Vertical and horizontal educational mismatches:

The direct and indirect wage effects of academic characteristics[#]

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Abstract

This study considers both vertical and horizontal educational mismatches, with the former referring to overeducation and undereducation, and the latter to the mismatch between college major and job. It is found that the wage premium of the vertical educational match is greater than that of the horizontal educational match. A better vertical match augments the wage premium of an improvement in the horizontal match, and vice versa. Graduates from highly-ranked colleges are privileged to not only have high earnings but also to have low probabilities for the vertical and horizontal mismatches. These low probabilities indirectly raise their earnings. The horizontal educational mismatch is likely to be an extended scenario of overeducation because graduates from colleges with low rankings have a higher probability of being vertically overeducated as well as horizontally mismatched. Good college grades do not directly raise earnings but improve the educational match, and hence indirectly raise earnings.

JEL Classification: I20

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1. Introduction

The issue of educational mismatch has been intensively examined in recent decades, with the focus in recent years having been on explaining the prevalence of overeducation.[1] Allen and van der Velden (2001) indicated that overeducation and undereducation simply reflect different levels of human capital for workers with the same level of educational attainment. This argument within human capital theory suggests that overeducation reflects the consequences of a low level of human capital. Alternatively, Sicherman (1991), Alba-Ramirze (1993), and de Oliveira, Santos, and Kiker (2000) have pointed out that overeducated workers might intentionally take on a low-level job in order to invest in more human capital and thereby jump to another better job. They stressed that overeducation is not necessarily a reflection of a low level of human capital but rather a stepping stone to a better job.

It should be emphasized that, in existing research, an educational mismatch often means that workers have either more or less education than that which is required for the job. As the numbers and sizes of colleges increase in most countries, college graduates account for a substantial portion of their labor force. A vertical educational mismatch, i.e., overeducation or undereducation, which results in a misallocation of educational resources among the labor force is not the only concern. A horizontal educational mismatch, i.e., where there is a mismatch between a person's major and the available jobs, has also surfaced as an emerging challenge that is being faced by

[1] At least three theories are usually employed when explaining the existence of overeducation. They are the assignment theory, the heterogeneous skill theory, and the human capital theory. Studies usually use the relationship between overeducation and being too highly skilled to verify whether the assignment theory or the heterogeneous skill theory provides an explanation of the existence of overeducation. See Allen and van der Velden (2001), Hartog (2000), Dolton and Vignoles (2000), Di Pietro and Urwin (2006), and Green and McIntosh (2007) for more detail.

the educational authorities. It is important to point out that ignoring or not controlling for a horizontal educational mismatch might lead to problematic conclusions in regard to the impact of overeducation on the wage. Variables for the horizontal educational mismatch that are omitted could bias the estimators if they are correlated with the vertical educational mismatch variables. While some studies, for instance, Allen and van der Velden (2001) and Di Pietro and Urwin (2006), do control for the horizontal educational mismatch in their regression models, the horizontal educational mismatch was never an issue that was emphasized until Robst (2007). Robst (2007) vindicated the importance of the horizontal educational mismatch, but the vertical educational mismatch seems to have been ignored in his study.

One of the purposes of the present study is to simultaneously investigate the wage effects of the vertical and horizontal educational mismatches of college graduates. The incorporation of both types of educational mismatch enables us to compare the wage penalties inflicted by the vertical and the horizontal educational mismatches, and shows us which of these two types of educational mismatch is more serious. In addition, the present study attempts to examine whether academic characteristics determine the vertical and horizontal educational mismatches. The academic characteristics to which we refer are the college grade, college type, and major. A number of studies have verified that these factors are determinants of the vertical educational mismatch. For example, Battu, Belfield, and Sloane (1999) demonstrated that the vertical educational mismatch is determined by the types of colleges. Dolton and Vignoles (2000) pointed out that graduates attending universities, rather than polytechnics, and those having better grades for their degrees were less likely to be overeducated. In addition, Green and McIntosh (2007) showed that the field of study (major) played a role in the vertical educational mismatch. However, while all of these studies focus on the vertical educational mismatch, the present study extends the analysis to the horizontal educational mismatch. The academic characteristics variables will also be employed in examining the wage effects of the vertical and the horizontal educational mismatches. As Robst (2007) stressed in his conclusion, the wage effects of an educational mismatch might be biased due to an ability sorting problem if the workers' abilities are not considered. Using workers' college grades and college ranking in the present model can mitigate such an ability bias problem.

Furthermore, Brewer, Eide, & Ehrenberg (1999) showed that an earnings gap exists across graduates between more-selective and less-selective colleges. Di Pietro and Urwin (2006) showed that good college grades raise wages and Green and McIntosh (2007) indicated that high achievements in mathematics also caused wages to rise. That is, the academic characteristics of college graduates are direct determinants of their wages. As pointed out above, the academic characteristics affect the likelihood of overeducation, and the overeducation causes the wage to decline. Consequently, academic characteristics affect the wage through at least two paths. They directly affect the wage and the likelihood of overeducation, which in turn indirectly affects the wage. The third purpose of this study is to estimate these direct and indirect effects of academic characteristics on the wage.

The remainder of this paper is organized as follows. Section 2 defines the vertical and horizontal educational mismatches, and introduces the data and describes their characteristics. Three models are then specified in Section 3. The data used relate to college graduates who graduated within the last two years. Some graduates are currently working, some are unemployed, and some are graduate students. Since the observed wage of full-time workers might be subject to sample selection bias, in order to correctly estimate the wage effects of the academic characteristics, a first-stage multinomial logit model of career choice and a second-stage wage equation are established. The third model is an ordered probit model which considers two types of educational mismatches in order to examine the relationship between the academic characteristics and the vertical and horizontal educational mismatches. The empirical results are presented and discussed in Section 4. Section 5 estimates the direct and indirect wage effects, via educational mismatches, of the academic characteristics. Finally, Section 6 concludes.

2. Definition of educational mismatches and data sources

Definition of educational mismatches

In most educational mismatch surveys, two questions are usually asked. One question asks employed respondents whether their jobs are highly, partly, or not related to their college major. The answer to this question is used to evaluate the extent to which the major matches the job, and is referred to as a horizontal educational mismatch. The other question, for example, in the survey that the present study uses, asks the respondents what is the appropriate educational attainment needed to be qualified for the current job. There are seven choices, namely, junior high school, senior high school, vocational senior high school, junior college, college, masters, and Ph.D. Since all respondents are college graduates, the first 4 choices are classified as overeducation, "college" as adequate education, while "masters" and "Ph.D." are classified as undereducation. Overeducation, adequate education, and undereducation are used to construct the degree of the vertical educational mismatch. As a result, there are 3 degrees of horizontal educational mismatch as well as 3 degrees of vertical educational mismatch. By considering the vertical and the horizontal educational mismatch together, there are 9 types of educational mismatch as presented in Table 1. Because of insufficient observations for undereducation, all of the 3 groups classified as undereducation are merged into a single group.[2]

Since it is unclear at this moment as to how to assign the degree of educational mismatch for each group represented in Table 1, we propose that the degree of educational mismatch for these groups be based on the rankings of their wages. The empirical results from Allen and van der Velden (2001) and Di Pietro and Urwin (2006) provide us with preliminary information regarding the wage ranking. First, in Model 4 of Table 4 in Allen and van der Velden (2001), overeducation, undereducation, and "skill outside own field" are considered. Overeducation and undereducation capture the effects of the vertical educational mismatch, while "skill outside own field" captures the effect of the horizontal educational mismatch. Their results show that there are significantly positive returns to undereducation and significantly negative returns to overeducation. In addition, the absolute effect of overeducation is greater than that of undereducation, and the latter is greater than the insignificant effect of "skill outside own field." Moreover, the former two effects are significant at the 1% level, while the effect of the "skill outside own field" is not significant. In Specification 4 in Table 4 in Di Pietro and Urwin (2006), the vertical educational mismatch (overeducation and undereducation) and horizontal educational mismatch (skimis) both appear in the model. Although the absolute effect of the overeducation is the greatest, the absolute effect of the undereducation is the least and is insignificant. The absolute effect of the horizontal educational mismatch is significant and greater than that for undereducation, but less than that for overeducation. It appears that existing studies agree that the educational match is

[2] The expansion of higher education in Taiwan has been quite phenomenal recently. Take the decade right before the data year of this study (i.e., 2003) as an example. In 1992, the numbers of students who graduated from colleges and graduate schools were 59,478 and 9,017, respectively. In 2002, both numbers skyrocketed to 176,044 and 30,858, respectively. There were 50 colleges in 1992, but the number of colleges sharply rose to 139 in 2002. All these facts imply that overeducation is more likely to occur than undereducation. This illustrates why the number of observations for undereducation is insufficient.

getting better from type 0 to type 4 as defined in Table 1, but there is no consistent conclusion regarding the order of type 5 and the regrouping of types 6, 7, and 8. For this reason, Table 1 does not rank these two groups but denotes these two groups as MS_5^A and MS_5^a, respectively. The degree of the educational mismatch of these two groups will be verified by their wages, and the group with the higher wage will be assigned MS_6, while the group with the lower wage will be assigned MS_5.

Place Table 1 here.

Data source and statistics

The data used are compiled by the Center for Higher Education Research at National Tsing Hua University, and they are sponsored by Taiwan's National Science Council as well as its Ministry of Education. The respondents in the survey were college graduates who graduated in June 2003, and were surveyed between August 2004 and January 2005, i.e., between one year and two months and one year and seven months after their graduation. The advantage of using the entry wage is that the impacts of the difficultly controlled part, i.e., on-the-job training, are completely ruled out. Imagine a college graduate who takes a masters-level job, who is undereducated, and at the outset is insufficiently skilled. To make up for the deficiency in capability needed for his job, he devotes more time to his job, and participates in on-the-job training as much as he can. Years later, he was finally sufficiently capable of doing his job. When he was surveyed, he answered that he was undereducated but not under-skilled at the time of the survey, though he was under-skilled at the outset. Because of his capability, his wage is probably similar to that of someone with adequate education and the right skills. This example emphasizes the possible problem of using experienced workers as the surveyed sample. The original data contained 12,263 female and male college graduates, who made up about 8% of all college graduates for the year 2003. Because most male college graduates are obliged to perform one year and ten months of military service, most of the male college graduates were not in the labor market when the survey was conducted. Consequently, the male respondents are excluded from the sample. Only the female graduates left in the data set are used in this study. To maintain the consistency of all observations, the college graduates from two-year colleges were deleted, leaving only four-year college graduates in the sample. Finally, after deleting some missing data, the final sample used in this study comprised 6,725 observations, which consisted of 3,923 full-time workers and others (unemployed, graduate students, and part-time workers). The variables used in the survey included the respondents' employment status, occupation, college major, grade, and extracurricular activities.

Table 2 summarizes the relationships between the college graduates' academic characteristics and the types of educational mismatch (MS). The mean monthly wages are reported based on academic characteristics and MS type. Note that the higher values of the subscripts in MS indicate better educational matches, although it is not clear at this moment if MS_5^A or MS_5^a represents a better match. Basically, the mean wage also rises as the value of the MS subscript increases. First, we group colleges into four types, namely, public colleges, private colleges, public technology colleges and private technology colleges according to the ranking in terms of reputation in descending order. Colleges and technology colleges are respectively similar to the universities and polytechnics presented in Dolton and Vignoles (2000). The former is more academically-oriented, while the latter is more vocationally-oriented. In Taiwan, most college freshmen are from senior high school, whereas most technology college freshmen are from senior vocational high school. In general, admission to a college is more competitive than that to a technology college. The ranking of the mean wage coincides with the ranking of the college types, while the mean wage of the public technology colleges is close to that of private colleges. Furthermore, for graduates from public colleges, the proportions of those falling into better matches are the highest, while the proportions of those falling into worse matches are the lowest. Table 2 also shows that, the higher the grade, the higher the wage and the higher the proportion of those falling into better matches. Regarding the performance of each type of major, we find that the graduates majoring in medicine, law, literature and social science earn relatively more than those taking other majors. These graduates also have a higher propensity to have better matches and fall in the types MS_5^A and MS_5^a. In particular, the percentages of them falling into MS_5^A, being adequately educated and having majors that are highly related to their jobs, are all above 30%. It is also surprising that literature and social sciences are included in the previous more-satisfactory list while the engineering major is not. We suppose that this is partly because a majority of graduates who major in engineering graduated from private technology colleges, which have lower college rankings.[3] By contrast, graduates from business or media majors perform worst, in that more than 60% are overeducated and only 12%-16% of them fall into MS_5^A. Finally, the second row from the bottom of Table 2 indicates that a half of the graduates reported that they were overeducated. This high feature of overeducation is likely to be a consequence of the rapid expansion of higher education in recent years in Taiwan.

Place Table 2 here.

Although Table 2 shows that academic characteristics might differentiate wages,

[3] In the full sample, 20%, 39%, 9%, and 32% of the graduates are respectively from public colleges, private colleges, public technology colleges and private technology colleges. In the full sample, 283 graduates majored in engineering. In this sub-sample, 10.6%, 22.6%, 20.9% and 45.9% of them respectively graduated from those four types of colleges. More of the graduates who majored in engineering are from private technology colleges.

other variables are not controlled and the results might be misleading due to selection bias. For example, college graduates with higher grades and from public colleges might be more likely to pursue a masters degree. When this sample selection is considered, the mean wage for those corresponding categories might be even higher. Consequently, it is necessary to consider the sample selection problem, if it is serious, while estimating the wage equation.

3. The models

In this section, three models will be established. Our first concern is how vertical and horizontal educational mismatches and academic characteristics impact the entry wages. The problem is that not all college graduates' wages are observed, but only those of the full-time workers whose wages are fully observed. The relationship between the entry wages and the other variables in the data on the full-time workers' wages might be obscured due to sample selection bias. Therefore, it is necessary to employ Heckman's two-stage regression. The first stage involves the use of a multinomial logit model of beginning status choice, and the second stage consists of the corrected wage equation after taking into consideration the selection term. It is assumed that college graduates choose their initial career to maximize their perceived career benefit (CB^*). The perceived career benefit is not observed, but the choice of the beginning status (CB) is observed, where CB=0, 1, 2, and 3 if a respondent is unemployed, a graduate student, a part-time worker, and a full-time worker, respectively. The multinomial logit model of beginning status choice is presented below. The superscript (CB) of the coefficients in equation (1) indicates which beginning status the coefficient represents:

$$\text{Prob(CB=j)}=\exp(\mathbf{Z\mu}^{CB})/[1+\sum_{j=1}^{3}\exp(\mathbf{Z\mu}^{CB})]\text{, j=1,2,3, and}$$

$$\text{Prob(CB=j)}=1/[1+\sum_{j=1}^{3}\exp(\mathbf{Z\mu}^{CB})]\text{, j=0,}$$

$$\text{where } \mathbf{Z\mu}^{CB}=\beta_0^{CB}+\sum_{i=1}^{3}\beta_i^{CB}C_i+\sum_{i=2}^{5}\delta_i^{CB}S_i+\sum_{i=1}^{7}\lambda_i^{CB}M_i+\gamma^{CB}\text{Exa}\text{, CB=1, 2, and 3.} \qquad (1)$$

In equation (1), $\mathbf{Z}$ and μ denote the explanatory variables matrix and the coefficients vector, respectively, where μ is a vector of regression coefficients β, δ, λ, and γ. C_1, C_2, and C_3 denote public colleges, private colleges, and public technology colleges, respectively. The private technology college is the comparison base. S_2, S_3, S_4, and S_5 represent college grades, and are introduced in Table 2. The worst grade, 60 to 70, is the comparison base. M_1 to M_7 are majors illustrated in Table 2, and media and law are the comparison base.[4] Exa is the number of extracurricular activities in college in which a worker participated. Apart from academics, extracurricular activities sharpen the students' abilities, such as communications skills, organization, and leadership. Persico, et al. (2004) argued that by participating in social activities young teens can facilitate the accumulation of human capital from social adaptability. This might help them to adapt to the labor market.

In addition to the academic explanatory variables in model (1), the explanatory variables in the entry wage model include 6 educational mismatch dummy variables, MS_1 to MS_4, MS_5^A and MS_5^a, and 7 occupational dummy variables.[5] Lambda is the sample selection term, and η is its regression coefficient. Lambda=

[4] It is not our intention to set two majors as the comparison base. This is because the number of law major observations is limited (see Table 2), because most technology colleges do not have a law school, and some of the mismatch groups do not have law observations. The ordered probit model, i.e., equation (3), cannot converge if law is an independent major. Therefore, the law major is also included in the comparison base.

[5] Occupations are divided into eight categories, namely, business executives and managers (O_1 =1), professionals (O_2 =1), teachers (O_3 =1), associate professionals (O_4 =1), technicians and professionals assistants (O_5=1), clerks and other staff ($O6_7$ =1), others (O_7 =1), and salesmen (O_8 =1). O_8 is the reference base.

$\phi[\Phi^{-1}(\mathbf{Z\mu}^3)]/\Phi[\Phi^{-1}(\mathbf{Z\mu}^3)]$, where ϕ, Φ, and Φ^{-1} are the standard normal PDF, the standard normal CDF, and the inverse function of the standard normal CDF. The superscript "3" indicates that the full-time earnings can be observed only if respondents are full-time workers. The significance of η indicates whether the sample selection problem is serious. In equation (2), the coefficients of the explanatory variables, which are in equations (1), are superscripted with "W" to differentiate them from those in equations (1). π and θ are the coefficients of occupations and educational mismatches, respectively. W is the monthly wage.

$$W=\beta_0^W+\sum_{i=1}^{3}\beta_i^W C_i+\sum_{i=2}^{5}\delta_i^W S_i+\sum_{i=1}^{7}\lambda_i^W M_i+\gamma^W Exa+\sum_{i=1}^{7}\pi_i O_i+\sum_{i=1}^{6}\theta_i MS_i+\eta\cdot lambda+\varepsilon^W . \quad (2)$$

The third model will be specified to explore the relationship between the degree of educational mismatch and academic characteristics. The types of colleges contain information regarding college ranking. Battu, Belfield, and Sloane (1999), Dolton and Vignoles (2000), and Green and McIntosh (2007) indicated that academic characteristics determine educational mismatches. The educational mismatch in their study refers to the vertical educational mismatch. Although Di Pietro and Urwin (2006) took college grades into account while estimating the impacts of vertical educational mismatches on wage, they did not examine whether college grades affect vertical educational mismatches.

The educational mismatch ordered probit model has a dependent variable that is defined in Table 1. This ordered probit model differs from those in the literature in that it includes both vertical and horizontal educational mismatches. The model is expressed as equation (3). Assume that MS^* is an unobserved and continuous variable indicating the quantity of educational mismatches. What can be observed is MS, a discontinuous variable of the degree of educational mismatch. MS=0 if overeducation and the major are not related with the job, and MS=1, 2, 3, 4, 5, and 6, respectively correspond to the same subscript values of MS in Table 1 and to their definitions, except that groups 5 and 6 are not identified at this moment. The order of the MS groups will be based on the results of the wage equation. The worse the education mismatch is in terms of the wage penalty, the smaller the value of MS that will be assigned.

$$MS^{*}=\beta_0^{MS}+\sum_{i=1}^{3}\beta_i^{MS}C_i+\sum_{i=2}^{5}\delta_i^{MS}S_i+\sum_{i=1}^{7}\lambda_i^{MS}M_i+\gamma^{MS}Exa+\varepsilon^{MS},$$

$MS=0$ if $MS^{*}\leq 0$, $MS=1$ if $0<MS^{*}\leq Mu(1)$,

$MS=J$ if $Mu(J-1)<MS^{*}\leq Mu(J)$, $J=2, 3, 4, 5$, and $MS=6$ if $Mu(5)\leq MS^{*}$ (3)

In equation (3), the coefficients of the explanatory variables, which are in equations (1) and (2), are superscripted with "MS" to differentiate them from those in equations (1) and (2). The Mu's are unknown parameters of thresholds to be estimated. It should be noted that the academic variables are included in both models (2) and (3). The coefficients of the academic variables in model (3) and the coefficients of the educational mismatches in model (2) can be used to estimate the indirect wage effects of the academic characteristics. The coefficients of the academic variables in model (2) provide direct wage effects of the academic characteristics.

4. Empirical results and discussions

(1) Determinations of the post-school choice and the entry wage

Determinations of the post-school choice

Because only the wages of full-time workers are observed, it is necessary to employ Heckman's two-stage regression in order to correct the sample selection bias. In the first stage, the independent variable in the multinomial logit model is the choice of beginning status which includes an unemployed worker, a graduate student, a part-time worker and a full-time worker, respectively.[6] The estimated coefficients and the corresponding marginal effects at the mean values are presented in Table 3. The discussions below are based on the results of the marginal effects. First, the graduates who are more involved in extracurricular activities in college tend to choose full-time jobs. In addition, the graduates of public colleges have higher probabilities of becoming graduate students and of being unemployed. The reason for the higher unemployment rate of graduates from public colleges is probably that they expected to find better matches which are verified in Table 2. They also have lower probabilities of starting their part-time or full-time jobs. By contrast, the public technology college graduates have higher intentions of starting their full-time jobs and lower propensities to continue studying. These results coincide with the purpose of the vocational education. Furthermore, the higher the college grades, the more likely it is that graduates will continue their studies in masters programs and will be less likely to participate in the labor market. Compared with graduates with the base major, graduates with most other majors have lower probabilities of being unemployed. The graduates majoring in business, science and engineering are more likely to choose more schooling while the opposite applies to the graduates majoring in literature. By contrast, the literature and medicine graduates tend to choose full-time jobs while the opposite applies to the graduates majoring in science and engineering. To sum up, most academic characteristics significantly affect the beginning status choice in the

[6] The chi-squared tests of the independence of irrelevant alternatives (IIA) of the multinomial logit model with dropping CB=1, CB=2, and CB=3 are 2.35, -3.45, and 1.38, respectively. The negative value seems unreasonable. However, as the limdep 8.0 manual notes (page E19-37), the right conclusion of a negative value is probably that it should be zero. The p values of the other two tests with degrees of freedom equal to 16 are close to 1, suggesting that the null hypotheses cannot be rejected.

first place, and the self-selection term derived here will be included when we estimate the equation for earnings later.

Place Table 3 here.

Determination of the entry wage

The explanatory variables in the entry wage model include pervious variables related to academic characteristics, 6 educational mismatch dummy variables, 7 occupational dummy variables and the sample selection term, Lambda. The regression results are presented in Table 4. First of all, the coefficient of Lambda is not significantly different from zero, indicating that the sample selection problem is not serious. Hence, we re-estimate the wage model without the sample selection term and thereafter we will only focus on this OLS regression when interpreting the results. The results show that, in descending order, the wage ranking starts from public colleges, and extends to private colleges, public technology colleges and then private technology colleges. The graduates with higher grades also have higher earnings, but the coefficients are not significant. More involvement in extracurricular activities does not increase earnings significantly. After controlling for the occupations, the graduates with medicine, literature, science and business majors earn more than those with the base major. In particular, the business major graduates earn more than those with majors in several other disciplines. After controlling for the types of colleges and types of occupations, the earnings of engineering major graduates are not significantly different from those of the base major. However, we have to note that the coefficients here only estimate the direct wage effects of the academic characteristics. The comprehensive analysis on wage effects needs to include indirect effects until Table 6 and will be presented in Table 7.

Last but not least, Table 4 also demonstrates that the coefficients of MS_i are all significantly positive, and basically the coefficients are increasing as the subscript values of MS increase. That is, the wages rise with the degree of educational matches. More importantly, the coefficients of the educational mismatches verify that $MS_5^a = MS_5$ and $MS_5^A = MS_6$. This confirms and completes our previous ordering of the educational mismatch.

Place Table 4 here.

The wage effects of all types of educational mismatches in Table 4 allow us to compare the direct effects of these educational mismatches. Table 5 summarizes all the comparisons. The comparisons are made by using the coefficients of the first row variable minus the coefficients of the first column variable and we also report the corresponding t test for each comparison. All the educational mismatch coefficients are from Table 4. Before interpreting Table 5, recall that MS_5^a is undereducation in the vertical educational mismatch but, because of the limitation of observations, does not control the horizontal educational mismatch. Hence, it is suggested that MS_5^a be temporarily ignored and this is why Table 5 places MS_5^a in the most right column. The values in Table 5 in real-line blocks indicate that they contain only the effects of the horizontal educational mismatches. For example, the values in the upper left corner block are all in the same level of vertical educational mismatch — overeducation, and indicate only the differences among the horizontal educational mismatches. In this block, for example, the value 1,106 indicates the difference between “highly related” and “not related,” and is controlled at overeducation. The bottom right block can be interpreted in a similar manner. It is worth noting that the wage gaps between MS_1 and MS_0 and MS_4 and MS_3 are not significant. That is, the wage difference is insignificant between “partly related” and “no related” as the vertical educational mismatch is controlled. By contrast, the values in the dotted-line blocks contain only the effects of the vertical educational mismatches. For example, in the center dotted block, the value 2,063 represents the difference between adequate education and overeducation, controlled at the partly related level. All the other values not in blocks contain both the effects of the vertical and horizontal educational mismatches.

Place Table 5 here.

Given the type of educational mismatch being compared in the first column, it can be easily observed that the values rise from column MS_1 to column MS_5^A for all rows. Table 5A summarizes those values in the real-line and dotted-line blocks in Table 5 to further compare the magnitudes of the effects of the vertical and the horizontal educational matches. The left part of Table 5A shows that given the vertical match (the top row), the wage premium increases with an improvement in the horizontal match. The results emphasize that a better vertical educational match enlarges the wage premium of an improvement in the horizontal educational match. Note that the wage premium of “highly related” to “not related” (the bottom row) is the sum of its top two rows, i.e., (highly related – partly related)+(partly related – not related).

The right part of Table 5A indicates that, given the horizontal match (the left column of the right part), the wage premium rises with the improvement in the vertical educational match. The results stress that a better horizontal educational match augments the wage premium of an improvement in the vertical educational match. Therefore, the “marginal” return from improving the educational match, either vertically or horizontally, is increasing. It is worth waiting for a better match if one believes that finding a better job is just a matter of time. This explains why the unemployment rate of graduates of public colleges is higher as shown in Table 3.

Either type of educational match augments the wage premium of the other type of educational match. Table 5A also demonstrates that the premiums (penalties) of the vertical educational matches (mismatches) are greater than those of the horizontal educational mismatches. For example, for a graduate with a job characterized by overeducation that also has no relation to his/her college major, the wage premium is 1,106 if his/her horizontal match is improved to “highly related,” given that the vertical match has not been changed. For the same person, the wage premium is 1,669 if the vertical match is improved to “adequate education,” while the horizontal match has not been changed. Table 5A shows that the wage premium of the vertical improvement is greater than that of the horizontal improvement. It appears that the effect of the vertical educational match is more substantial than that of the horizontal educational match.

Place Table 5A here.

The interpretations of the most right column, MS_5^a, are not so straightforward since it contains all kinds of horizontal educational matches. The coefficient of MS_5^a is significantly greater than the coefficients of MS_1 to MS_4. These mean that the coefficient of undereducation (MS_5^a) is greater than the coefficients of overeducation with all kinds of horizontal educational mismatch and those of adequate education with a major not related to or only partly related to the job. The difference between MS_5^a and MS_5^A is insignificant.

(2) Determination of educational mismatch

The third model is equation (3) which is an ordered probit model whose dependent variable is the educational mismatch as defined in Table 1 and whose order is confirmed above. The independent variables are the academic characteristics and the number of extracurricular activities in college. The estimated coefficients and the corresponding marginal effects of the ordered probit model are presented in Table 6.

First, the coefficients for public colleges, private colleges and public technology colleges are all significantly positive. The good ranking in educational matches starts with public colleges, private colleges, public technology colleges and then private technology colleges. The ranking of college types in terms of educational matches accords with the ranking of wage performance reported above. In particular, it was found that graduates attending colleges with more academic orientation were more likely to be better matched than those attending technology colleges. Publicly established colleges also rank better than privately established ones. In terms of the marginal effect, there is a 37.1% increase in terms of falling in MS_6 if the student graduated from a public college as compared with a private technology college. To be more specific, the sum of the marginal effects of MS_3 to MS_6 represents the marginal probabilities of falling in better matches, adequate education or undereducation, in terms of the vertical educational mismatch. On the other hand, the sum of the marginal effects of the MS_0 to MS_2 represents the marginal probabilities of falling in worse matches, i.e., overeducation. Our regression results provide evidence of a clear trend that there are positive and increasing marginal probabilities of falling in better vertical matches and negative and decreasing marginal probabilities of falling in overeducation as the graduates move from lower to higher ranked colleges, i.e., from private technology colleges to C_3, C_2, and C_1.

Furthermore, the ranking of college types also has an impact on the degrees of horizontal educational mismatch. Let us control the same level of horizontal educational mismatch. Given the worse matches (i.e., overeducation), the marginal probabilities are negative and decreasing as the graduates move from lower-ranked to more highly ranked colleges. For example, compared to private technology colleges, the marginal probabilities of falling in the worst match (MS_0) are -0.035, -0.076, and -0.160 for public technology colleges, private colleges, and public colleges, respectively. That is, the graduates of the highly-ranked colleges are less likely to have jobs unrelated to their majors given that they are overeducated. A similar rule is also applied to MS_1. On the other hand, given the better matches (i.e., adequate education), the marginal probabilities are positive and increasing for MS_6 as the graduates move from the lower-ranked to the more highly ranked colleges. To be more specific, the marginal probabilities of falling in the best match (MS_6) are 0.056, 0.114, and 0.371 for public technology colleges, private colleges, and public colleges, respectively. That is, the graduates of the highly-ranked colleges are more likely to have jobs highly related to their majors given that they are adequately educated. To sum up, graduates from the lower-ranked colleges also have higher propensities to work for jobs that are not or partly related to their majors and suffer from the horizontal mismatch problem. Graduates of highly-ranked colleges attain better matches and avoid worse matches than gradates of the lower-ranked colleges.

In addition, more involvement in extracurricular activities is found to increase the propensity for better matches, although it does not significantly increase earnings as shown in Table 4. The higher the college grades, the better educational matches the graduates can achieve. The regression results indicate that the graduates majoring in medicine, social science and literature can significantly attain better matches and avoid worse matches than those of the base major. The coefficients of business, science and engineering are not significantly different from zero. However, according to the estimated marginal effects, the graduates majoring in science or engineering can also significantly attain better matches and avoid worse matches than the reference group. Business is the only major which does worse than the base major in terms of educational mismatch. The marginal probabilities for the business major are significantly negative for the adequate education and undereducation groups (MS_4 to MS_6) and the marginal probabilities are significantly positive for most overeducation groups (MS_0 and MS_1). That is, college graduates majoring in business are more likely to be overeducated and less likely to be adequately-educated or undereducated. However, according to Table 4, the earnings of graduates with a business major are significantly higher than those with the base major. In sum, the academic performances affect the level of educational mismatches significantly.

Place Table 6 here.

5. Estimation of the direct and indirect effects on the entry wage

The direct wage effects of the academic characteristics are straightforward, and are simply the coefficients of the wage equation (2). The indirect wage effects of the academic characteristics are, however, not so straightforward. The coefficients in model (3) are not the marginal effects of their corresponding variables. Table 6 presents the marginal probability of each explanatory variable, at its mean value, falling in each group of educational mismatch. Therefore, the indirect wage effects are computed by the formula below. In equation (4), $[P_i(X=1)-P_i(X=0)]$ is the "marginal" probability of falling in a type i educational mismatch (MS_i), X denotes any of the academic variables, and θ_i is the coefficient of a type i educational mismatch (MS_i) in equation (2). Note that X is not a continuous variable, the "marginal" probability means that the probability changes from X=0 to X=1. In a sense, the computations of the indirect wage effects are "expected" or average effects.

$$\text{Indirect wage effect} = \sum_{i=1}^{6} \{ [P_i(X=1) - P_i(X=0)] \big|_{\text{mean}} \cdot \theta_i \},$$

where X = academic variables. (4)

Table 7 presents the estimated direct, indirect, and total wage effects for all academic variables, i.e., type of colleges, college grade, and major. The total wage effects are the sum of the direct and indirect effects. College types are significant both for the indirect and total wage effects. The significant indirect wage effects suggest that the wage premium for the educational matches of the college graduates from public, private, and public technology colleges are significantly greater than those from private technology colleges. When compared with the worst college grade, all the direct wage effects of the college grade dummy variables are insignificant, but their indirect wage effects are significant. In particular, the magnitudes of the impacts on the wage through the indirect way by a good grade (S3 and S4) are substantial. The total wage effects are significant for the best two college grade groups. It is interesting to visualize that diligent study does not directly raise one's wage, but increases the likelihood of being adequately matched and then increases the wage. When compared with college graduates majoring in the base major, all indirect wage effects are significantly positive, except that for majoring in business which is significantly negative. However, the total wage effect for the business major is still significantly positive.

The results in relation to the business major are consistent with Green and McIntosh (2007). In Green and McIntosh (2007), the major of business and management is the reference base, and the coefficients of all other majors in the over-qualified (overeducation) regression are negative, while in their wage regression, the wage for the business major is higher than that for most majors. Their explanation is that the higher propensity of being overeducated for college graduates with a business major is probably because their jobs do not demand a college degree. By analyzing the samples from Taiwan, we also discover that the graduates majoring in business are most likely to face an unfavorable mismatch according to Table 6, but their earnings are not the worst as indicated in Table 7. Our empirical findings lead to a similar result to that found in the UK by Green and McIntosh (2007).

Place Table 7 here.

6. Conclusions

This study has attempted to simultaneously investigate the wage effects of the vertical and the horizontal educational mismatches of college graduates. Through the comparison of the wage penalties of both types of educational mismatches, we are able to order the seriousness of different kinds of educational mismatches. Furthermore, we also identify which academic characteristics determine these educational mismatches. In addition, graduates with particular academic characteristics can improve their degrees of educational matches and indirectly increase their earnings. We regard this as the wage premium of educational matches. As a result, a comprehensive analysis on the wage effects of academic characteristics needs to include these indirect effects as well as direct effects.

Our empirical findings are summarized as follows. An ordered probit model with the confirmed order of educational mismatch, which combines both vertical and horizontal educational mismatches, is employed to analyze the relationship between academic characteristics and the degree of educational mismatches. First, graduates of high-ranking colleges attain better matches and avoid worse matches than graduates of lower-ranked colleges. Second, a horizontal educational mismatch appears to be an extended scenario of overeducation because graduates from lower-ranked colleges also have higher probabilities of working for jobs that are not or are only partly related to their majors. In addition to college rankings, college grades are a determinant of educational mismatches.

As for the entry wage effects of academic characteristics, we report the total effects after the calculation of the wage premium for educational matches. The ranking of college types in terms of wage performance accords with the ranking of educational matches. A better college grade does not directly raise a person’s wage, but increases the likelihood of being adequately matched and then increases the wage. Similarly, more involvement in extracurricular activities is found to increase the propensity for better matches, although it does not directly increase earnings. Compared with the base major, the indirect wage effects for all fields of study are significantly positive, except that majoring in business is significantly negative. However, the total wage effect for a business major is still significantly positive. That is, the graduates majoring in business are most likely to face an unfavorable mismatch, but their earnings are not the worst. It is found that a better horizontal educational match augments the wage premium of an improvement in the vertical educational match, and vice versa. The wage premium of the vertical educational match is more substantial than that of the horizontal educational match.

Due to the rapid expansion of higher education in Taiwan, it is unfortunate that there are not enough observations in regard to undereducation to enable us to explore the full features of educational mismatches. Data obtained from other regions where higher education does not expand so rapidly might further explain the full features of educational mismatches.

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Table 1 Types of educational mismatch

Type	Content	Group
0	Overeducation and major not related to job	MS_0
1	Overeducation and major partly related to job	MS_1
2	Overeducation and major highly related to job	MS_2
3	Adequate education but major not related to job	MS_3
4	Adequate education but major partly related to job	MS_4
5	Adequate education and major highly related to job	MS_5^A
6	Undereducation and major not related to job	
7	Undereducation and major partly related to job	MS_5^a
8	Undereducation and major highly related to job	

Groups 6, 7, and 8 are merged to form a new group MS_5^a due to insufficient observations.

Table 2 Number of observations and average wage by educational mismatch and academic characteristics

Mismatch type	MS_0[2]	MS_1	MS_2	MS_3	MS_4	MS_5^A	MS_5^a	Obs.	Mean Wage[1]
Public college (C_1)	48 (6%)	54 (7%)	32 (4%)	33 (4%)	125 (16%)	431 (55%)	66 (8%)	789	36,356
Private college (C_2)	243 (16%)	314 (21%)	176 (12%)	103 (7%)	275 (18%)	343 (23%)	57 (4%)	1511	30,823
Pub. Tech. college (C_3)	55 (16%)	78 (22%)	78 (22%)	18 (5%)	50 (14%)	60 (17%)	13 (4%)	352	30,157
Private. Tech. college	302 (24%)	349 (27%)	233 (18%)	54 (4%)	131 (10%)	171 (13%)	31 (2%)	1271	26,768
Score 60-70	34 (31%)	19 (17%)	10 (9%)	8 (7%)	16 (15%)	20 (18%)	3 (3%)	110	28,672
Score 70-80 (S_2)	252 (20%)	296 (23%)	188 (15%)	82 (6%)	187 (15%)	233 (18%)	50 (4%)	1288	29,395
Score 80-90 (S_3)	260 (12%)	395 (19%)	280 (13%)	91 (4%)	320 (15%)	659 (31%)	100 (5%)	2105	31,539
Score above 90 (S_4)	10 (11%)	11 (13%)	7 (8%)	6 (7%)	17 (20%)	33 (38%)	3 (3%)	87	33,033
Forgot score (S_5)	92 (28%)	74 (22%)	34 (10%)	21 (6%)	41 (12%)	60 (18%)	11 (3%)	333	28,881
Business (M_1)	229 (19%)	408 (33%)	158 (13%)	62 (5%)	204 (17%)	149 (12%)	22 (2%)	1232	27,937
Social science (M_2)	23 (12%)	16 (9%)	5 (3%)	13 (7%)	42 (23%)	71 (38%)	16 (9%)	186	31,661
Literature (M_3)	107 (12%)	98 (11%)	44 (5%)	42 (5%)	144 (16%)	408 (45%)	55 (6%)	898	33,673
Science (M_4)	60 (19%)	80 (26%)	23 (7%)	10 (3%)	52 (17%)	78 (25%)	10 (3%)	313	29,893
Medicine (M_5)	45 (11%)	29 (7%)	149 (36%)	11 (3%)	28 (7%)	126 (31%)	21 (5%)	409	37,347
Engineering (M_6)	61 (22%)	63 (22%)	37 (13%)	24 (8%)	39 (14%)	43 (15%)	16 (6%)	283	28,061
Other (M_7)	68 (20%)	60 (18%)	52 (15%)	21 (6%)	42 (12%)	76 (22%)	20 (6%)	339	27,430
Law	3 (10%)	3 (10%)	0 (0%)	0 (0%)	7 (23%)	16 (52%)	2 (6%)	31	34,293
Media	52 (22%)	38 (16%)	51 (22%)	25 (11%)	23 (10%)	38 (16%)	5 (2%)	232	27,653
Total Obs.	648 (17%)	795 (20%)	519 (13%)	208 (5%)	581 (15%)	1,005 (26%)	167 (4%)	3,923	
Mean Wage (NT$)[1]	26,274	26,522	30,091	29,566	31,312	35,872	34,580		30,562

1. NT$ refers to the New Taiwan dollar. One US dollar is about 32 New Taiwan dollars.
2. See Table 1 for the definitions of MS_0 to MS_5^a .

Table 3 Results and marginal effects of multinomial logit of post-school choice

	Multinominal logit model						Marginal effects			
Status	Study		Part-time		Full-time		Unemploy.	Study	Part-time	Full-time
Variable	Coeff.	t ratio	Coeff.	t ratio	Coeff.	t ratio	Coeff.	Coeff.	Coeff.	Coeff.
Constant	-0.373	-1.021	0.167	0.398	0.063	1.173	-0.067 *	-0.282 *	-0.044 *	0.392 *
Extra. Activities (Exa)	0.009	0.147	0.019	0.251	-0.652	-4.970 *	-0.004	-0.008	-0.002	0.013 *
Public college (C_1)	0.052	0.373	-0.872	-4.839 *	0.102	0.527	0.038 *	0.121 *	-0.031 *	-0.128 *
Private college (C_2)	-0.074	-0.580	-0.647	-4.059 *	-0.026	-0.096	0.012	0.017	-0.036 *	0.007
Pub. Tech. college (C_3)	-0.169	-0.794	-0.082	-0.329	-0.129	-1.104	-0.001	-0.045 *	-0.007	0.053 *
Score 70-80 (S_2)	0.433	1.347	-0.191	-0.522	0.213	0.785	-0.007	0.088 *	-0.019	-0.062
Score 80-90 (S_3)	0.989	3.095 *	-0.114	-0.314	0.013	0.034	-0.031	0.154 *	-0.034 *	-0.089 *
Score above 90 (S_4)	1.030	2.421 *	-0.414	-0.771	-0.126	-0.423	-0.020	0.197 *	-0.047 *	-0.130 *
Forgot score (S_5)	0.713	2.060 *	-0.272	-0.679	0.645	3.930 *	-0.007	0.156 *	-0.025	-0.123 *
Business (M_1)	0.802	4.264 *	0.148	0.631	0.572	2.326 *	-0.051 *	0.052 *	-0.032 *	0.032
Social science (M_2)	0.589	2.155 *	0.353	0.998	0.444	2.635 *	-0.044 *	0.019	-0.011	0.036
Literature (M_3)	0.085	0.435	0.536	2.266 *	0.508	2.422 *	-0.028 *	-0.059 *	0.015	0.072 *
Science (M_4)	1.267	5.535 *	0.109	0.365	1.038	4.489 *	-0.054 *	0.159 *	-0.037 *	-0.068 *
Medicine (M_5)	1.067	4.168 *	0.317	0.997	0.760	3.242 *	-0.078 *	0.040	-0.042 *	0.080 *
Engineering (M_6)	1.659	6.594 *	0.153	0.465	0.307	1.544	-0.076 *	0.194 *	-0.052 *	-0.066 *
Other (M_7)	0.364	1.610	0.107	0.382	0.000	0.000 *	-0.024	0.021	-0.012	0.016
	X^2=390.12			# of Obs.=6,725						

* indicates significant at the 10% level.

Table 4 Wage equation of sample selection and OLS models

Model	Sample selection		OLS	
Variable	Coeff.	t-ratio	Coeff.	t-ratio
Constant	22819.800	5.072 *	23771.300	24.499 *
Public college (C_1)	5664.680	3.804 *	5973.780	14.042 *
Private college (C_2)	3193.790	9.809 *	3172.440	10.159 *
Pub. Tech. college (C_3)	2644.960	3.589 *	2520.830	5.410 *
Score 70-80 (S_2)	305.135	0.333	420.173	0.559
Score 80-90 (S_3)	880.813	0.808	1053.480	1.409
Score above 90 (S_4)	1373.020	0.813	1652.940	1.511
Forgot score (S_5)	481.212	0.329	742.009	0.891
MS_1	308.471	0.766	309.364	0.763
MS_2	1106.140	2.348 *	1106.330	2.333 *
MS_3	1664.800	2.739 *	1669.420	2.731 *
MS_4	2368.110	5.253 *	2372.020	5.232 *
MS_5^A	4237.710	9.565 *	4239.510	9.510 *
MS_5^a	3896.400	5.740 *	3900.250	5.711 *
Extra. Activities (Exa)	189.006	0.932	157.649	1.103
Business (M_1)	1344.380	1.897 *	1240.270	2.368 *
Social science (M_2)	622.834	0.696	511.808	0.694
Literature (M_3)	1961.830	2.041 *	1792.970	3.172 *
Science (M_4)	1919.540	1.929 *	2083.980	3.220 *
Medicine (M_5)	8928.470	7.813 *	8721.420	13.851 *
Engineering (M_6)	795.218	0.750	973.405	1.448
Other (M_7)	-631.934	-0.924	-687.258	-1.077
Managers (O_1)	4909.800	5.116 *	4910.950	5.085 *
Professionals (O_2)	15933.400	11.458 *	15939.600	11.395 *
Teachers (O_3)	2994.340	5.527 *	2981.600	5.501 *
Associate Professionals (O_4)	1205.690	2.439 *	1206.360	2.425 *
Technicians (O_5)	-1350.590	-2.465 *	-1349.510	-2.447 *
Clerks and other staff (O_6)	-1917.310	-4.374 *	-1916.960	-4.346 *
Others (O_7)	-201.403	-0.402	-201.332	-0.400
Lambda	1609.810	0.217		
R^2	0.359		0.359	
# of Obs.	3923		3923	

* indicates significant at 10% level of significance.

Table 5 Comparisons of all types of educational mismatches[1]

	MS_1	MS_2	MS_3	MS_4	$MS_5^A = MS_6$	$MS_5^a = MS_5$
MS_0	309	1106	1669	2372	4240	3900
(t ratio)	(0.763)	(2.333) **	(2.731) ***	(5.232) ***	(9.510) ***	(5.711) ***
MS_1		797	1360	2063	3930	3591
(t ratio)		(1.768) *	(4.755) ***	(7.286) ***	(12.981) ***	(11.976) ***
MS_2			563	1266	3133	2794
(t ratio)			(0.889)	(3.645) ***	(9.584) ***	(8.234) ***
MS_3				703	2570	2231
(t ratio)				(1.145)	(4.914) ***	(4.258) ***
MS_4					1867	1528
(t ratio)					(4.536) ***	(4.521) ***
MS_5^A						-339
(t ratio)						(-0.535)

1. All comparisons are made by using the coefficients of the first row variable minus the coefficients of the first column variable. All the coefficients are from Table 4. The real-line and dotted-line blocks indicate that they contain only the effects of the horizontal and only the effects of the vertical educational mismatches, respectively.
2. MS_1, MS_2, MS_3, MS_4, MS_5^a, and MS_5^A are defined in Table 1, where MS_5^a = MS_5, and MS_5^A MS_6.
3. *, **, and *** indicate significance at the 10%, 5% and the 1% levels, respectively.

Table 5A Wage premiums of horizontal and vertical educational matches

Vertical cond. / Horizontal diff.	Over-education	Adequate education	Vertical diff. / Horizontal cond.	Adequate education – overeducation
Partly related – not related	309	703	Not related	1669
Highly related – partly related	797	1867	Partly related	2063
Highly related – not related	1106	2570	Highly related	3133

The values in Table 5A are summarized from Table 5.

Table 6 Results and marginal effects of ordered probit model of educational mismatches

	Ordered probit		Marginal effects						
	Coeff.	t ratio	MS_0	MS_1	MS_2	MS_3	MS_4	MS_5	MS_6
Constant	0.240	1.889 *							
Extra. Activities (Exa)	0.095	4.667 *	-0.02 *	-0.01 *	-0.00 *	0.000	0.006 *	0.003 *	0.029 *
Public college (C_1)	1.057	18.796 *	-0.16 *	-0.15 *	-0.06 *	-0.01	0.008	0.018 *	0.371 *
Private college (C_2)	0.367	8.653 *	-0.07 *	-0.05 *	-0.01 *	0.000	0.020 *	0.011 *	0.114 *
Pub. Tech. college (C_3)	0.177	2.762 *	-0.03 *	-0.02 *	-0.00	0.000	0.009 *	0.005 *	0.056 *
Score 70-80 (S_2)	0.179	1.679 *	-0.03 *	-0.02 *	-0.00	0.000	0.010 *	0.005 *	0.055 *
Score 80-90 (S_3)	0.430	4.071 *	-0.09 *	-0.06 *	-0.01 *	0.002	0.027 *	0.014 *	0.128 *
Score above 90 (S_4)	0.561	3.575 *	-0.08 *	-0.08 *	-0.03 *	-0.00	0.009	0.012 *	0.198 *
Forgot score (S_5)	0.067	0.570	-0.01 *	-0.01 *	-0.00	0.000	0.004 *	0.002	0.021 *
Business (M_1)	-0.112	-1.544	0.025 *	0.017 *	0.003	-0.00	-0.007 *	-0.00 *	-0.03 *
Social science (M_2)	0.373	3.584 *	-0.06 *	-0.05 *	-0.02 *	-0.00	0.012 *	0.010 *	0.126 *
Literature (M_3)	0.326	4.216 *	-0.06 *	-0.05 *	-0.01 *	-0.00	0.015 *	0.009 *	0.105 *
Science (M_4)	0.142	1.582	-0.02 *	-0.02 *	-0.00	0.000	0.007 *	0.004 *	0.045 *
Medicine (M_5)	0.471	5.542 *	-0.08 *	-0.07 *	-0.02 *	-0.00	0.014 *	0.012 *	0.160 *
Engineering (M_6)	0.066	0.712	-0.01 *	-0.01 *	-0.00	0.000	0.004 *	0.002	0.020 *
Other (M_7)	0.103	1.162	-0.02 *	-0.01 *	-0.00	0.000	0.006 *	0.003	0.032 *
Mu(1)	0.695	37.686 *							
Mu(2)	1.081	54.820 *							
Mu(3)	1.236	60.592 *							
Mu(4)	1.700	75.718 *							
Mu(5)	1.849	78.136 *							
X^2	861.849								
# of Obs.	3923								

* indicates significance at the 10% level.

Table 7 Estimations of direct and indirect effects of academic characteristics on the wage

	Direct effect	t ratio	Indirect effect	t ratio	Total effect	t ratio
Public college (C_1)	5974	14.04 *	1516	11.03 *	7490	17.82 *
Private college (C_2)	3172	10.16 *	542	11.08 *	3714	11.96 *
Pub. tech. college (C_3)	2521	5.41 *	263	11.11 *	2784	5.98 *
Score 70-80 (S_2)	420	0.56	264	11.07 *	685	0.91
Score 80-90 (S_3)	1053	1.41	629	11.00 *	1682	2.25 *
Score above 90 (S_4)	1653	1.51	829	11.09 *	2482	2.27 *
Forgot score (S_5)	742	0.89	100	11.07 *	842	1.01
Business (M_1)	1240	2.37 *	-164	-3.31 *	1076	2.05 *
Social science (M_2)	512	0.69	556	16.21 *	1067	1.45
Literature (M_3)	1793	3.17 *	485	10.50 *	2278	4.02 *
Science (M_4)	2084	3.22 *	211	9.92 *	2295	3.54 *
Medicine (M_5)	8721	13.85 *	699	11.76 *	9420	14.93 *
Engineering (M_6)	973	1.45	97	3.83 *	1070	1.59
Other (M_7)	-687	-1.08	152	13.68 *	-535	-0.84

* indicates significance at the 10% level.
The effects are measured in NT$.