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Changes in Earnings Returns to Higher Education in Taiwan since the 1990s

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Abstract

Taiwan has experienced a rapid expansion in higher education since the 1990s. To gauge changes in earnings returns to higher education caused by this expansion, this paper estimates college effects on earnings using both the conventional Mincer-type regression model and the revised truncated-sample model that adjusts for the selection mechanisms into college. We also apply Xie and Wu's (2005) hierarchical linear model approach to test if the treatment effects of higher education vary as a function of propensity scores strata estimated. Using nationwide data collected in the early 1990s and the early 2000s, we focus on young entrants to the labor market. Our results indicate that average returns to college education remain stable over time. We also find that in both periods, there is a strong negative selection mechanism at work: when workers with a low latent propensity of receiving college education indeed did go to college, they benefit the most from the college attendance.

Keywords

Return to education, Taiwan, marginal treatment effect, propensity score, causal inference

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1. Introduction

Taiwan has experienced a rapid expansion in higher education since the 1990s, a period during which the demand for technically trained personnel has also increased worldwide. In 1990, there were 121 institutions of higher education with a total of 576,623 students; by 2004, the number of institutions was 159, serving 1,285,867 students (ROC Ministry of Education 2005). As a result of this expansion, 29 percent of the adult population aged 25-64 received higher education in 2004, a percentage almost twice as large as a decade ago.

There are good reasons to suspect that earnings returns to higher education have changed in Taiwan, as in many other countries, in recent years. How can we assess this change quantitatively? A simple approach is to compare estimated returns over time with a Mincer-type regression model based on human capital theory. However, this approach relies on an unrealistic assumption that returns to higher education are homogeneous across different members of a population. Recent work by Heckman and his associates (e.g., Heckman and Sedlacek 1990; Heckman, Layne-Farrar, and Todd 1996; Heckman 2001; Carneiro and Heckman 2002; Carneiro, Hansen, and Heckman 2003; Heckman and Li 2004; Heckman and Navarro-Lozano 2004; Heckman and Vytlačil 2005) suggests that returns to higher education should be conceptualized as heterogeneous at the individual level and that, due to self-selection, persons for whom the returns are greatest may be mostly likely to receive higher education when it is limited to only a small proportion of the population. Consideration of the treatment effects of higher education specific to those individuals who are at the margin of attending college is crucial for a study of how educational expansion changes earnings returns to college education. In this paper, we reformulate a “marginal treatment effect” approach, with the marginal treatment effect defined as the average treatment effect of persons at the margin of enrolling in college based on observed covariates.¹

The conventional wisdom in economics is that persons are positively selected into college education in the sense that those who actually attend college have higher returns to college education than those who do not attend college. This conjecture is based on the principles of self-selection and comparative advantage, so that the most “college worthy” individuals, in the sense of having the highest returns to college, are the most likely to select into college (Averett and Burton 1996; Carneiro, Hansen, and Heckman 2003; Carneiro, Heckman, and Vytlačil 2005; Roy 1951; Willis and Rosen 1979). If this conjecture is correct, the expansion of the higher education system is tantamount to giving higher education to persons at the margin for whom earnings returns to higher education are smaller on average than persons who would receive higher education in the absence of the expansion. Thus, the comparison of the “return” estimates in the Mincer-type regression model over time during which higher education expanded rapidly tends to exert a downward “bias” on the estimate in a more recent period.

In this paper, we apply our marginal treatment effect approach in order to recover the true changes in earnings return to higher education in Taiwan. The empirical work is based on data from the 1991, 1992, 1993, 2001, 2002 and 2003 Taiwan Social Change Surveys (TSCS). We group data from years 1991-1993 as the “earlier period,” and data from years 2001-2003 as the “later period” and look for changes between the two periods, focusing on young entrants (aged 25 to 34) to the labor market in the two periods and breaking down our statistical analyses into two parts. First, we compare earnings returns to higher education for the new entrants between the two periods using two approaches: the traditional Mincer-type regression model and the marginal treatment effect approach. And second, we apply Xie and Wu’s (2005) hierarchical linear model (HLM) approach to examine whether there is evidence for self-selection into higher education and whether college treatment effects are a function of propensity scores of receiving college education.

¹ This approach differs from the “marginal treatment effect” approach of Heckman and his associates (see Heckman, Urzua, and Vytlačil 2006), an approach that assumes that the propensity of treatment is a function of not only observed covariates but also an unobserved term. The approach of Heckman and his associates requires instrumental variables for identification.

Our results indicate stable average returns to college education, while the returns for workers at the margin of college attendance significantly are large as a consequence of the recent educational expansion. Surprisingly, the size of the treatment effect significantly declines with the propensity of college attendance, indicating that when workers with a low latent propensity of receiving college education indeed did go to college, they benefitted the most from the college attendance.

The remainder of the paper is organized as follows. We first explain the Taiwanese context under study. We then discuss methodological problems involved in the estimation of returns to schooling. After a description of the data used, we illustrate the methods used for evaluating the consequence of educational expansion on returns to college education. We finally present empirical results and conclude with discussions.

2. The Setting

In this analysis, we consider an economy in which workers can be split into two types – skilled and unskilled – skills being acquired by attaining higher education. In Taiwan, higher education refers to education provided by junior colleges, colleges, universities, and graduate schools. Junior colleges are designed to train skilled workers, constituting the lowest tier of education at the tertiary level, whereas the main task of other institutes at the same level is to provide advanced study and educate professional personnel. For simplicity, we limit our focus on earnings disparities between workers with college education – designated as skilled workers – and those without college education, designated as unskilled workers. This is clearly an oversimplification. Yet, treating higher education as a simple dichotomous treatment allows us to borrow from the literature on causal inference and to focus on the main points of the paper.

In Taiwan, educational expansion is an important exogenous factor that rapidly increases the supply of college-educated workers to the labor market. To meet the growing demand for skilled workers generated by industrialization, national manpower planning has been part of the economic development plans implemented by the state, as early as the 1960s. Prior to the lifting of martial laws in 1987, higher education was highly centralized and the “low-tuition” policy was enforced with an explicit purpose to reduce class inequality in educational opportunity by lowering the economic barrier to access higher education. During the 1990s, the state exercised less and less control over educational policies; civil society in Taiwan became more influential. To meet the increasing social demand for higher education, higher education has expanded through two major ways since the 1985 deregulation: building or licensing more new institutions; and, especially after 1997, upgrading existing ones from the lower to the higher tier. A total of 55 institutions were upgraded during the period of 1997-1999; see Tsai and Shavit (2007) for details.

Demand for higher education has always exceeded supply in Taiwan. To restrict access, Taiwan has used stringent eligibility examinations. Prior to 1995, the “Joint Entrance Examinations (JEE)” held in early July were the only mechanism for selection into colleges and universities. Those who passed the entrance examination were assigned to specific institutions and departments within these institutions, and those who failed the examination could retake it again in subsequent years. During the period of 1995-2002, certain departments in some universities were allowed to hold their own matriculation examinations and to recruit preferred students up to a certain proportion of the total intake (from 5 to 30 percent). Since 2002, almost all institutions of higher education have been granted the freedom to select preferred students up to a preferred proportion in spring first – using student’s performance in the nationwide “basic academic test” held in winter as a major qualification consideration² – and then recruit the remainder intake in the summer through the JEE. In 2004, 80 percent of graduates from

² The “basic academic test” is sponsored by the College Entrance Examination Center, which was a national agent prior to 1993. The test started in 1994, with 8,224 senior high students as participants in that year. In 2004, 143,759 senior high/vocational students took the test. The test result was decisive for passing the matriculation examination held by a specific department in a specific institute to which the student applied for admission based on rational choice.

senior high schools and 67.2 percent of those from senior vocational schools moved on to the tertiary level (ROC Ministry of Education 2005). The corresponding figure in 1990 was much lower: 48.6 percent and 12.9 percent for students from these two types of schools, respectively. As a result, the proportion of college educated persons in the adult population aged 25-34 increased from 21.8 percent in 1990 to 45 percent in 2004.

According to the economic reasoning of supply and demand, the “skill price” of college graduates in the labor market is determined by two competing forces: the *negative* supply effect and the *positive* labor demand effect. On the one hand, the rapid increase in the supply of skilled workers would decrease skill prices of college graduates, theoretically. On the other hand, if the economy moves toward more technologically based industry, in which human capital raises productivity and hence earnings, then shifts in labor demand favoring skilled workers at the expense of unskilled workers would increase earnings disparities between college-educated workers and their non-college-educated counterparts. Empirical studies using conventional Mincerian wage equations often indicate a rise in the return to schooling in almost all industrialized societies since the 1980s (Machado and Mata 2005). It is a common expectation that economic development in contemporary societies will be accompanied by an increase in college-educated workforce, as well as a rise in returns to college education (e.g., Levy and Murnane 1992; Juhn, Murphy, and Peirce 1993; Gottshalk and Smeeding 1997). Nevertheless, whether or not the average return to college education may increase over time results from the interplay between the rise in the demand for college a educated labor force on the one hand and the rise in the supply of college graduates on the other hand.

Over recent decades, Taiwan’s export-oriented economy has shifted from a high degree of labor intensity to a medium-to-high degree of technology intensity, which demands skilled labor. Besides the continued increase in the supply of college educated workers by educational expansion, international trade and technological change – which induces productivity growth – are two prominent factors contributing to economic development. In Taiwan, as in many larger societies, the upgrading of technology and international trade raise the wage disparity between skilled and unskilled workers (Chan, Chen, and Hu 1999; Firebaugh 2000; Chang 2003). Indeed, earlier studies found a rise in the importance of human capital accumulation between 1980 and 1992, with men in white-collar occupations enjoying especially high returns to schooling (e.g., Tsai and Mai 1998).

In this analysis, we focus on the supply-driven change in returns to college education since the 1990s, when shifts in the labor demand were characterized by a continued trend of more international trade and further technological upgrading, notably by the use of computers. In considering the causal impact of the educational expansion, we take seriously the issue of population heterogeneity and consider three strata: persons who would still go to college in the absence of the expansion (upper stratum), persons who would not go to college even with the expansion (lower stratum), and persons who would go to college with the expansion (the middle stratum). This conceptualization borrows heavily from the stratification approach advanced by Rubin and his associates (Angrist, Imbens, and Rubin 1996; Barnard, Frangakis, Hill, and Rubin 2003).

We speculate that it is the persons at the margin of going to college, i.e., the middle stratum, that benefit the most from the educational expansion, because the decrease in educational selectivity caused by educational expansion would attract new persons into college mostly from the margin of the ability distribution. Persons in the upper stratum would go to college, even in the absence of the education expansion. Persons in the lower stratum would not go to college even when college entrance became less difficult as a result of the educational expansion. As a result, the average return (i.e., the return for average persons) would decrease as a consequence of the recent expansion of the higher education system.

Ability is an individual trait that is not directly observable, and hence how to identify a latent group of people at the margin represents a difficult task in the evaluation of changes caused by educational expansion. We next discuss the methodological problem involved with estimating the causal effect of schooling from a cross-section of data on earnings and how we deal with the problem.

3. Methodological Problems

Did the recent higher education expansion significantly change returns to college education among the young entrants to the labor market? A conventional way to answer this question is to estimate a Mincer-type wage equation of the form:

$$\ln(Y_{it}) = \beta_t S_{it} + \gamma_t X_{it} + U_{it}, \quad (1)$$

where Y is earnings; S is a dummy variable representing whether or not the respondent receives college education ($S = 1$, if yes; $= 0$ otherwise); β is the parameter of primary concern, which is the rate of the return to college education, after controlling for the effects of X , a vector of other earnings determinants including the constant term, years of Mincer experience (defined as age – years of schooling – 6), Mincer experience-squared, gender, ethnicity, employment sector, and region; γ is a vector of coefficients; U is the error component of log earnings that includes unobserved ability; i and t are subscripts for individuals ($i = 1, \dots, n$) and periods ($t = 1, 2$), respectively.

In this expression, we estimate β separately for each period. To test if the period-specific estimates of β significantly differ in magnitude between the two periods, we estimate an equivalent (“pooled”) model that can be expressed as (for notational convenience, we will henceforth suppress the subscript i):

$$\ln(Y) = \beta S + \gamma X + \delta_s I_s + \delta_x I_x + U, \quad (2)$$

where $I_s = tS$ and $I_x = tX$; t is a scalar dummy variable representing period (the later period = 1); δ_s is the parameter of major concern here, which captures change in the return to college education over time, and δ_x is a vector of parameters representing the interaction effects between the covariates (X) and period (t).

We start our empirical analysis by estimating the model in both forms, although we are aware of the limitations of the Mincer-type approach. Social scientists have been cautioned on drawing strong inferences about the causal effect of schooling from observed data, despite the conventional wisdom that earnings increase with education; see Card (1999, 2001) for a recent survey of the literature. In the absence of evidence from randomized experiments, it is difficult to pin down precisely how much the higher earnings observed for college-educated workers are caused by their higher education, or whether workers with greater earnings capacity – e.g., unobserved ability – select (or are selected) into higher education. It is well-known that if unobserved ability is positively correlated with schooling choice and earnings, the *OLS* estimate of the return to schooling that fails to take account of ability will be upwardly biased; see Griliches’ (1977) classic statement of this problem.

Moreover, there is no such thing as “the” return to college education in a population, given the inherent heterogeneity of human behavior (Xie 2007). It is unrealistic to assume a single effect of schooling choice. More realistically, different members in a population can have different causal effects of education. Indeed, theories of educational attainment based on rational choice – be they of the economic “human capital” (Becker 1964; Mincer 1974) or the sociological varieties of “maximally maintained inequality” (Raftery and Hout 1993) or “formal rational action” (Breen and Goldthorpe 1997) – posit that individuals and their families choose among the different educational options available to them on the basis of their cost-and-benefit evaluations and their perceived probabilities of more or less successful outcomes. This principle of human rationality forms the basis for the expectation that persons with potentially higher returns to education are more likely to choose (or should we say, to be chosen) to go to college, which, in turn, will benefit them more than others in terms of labor market outcomes such as earnings.

When there is individual heterogeneity and self-selection in educational attainment, there can be potential selection biases in estimating the causal effect of schooling based on observed data alone. Conventional approaches to selection and missing data problems do not account for the heterogeneity in responses to schooling, i.e., persons choose to go to college based on their own idiosyncratic return

(conditional on X). Recently, Heckman and his associates developed a new micro-econometric semi-parametric framework that accounts for heterogeneity and selection (see, for example, Heckman and Sedlacek 1990; Heckman, Layne-Farrar, and Todd 1996; Heckman 2001; Carneiro and Heckman 2002; Carneiro, Hansen, and Heckman 2003; Heckman and Li 2004; Heckman and Navarro-Lozano 2004; Heckman, Urzua, and Vytlačil 2006; Heckman and Vytlačil 2005). Roy (1951) outlines a prototypical model of economic choice based on comparative advantage in skills. The classical Roy model has been successfully applied by Willis and Rosen (1979) in an empirical setting and, more recently, further clarified and extended by Heckman and his associates (Heckman and Honoré 1990; other works cited above).³

According to this new line of work by Heckman and his associates, returns to higher education should be conceptualized as heterogeneous at the individual level, because the treatment effect is a person-specific counterfactual. For person i it answers the question, what would be the outcome if the person received the treatment compared to the case where the person had not received the treatment? In the notations of equation (1), the two potential selection outcomes for each person are:

$$\ln(Y_1) = \gamma_1 X + U_1 \quad \text{if } S = 1 \quad (3a)$$

$$\ln(Y_0) = \gamma_0 X + U_0 \quad \text{if } S = 0 \quad (3b)$$

where $E(U_1 | X) = 0$ and $E(U_0 | X) = 0$ in the population. The individual-level treatment effect of college education is $\Delta = \ln(Y_1) - \ln(Y_0) = (\gamma_1 - \gamma_0) X + (U_1 - U_0) = \beta$, which is the casual effect of education.

A person would go to college if $\beta > 0$, according to Roy's classical self-selection model. Nevertheless, there are two potential methodological problems, further complicating the well recognized problem of ability bias arising from the correlation between S and U_0 (i.e., more able person receives more education). First, if β is correlated with S – i.e., schooling decisions are made with rational expectation of β to some degree – then β for persons who attend college are higher than those who do not attend college. Second, β may be correlated with U_0 , which means the possibility to obtain β may be dependent on the level of earnings one would make if the person did not go to college, as in the Roy model. In such a situation, the best person without college education (those with high U_0) may have the lowest return to college education, or people who go to college may be the worst persons in the Y_0 distribution even though they could be the best persons in the Y_1 distribution (Willis and Rosen 1979). In short, when β varies in the population, there can be comparative advantage. This means that there is a distribution of treatment effect for different groups, i.e., conditioning on different sets.

With respect to the evaluation of the impact caused by educational expansion, a basic problem is that we do not observe the same person in both treated and untreated states at the same time. Thus, it is impossible to observe both Y_1 and Y_0 for any one person. Only one state of the two can be observed: information on Y_1 is missing for workers without college education, whereas Y_0 cannot be observed for workers with college education. We can compute averages in earnings for workers with college education and for workers without college education. In other words, it is easy to construct the means $E(Y_1 | X, S = 1)$ and $E(Y_0 | X, S = 0)$. However, we never know

$E(Y_1 | X, S = 0)$, which is the expected average earnings of non-college-educated workers (conditional on X) if they had attended college education, and

$E(Y_0 | X, S = 1)$, which is the expected average earnings of college-educated workers (conditional on X) if they had not received college education.

³ The Roy model has also been widely applied to a variety of labor market settings, including female labor force participation (Heckman 1974), union versus nonunion employment (Lee 1978), choice of industrial sectors (Heckman and Sedlacek 1985, 1990; McLaughlin and Bils 2001), and choice of migration (e.g., Borjas 1987; Shumway and Hall 1996; Dahl 2002; Chiquiar and Hanson 2005).

Thus, conventional methods fail to identify the treatment effects of concern, unless selection into higher education is inconsequential, in which case, we can assume

$$E(Y_1 | X, S = 1) = E(Y_1 | X, S = 0) \text{ and}$$

$$E(Y_0 | X, S = 1) = E(Y_0 | X, S = 0).$$

This condition can be satisfied if selection into higher education is random. However, as well known, higher education is a valuable resource – economically as well as socially – that is often unevenly distributed across different social groups, such as those defined by gender, ethnicity, and class. The essays in Shavit and Blossfeld (1993) and Shavit, Arum, and Gamoran (2007) indicate the universal importance of family influences on educational attainment.

The impossibility of observing the same person in both treated and untreated states leads to the necessity of what Holland (1986) calls “statistical solution” – use of a variety of average treatment effects for a defined population or subpopulation. For example, the average return to college education can be defined as the difference in mean earnings if the whole population attends college versus if the whole population does not attend college. Three parameters of differential population means conditional on the covariates are of particular relevance to the evaluation of the implementation of new educational policies. They are:

- (1) ATE = $E(Y_1 - Y_0 | X)$, which is the average treatment effect (i.e., the effect of randomly assigning a person with characteristics X to college education);
- (2) MTE = $E(Y_1 - Y_0 | X, S)$, which is the marginal treatment effect (i.e., the average return to college education given characteristics X and unobserved individual heterogeneity U); and
- (3) ATT = $E(Y_1 - Y_0 | X, S = 1)$, which is the average treatment on the treated (i.e., the average return to college-educated workers with characteristics X).

Each of these estimands, or quantities of interest, is a mean of the individual treatment effect, but with different conditioning sets. Estimating these treatment effects is not a straightforward matter. We next discuss how we estimate the average return (i.e., the return for average persons), the marginal return (the return for persons at the margin), and their changes over time.

4. Data and Methods

In this section, we illustrate the methods that we employ to assess changes in earnings returns to college education between the 1990s and the 2000s, using data from the Taiwan Social Change Surveys (see <http://www.ios.sinica.edu.tw/sc1/> for details of the surveys). Descriptive statistics of variables for the two types of workers analyzed are presented in Table 1; see Appendix A for details of the sample selection and measurements of the variables used.

As shown in Table 1, the percentage of college-educated workers among the young entrants (aged 25-34) to the labor market increased from 29% in the early 1990s to 52.7% in the early 2000s. In both periods, the average earnings of college-educated worker was significantly higher than that of non-college-educated workers ($\alpha = .05$). We observe that college-educated workers were more likely to reside in major cities and to hold a job in the public sector, but less likely to be self-employed or on a farm. In addition, they were more likely to come from better-educated families, with both father’s and mother’s years of schooling significantly higher, on average, than those of non-college-educated workers. These patterns illustrate the importance of seriously considering the selection of college attendance.

Table 1. Descriptive Statistics: Two Types of Workers Aged 25-34 in the Two Periods

Variable	Earlier Period			Later Period		
	Total	College-educated	Non-college-educated	Total	College-educated	Non-college-educated
1.N [%]	2,522 [100]	731 [29.0]	1,791 [71.0]	1,652 [100]	871 [52.7]	781 [47.3]
2. Discrete Variable: %						
Male	57.4	61.0	55.9	55.0	52.5	57.7
Ethnicity						
Hokkien	73.1	67.2	75.5	74.2	71.8	77.0
Hakka	11.2	9.2	12.1	12.6	13.0	12.3
Mainlander	14.6	23.2	11.0	11.1	14.6	7.3
Aborigine	1.1	.4	1.3	2.0	.7	3.4
Employment sector						
Private employee	66.1	62.5	67.6	76.4	74.0	79.0
Public employee	10.7	23.2	5.6	12.4	20.2	3.7
Self-employment	19.3	13.4	21.7	9.8	5.4	14.7
Farming	3.9	.8	5.1	1.4	.3	2.6
Region of residence (= 1, if major city)	32.8	45.0	27.9	30.5	37.0	23.3
3. Continuous Variable: Mean						
Monthly Earnings	31,982 (23,113)	36,546 (21,537)	30,120 (23,478)	36,819 (24,610)	40,092 (23,858)	33,169 (24,935)
Log of Earnings	10.203 (.553)	10.382 (.479)	10.130 (.564)	10.380 (.500)	10.487 (.459)	10.259 (.517)
Mincer experience (= age - schooling - 6)	11.980 (4.361)	8.286 (2.952)	13.488 (3.922)	10.112 (3.890)	8.007 (3.115)	12.460 (3.276)
Father's years of schooling	6.304 (4.244)	8.784 (4.264)	5.292 (3.796)	8.247 (3.823)	9.468 (3.924)	6.885 (3.199)
Mother' years of schooling	3.816 (3.678)	5.647 (3.912)	3.069 (3.299)	6.370 (3.622)	7.393 (3.699)	5.230 (3.168)

Note: Numbers in parentheses are standard errors.

Since survey data usually do not directly measure factors (such as ability) that underlie selection into college attendance, four analytical strategies are used in the literature: (1) the instrumental variable (*IV*) estimation, (2) the fixed effect method (e.g., twin studies), (3) proxy measurement for such factors as ability, and (4) multivariate analysis controlling a large number of observed covariates.⁴ In this analysis, we apply the last method under the assumption of ignorability. Specifically, we use the propensity score matching method to adjust for observed covariates that may account for selection, under the assumption of ignorability (Holland 1986). We do not necessarily believe the validity of the ignorability assumption but invoke it to facilitate data analysis. Under this provincial assumption, we are able to determine who benefits and who loses from recent educational expansion. Following Xie and Wu (2005), we will later critique the assumption after examining the results that are derived from the assumption.

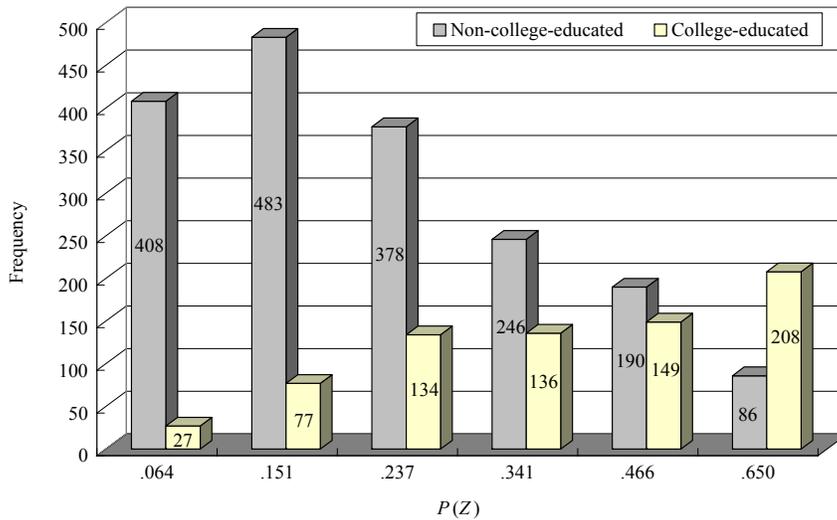
It appears contradictory that we assume “ignorability” but consider heterogeneous treatment effects in our analysis. This is not a contradiction, because we assume heterogeneity in treatment effects, as well as heterogeneous propensity to treat (i.e., go to college), and indeed estimate these forms of heterogeneity as functions of observed covariates. In our analysis, we break down the sample into groups by estimated propensity score and then analyze group-differences in treatment effects. The combination of heterogeneity in treatment propensity and heterogeneity in treatment effects reveals selection biases at the group level (Xie and Wu 2005).

Our approach goes like this: we first use binary logistic regressions predicting the odds of receiving college education for both periods and derive a propensity score $P(Z)$ for each person included in the

⁴ These methods are very different. However, Ashenfelter, Harmon, and Oosterbeek (1999) report that their empirical results are not sensitive to methods used.

sample.⁵ The support of the estimated $P(Z)$ is shown in Figures 1 and 2, where the distribution of different types of workers across 6 $P(Z)$ strata is depicted for the two periods, respectively; see Part A of the figures for comparisons between workers with college education (i.e., the treatment group) and those without it (i.e., the control group). As expected, there are opposite patterns of the frequency distribution for the treatment and control groups, irrespective of period. In the case of college-educated workers, the frequency count increases with the median of the propensity scores, whereas it decreases across propensity score strata in the case of non-college-educated workers, with a minor exception.

A. Comparing Workers with and without College Education



B. Comparing Middle Stratum and Lower Stratum within Non-college-educated Workers

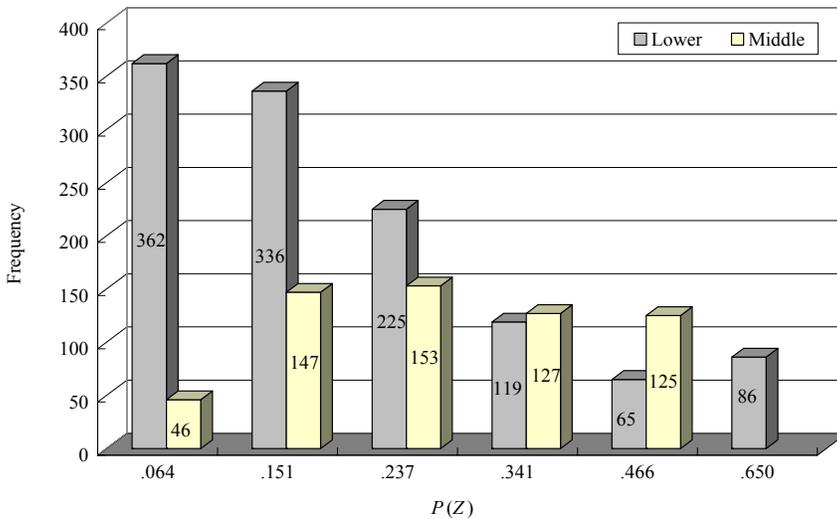
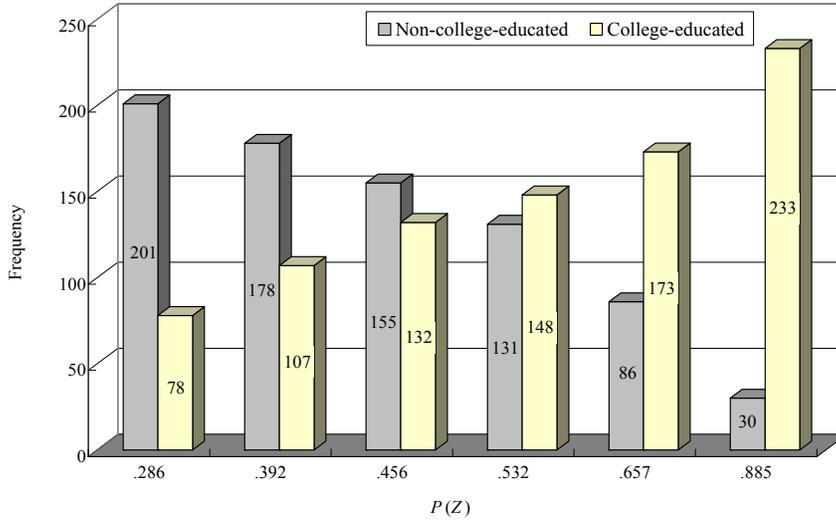


Figure 1. Histogram of the Estimated Propensity Score for Different Types of Workers in the Earlier Period

⁵ $P(Z)$ is derived from a binary logit regression predicting the log-odds of attaining higher education in each period. We include the following variables as predictors in the propensity score model: gender, dummy variables for ethnic groups and whether or not father/mother receives higher education, father's years of schooling and mother's years of schooling (including their square term and interaction), birth-year specific dummy variables for cohort, and many interactions between gender/ethnicity/cohort and parental education.

A. Comparing Workers with and without College Education



B. Comparing Upper Stratum and Middle Stratum within College-educated Workers

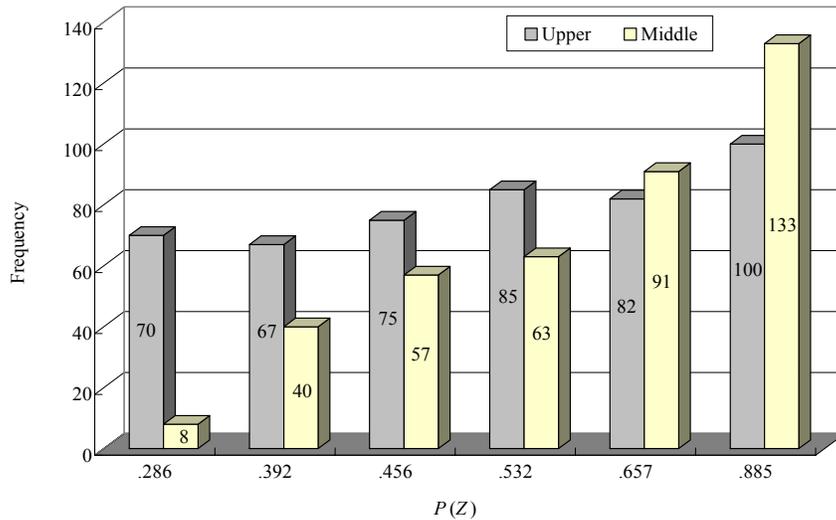


Figure 2. Histogram of the Estimated Propensity Score for Different Types of Workers in the Later Period

The propensity score $P(Z)$ means the probability that a person goes to college. Differences in estimated propensity scores among those who do not attend college mean that they have different likelihoods to attend college. When college enrollment expands, we can use this information to simulate a subset of workers without college education in the earlier period as marginal persons, by randomly sampling them using $P(Z)$ up to the desired proportion,⁶ as shown in Part B of Figure 1. We also apply the same method to identify a subset of college-educated workers in the later period as marginal persons; see Part B of Figure 2.

Because in the earlier period 29% of workers received college education and in the later period 47.3% of workers did not go to college, we take the former percentage as the size of “upper stratum” who would go to college even in the absence of educational expansion, and the latter percentage as the size of the “lower stratum” who would not go to college even when higher education is transformed from “elite” education to “mass” education. We then compute the percentage of workers induced to attend higher education by the recent expansion to be 23.7% (= 100 - 29 - 47.3). This latent “middle stratum”

⁶ The values on the X-axis in Figures 1 and 2 are the medians of the 6 propensity score strata. In our identification of the marginal-ability group, we use values of $P(Z)$ between 5% and 95%; see Carneiro, Heckman, and Vytlacil (2005: 25) for the importance of this trimming of the observations in the sample.

consists of marginal persons who would not go to college in the pre-expansion regime but would go to college in the post-expansion regime. While in actual data we do not observe them in either period, we use our estimated propensity score to construct a simulated “middle stratum” that is statistically comparable between the two periods.

We finally employ the regression method to compare the earnings disparities across the three strata identified – namely, upper, middle, and lower stratum – using the “truncated-sample” model that adjusts for the selection based on observables. We also estimate period-specific treatment effects of college education through a hierarchical linear model (HLM); see Xie and Wu (2005) for details of the HLM approach applied here.

5. Results

5.1 Stability in the return to college education?

At the beginning of the empirical analysis, it is constructive to estimate the Mincer-type model – as specified in Equations 1 and 2 – and report the result in Table 2. Inspection of the table reveals that after controlling for the effects of the covariates (X), the estimated average return to college education in the later period ($\beta = .255$) is larger than that in the earlier period ($\beta = .224$). Nevertheless, the increase in average treatment effect of college education over time ($\Delta\beta = .031$) is not statistically significant at the level of $\alpha = .05$.

Table 2. Results from the Mincer-type Model of the Return to College Education

Independent Variable	(1) Earlier Period	(2) Later Period	(3) = (2) – (1) Change
Intercept	9.863* (.040)	9.980* (.050)	.117 (.065)
College attendee (= 1, if yes)	.224* (.027)	.255* (.028)	.031 (.039)
Mincer experience	-.001 (.003)	.011* (.004)	.012* (.005)
Experience ²	-.002* (.000)	-.005* (.001)	-.003* (.001)
Male (= 1, if yes)	.394* (.020)	.267* (.022)	-.127* (.030)
Ethnicity (relative to Hokkien)			
Hakka	.068* (.031)	.084* (.034)	.016 (.046)
Mainlander	.062* (.028)	.086* (.036)	.024 (.046)
Aborigine	-.126 (.092)	-.036 (.080)	.090 (.123)
Employment sector (relative to private employee)			
Public employee	.065* (.032)	.173* (.035)	.108* (.048)
Self-employment	.292* (.025)	.230* (.038)	-.062 (.047)
On farm	-.120* (.051)	-.137 (.096)	-.017 (.111)
Region of residence (= 1, if major city)	.091* (.021)	.053* (.025)	-.038 (.033)
R ²	.263	.195	.259
N	2,522	1,652	4,174

* Significant at the level of $\alpha = .05$; Numbers in parentheses are standard errors.

Does this finding imply stability of the causal effect of college education since the 1990s? Or is this stability simply a biased result of *OLS* estimators? Conceptually, the negative supply effect would lead to a decrease in the average return to college education between the two periods. However, the labor demand shifts in favor of skilled workers at the expense of unskilled workers, so that the

supply-driven decrease could be counterbalanced by the potential increase in positive effects of demand-side forces. This counterbalance may yield a stable average return to college education over time.

Further, one problem with this model is that unobserved ability may bias period-specific estimates of β_t downward (Griliches 1977). An implication of this ability bias for cross-period comparisons is that change in β_t ($\beta_\Delta = \beta_2 - \beta_1$) can be biased either downward or upward, depending on whether variation in the share of skilled workers over time is driven by supply factors or (unobserved) demand factors. Because in Taiwan educational expansion serves as a key driving-force, we conjecture that the comparison of the return estimates in the Mincer-type regression model over time during which higher education expanded rapidly tends to exert a downward “bias” on the estimate in a more recent period.

5.2. Downward bias in the conventional estimator in the later period?

To gauge “true” returns to college education, we next estimate the truncated-sample model that allows for the selection of college attendance and adjusts for the selection statistically based on observed covariates. This estimation result is reported in Table 3, which shows consistent findings with Table 2, as far as the effects of the covariates X and their pattern of change over time are concerned (e.g., declining male advantage and stable pattern of earnings disparities across ethnic groups). Comparison between Tables 2 and 3 reveals the extent to which the earnings return to education for the middle stratum resembles the return for the upper stratum.

Table 3. Results from the Truncated-sample Model

Independent Variable	(1) Earlier Period	(2) Later Period	(3) = (2) – (1) Change
Intercept	9.872* (.042)	9.983* (.050)	.111 (.066)
Stratum (relative to lower)			
Upper	.216* (.028)	.268* (.031)	.052 (.042)
Middle	-.019 (.024)	.236* (.034)	.255* (.042)
Mincer experience	-.001 (.003)	.011* (.004)	.012* (.004)
Experience ²	-.002* (.000)	-.005* (.001)	-.003* (.001)
Male (= 1, if yes)	.394* (.020)	.267* (.022)	-.127* (.030)
Ethnicity (relative to Hokkien)			
Hakka	.067* (.031)	.084* (.034)	.017 (.046)
Mainlander	.062* (.028)	.087* (.036)	.025 (.046)
Aborigine	-.130 (.093)	-.039 (.080)	.091 (.123)
Employment sector (relative to private employee)			
Public employee	.065* (.032)	.175* (.035)	.110* (.048)
Self-employment	.292* (.025)	.229* (.038)	-.063 (.047)
On farm	-.120* (.051)	-.139 (.096)	-.019 (.111)
Region of residence (= 1, if major city)	.091* (.021)	.054* (.025)	-.037 (.033)
R ²	.263	.196	.259
N	2,522	1,652	4,174

* Significant at the level of $\alpha = .05$; Numbers in parentheses are standard errors.

As shown in Table 3, in the later period the difference in average returns to college education between the upper stratum and the lower stratum is estimated to be .268, indicating that predicted earnings of workers in the always-college-attende stratum are significantly higher than their never-college-attende counterparts by 26.8% in the log form. This average treatment effect for the upper stratum is slightly larger than the average effect reported in Table 2 (i.e., $\beta = .255$ for earnings disparities between the treatment group and the control group). By comparison, the average treatment effect for the upper stratum (i.e., the treatment group) in the earlier period is lower as we move from Table 2 ($\beta = .224$) to Table 3 ($\beta = .216$). These observed patterns are consistent with the speculation of a greater downward bias in the conventional *OLS* estimator in a more recent period.

5.3. Who benefits and who loses from educational expansion?

In the early 2000s, skilled workers in the upper stratum remain the ones who get ahead in the labor market. Their earnings are significantly higher than predicted earnings of their lower-stratum counterparts, irrespective of period. In Table 4, we report predicted earnings for every stratum in each period, based on the estimation result reported in Table 3. As we noted earlier, the upper stratum had significantly higher earnings over the lower stratum in both periods, ever after isolating the influence of educational expansion in Table 3 ($\beta = .216$ in the earlier period and an estimate of $\beta = .268$ in the later period). However, the difference in magnitude between these two coefficients is tiny (.052) and statistically non-significant. We thus find that earnings disparities between the stratum that always go to college and the stratum that never go to college remain stable over time.

Table 4. Predicated Earnings: by Types of Workers and Period

Types of Workers	Earlier Period	Later Period
1. Under the Mincer-type model		
College-educated workers	33,209 (7,835)	36,520 (7,037)
Non-college-educated workers	25,993 (6,924)	29,052 (5,452)
2. Under the truncated-sample model		
Upper stratum	33,210 (7,842)	37,270 (7,278)
Middle stratum	26,394 (6,578)	35,616 (6,711)
Lower stratum	25,794 (7,094)	29,052 (5,451)

Note: Numbers in parentheses are standard errors.

It is hardly surprising that unskilled workers in the lower stratum are the ones who lose from educational expansion. As we can see in Table 3, the contrast between the lower stratum and the middle stratum yields an estimate of $\beta = -.019$ in the earlier period and an estimate of $\beta = .236$ in the later period. The former is negligible, but the latter is large and significant, yielding a significant change in their contrast over time (.255). In other words, there has emerged a profound earnings gap between the lower stratum and the middle stratum since marginal persons were selected into college, leaving lower-stratum people behind. As shown in Table 4, in the later period predicted earnings for the lower stratum (NTD\$29,052) is significantly lower than that of the middle stratum (NTD\$35,616), which is significantly lower than that of their upper stratum counterparts (NTD\$37,270).

Marginal persons are the ones who benefit from recent expansion of the higher education system. In the earlier period, people in the middle stratum were not treated into college education, because they were hindered by limited educational resources, both private and public. As a result of not going to college, the middle stratum as unskilled workers suffered in the labor market, making earnings significantly lower than college-educated skilled workers. Due to the opening-up of educational policies, the middle stratum became part of the treatment group; in the later period their earnings (conditional on the covariates) are not significantly different from their upper stratum counterparts, albeit still lower by 3.2% in the log form. Between the period, the middle stratum stood to gain, relative to the upper stratum by .203 (with a standard error of .044; not shown in Table 3). This is a

significant effect.

5.4. Treatment effects as a function of propensity scores?

Our final task in this analysis is to test if treatment effects are a function of propensity scores estimated. More precisely, we apply Xie and Wu's (2005) approach to test if there are heterogeneous treatment effects between college-educated workers and non-college-educated workers, and if the heterogeneity in treatment effects is correlated with the propensity of treatment. That is to say, we first estimate the treatment effect specific to propensity score strata. We then pool the results across strata and allow for heterogeneous treatment effects through a hierarchical linear model.

Summary findings of parallel period-specific analysis are presented in Figure 3, in which dots represent point estimates of stratum-specific treatment effects, with corresponding t values (adjacent to the dots) for earnings comparison between college-educated workers (the treatment group) and non-college-educated workers (the control group). The linear plot is based on the HLM estimates (level-2 model with slopes from level-1 model as outcomes regressed on propensity stratum rank).

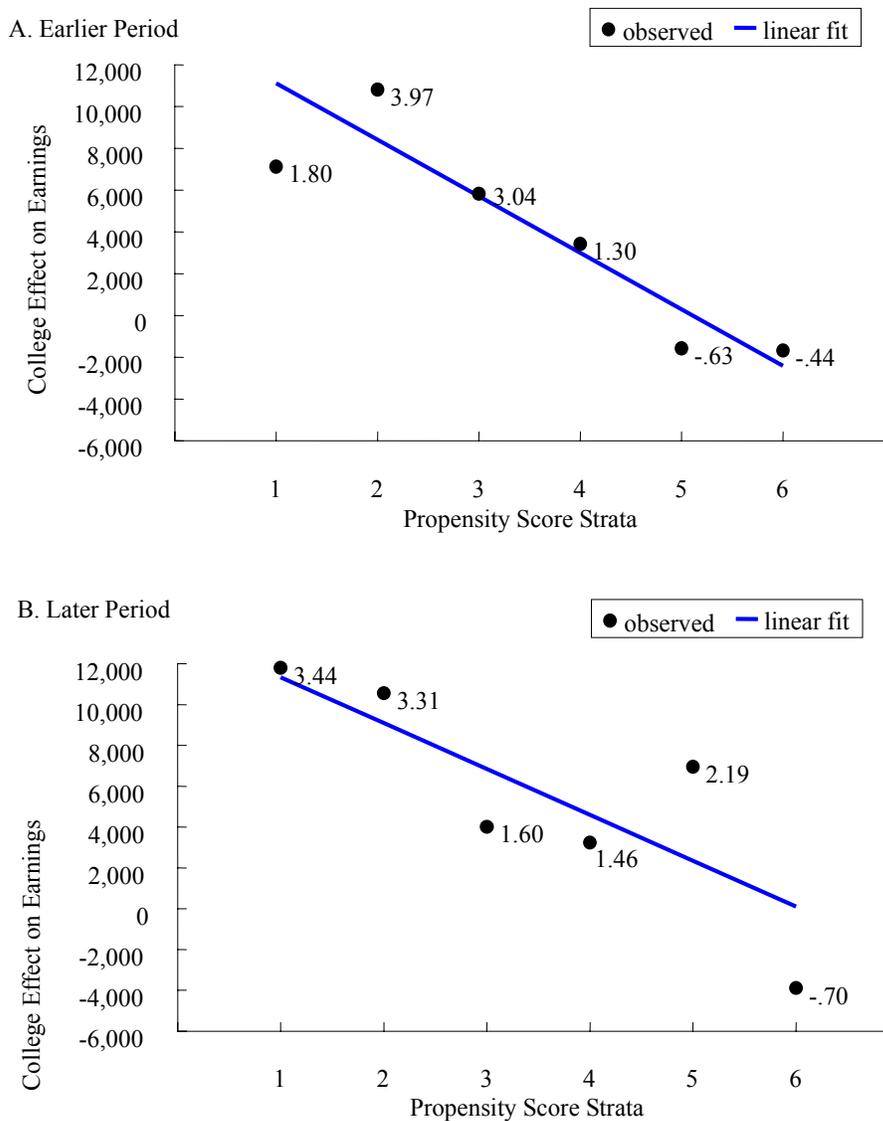


Figure 3. Treatment Effect on Earnings by Propensity Strata: College-educated Workers vs. Non-college-educated Workers

Inspection of Figure 3 indicates that period-specific findings are similar to each other in two ways. First, the t value (for the null hypothesis that the stratum-specific treatment effect is zero) is not consistently greater than 1.96 across the 6 stratum estimated. In other words, the earnings gap between the treatment and control groups is not statistically significant within every propensity score stratum. Second, the downward linear plot depicted in the figure shows that the treatment effects decline with the propensity stratum rank. The effect of propensity stratum rank in the earlier period is large and statistically significant (with a t ratio = -5.52, $df=4$, and p -value = .001), and so is the effect in the later period (t ratio = -3.23, $df = 4$, p -value = .041). In both periods, the size of the treatment effect strongly and negatively depends on the propensity of college attendance, with a unit change in stratum rank (i.e., crossing a propensity score stratum) associated with a reduction of NTD\$2,705 in the treatment effect in the earlier period, and NTD\$2,249 in the later period. In other words, the benefit of going to college is the greatest among those who were least likely to go to college and diminishes with the propensity of going to college. We thus find a strong selection mechanism at work: when workers with a low latent propensity of receiving college education indeed did go to college, they benefit the most from the college attendance.

6. Conclusion and Discussions

One of the well-established empirical regularities from around the world is that on average, college-educated workers earn higher wages than their less-educated counterparts.⁷ The earnings disparity between these two types of workers is a useful measure of the college premium. Since the return to schooling was introduced as a central concept in human capital theory (Becker 1964; Mincer 1974), numerous studies have sought to estimate the “true” amount of college premium to determine whether there is overinvestment in higher education or underinvestment in higher education.

In this analysis, we compare the Mincerian estimators of college effects with those obtained from using our marginal treatment effect approach that adjusts for the selection of college attendance based on observed covariates. A central purpose is to evaluate the impact of the rapid increase in the supply of college-educated workers upon earnings disparities between skilled and unskilled workers starting from a baseline economy that described Taiwan in the early 1990s. We focus on the supply-side change in college treatment effects on earnings, with a convenient assumption that the labor demand for young workers in the earlier 2000s are characterized by a continued trend favoring skilled workers at the expense of unskilled workers.

Our empirical result indicates that average returns to college education remain stable over time. Besides, there are heterogeneous college effects on earnings, irrespective of period. While the economic theory suggests that the premium to education should be higher for persons who have higher propensities of receiving education (Heckman 2001), our finding is the opposite. One possible explanation for this unexpected finding is that the observed covariates in our propensity model are mostly ascribed socioeconomic variables rather than ability. If all children from high SES families attend college, but only high-ability children from low SES families attend college, the observed premium of college education would be higher for persons from low SES families, who also have low propensities to attend college. Thus, we suggest a strong negative, unobserved selection mechanism at work: when workers with a low latent propensity of receiving college education do indeed go to college, they benefit the most from the college attendance.

It is commonly believed that as a society becomes industrialized, differentiation of societal structure allows the emergence of the normative principle of meritocracy and that higher education represents to some degree the kind of merit that the society would like to see rewarded, most notably in the thesis of industrialism. While higher education plays an increasingly important role in industrialized societies, there is a possibility that the market value of college education might be diluted to some extent by rapid expansion of the higher education system at a large scale. This dilution, however, may

⁷ For example, see Alderson and Nielsen (2002) for cases of more economically developed countries and Glewwe (2002) for less developed ones.

be reconciled by a rise in the average return to college education caused by the increasing demand for skilled workers since the 1990s, when the economy continues to be “upgraded” from an industrial to a digital one. As a result of equilibrium in these two competing forces, the average return to college education may remain stable over time.

It is self-evident that expansion of higher education is important, not only because it may increase the return for marginal persons, but also because the attainment of higher education may help those who were handicapped by limited educational resources to escape from disadvantaged backgrounds and to improve their economic well-being. Our study shows that, in contemporary Taiwan, the earnings return to higher education is indeed higher for those who are unlikely to attend college than those who are in such privileged social positions so as to be likely to attend college.

Appendix A

Details of the Sample Selection and the Variables Used

The Taiwan Social Change Survey (TSCS): TSCS is a series of island-wide surveys conducted by the survey office at Academia Sinica. It is an ongoing project designed to create data sets on the main themes of Taiwan’s changing society. From 1990 onward, the data are collected annually on repeated cross sectional representative samples. For this analysis we use the TSCS data collected in the earlier period (i.e., 1991, 1992, and 1993) and the later period (i.e., 2001, 2002, and 2003).

In order to compare young entrants (aged 25-34 when surveyed) to the labor market over time, we selected 2,522 workers born between 1957 and 1968 from the early period samples and 1,652 workers born between 1967 and 1978 from the later period samples. Our analysis is based on the information ascertained from these 4,174 workers who reported non-zero earnings and who provided complete information on parental education and education, among other things.

In addition to age/cohort/period and gender (scored 1 if male; 0 if female), the variables considered are: college education, earnings, labor force experience, region, sector, ethnicity, and parental education. Next, we discuss each of these variables in turn.

College education: The binary treatment into college education is indicated by a dummy variable scored 1 if the respondent’s highest level of education is junior college or higher (i.e., 14 years of schooling or higher); 0 if otherwise (i.e., 12 years of schooling or lower).

Earnings: TSCS surveys asked information on respondents’ monthly earnings using a close-form question with categories that truncated the highest earnings at NTD\$200,000 in the earlier period and at NTD\$300,000 in the later period. About 0.31% of the earlier period samples gained earnings more than NTD\$200,000 per month. A decade later, the percentage of this category increased to 0.49%; in cohort 1966-78 the top 0.33% earned NTD\$300,000 or higher per month. Because of this difference, whenever the two data sets are pooled together, a dummy variable controlling for period is included in the earnings regressions, in which monthly earnings are measured in the (natural) log form.

Labor force experience: TSCS data are short of a direct measure of labor force experience, and hence we use Mincer’s definition of labor force experience as age minus years of schooling minus six. A variable of the square of experience is also considered in the earnings equations. Because there is a high correlation between experience and experience², we subtract the variable of Mincer experience from its own mean in computing the variable of experience², in order to avoid the problem of multicollinearity in the regression analysis.

Region: Region of residence was measured by a dummy variable, which is scored 1 if the respondent lived in one of the seven major cities in Taiwan (including two metropolitan cities – Taipei and Kaohsiung– and five main cities at the provincial level) when surveyed; 0 otherwise.

Sector: Employment sector is a multidimensional measurement involving industry and class. We first

use a dummy variable (= 1 if the respondent was on farm; = 0 otherwise) to single out the declining tiny agriculture sector whose workers were at disadvantages in earnings. For workers in non-agriculture sectors, we then use two dummy variables to contrast earnings disparities between employees in the private sector (the reference group in the earnings equations) with those in the public sector and those who were self-employed.

Ethnicity: Ethnicity refers to the contrast between the Hokkien (the numerical majority) and the other three groups (the Hakkas, the Mainlanders, and the Aborigines). The Hokkien and Hakka (the minority) are descendents of early Chinese immigrants, and are differentiated primarily by their dialects and the areas on Mainland China from which they came. Together, the Hokkien and Hakka constitute the majority of “Taiwanese.” By contrast, Mainlanders – post-World War II immigrants from the mainland and their Taiwan-born offspring – currently make up about 14 percent of the total population. There is also a small (less than 2 percent) Aboriginal population in Taiwan. The ethnic composition in the analysis sample is close to that of the population.

Parental education: Parental education was measured in two ways: years of schooling completed and dummy variables indicating whether or not father/mother received higher education. Variables related to parental education are used in the treatment selection equations, but not in the earnings equations.

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