different education levels. For 2-year college graduates, the income penalty on over-education is mostly insignificant. Even if the penalty is significant for the 5th and 8th decile groups, its size is not greater than 2.3% of well-matched workers' earnings. In contrast, the income penalty on over-education is mostly significant for 4-year college and graduate school graduates, except for those in the 9th decile group.

Table 14 reports the regression results from female workers. Female two-year college graduates are even more likely to make higher earnings by choosing jobs that do not match their fields of study. For many decile groups, horizontal mismatch has a positive income effect. However, for female workers with 4-year college educations, horizontal mismatch has a significant negative effect even for the 9th decile group. This result is similar to the result from male workers. However, for female workers with graduate school degrees, horizontal mismatch generally has an insignificant income effect. The income effect is significantly negative only for the 1st decile group. This is a different result from what we find from Table 13. Horizontally mismatching jobs cause higher income loss for male workers with graduate school educations than for their counterpart female workers.

Table 14 also reports the estimates of income loss by over-education from female workers. The income effect of over-education is significantly negative for both 2-year and 4-year college graduates, regardless of the decile of conditional income. Even for female workers with graduate school educations, the income effect of over-education is significantly negative or insignificant at most of the deciles of conditional income distribution although it is significantly positive for workers at the 9th decile. We do not have a reasonable explanation for this positive income effect. Because no previous studies have considered interaction effects of education level and education-job mismatches, we are unable to determine whether the unexpected positive income effect from female graduate degree holders with very high ability levels is a general phenomenon that can be found in many countries or a phenomenon specific to the Korean labor market. Further study on this issue would be interesting. However, for this paper,

TABLE 14. THE EFFECT ON INCOME PENALTY BY EDUCATION LEVEL: FEMALE

		Deciles of yearly earnings								
		1th	*2nd*	*3rd*	*4th*	*5th*	*6th*	*7th*	*8th*	*9th*
2-year College	HM_2	0.029	0.022	0.041**	0.042***	0.024**	0.039**	0.039***	0.049***	0.049***
		(0.030)	(0.018)	(0.016)	(0.012)	(0.012)	(0.017)	(0.014)	(0.011)	(0.014)
	VM_2	-0.051*	-0.300*	-0.030*	-0.054***	-0.059***	-0.064***	-0.076***	-0.041***	-0.049***
		(0.030)	(0.018)	(0.016)	(0.012)	(0.012)	(0.017)	(0.014)	(0.011)	(0.014)
4-year College	HM_2	-0.079**	-0.084***	-0.072***	-0.074***	-0.071***	-0.096***	-0.079***	-0.064***	-0.042***
		(0.035)	(0.021)	(0.019)	(0.014)	(0.013)	(0.019)	(0.016)	(0.012)	(0.016)
	VM_2	-0.097***	-0.118***	-0.100***	-0.075***	-0.077***	-0.084***	-0.095***	-0.099***	-0.046***
		(0.034)	(0.021)	(0.019)	(0.014)	(0.013)	(0.019)	(0.016)	(0.013)	(0.017)
Graduate School	HM_2	-0.441***	0.015	-0.023	-0.004	-0.054	-0.064	-0.029	-0.064	0.008
		(0.103)	(0.064)	(0.054)	(0.043)	(0.042)	(0.060)	(0.051)	(0.039)	(0.053)
	VM_2	-0.311***	-0.095*	-0.078	-0.104***	-0.081**	-0.019	0.029	0.035	0.112**
		(0.081)	(0.106)	(0.052)	(0.038)	(0.037)	(0.053)	(0.045)	(0.035)	(0.046)

it would still be fair to say that the income effect of over-education is generally negative for both male and female workers.

Overall, the results from the regressions with interaction terms between education level and education-job mismatches reveal that the income effects of education-job mismatches vary across different education levels. For both male and female workers with 4-year college educations, the income effects of horizontal mismatch and over-education are significantly negative at most of deciles of conditional income distribution, except for male workers at the 9th decile. For workers with 2-year college or graduate school educations, the income effects of horizontal mismatch and over-education vary more widely across different genders and across different ability levels. However, the regressions with interaction terms also indicate that both horizontal education-job mismatch and over-education have income effects. Regressions ignoring one type of mismatch would exaggerate the income effect of the other type of mismatch.

Another issue we consider is the possible sample selection problem that may be caused by using the data of employed workers only. None of the previous studies have addressed this selection bias problem. There are two hurdles in addressing this problem. First, for unemployed workers, their earnings and statuses of education-job mismatches are not observed. Second, the (nonparametric) identification of the effects of regressors in the earnings equation requires that at least one regressor exists that appears in the employment-decision equation, but not in the earnings equation.[15] Unfortunately, such variables are not readily available in our data. Because of these problems, we can address the selection problem only in a limited way.

We re-estimated the earnings equation using Heckman's two-step method. The earnings equation is the same as the one in our quantile regression model while the variables for education-job mismatches are omitted from the employment-decision equation. The main results are the following. First, the results from the OLS estimation of the earnings equation with selection variables (inverse mills ratios) are almost identical to the OLS estimation results (without selection variables) that are reported in Table 7. Second, the selection variables are insignificant for both male and female workers. Thus, there is little evidence for sample

[15] For more details, see Buchinsky (2001).

selection bias, although our test for sample selection is not a comprehensive one. To save space, we do not report the two-step estimation results. They are available upon request from us.

VII. *Summary and Conclusions*

Through analyzing the data from a cohort of Korean college graduates, we have examined how large income penalties are on horizontal and vertical education-job mismatches. Quantile regressions are used to study how the two income penalties vary across workers with different ability levels. Previous studies of education-job mismatches have examined the data from Western countries only. None have examined the data from Asian countries. In this paper we analyze Korean data. The findings in this paper may apply to other Asian countries, particularly East Asian countries because they have very similar higher-education systems.

Our main findings are as follows. First, we find that the income penalties on horizontal education-job mismatch and over-education should be jointly estimated. Regressions ignoring one type of mismatch would over-estimate the income effect of the other type of mismatch. Second, we find that income penalty on over-education is pervasive for most deciles of the conditional distribution of earnings we consider. Even highly talented workers can suffer from income loss when they are over-educated for their jobs. This result is contradictive to the prediction of the Human Capital Theory that the penalty on over-education is a biased estimation result caused by the regressions conducted omitting some important human capital related variables such as on-the-job training and ability. Our result, rather, is consistent with the Assignment Theory. Over-education would be an outcome caused by the labor market's inefficiency in, for example, high job-search costs or imperfect information on the labor demands of different occupations. Third and finally, income penalty on horizontal mismatch generally occurs for the workers at the lower and middle segments of the earnings distribution. Workers with horizontally mismatched jobs are likely to lack occupation-specific skills needed for their jobs. Naturally talented workers could learn such skills quickly and avoid substantial income loss. However, less talented workers may need longer times to acquire the necessary skills for their jobs. In the meantime, they may have to bear substantial income losses. These findings are consistent with the prediction of the Assignment Theory.

Our results indicate that the income penalty on horizontal education-job mismatch is also significant in Korea, particularly for 4-year college graduates (10% of the earnings of well-matched workers). Nordin, Person and Rooth (2010) found a similar result from their Swedish data. Their estimation results indicate that in Sweden, the income penalty on horizontal mismatch exceeds 30% of the earnings of well-matched workers although this penalty estimate is likely to be an upward biased one because the penalty is estimated ignoring the income effect of vertical education-job mismatch. Interestingly, both Korea and Sweden are countries whose higher education systems offer excessively large numbers of study fields compared to many other countries. The estimation results from Korean and Swedish data suggest a possibility that too many fields of study offered by colleges and graduate schools may have negative effects on students' future earnings. Recommended for the two countries may be an educational policy that reduces the number of fields of study. Such a policy would be an effective way to decrease the income penalty on horizontal education-job mismatch.

Our quantile regression approach is not without a limitation. As discussed in sections I and IV, our approach is based on the assumption that workers' individual characteristics including their education-job mismatch statuses are exogenous to (uncorrelated with) their unobservable ability levels. Whether workers' education related variables are exogenous or endogenous, the main finding of this paper would be still valid. That is, the income effects of vertical and horizontal education-job mismatches should be estimated jointly. However, when workers' education-job mismatches are in fact the outcomes of their endogenous decisions, our estimates of the two income effects are likely to be biased ones. Some instrumental variables are required to estimate the income effects more precisely. Appropriate instruments can be found based on a theory that can explain workers' endogenous decisions on education-job mismatches. To our knowledge, such a theory is not yet available in the literature. Developing a theory of workers' potential endogenous decisions on education-job mismatches should be an important future research agenda.

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