Education and Skill Mismatches in Maptaphut Industrial Estate, Thailand

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Abstract: This paper examines educational and skill mismatches by using primary data from Maptaphut Industrial Estate, Rayong Province, Thailand, conducted from 226 respondents. Ordinary least squares (OLS) and unconditional quantile (UQR) regressions are used to examine the mismatches on earnings. The empirical findings are as follows: (1) returns to education of high income workers are larger than average income workers; (2) education mismatches affect earnings, such that over-education is statistically significant, whereas under-education is not significant, for both the OLS and UQR estimates; (3) UQR provides more information on size of the over-education to the returns on schooling; (4) specific training for some job positions also indicates educational and skill mismatches; and (5) firms should invest in training for workers to reduce weaknesses in educational mismatches.

Keywords: Over-education, Under-education, Skill Mismatches, Specific Training, Earnings, Maptaphut Industrial Estate.

1. INTRODUCTION

Maptaphut Municipality, an industrial area in Rayong Province, Thailand, has a range of educational levels of schools from 10 lower secondary schools, two secondary schools, and two vocational colleges. Some of the secondary and vocational graduates may find jobs in Rayong and nearby provinces. This follows economic development theory that the benefits of an industrial development is employment in local areas or nearby.

It is important to examine whether graduates from Rayong have skills that match local work and employer demand for labor in the industrial sector. In addition, developed countries such as Germany develop industrial work potential, on-the-job training and education in factories that have already expanded to some industrial areas in Thailand as foreign direct investment (FDI), particularly manufacturing with vocational college graduates.

The paper examines mismatches between educational skills and skills that employers expect graduates to have. The paper examines Maptaphut Municipality and schools in the area because useful information for course management and development provide a strategy for Maptaphut Municipality's Development Plan that determines the matches between education development and local needs.

The paper considers two research questions: 1) Mismatches between education and necessary skills that affect earnings; and 2) Training to overcome the mismatches between education and necessary skills.

The remainder of the paper is as follows. A brief literature review is given in Section 2; description and sources of data are in Section 3; the econometric model is presented in Section 4; the results are analyzed in Section 5; and recommendations are suggested in Section 6.

2. LITERATURE REVIEW

According to Assignment Theory (Duncan and Hoffman, 1981), it is expected that over-education will have a negative impact on earnings because the job position may require lower education, which is under-level work, while under-education should have a positive impact on earnings for the opposite reason.

Regarding over-education and under-education, there are three approaches, as follows (see Hartog, 2000): (i) based on the profession, job analysts have assessed an optimal level of education and skill for job position, called Job Analysis (JA); (ii) workers are asked to self-assess whether their jobs match their education, known as Worker Self-Assessment (WA); (iii) workers are asked an appropriate year of education for their jobs to calculate an average year of education as a benchmark, which is used for comparison with individual education.

A worker is over-educated if their years of education are higher than the benchmark, then the years of over-education are positive. A worker is under-educated if their years of education are less than the benchmark, so that the years of under-education are negative. Thailand does not have any information on the first

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method. This paper uses the second method for defining mismatches as it can be used to acquire data. Although the third method uses the same data as the second method, there is a limitation in computation in the presence of outlying data.

Developing skills enables workers to understand and perform better to improve productivity and wages (Hanushek and Woessmann, 2015). Skill mismatches occur when skills possessed by workers are lower or higher than those required at the workplace. Workers can be over-skilled by having greater skills than are actually needed, or under-skilled by having lower skills than needed, for their respective jobs.

Educational and skill mismatches impact on earnings and job satisfaction (Allen and Velden, 2001). Over-education has a negative impact on wages, which implies that a higher level of education of workers would not increase earnings, whereas under-education positively affects earnings. Over-skilled workers expect a wage penalty, whereas under-skilled workers receive a wage reward. The impacts of mismatches on job satisfaction are similar to those on earnings.

By using Nash bargaining between workers and employers, mismatches also assert a wage penalty for over-education and a wage reward for under-education (Hartog and Sattinger, 2013). The effects of educational mismatches on wages in European countries from 2006 to 2009 confirm that over-educated workers suffer a wage penalty of similar size to the returns on education (Iriondo and Amaral, 2016).

The opportunity costs of over-education for university graduates in Japan are high, and cause wage penalties for workers (Kucel, Molina, and Raya, 2016). In analyzing the wage penalty of skill mismatches among young Korean workers, OLS estimates suggest 3.8% for men and a much higher 5.6% for women (Kim and Park, 2016). The wage penalties of mismatching in Germany are different from many countries, such that large shares of over- or under-educated workers have skills that match their job requirements (Schmidt and Tiemann, 2016).

3. DATA

Data used for the empirical analysis were collected by interviewing workers of 58 companies located in Maptaphut Industrial Estate, Rayong province, Thailand, with most being in the petrochemical industry. The total sample size is 226 observations. The survey team collected data while workers were shopping for consumption goods and food at local markets, parks, and temples.

Table **1** gives the descriptive statistics of the variables. Most of the respondents are male (83.20%), with on average age of 36, 15 years of education, and approximately 19 months of work experience. The respondents were assessed on the relationship between education and work positions. Of all the workers, 7.2% are over-educated, and 47.10% are under-educated, with the remainder (45.70%) indicating appropriate matching. It is noticeable that most of the respondents have to obtain specific training during their employment.

Table 1: Descriptive Statistics

Variable	Number of Observations	Mean	SD	Min	Max
Male_dummy	226	0.832	0.375	0	1
Age (yr)	207	36.63	8.080	21	62
Schooling (yr)	223	14.92	3.569	9	21
Exp (mo)	204	18.99	9.330	1	49
Over_edu	221	0.072	0.260	0	1
Under_edu	221	0.471	0.500	0	1
Specific_training	207	0.860	0.349	0	1
Earnings (baht/mo)	218	27,415.40	41,325.80	5,500	500,000

4. ECONOMETRIC MODEL

The paper uses the standard Mincerian semi-logarithmic earnings equation. Three models are given, as follows:

Model 1: Mincer Model (1974):

$$ln\ (Earnings_i) = a_0 + a_1\ Male\_dummy_i + a_2\ Schooling_i + a_3\ Exp_i + a_4\ Exp_i^2 + u_{1i}, \quad (1)$$

where ln(•) represents logarithms, Earnings represent worker salaries (baht per month), as the dependent variable; Male_dummy is a dummy which takes the value 1 if the respondent is male, and 0 otherwise; Schooling is years of education; Exp is work experience (in months); Exp^2 represents squared work experience; and u_{1i} is the random error term.

Model 2: Mincer Model with Mismatching education variables:

Model 2 adds two dummy mismatch variables to Model 1, namely over-education (Over_edu) and under-education (Under_edu), as shown in equation (2):

$$ln\ (Earnings_i) = a_0 + a_1\ Male\_dummy_i + a_2\ Schooling_i + a_3\ Exp_i + a_4\ Exp_i^2 + a_5\ Over\_edu_i + a_6\ Under\_edu_i + u_{2i}, \quad (2)$$

Model 3: Mincer Model with Mismatching education and Mismatching specific training:

Model 3 adds a dummy mismatch specific training (Specific_training) to Model 2. The specific training indicates workers who do not have adequate or suitable skills for their positions, so they need to have specific training for employment. According to assignment theory, under-skill for positions would expect a negative impact on earnings:

$$ln\ (Earnings_i) = a_0 + a_1\ Male\_dummy_i + a_2\ Schooling_i + a_3\ Exp_i + a_4\ Exp_i^2 + a_5\ Over\_edu_i + a_6\ Under\_edu_i + a_7\ Specific\_training_i + u_{3i}. \quad (3)$$

The results of Ordinary Least Squares (OLS) and Unconditional Quantile Regression (UQR) estimates are given in Table **2**. The OLS estimates show the impact of the explanatory variables on the dependent variable, while the UQR estimates show the effects of the explanatory variables on the unconditional marginal quantiles of the dependent variable. The UQR measures the effect of small changes in education on the unconditional income distribution. Over-education, under-education, and specific training affect earnings at different quantiles, namely 25th (low), 50th (median), and 75th (high) quantiles, respectively.

5. EMPIRICAL RESULTS

Table **2** presents a summary of the estimates of the wage equations. It is noticeable that the results of OLS estimation from the 2012 survey data (cross section) shows the adjusted R^2 values between 28.09% and 30.81%.

In Model 1, the explanatory variables (gender, level of education, work experience, and work experience squared) would affect a change in the dependent variable, ln (Earnings), with adjusted R^2 of 28.09%. Considering human capital investment, the returns to schooling are significant at 9.9%. The greater the years of educational investment, the higher are average earnings. Therefore, the return to education investment is worth more than the annual bank deposit interest rate.

Work experience also has a positive effect on earnings. The greater the work experience, the higher are the earnings of workers, such that workers would receive higher average earnings of 6.4%. Although higher work experience leads to an increase in earnings, the earnings would rise at a diminishing rate (negative sign of Exp^2), which is consistent with Mincer's wage theory.

For earnings differences by gender, male workers have 39.2% higher earnings than female workers. Most of the respondents work in the petrochemical industry, which has a disproportionate emphasis on men (male workers are 83.2%, as shown in Table **1**).

Model 2 in Table **2** reports the results of over-education and under-education. An increase in adjusted R^2 to 30.81% indicates that the dependent variable would be affected more by the explanatory variables than in Model 1. Considering mismatches, the results report that over-education reduces earnings by 37.8%, which suggests a negative correlation between over-education and earnings, as expected.

For under-education, the estimates indicate that it would not affect earnings. Working in the petrochemical industry, which is sensitive to safety in the workplace, the environment of the Maptaphut Industrial Estate would require optimal education and experience. Although the coefficient of under-education is not significant, the sign of the estimate is still positive, according to Assignment Theory.

Table 2: OLS and UQR Estimates

Variable	OLS			UQR		
	Model 1	Model 2	Model 3	Model 4 Q25	Model 5 Q50	Model 6 Q75
Dependent Variable: ln (earnings)						
Independent Variables: Male_dummy	0.392* (0.114)	0.351* (0.114)	0.353* (0.121)	0.401* (0.156)	0.215 (0.139)	0.396 (0.203)
Schooling	0.099* (0.014)	0.119* (0.015)	0.117* (0.016)	0.089* (0.017)	0.126* (0.018)	0.167* (0.033)
Exp	0.064* (0.016)	0.062* (0.017)	0.064* (0.018)	0.032 (0.023)	0.073* (0.018)	0.114* (0.028)
Exp^2	-0.001* (0.0004)	-0.0009* (0.0004)	-0.00093* (0.0004)	-0.0005 (0.0005)	-0.00139* (0.0004)	-0.0019* (0.0006)
Over_edu		-0.378* (0.167)	-0.388* (0.174)	-0.301 (0.210)	-0.516* (0.221)	-0.941* (0.322)
Under_edu		0.178 (0.100)	0.151 (0.107)	0.155 (0.114)	0.183 (0.121)	0.105 (0.222)
Specific_training			0.021 (0.114)	-0.035 (0.149)	0.092 (0.135)	0.126 (0.184)
Constant	7.336* (0.293)	7.021* (0.311)	7.016* (0.327)	7.404* (0.383)	6.791* (0.337)	6.162* (0.652)
$\bar{R}^2$	0.2809	0.3081	0.2990	0.1588	0.2533	0.1734
n	198	196	181	181	181	181

Note: * Significant at the 0.05 level. Entries in parentheses denote standard errors.

Adding the education mismatch variables in Model 2 causes a larger effect on returns to education than in Model 1. The size of returns on schooling in Model 2 is 11.9%, compared with 9.9% in Model 1, so that the returns on years of education is higher by 2%. This would be a reason for an individual to invest too much on education. The evidence shows that education mismatches not only initiate earnings, but also affects returns on education investment. The size of the work experience effect on earnings in Model 2 (6.2%) is similar to that in Model 1 (6.4%).

Under-education in Model 2 is not significant, even though its sign is positive, corresponding to Assignment Theory. Adapting Model 2 with specific training shows that, in Model 3, under-education and specific training are still not significant, and worsens the adjusted R^2 of Model 3 to 29.9%. This asserts the findings that specific training does not affect earnings of workers as they would receive direct benefits from having greater skills and knowledge. The workers could adapt knowledge for their work, which results in greater efficiency. Although the expenses on specific training may be a burden for firms, they do not want to raise the wages of workers, so that the results in Model 3 support those of Model 2.

Earnings vary with education, education and skill mismatches. At the 25^{th} (low), 50^{th} (median), and 75^{th} (high) percentiles of the earnings distribution, the results of UQR estimates are given in Models 4, 5, and 6, respectively, in Table **2**. The returns to education are significantly different among the three groups: high earnings workers receive 16.7%, medium earnings workers receive 12.6%, and low earnings workers receive 8.9%. These results indicate that higher investment in education would be more informative than the OLS average returns of 11.7%.

Considering how work experience affects the distribution of earnings, it is significantly positive for medium and high earnings workers. With an increase in work experience, workers in the high earnings group would acquire higher earnings of 11.4%, 7.3% in the medium earnings group, but otherwise not significant for low earnings workers.

The effect of education mismatches on the distribution of earnings shows that the rate of return to over-education is significantly negative for all three groups of workers, which is similar to the OLS estimates. However, the sizes of returns to over-education for each income groups are different. The over-education of high income workers would harm earnings by -0.941, and -0.516 for medium income workers.

Over-education does not affect the earnings of the low income group. Investigating under-education and specific training using UQR, neither coefficient affects the distribution of earnings for all three earnings groups, which is similar to the OLS estimates.

6. CONCLUSION AND RECOMMENDATIONS

The paper is one of the first in Thailand to consider the following issues:

(1) Returns to education of high income workers based on UQR estimates are larger than for average income workers based on OLS;

(2) Educational and skill mismatches have negative affect on earnings;

(3) Specific training arranged by companies indicates that such education and skills lead to mismatches.

The empirical findings indicate that over-education is significant, whereas under-education is not significant, in the OLS and UQR regressions. UQR provides more informative on the negative effect of over-education to the rate of returns on schooling, where an increase in highly–educated workers would raise earnings inequality. It is necessary for companies to invest in training for employees, especially training for work safety, to reduce the weakness of education mismatches.

The data collection in this paper may have a downward bias as most of the target respondents had lower levels of education, so that the appropriate number of observations might be an issue. This serious topic is left for future research.

There are several additional topics for future research:

(i) the sample size could be increased to reduce the possible bias from respondent replies;

(ii) self-assessment measures regarding over-education or under-education could be enhanced;

(iii) comparisons with other industrial estates in Thailand and overseas might be considered.

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