Heterogeneity, Comparative Advantage, and Return to Education: The Case of Taiwan

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Abstract

By considering heterogeneity in abilities and self-selection in educational choice, this paper adopts the heterogeneous human capital model to estimate rate of return to university education using data from the 1990 and 2000 Taiwan's Manpower Utilization Surveys. The Taiwan empirical study shows that significant heterogeneous return to education does exist, and that the educational choice was made according to the principle of comparative advantage. The estimated rates of return for attaining university were 19% and 15%, much higher than the average rate of return of 11.55 and 6.6%, for 1990 and 2000, respectively. The declining trend of return to university education may have been caused by the rapid expansion of the number of colleges and universities and the increasing supply of college graduates in the 1990s.

Keywords: Heterogeneous human capital; Sorting gain; Selection bias; Return to education; Marginal treatment effect; Average treatment effect

JEL: I21, I28, C23

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I. Introduction

According to human capital theory, people invest in education to accumulate human capital, enhance personal productivity, and in return receive higher life-cycle earnings profiles.[1] The economic return to education not only affects the individual's educational choice and hence his life-cycle earnings but also influences the labor quality of the whole society, an important factor for the aggregate performance of the economy and for the planning of government educational policy. Thus, the estimation of the return to education has become one of the most essential issues in modern labor economics.

What is the "true" rate of return to education? Education is a form of human capital investment and accumulation; however, the formulation and identification of human capital may be quite diverse and usually result in different estimation methods for the rate of return to education. There are two viewpoints on the formulation of human capital. One is, as Griliches (1977) pointed out, that human quality can be measured based on the efficiency units; i.e., human capitals are homogenous, and people may choose to have different units of human capital through investment like education and on-the-job training, ending up with different stocks of human capital by themselves. Following this line of view, researchers use the common coefficient model to estimate the return to education from the Mincerian wage equation and emphasize the problems of ability bias and measurement error. The OLS or instrumental variables methods are usually employed. Another opinion, as in Roy (1951),Willis and Rosen (1979), and Willis (1986), views human capitals as

1 See, for example, Card (1999) for a complete theoretical and empirical survey on the relationship between education and earnings.

heterogeneous multidimensional attributes, and people choose their educational attainment based on the comparative advantage of their different attributes of abilities. In the case of heterogeneous human capital, the random coefficient model is usually adopted to estimate the returns on education.

A major problem in the estimation is that education is an investment decision, and thus the schooling variable is endogenous, which is against the basic exogeneity assumption of explanatory variables in OLS estimation. Moreover, education is a self-selection process. In the real world, the data that we observe are results after selection, and thus not a random sample. For example, it is not possible to find the wages for those who have received college and university education if instead they enter the labor market right after they graduate from high school. As a result, the error term in the regression equation is truncated, and it renders selection bias for the estimator. If human capital is heterogeneous, as in the Roy model, then heterogeneity in abilities will reinforce the process of self-selection and thus exacerbate the effect of selection bias.

Following Roy's (1951) heterogeneous human capital model and Bjorklund and Moffitt's (1987) concept of marginal treatment effect (MTE), Heckman and Vytlacil (1999, 2000), and Carneiro, Heckman, and Vytlacil (2001) develop a model to estimate the return to education with heterogeneous human capital.[2] The main features of the model are that the estimation results can be used to test the hypothesis of heterogeneous human capital and further estimate the average treatment effect (ATE) and trace the selection bias.

2 The marginal treatment effect is the average return for those who are at the critical status of receiving or not receiving education but eventually decide to take the education. The selection process is based on the characteristics of the individual's unobserved abilities. For a detailed description, see, for example, Heckman and Li (2004) and Heckman, Urzua and Vytlacil (2006).

For the past four decades, Taiwan, a small island of 36,000 kilometers with limited natural resources, has achieved a so-called "economic miracle," with an average annual economic growth rate of 8.45% between 1960 and 2000. The investment in education has expanded greatly in Taiwan. The average years of education for employed workers in Taiwan have increased tremendously from 7.18 years in 1978 to 11.03 years in 2006, while for the same period, the per capita income rose from US$1,461 to US$14,455, a roughly ten-fold increase. Thus, the estimation of the economic return from education is especially relevant. Using data from the 1990 and 2000 Taiwan's Manpower Utilization Surveys, this paper adopts the heterogeneous human capital model to estimate the rate of return to college and university education in Taiwan and compares the estimation results with that from the conventional OLS or IV estimation methods.

This paper is organized as follows. Section 2 lays out the theoretical framework and empirical method for the heterogeneous human capital model. Section 3 contains data description and analysis. Section 4 presents estimation results of Taiwan's empirical study. The conclusion follows in Section 5.

2. An empirical model for heterogeneous human capital

Heterogeneous return on education

In the conventional Mincerian earning equation with the assumption of homogeneous human capital, the common coefficient model can be expressed as

$$\ln Y_i \quad S_i \quad X_i \quad U_i \quad , \qquad (1)$$

where is an index for the individual; is the worker's average hourly real wage in logarithmic form; is years of schooling; represents other variables that influence an individual's real wage, including tenure, work experience, sex, marital status, affiliated industry, and firm size; and is random error. The coefficient is the rate of return to an additional year of education.

Due to ability bias and selection bias, OLS estimation for equation (1) will result in the estimation of the average marginal rate of return to education being biased. A useful tool to deal with the problem is the instrumental variable method, that is, to find a set of relevant instruments which is correlated with the schooling variable but uncorrelated with the real wage or error term; see, for example, Angrist and Krueger(1991), Trostel, Walker, and Woolley(2002), Patrinos and Sakellariou (2005), and Sakellariou (2006). Some researchers use twin or sibling data to control for the family fixed effect; see, for example, Ashenfelter and Krueger (1994), Arias, Hallock, and Sosa-Escudero (2001), and Bronars and Oettinger (2006). Other studies include ability proxies such as IQ scores, mathematics and science test scores, and cognition skills to directly control for an individual's unobserved abilities.

However, the major problem of the above mentioned methods is that most acquired data do not contain enough information, such that the error term can be completely separated, and thus the inherited bias tends to be deteriorated. Empirically, it is very difficult to find relevant instruments. Carneiro and Heckman (2002) point out that most empirical studies on return to education in the literature used invalid instruments which tend to have high correlation with the omitted personal unobserved abilities.[3]

If human capital is heterogeneous, the empirical earning equation allowing for heterogeneous return to education can be specified as

$$\ln Y_i = \alpha + \beta_i S_i + X_i \gamma + U_i , \qquad (2)$$

where β_i stands for heterogeneous rate of return to education. Suppose the educational choice is whether to attain a university education or not. If $S_i = 1$ denotes to attain university and $S_i = 0$ is not to do so, and earn only a high school diploma, then after selection into different educational attainments, the wage profiles for the two statuses will be different and can be expressed as

$$\ln Y_{0i} = X_i \beta_0 + U_{0i} , \text{ if } S_i = 0 ; \qquad (3a)$$

$$\ln Y_{1i} = X_i \beta_1 + U_{1i} , \text{ if } S_i = 1 ; \qquad (3b)$$

3 Heckman (1997) and Heckman and Navarro-Lozano (2003) claim that only when individual unobserved heterogeneity does not exist or does exist but is uncorrelated with an individual's schooling choice, the estimated rate of return to education using the IV method can be a consistent estimator.

where and . After selection, it is not possible for any cross-sectional data to have both and for the same individual. That is, the distributions and are not available, and what can be obtained is the distributions of and , respectively. Therefore, in the case of heterogeneous human capital, estimation using the conventional OLS or IV methods is not valid.

Further rearranging equations (3a) and (3b) yields

$$\ln Y_i = S_i \ln Y_{1i} + (1 - S_i) \ln Y_{0i}$$

$$= [(\beta_1 - \beta_0) X_i + (U_{1i} - U_{0i})] S_i + \beta_0 X_i + U_{0i}$$

$$= \rho_i S_i + \beta_0 X_i + U_{0i} \qquad (4)$$

where

$$\rho_i = (\beta_1 - \beta_0) X_i + (U_{1i} - U_{0i}) \qquad (5)$$

The term represents heterogeneous return to education for individual . From equation (5), the term includes observed heterogeneity and unobserved heterogeneity (). As these two components are different among people, thus the heterogeneous return will be a random variable following certain distribution. For a given , the mean value of is:

$$= E(\ _j | X_j) = E[\ _1 - \ (\ ) | X_j]$$

. (6)

Suppose people decide whether to go or not to go to university based on the following rule:

$$S_i^* = P_i(Z_i) - U_s$$

,

$$S_i = \begin{cases} 1 & if\, S_i^* \geq 0 \\ 0 & if\, S_i^* < 0 \end{cases}$$

(7)

[illegible]

where is a latent variable which stands for the net return from receiving university education, is a vector of observable variables that affect the individual's schooling decision, is the probability of receiving a university education for individual , and represents all the individual's unobservable heterogeneity which influences the schooling decision.[4] For any individual, whether he will receive a university education or not is mainly determined by the observable heterogeneity, , and unobservable heterogeneity, . The smaller the is, the greater the probability of entering a university will be.

Selection bias and marginal policy effect

[illegible]

First, according to the study of Carneiro et. al. (2001) and Heckman and Vytlacil (1999, 2000), we define selection bias= as the difference of mean value of unobserved

4 follows a smooth distribution between [0,1], see Heckman and Vytlacil (1999).

attributes for not receiving university education between those who do undertake university education and those who do not. Further defining treatment on the treated (TT) as the average policy effect for those who participate in the program (), i.e., those who receive university education and express it as TT=, the mean effect on those who receive university education to those who receive university education but instead choose not to do so. Treatment on treated can also be expressed as

[illegible]

, (8)

[illegible]

where the average treatment effect () as the mean value of the sample with particular characteristics, and is defined as sorting gain, the mean difference of the unobserved heterogeneity between going to university and not going to university for those who choose to have university education. Thus, from equation (8), we have sorting gain (=) is equal to the rate of return for receiving university education minus the average rate of return to university education from a random sample with similar observable attributes .

By the definitions above, the rate of return to education under OLS can be expressed as

$$\beta_{OLS}$$

=ATE + Bias

=ATE + Sorting gain + Selection bias

=TT + Selection bias.

$$\beta_{OLS}$$

Therefore, the bias between and average treatment effect (ATE) is sorting gain plus selection bias, and the bias between and treatment on the treated (TT) is selection bias.

$$\bar{S}\,E(U_{1i}-U_{0i} \mid S_i=0)$$

Likewise, treatment on the untreated (TUT) is the average policy effect for those who do not attend the program, i.e., those who are not receiving university education (). Treatment on the untreated is the average return to university education for those who do not attend university to those who do not attend university but instead choose to receive a university education.

3. Data Analysis

This paper adopts data from the 1990 and 2000 Taiwan Manpower Surveys. Table 1 shows all the variables used in the paper and their definitions. Table 2 presents basic statistics of the variables. The samples for 1990 and 2000 are 7,193 persons and 7,626 persons, respectively.[5] Among them, 6% and 12.5% received university education, respectively, implying that the number of workers receiving university education doubled between 1990 and 2000. The tenure is 3.55 years and 4.30 years, and previous work experience is 6.09 years and 6.56 years for 1990 and 2000, respectively. The percentages of females in the sample are 34% and 31%, and the percentages of married individuals are 31% and 35% for 1990 and 2000, respectively.

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5 For the purposes of comparison between the conventional OLS and IV models and our heterogeneous human capital model, we only choose samples with completely intergenerational information such as the number of siblings, which can only be obtained from the sample's mother and is used as an instrumental variable for education. However, we also do the estimation on return to education for all models by using the large samples without restrictions on intergenerational information and the estimated results are similar to what we report here.

For the same period, the percentages of those working in manufacturing are 38% and 30%, respectively, followed by wholesale, retail, and restaurant, 18% and 23%, and public and personal services, 17% and 16%. As for the firm size, most of the workers work in small and medium enterprises (below 50 persons) with percentages of 70% and 72% for 1990 and 2000, respectively, while the percentages of those who work in large enterprises (above 500 persons) are 3.7% and 4.6%, respectively. There were respectively 8.7% and 7.2% of workers in the public sector in 1990 and 2000.

Table 1. Variable names and definitions

Name	Definition
Wage	Real hourly wage in logarithmic form.
University education	Schooling dummy: 1 for receiving university education and zero otherwise.
Work experience	Age-years of education-6 as the proxy for work experience. As males in Taiwan have to attend military service for two years, an additional two years will be further subtracted for the male sample. In some cases, we further separate work experience as tenure (work experience in current job) plus general work experience (experience before current job).
Sex	Gender dummy: 1 for male and zero for female.
Marital status	Dummy variable: zero for not married and 1 for others.
Industry	Industry dummies: The eight industries include agriculture, forestry, fishery, and husbandry; manufacturing; water, electricity, and coal; construction; wholesale, retail, and restaurant; transportation, storage, and communication; financial, insurance, and real estate; personal and public services; with wholesale, retailer, and restaurant as the reference group.
Firm size	Firm size dummies: firm size is classified by the number of employees, 1-9 persons, 10-49 persons, 50-99 persons, 100-499 persons, above 500 persons, and work in the public sector, with 1-9 persons as the reference group.

Table 2. Basic statistics of the variables

	1990		2000	
Variable name	Mean	S.D.	Mean	S.D.
Wage	4.684	0.441	4.995	0.506
University education	0.060	0.238	0.125	0.331
Tenure	3.548	4.172	4.299	4.728
Work experience	6.087	5.703	6.565	6.069
Sex	0.663	0.473	0.690	0.463
Marital status	0.318	0.466	0.354	0.478
Industry				
Agriculture	0.046	0.210	0.035	0.184
Manufacturing	0.381	0.486	0.295	0.456
Water, electricity, and coal	0.005	0.072	0.002	0.044
Construction	0.105	0.307	0.121	0.326
Wholesale, retail, and, restaurant	0.183	0.387	0.227	0.419
Transport, storage, and communication	0.059	0.235	0.049	0.215
Finance, insurance, and real estate	0.054	0.227	0.041	0.198
Personal and Public services	0.167	0.373	0.155	0.362
Firm size				
1-9 persons	0.439	0.496	0.448	0.497
10-49 persons	0.258	0.438	0.273	0.445
50-99 persons	0.073	0.261	0.065	0.247
100-499 persons	0.105	0.307	0.096	0.295
Above 500 persons	0.037	0.189	0.046	0.208

Public sector	0.087	0.281	0.072	0.259
Samples	7193		7626	

Source: Taiwan Manpower Utilization Survey,1990 and 2000.

4. **Estimation results**

For comparison, we first estimate the rates of return to university education for 1990 and 2000, respectively, by using the conventional OLS and IV methods. The results are shown in Table 3. As expected, the Durbin-Wu-Hausman test suggests that the education variable is endogenous and thus the estimated return to education by OLS will be biased and inconsistent. If the education variable is not exogenous, Griliches (1977) proposes the use of the instrumental variable method to tackle the problems of ability bias and endogeneity. The use of instrumental variables to estimate return to education requires that instrumental variables satisfy the instrument relevance and instrument exogeneity conditions; i.e., the instrumental variable should be correlated with one's educational choice, but uncorrelated with one's wage rate.[6]

From a policy perspective, the implementation of a compulsory educational policy significantly enhances the structure of labor quality of the developing countries, especially for those groups that are subject to family liquidity constraints. Compulsory educational policy is an institutional change which includes building of new junior high schools and recruiting new educational staff and teachers, and thus it is closely related to an individual's educational investment but has no direct relationship with individual's ability.[7] As educational resources are different among different residential areas, they thus have different impacts on individual's educational achievement but nothing to do with an individual's ability.[8] Moreover, given family

6 See, for example, Heckman and Vytlacil (1999) and Blundell *et al.* (2003) for detailed discussion on this point.

7 Numerous studies have shown that a compulsory educational policy has a significant effect on return to education, see, e.g., Angrist and Krueger (1991); Cruz and Moreira (2005); and Sakellariou (2006), among others.

8 For example, Duflo (2001) chooses personal residential area as an instrument, since the educational

budget constraints, the greater the number of siblings there are, the smaller the educational resources that are available to each child. We therefore use the nine-year compulsory education policy, residential area, and the number of siblings as instrumental variables for educational choice, as they will be correlated with an individual's educational achievement but have no correlation with an individual's ability or wage.

For the validity of the IV method, the relevant tests include using the partial coefficient of determination or F-test to test the explanatory power and sign of the instrumental variable on the endogenous education variable at the first step of regression. As for the exogeneity test, to ensure that the selected instruments have no relationship with the unobserved error term, the over-identifying restrictions test is used as the orthogonality condition for all the instruments. The results in Table 3 show that the instrumental variables we choose satisfy both the instrument relevance and instrument exogeneity conditions.[9]

The estimated wage premiums for university education for OLS and IV methods are 39.27% and 82.14% (corresponding to average annual rate of return at 9.82% and 20.54%) in 1990 and 33.33% and 69.12% （corresponding to average annual rate of

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resources may be different among regions under different policies. Moretti (2004) uses demographic structure in the city and land-grant university as instrumental variables to estimate the spillover effect of education and social rate of return to education.

9 We also conducted separate tests for each instrument; they all satisfied the required conditions for a valid instrument. However, we find that the inclusion of further IVs will increase the explanatory power for education achievement at the first stage; moreover, the inclusion of all three variables provides the minimum mean square error (MSE) for the estimation of rate of return to education at the second stage wage regression. It means that the combination of the three IVs is the most effective valid instrument. We thus adopt the nine-year compulsory education policy, residential area, and the number of siblings as our instrumental variables.

return at 8.33% and 17.28%) in 2000. Annual rates of return to tenure for the two methods are 4.02% and 3.83% in 1999 and 4.59% and 4.46% in 2000, while those to previous work experience are 1.12% and 0.85% in 1990 and 1.24% and 0.99% in 2000. The results in Table 3 show that the estimated rate of return to university education is higher, about double, in the IV method than in the OLS; moreover, the rate of return is higher in 1990 than in 2000. The decline in the rate of return may reflect the large expansion of university education, which has increased the supply of college graduates since 1990.[10] As for other explanatory variables, marital status, industry, and firm size all significantly affect the worker's wage. In general, workers who are married, work in construction, transportation, storage, communication, finance, insurance, or real estate, and work in large enterprises, tend to receive high wages. These results are consistent with the literature.

Table 3. Rate of return to education—OLS and IV methods

	1990		2000	
	OLS	IV	OLS	IV
University education	0.3927***	0.8214***	0.3333***	0.6912***
	(22.20)	(18.25)	(21.66)	(15.38)
Tenure	0.0402***	0.0383***	0.0459***	0.0446***
	(17.03)	(15.21)	(17.98)	(15.35)
$(\text{Tenure})^2$	-0.0015***	-0.0015***	-0.0013***	-0.0013***
	(-15.27)	(-14.75)	(-11.70)	(-9.32)
Work experience	0.0112***	0.0085***	0.0124***	0.0099***
	(5.68)	(2.80)	(5.66)	(4.42)
$(\text{Work experience})^2$	-0.0003***	-0.0002***	-0.0004***	-0.0003***
	(-4.23)	(-2.92)	(-4.30)	(-3.28)
Sex	0.2870***	0.2837***	0.1778***	0.1689***
	(27.40)	(26.75)	(14.87)	(13.88)
Marital Status	0.1047***	0.1215***	0.1064***	0.1058***
	(9.12)	(10.50)	(8.16)	(7.99)
Industry				
Agriculture	-0.3989***	-0.3595***	-0.4828***	-0.4667***
	(-15.99)	(-14.18)	(-14.99)	(-14.27)
Manufacturing	-0.0819***	-0.0736***	-0.0533***	-0.0546***
	(-6.26)	(-5.55)	(-3.85)	(-3.87)
Water, electricity, and coal	0.1094	0.1030	-0.0172	-0.0473
	(1.41)	(1.31)	(-0.12)	(-0.33)
	(1.41)	(1.31)	(-0.12)	(-0.33)
Construction	0.0904***	0.1152***	0.1080***	0.1216***

10 Due to government policy on expanding higher education facilities, the number of colleges and universities in Taiwan has increased from 46 in 1990 to 127 in 2000. As a result, the enrollment rate of colleges and universities has increased tremendously, climbing from about 40% in 1990 to 57.7% in 2000, implying easy access to college and university education. It should be mentioned that in 2007, the college and university enrollment rate had soared to nearly 100%.

	(5.32)	(6.68)	(6.05)	(6.69)
Transport, storage, and communication	0.0418**	0.0379*	0.0550**	0.0443*
	(2.02)	(1.81)	(2.32)	(1.84)
	(2.02)	(1.81)	(2.32)	(1.84)
Finance, insurance, and real estate	0.1119***	0.1257***	0.0480*	0.0631**
	(5.38)	(5.99)	(1.94)	(2.51)
	(5.38)	(5.99)	(1.94)	(2.51)
Personal and public services	-0.0657***	-0.0456***	-0.0004	0.0252
	(-4.26)	(-2.93)	(-0.03)	(1.61)
	(-4.26)	(-2.93)	(-0.03)	(1.61)
Firm size				
10-49 persons	0.0733***	0.0738***	0.0817***	0.0891***
	(6.51)	(6.48)	(6.48)	(6.96)
50-99 persons	0.0784***	0.0935***	0.1242***	0.1529***
	(4.38)	(5.18)	(5.88)	(7.16)
100-499 persons	0.0982***	0.1096***	0.1635***	0.1925***
	(6.23)	(6.89)	(8.82)	(10.28)
500+ persons	0.1230***	0.1188***	0.1744***	0.2093***
	(5.25)	(5.01)	(6.89)	(8.180)
Public sector	0.1922***	0.2090***	0.2115***	0.2814***
	(10.80)	(11.65)	(9.92)	(13.31)
Constant	4.2783***	4.2605***	4.5538***	4.5380***
	(295.00)	(287.98)	(292.63)	(281.90)
Validity test of instruments for education				
F-test		81.24***		66.49***
Over-identifying restrictions test		3.12 [0.2101]		2.79 [0.2478]
Durbin-Wu-Hausman (DWH) endogeneity test	-6.22***		-7.45***	
Observations	7193	7193	7626	7626
Adj-R^2	0.3316	0.3174	0.2332	0.2105

Notes: 1. Figures in the parentheses and square bracket are t-statistics and p-value, respectively; and *, **, and *** stand for statistical significance levels at 90%, 95%, 99%, respectively.

2. Reference groups: wholesale, retail, and restaurant for industry; 1-9 persons for firm size.
3. Instrumental variables for education include nine-year compulsory educational policy, urban and rural regions, and number of siblings.
4. The F-test is for the instrument relevance condition (the significance of coefficients of all the instrumental variables). A rule of thumb is that F statistics should be greater than 10 and any values below 10 imply that the selected instrumental variables have insignificant explanatory power and thus generate estimation bias.
5. The Null hypothesis of over-identifying restrictions test is that all the including instrumental variables are jointly exogenous.
6. The Null hypothesis of the Durbin-Wu-Hausman test is that the potential endogeneity of the variable does not bias the estimated coefficients.

Under heterogeneous human capital, figures 1 and 2 show estimated marginal treatment effects for 1990 and 2000. The marginal treatment effect measures the average price that an individual is willing to pay for university education under given personal characteristics and unobserved heterogeneity. From figures 1 and 2, MTE declines as individual's unobservable heterogeneity (Us) increases, but at a decreasing rate. Suppose that individuals choose to have university education according to equation (7). Results in figures 1 and 2 imply those who are likely to have university education (with smaller Us) are willing to pay a higher price, i.e., higher MTE; while those who are less likely to have university education (with greater Us) tend to pay a lower price, i.e., smaller MTE. In other words, those who receive university education tend to have a higher marginal rate of return to education. Thus, the selection process of schooling undertaken is based on the principle of comparative advantage.[11] Those who are suitable for university education choose to enter university, and those who are better suited to solely having a high school education choose not to enter university and instead go into the labor market after graduating from high school. This phenomenon is consistent with the saying that "Every trade has its master." For example, if individuals who acquire more schooling become lawyers and those who do not become cooks, then the former are better lawyers than the average cooks would be if they became a lawyers; the latter are better cooks than the average lawyers would be if they became a cooks. Hence, the policy implication derived from the analysis supports the education system that separates vocational and technical education from the general educational track, as not all people are suitable to receive a college or university education.

Comparing the estimated MTE in 1990 and 2000 from Figures 1 and 2, we find that though the shape looks the same, MTE is greater in 1990 than in 2000, implying that for equal probability of entering university, the marginal rate of return to university education is higher in 1990 than in 2000. It should be reasonable to infer that easy access to colleges and universities under the college expansion policy in the 1990s and the increased supply of college and university graduates caused the decline in marginal return to education.

11 See also Willis and Rosen (1979) for the similar results of selection according to comparative advantage.

The estimation results from the Taiwan study firmly support the theory of heterogeneous human capital and hence heterogeneous return to education. Unobserved heterogeneity (Us) determines heterogeneous MTE and hence heterogeneous marginal rate of return to education, and the declining trend of MTE curve justifies the selection on the unobservable heterogeneity. Therefore, the estimated results from the conventional OLS and IV methods do not consider the unobserved heterogeneity among individuals and thus fail to correctly infer the "true" rate of return to education.

Figure 1. The estimated marginal treatment effect (MTE) for 1990

Figure 2. The estimated marginal treatment effect (MTE) for 2000

The estimation bias can be further calculated. Table 4 lists various estimated policy effects for 1990 and 2000. The average treatment effect (ATE) is 45.99% for 1990, implying that given individual personal characteristics, the average annual rate of return for four years university education is 11.5%. Using the conventional OLS method, the estimated coefficient is 39.27% (9.82% annually), implying an underestimation for OLS; while the estimated value for the IV method is 82.14% (20.54% annually), implying an overestimation for the IV method.[12] Comparing the estimation results, we have for 1990 and for 2000, and in all cases, the estimated coefficients are always larger in 1990 than in 2000. The difference between estimates is attributed to selection bias and sorting gain.

12 Depending on the choice of instruments, the estimation results of the IV method may likely represent the rate of return to schooling for a specific group, i.e., a local average treatment effect. See, for example, the discussion in Griliches (1977) and Card (2001).

The treatment effect on the treated (TT) is 77.45% (19.36% annually) in 1990, implying that the annual wage for those who have university education is 19.36% higher than what they will get provided that they do not enter university and go to labor market after graduating from high school. The treatment effect of the untreated (TUT) is 64.7% (16.18% annually), implying that for those who do not go to university, their annual wage would be 16.18% higher if they did enter university after graduating from high school. Comparing the results of TT and TUT in Table 4, we again find that the selection process works according to the principle of comparative advantage, for the wage premium for those who receive university education is indeed higher than for those who receive high school education but instead choose to enter university. Thus, under self-selection, those who receive university education are indeed more suitable to enter university, as their rate of return to education is higher than those who do not enter university.

The treatment effects on the treated and on the untreated are 59.87% and 47.14% (14.97% and 11.79% annually), respectively, in 2000. Similar implications are for the selection but smaller in estimated value than that in 1990, implying a declining trend of rate of return to education in the 1990s. However, on average, the difference between TT and TUT remains stable, at about 3.2 percentage points annually.

Table 4. Comparison of estimated coefficients for different methods

	Estimated value (1990)	Estimated value (2000)
OLS	0.3927 (0.0982)	0.3333 (0.0833)
IV	0.8214 (0.2054)	0.6912 (0.1728)
ATE	0.4599 (0.1150)	0.2655 (0.0664)
TT	0.7745 (0.1936)	0.5987 (0.1497)
TUT	0.6470 (0.1618)	0.4714 (0.1179)
Bias	-0.0672 (-0.0168)	0.0678 (-0.0170)
Selection bias	-0.3818 (-0.0955)	-0.2654 (-0.0664)
Sorting gain	0.3146 (0.0786)	0.3332 (0.0833)

Notes: 1. Figures in the parentheses are the annual rate of return.
2. Bias = OLS – ATE.
3. Selection bias = OLS – TT.
4. Sorting gain = TT – ATE.

$$\overline{\beta}$$

According to equation (13), the discrepancy between the estimated rate of return to education by OLS and average treatment effect is the bias caused by selection bias and sorting gain. From Figure 4, selection bias is significantly negative, 38.18% (9.55% annually), in 1990, implying sorting on the unobservable heterogeneity, and the selection process is significant in Taiwan. The sorting gain is 31.46% (7.86% annually) in 1990, implying that the rate of return to university education is much higher than the average treatment effect, i.e., average rate of return to university education (). These results reconfirm the sorting on the heterogeneous attributes according to the principle of comparative advantage in making the individual's educational decision. Comparing the results from 1990 and 2000, we find that selection bias tends to decline while sorting gain tends to increase, though at a moderate scale, in the 1990s.

In sum, due to selection bias and sorting gain, the estimated rate of return to education by the conventional OLS and IV methods are subject to bias, though the bias is not sizable, at around 1.7 percentage points, because of the offsetting consequence by selection and sorting.

We further conduct a numerical analysis to estimate the heterogeneous returns to education in Taiwan in 1990 and 2000. The results are shown in Figures 3 and 4. We find the expected rates of return to education in 1990 and 2000 are a random variable that follows certain distribution, representing the distribution of underlying heterogeneity in human capital. The expected rate of return to education in 2000 is skewed to the left and less dispersed than that in 1990.

Figure 3. The distribution of the expected rate of return to education, 1990

Figure 4. The distribution of the expected rate of return to education, 2000

5. Concluding remarks

Due to heterogeneity in human capital, the individual will self select his or her educational attainment. In this situation, sorting and selection on unobserved heterogeneity results in a bias estimator for rate of return to education using the conventional OLS and IV methods. The OLS tends to underestimate, while the IV method tends to overestimate. By considering heterogeneity in an individual's abilities and self selection in education, this paper estimates the rate of return to university education in Taiwan using Manpower Utilization survey data for 1990 and 2000.

Estimation results show that without considering an individual's heterogeneity in abilities and selection in educational choice, the OLS and IV methods will generate bias and inconsistent estimators for the rate of return to education. The estimated marginal treatment effect confirms the heterogeneous human capital hypothesis, that there is a heterogeneous rate of return to education among individuals. The declining trend of the MTE curve further justifies the self selection on unobserved heterogeneity according to the principle of comparative advantage, that those who attain university are more willing to pay a higher price for schooling and hence tend to obtain a higher return on education.

The estimated average annual rates of return to university education are 11.5% and 6.64% in 1990 and 2000, respectively, higher than the coefficients estimated by OLS. However, for those who receive university education, their marginal rates of return to education are 19% and 15% for 1990 and 2000, respectively, higher than the average rate of return. Moreover, the expected rates of return to education in 1990 and 2000 are a random variable that follows certain distribution. These results are all consistent with the theory of self selection on unobserved heterogeneous abilities. As for the declining trend of rate of return to university education, it may be caused by the rapid expansion of colleges and universities and the increasing supply of college graduates in the 1990s.

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