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Revisiting Selection in Heterogeneous Returns to College Education*

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ABSTRACT

Sociologists describe the pattern of selection in heterogeneous returns to college education as negative, in contrast to the positive selection proposed by economists. This article moves beyond such a conflicting contrast, suggesting that the contradictions between "selection on observables" and "selection on unobservables" are at the heart of the contradictions between these two selection hypotheses. Employing both sociological and econometric counterfactual approaches to estimate college treatment effects, this article shows that the negative pattern of social selection based on family background characteristics and the positive pattern of self-selection based on the principle of comparative advantage are not mutually exclusive—both patterns emerged in the early 1990s, when Taiwan's higher education systems were rationed with structural barriers. Since Taiwan's swift expansion in higher education over the last two decades, nevertheless, there have emerged signs of decline in the treatment effect for the treated, coupled with a sorting loss in the face of negative social selection.

Key Words: social selection, self-selection, sorting gain, college treatment effect, counterfactual analysis

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I. Introduction

In a 2010 *American Sociological Review* article, Brand and Xie provide evidence for *negative* selection in heterogeneous returns to college education, using two American data sets, one from the National Longitudinal Survey of Youth (NLSY) and another from the Wisconsin Longitudinal Survey. They find that individuals who are *least* likely to obtain a college education benefit most from college, contradictory to the prediction of the *positive* selection hypothesis in economics, namely, individuals who are *most* likely to obtain a college education benefit most from college. The positive selection hypothesis is supported by the prominent work of Heckman and his associates, among others. It suffices to cite an example here. In a 2011 *American Economic Review* article, Carneiro, Heckman, and Vytlacil provide evidence of positive selection for the United States, using an NLSY data set and a measure of ability (Armed Forces Qualification Test).

Why are the leading hypotheses and findings in sociology and economics contradictory? Brand and Xie (2010) provide two explanations. One is given in the text (Brand and Xie, 2010: 291), saying that: "Empirical support for positive selection is sometimes based on models that omit key variables such as ability, high school academic performance, and parents' and teachers' encouragement. Omitting these important confounders may introduce a distortion to the observed pattern of selection from negative to positive." Another explanation is given in Footnote 28 (Brand and Xie, 2010: 298), indicating that Heckman and his associates do not accept the ignorability assumption invoked in their study. The ignorability assumption is also called "selection on observables" or "unconfoundedness", assuming that potential outcomes are uncorrelated with treatment status, conditional on observed covariates.

There are, of course, other explanations for the controversy of negative selection vs. positive selection. In this article, I suggest that such seemingly contradictory hypotheses and findings between sociology and economics are primarily due to between-discipline differences in selection mechanisms of concern and methodologies developed to address the discipline-specific concern. The work of Brand and Xie (2010) tackles selection bias due to observed individual attributes, using a statistical method which is later called "SM-HTE" (stratified-multilevel method of heterogeneous treatment effects) in Xie et al. (2012). In contrast, unobservables are at the heart of the positive selection proposed in Carneiro et al. (2011), although observables also play a part in self-selection based on the principle of comparative advantage. Using Heckman, Urzua, and Vytlacil's (2006) "MTE" (marginal treatment effect) approach, Tsai and Xie (2011) find some evidence of *positive* selection for Taiwan in the early 2000s, inconsistent with Tsai and Xie's (2008) earlier conclusion of *negative* selection at work in Taiwan, based on the "SM-HTE" results. Is this inconsistency an artifact of the methods used? Reflection on this question prompts a more general analysis, of which the primary objective is to clarify whether and in which ways sociological and econometric approaches may yield contradictions in pattern of selection observed with the same observational data that do not contain information on ability and other confounders (such as scholastic performance in high school, significant others' influence, and aspiration).

In this study, I build upon previous work both theoretically and empirically. First, I assume that college attainment is determined by two kinds of selection: social selection and self-selection. By social selection, I mean selection into college education by structural forces that are observable: at the population level, the nature of education regime under which individuals attain college education and previous levels of education; and at the individual level, family background characteristics that influence one's propensity of obtaining at least a college diploma, such as parental education. By self-selection, I mean selection into college education by unobservable personal traits, such as inner ability, anticipatory utility of college education, determination, and efforts. Second, I examine pattern of selection in heterogeneous economic returns to college education by employing Xie's statistical method (SM-HTE) and Heckman's econometric approach (MTE), both of which involve advanced counterfactual methodologies developed in the respective disciplines. Finally, I assess the impact of educational expansion upon selection in heterogeneous returns to college education, using Taiwan's large-scale survey data that cover two periods in time: an earlier period (1990–1995) and later period (2005–2011). In other words, I compare "older cohorts" (birth cohorts of 1956–1970, for whom college education was rationed) with "younger cohorts" (birth cohorts of 1971–1986, for whom college education was expanded) in their experiences of college attainment and early labor market outcomes.

The remainder of the article is organized as follows. I first explain the two selection hypotheses of concern, followed by an illustration of the related causal models and methodological issues. I then highlight the Taiwanese context under study. After introducing data and variables, I report the empirical results. I finally conclude with discussions of the findings.

II. Two Selection Hypotheses

In seeking to determine the pattern of selection in heterogeneous returns to college education, it is fruitful to distinguish two competing hypotheses in social sciences: negative selection in sociology and positive selection in economics. The two hypotheses alike concur that in the presence of non-random assignment of persons to college (such as merits-based competition for college attainment), treatment effects (that is, returns to college education) may be heterogeneous, departing from the conventional assumption that returns are homogeneous across all units with the same observed individual attributes (Mincer, 1974). However, the two hypotheses disagree on who would benefit more from college education. This contradiction in theoretical arguments is concerned with which selection mechanism matters most. Viewing education as a means of social mobility, sociologists are keen to attribute the observed negative pattern of social selection to unequal access to resources and opportunities of educational and socioeconomic success at the group level, particularly in the form of class inequality. In contrast, economists typically view college education as an investment in human capital, in which individuals' rational schooling choices are involved. Below, I briefly review the relevant literature, and discuss important policy implications of these two hypotheses, respectively.

A. Negative Social Selection: Class Inequality as Selection Mechanism

In sociology, the negative selection hypothesis conjectures that persons with a low propensity to receive a college education due to observable individual attributes (such as low socioeconomic background) benefit most from college education. For instance, Brand and Xie (2010) suggest that this negative pattern of social selection emerges as a result of heterogeneity in mechanisms governing college-going behavior, mainly because the relative importance of cultural and economic mechanisms may vary across social strata. It is suggested that members of socially advantaged groups—whose propensity for receiving higher education is high and whose earnings prospects are lucrative—are culturally expected to obtain at least a college diploma. By contrast, members of socially disadvantaged groups—whose propensity for going to college is low and whose earnings prospects are bleak—have limited in access to resources and opportunities. When individuals from low propensity strata, for whom college attendance is a novelty, overcome considerable odds to attend college, they are either uniquely driven by the economic rationale or more selective than persons of high propensity. Thus, due to differential selectivity and earnings prospects, returns to college education estimated at lower propensity strata are larger than returns estimated at higher propensity strata, as first shown in Tsai and Xie (2008) for Taiwan and then in Brand and Xie (2010) for the USA.

Regarding the impact of educational expansion, recent stratification theories predict that class inequality in educational attainment will be maintained, either "maximally" (Raftery and Hout, 1993) or "effectively" (Lucas, 2001), despite expansion of education systems. That is to say, negative selection will continue to be a dominant pattern in social selection based on family background, as long as there are class inequalities in educational and socioeconomic achievements. An important policy implication of the negative selection hypothesis is that it is socially and economically beneficial to expand higher education systems in a society where class inequality in college attainment is severe, as the expansion is tantamount to giving college education to socially disadvantaged persons, who would otherwise not receive it and for whom earnings returns to college education are larger on average than those for socially advantaged persons, who would receive college education even in the absence of the expansion.

B. Positive Self-Selection: Unobservables as Selection Mechanism

In economics, positive selection hypothesis is derived from Becker's (1964) human capital theory and in particular cost-benefit analysis, where willingness to pay tuition and other costs to go to college is specific to each person, most notably in recent work of Heckman and his associates (e.g., Carneiro et al., 2003; Carneiro and Heckman, 2002; Carneiro et al., 2011; Heckman, 2001a; 2001b; Heckman, Lochner, and Todd, 2006; Heckman, Urzua, and Vytlacil, 2006; Heckman and Vytlacil, 1999; 2000; 2005). In this body of research, a key theoretical assumption is that persons who benefit most from college education are most likely to attend college, so that the average student going to college should have higher earnings returns to college than the marginal student who is ambivalent between going or not. An important implication of the positive selection hypothesis is that policy efforts to expand higher education systems are not necessarily profitable—whether or not the expansion will pay off is contingent on what kinds of students are at the margin and whether the society is characterized by under-education or over-education.

A crucial task involved in policy evaluation concerns how to estimate marginal treatment effects for a latent group of people who are just at the margin of receiving treatment. To address this issue, economists look at two major sources of variability among observationally identical people. One source is due to unobserved personal endowments, such as mental ability and work habits, which are positively associated with both schooling and earnings. Another source is related to unobserved personal expectation of college education. Selection on this mechanism is based on unobservable idiosyncratic responses to college education and also dependent on the potential outcomes. On this type of selection, a prevailing idea among economists is that individuals who expected a positive gain (benefit-cost) from college are most likely to attend college and also most likely to benefit from college education. This idea is analogous to Roy's (1951) classic model of sorting gain selection due to comparative advantages. Willis and Rosen (1979) extended the Roy model to allow for endogenous self-selection into college education, with the difference in expected utility between college education and high school education determining the likelihood of college education. Using a switching regression, they found evidence for sorting gain selection, as individuals who attended college would have earned less as high school graduates than observably similar persons who stopped schooling after high school, and individuals who did not attend college would have earned less as college graduates than observably similar persons who did attend.

The above two mechanisms of selection on unobservables may be both at work. That is to say, observationally identical people not only possess different latent abilities but also differ in reaping potential economic benefits from college education, a phenomenon called "essential heterogeneity" (Heckman, Urzua, and Vytlacil, 2006). In the past three decades, econometricians made efforts to develop innovative methodologies for studying unobserved heterogeneity and selectivity. In brief, Heckman and Robb (1985) first established the importance of heterogeneous treatment effects in general terms, and then Heckman and Robb (1986) introduced an important distinction between evaluation models where participation in the program being evaluated is based, at least in part, on unobservable idiosyncratic responses to treatment and models where participation is not based on unobserved idiosyncratic responses. This is the distinction between selection on unobservables and selection on observables. Later, Björklund and Moffitt (1987) introduced the parameter of marginal treatment effect (MTE) into the literature in a parametric context. Imbens and Angrist (1994) identified a discrete approximation to this parameter as a local average treatment effect (LATE) using the instrumental variable (IV) approach. Recent work of Heckman and his associates (e.g., Heckman, Urzua, and Vytlacil, 2006) extended the "MTE" idea to a semiparametric approach, with the propensity score for treatment consisting of at least some instrumental variables. In a nutshell, Heckman had made profound contributions in developing structural econometric models that explicitly account for selection on unobservables in heterogeneous treatment effects.

III. Causal Models and Methodological Issues

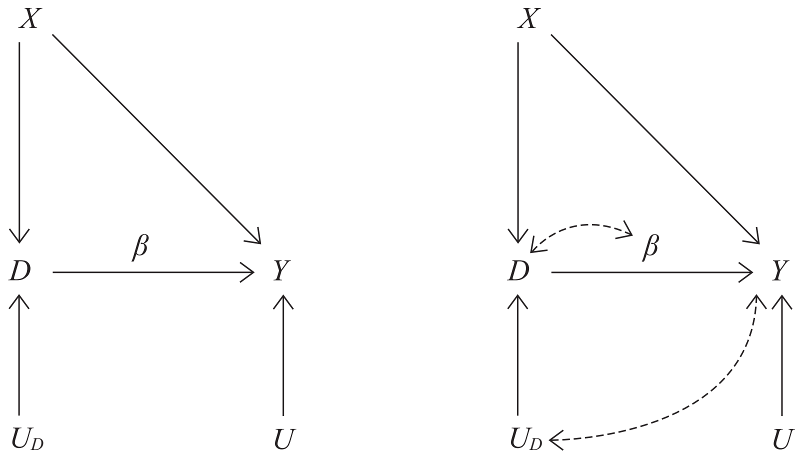
Not only do sociological and econometric approaches differ on theoretical thinking, but they also invoke different methodological assumptions, despite the fact that both approaches involve methodologies that consist of several steps, in which the "propensity score"—that is, the estimated possibility of college attainment for each sample—plays a central role. Below, I first explain differences between selection on observables and selection on unobservables, within a structural model framework, and then illustrate the two approaches used in counterfactual analyses of college treatment effects.

A. Selection in the Causal Relationship between Education and Earnings

In this analysis, I consider a structural equation model that consists of two equations: an education equation and an earnings equation. In the model, there are four types of variables: treatment variable, outcome variable, covariates, and unobservables. The treatment variable (D) is a dummy variable indicating the status of college attendance ($D=1$ if college education is received; 0 if otherwise). The outcome variable (Y) is observed earnings, with Y_1 denoting earnings of the college-educated ($D=1$) and Y_0 earnings of the non-college-educated ($D=0$). To the extent that education and earnings are not explained by the measured exogenous variables (X), they are determined by the unobservables (U_D and U). Fig. 1 depicts causal graphs for selection on observables and selection on unobservables, with β representing the returns to higher education, net of covariates. Also see Morgan and Winship (2007: 81).

Prior to the 21st century, it was legitimate to estimate the two equations sepa-

Fig. 1: Casual Diagrams for Selection on the Observables and Selection on the Unobservables



(a) Selection on the observables (b) Selection on the unobservables rately, given the conventional OLS assumptions that the unobservables are independent of the exogenous variables and uncorrelated with each other. Within the human capital framework, Mincer (1974) developed a "standard" earnings equation to empirically estimate the rate of returns to schooling, under the assumption of homogeneity. The Mincer equation—which uses OLS regression with logged earnings as the dependent variable and years of schooling as a primary independent variable, along with a separable quadratic function in work experience—was regarded as "one of the great success stories of modern labor economics" (Willis, 1986: 526). Not until recently was the Mincer model seriously criticized, by Heckman, Lochner, and Todd (2006).

To tackle selection issues, I begin by estimating a Mincer-type model that assumes college education to be exogenous and the economic return to college education homogeneous across all units with same observed individual attributes. The conventional earnings equation takes the form

$$Y_i = \beta D_i + \gamma X_i + U_i , \tag{1}$$

where Y is earnings in the logarithm form; i $(= 1, \ldots, n)$ is the subscript denoting person i; D is a dummy variable representing whether or not the person attended college; β is the return to college education, after controlling for X, a vector of other earnings determinants including Mincer experience and its squared term; γ is a vector of coefficients; and U is the residual unexplained by the model. A necessary assumption for estimating β in equation (1) via OLS is that the unobservables are independent of D, conditional on X.

However, as discussed earlier, there are two potential sources of selection bias. These are two situations in which the OLS assumptions of equation (1) are violated. The first type of selection bias occurs if U_D is correlated with both D and Y (e.g., high-ability and hard-working people choose to go to college and also earn more in the labor market). This is the so-called "ability bias", a bias due to differences in pre-existing attributes (such as mental ability and personality traits) between those who attend college and those who do not attend college. The second type of selection bias occurs if β is heterogeneous at the individual level and is correlated with D. This is the so-called "sorting gain" bias, a bias due to schooling decisions made on the basis of the expected gain β. Both types of selection bias may threaten the validity of causal inference with observational data. An important task of this analysis is to employ Heckman's new approach to can separate out the two types of selection bias and thus demonstrate how educational expansion may affect selection in heterogeneous returns to higher education.

With respect to the policy evaluation, a fundamental problem is that treatment effect is a person-specific counterfactual ($\Delta_i = Y_{1i} - Y_{0i}$), yet it is impossible to observe the same person in both the treated and untreated state at the same time; only one state (Y_{1i} or Y_{0i}) can be observed. Thus, information on Y_1 is missing for workers without college education ($D=0$), whereas Y_0 cannot be observed for workers with college education ($D=1$). In other words, it is easy to construct the means $E(Y_1|X, D=1)$ and $E(Y_0|X, D=0)$, which are the averages in observed earnings for workers with college education and for workers without college education, conditional on X. However, we never know $E(Y_1|X, D=0)$, which is the average earnings of the non-college-educated workers if they had attended college education, and $E(Y_0|X, D=1)$, which is the average earnings of the college-educated workers if they had not received college education. Both means are also conditional on X. The use of conventional methods thus fails to identify the treatment effects of concern.

B. Xie's Statistical Approach: SM-HTE

One way to resolve the fundamental identification problem in causal inference is to argue that selection into college education is inconsequential, in which case, the researcher can assume

$$E(Y_1|X, D=1) = E(Y_1|X, D=0) \text{ and}$$
$$E(Y_0|X, D=1) = E(Y_0|X, D=0). \tag{2}$$

In sociology, it is legitimate to assume that the unobserved component of the treatment equation is random, after controlling for a vector of earnings determinants that also influence the probability of completing college (Sobel, 2005). Thus, under the ignorability assumption, the condition specified in Equation (2) is assumed to be satisfied.

To test for a negative pattern of social selection based on family background, I employ Xie's SM-HTE method, which invokes the ignorability assumption. This statistical method consists of the following steps: (1) estimate propensity score for all observation units for the probability of treatment given a set of observed covariates, using probit or logit regression models; (2) construct balanced propensity score strata where there are no significant differences in the average values of covariates and the propensity score between the treated and untreated groups; (3) estimate propensity score stratum-specific treatment effects within strata; and (4) estimate a trend across the propensity strata for treatment effects of college education through HLM (Hierarchical Linear Modeling). See Xie et al. (2012) for a detailed discussion of the method, including its shortcomings: (1) the full range of the propensity score is divided into a limited number of strata within which neither pretreatment nor treatment effect heterogeneity bias is assumed (that is, a form of within-group homogeneity is imposed so that treated and untreated observations are considered interchangeable within strata); and (2) across the strata, a higher-level (linear) regression is imposed so that a pattern of treatment heterogeneity can be detected.

C. Heckman's Econometric Approach: MTE

To test for positive self-selection, I employ Heckman's econometric approach, which enables the researcher to explicitly account for selection on unobservables in heterogeneous returns, without invoking the ignorability assumption. To be more precise, I now consider a selection model that consists of the following two equations: an outcome equation with person-specific returns to college education (β_i), and a selection equation that allows treatment (D_i) to be endogenous. The two equations can be expressed as

$$Y_i = \beta_i D_i + \gamma X_i + U_i \ , \tag{3}$$

$$P_i(Z_i) = \text{Prob}(D_i = 1) = F(Z_i \delta), \tag{4}$$

where β_i represents the *heterogeneous* returns to college attendance; D_i is an *endogenous* dummy variable denoting whether or not person i attended college; Z is a vector of observed exogenous covariates that are used to predict college attendance; δ is a vector of coefficients for Z; F is an inverse link function that transforms the index function, $Z_i\delta$, into a probability; typically, $F()$ takes the functional form of either the cumulative standard normal or cumulative standard logistic function, respectively, for the probit or logit model. Other notations remain the same as in equation (1).

Note that the following decision rule is used to predict the binary selection into college:

$$D_i = 1 \text{ if } D_i^* > 0;\ D_i = 0 \text{ otherwise,}$$

$$D_i^* = P_i\ (Z_i) - U_{Di} \tag{5}$$

where D_i^* is an unobserved latent variable indicating the net gain to person i from receiving college education; $P_i(Z_i)$ is the person's "propensity score" for receiving college education, which is given in equation (4); U_{Di} is the unobserved individual-specific component in the selection equation. Within this framework, $P_i(Z_i)$ and U_{Di} in the schooling choice equation (5) may be interpreted respectively as observed and unobserved costs of education (Carneiro and Heckman, 2002). The higher the propensity score $P_i(Z_i)$, the more advantaged the family background, and the lower the observed cost of education. By contrast, the larger the unobserved component U_{Di}, the larger the unobserved cost of education, and the less likely it is that the person will receive college education, everything else being equal. If $P_i(Z_i) = U_{Di}$, then person i is assumed to be indifferent between going to college or not.

This schooling decision rule is brought into the earnings equation (3), in which the two potential selection outcomes (Y_{0i}, Y_{1i}) for each person i are:

$$Y_{0i} = \gamma_0 X_i + U_{0i} \qquad \text{if } D_i = 0. \tag{6a}$$
$$Y_{1i} = \gamma_1 X_i + U_{1i} \qquad \text{if } D_i = 1. \tag{6b}$$

where $E(U_{0i}|X_i) = 0$ and $E(U_{1i}|X_i) = 0$ in the population. And the individual-level treatment effect is $\Delta_i = Y_{1i} - Y_{0i} = (\gamma_1 - \gamma_0) X_i + (U_{1i} - U_{0i}) = \beta_i$. But, recall that Y_1 cannot be observed for those who did not go to college ($D = 0$), while information on Y_0 is missing for those who attended college ($D = 1$). And hence, the individual treatment effect is defined as the effect associated with moving an otherwise identical person from "0" to "1". The effects on earnings of a *ceteris paribus* move from untreated state to treated state are causal effects; see Heckman (2005a; 2005b) and Sobel (2005) for interdisciplinary exchanges in ideas regarding "the scientific model of causality".

As shown in Heckman, Urzua, and Vytlacil (2006), in the notation of equation (3), the observed outcome can be written as a switching regression model of the form:

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i}, \text{ and } U_i = D_i U_{1i} + (1 - D_i) U_{0i}. \tag{7}$$

Using equations (6a), (6b), and (7), equation (3) can be expressed as:

$$Y_i = \beta_i D_i + \gamma_0 X_i + U_{0i}, \text{ where } \beta_i = (\gamma_1 - \gamma_0) X_i + (U_{1i} - U_{0i}). \tag{8}$$

When there is individual heterogeneity either in observed term $(\gamma_1 - \gamma_0) X_i$ or in unobserved term $(U_{1i} - U_{0i})$, β_i varies in the population even after controlling for X, and the return to college education (conditional on X) is a random variable with a distribution. If the two groups differ in the observed characteristics (i.e., $\gamma_1 \neq \gamma_0$), the distribution of β_i is degenerate. That is to say, every person either benefits or loses from change in educational policies that may influence selection into college, such as increase in the overall level of educational opportunities caused by educational expansion. By contrast, if the treated and untreated groups differ in the unobserved heterogeneity (i.e., $U_1 \neq U_0$), the distribution of β_i (conditional on X) is not degenerate. In such a case, there may be sorting on the gain.

An Empirical test for positive sorting gain selection involves the estimation of a wide range of counterfactual (causal) effects of college education for different members in a population. According to Heckman (2001a; 2001b), three population-level treatment parameters are particularly relevant to policy evaluation: (1) the average treatment effect (ATE)—the mean effect of college education on earnings if persons with the same observed characteristics were randomly assigned to college education; (2) the treatment effect for the treated group (TT)—the mean (observed) earnings of college-educated persons compared to what they would have been in the absence of college education; and (3) the treatment effect for the untreated group (TUT)—the mean (potential) earnings of non-college-educated persons in the presence of college education compared to their (observed) earnings in the absence of college education. If TT is greater than TUT, we can say that there is positive sorting (or sorting gain); conversely, if TT is smaller than TUT, we can say that there is negative sorting (or sorting loss). Note that, within Heckman's econometric framework, the sorting gain is the mean gain of the unobservables for those who receive college education, which is defined as $E(U_1-U_0|D=1)$ and is equal to TT minus ATE.

I borrow Heckman's own software to estimate marginal treatment effects of college education on earnings at different levels of U_D, that is, at different latent levels of resistance to college education. Once MTE is known, all treatment parameters of concern (ATE, TT, and TUT) can be derived as weighted averages of MTE, using weights suggested by Heckman, Urzua, and Vytlacil (2006). By then, the conventional selection bias (=OLS−ATE) can be decomposed into two components: the ability bias (=OLS−TT) and the sorting gain (=TT−ATE). Later, I will rely on the estimates of these three treatment parameters and two types of selection bias to assess the impact of educational expansion. Next, however, I shall provide an introduction to the Taiwanese context under study.

IV. The Taiwanese Context

In the postwar era, the Taiwanese system of higher education developed through a nonlinear process that consisted of three main phases: expansion through growth of junior colleges until the early 1970s, stagnation, and rapid expansion with deregulation since the late 1980s. The vast majority of Taiwanese colleges and universities now in operation were established since 1990. In 1990, there were 46 institutions of four-year college education with a total of 239,082 students; by 2011, the number of institutions was 148, serving 1,032,985 students (Ministry of Education, ROC, 2012: 27). It is common speculation that such a large increase in the supply of college-educated workers by rapid educational expansion would dilute the market value of college education.

To evaluate the impact of policy change, I compare two broad cohorts who had experienced two different education regimes (one highly centralized and another deregulated), although both regimes had a basic structure of 6-3-3-4 years of schooling, the first 9 years being compulsory. In Taiwan, students usually begin college education at age 18. That is to say, "older" cohorts of 1956 to 1970 went to college in the years 1974 to 1988, a period of stagnation in development during which higher education was a valuable but scarce resource. Not only was higher education rationed with the structural barriers between vocational and academic tracks, but the transition from secondary education to tertiary education was based on stringent examinations. The “unified college entrance examination” held in the summer was 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, according to their examination scores. The state restricted the expansion of academic higher education and encouraged the proliferation of vocational colleges and programs. In 1974, the first four-year vocational college—which was upgraded and renamed the National Taiwan University of Science and Technology in 1997—was established to provide a channel for graduates of vocational schools to further their education. Since then, expansion through the parallel development of academic and vocational tertiary education has been policy.

In contrast, “younger” cohorts of 1971 to 1986 went to college in the years 1989 to 2004, a period of rapid growth of four-year colleges and universities through the establishment or licensing of new institutions and the upgrading of old institutions from the lower to the higher tier. The earlier structural barriers between vocational and academic tracks were broken down. As Taiwan moved toward democracy, the state exercised less and less control over educational policies in the past two decades. “Loosening-up” was a nexus in recent education reforms. Since deregulation, especially after 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 high school and in the “General Scholastic Ability Test” as a major qualification consideration—and then recruit the remaining intake in summer through the “Department Required Test”.

In 2011, 68 percent of the Taiwanese population aged 18–21 was enrolled in tertiary education; the corresponding figure was 42.5 percent a decade ago, 21 percent two decades ago, and only 11.5 percent three decades ago (Ministry of Education, ROC, 2012: 39). This rapid transformation of college education from elite to mass education by no means implies less competition among students in the process of educational attainment, as examinations still dominate school life. Students are now using various test scores—instead of standard scores of the entrance examination held in summer—to compete for entry into preferred departments in preferred public universities. The competition is “fair but unjust”—fair in the sense that student recruitment is largely based on merit, but unjust because students attending public universities, which receive higher government subsidies, tend to come from better-educated and economically better-off families (Liu et al., 2006). Despite educational expansion, class inequalities in access to and completion of college education still exist (Tsai and Shavit, 2007). However, the traditional gender inequality in schooling not only disappears but switches to a female advantage in younger generations (Tsai and Kanomata, 2011).

V. Data and Variables

Data for this analysis are derived from various islandwide social surveys, with different representative adult samples in each survey. This analysis relies heavily on data from the Taiwan Social Change Surveys (TSCS), particularly those that contain information on respondent's education, income, and parental education. To increase the sample size, this analysis also uses data from the 2005 SSM (Social Stratification and Mobility) survey and the 2009 "new" survey of PSFD (Panel Study of Family Dynamics in Taiwan) that focuses on young respondents aged 25 to 32. All of these surveys were conducted by the Survey Office at Academia Sinica, using similar sampling strategies. This analysis focuses on young entrants to the labor market. Accordingly, from each of the data sets used, I select respondents who were aged 25 to 34 and who completed at least 12 years of schooling, reported non-zero income, and provided information on parental education (see Appendix Table A1.). In total, 9,090 respondents in cohorts of 1956 to 1980 are selected. Note that the distribution of birth cohorts (1956–1986) in the analysis sample may not resemble that of the population, as the youngest and oldest cohorts included in the pooled data are certainly outnumbered by cohorts of 1961–1965 or cohorts of 1976–1980, which is a data limitation that I have to live with.

To explore temporal change in educational selectivity caused by educational expansion, I group data collected in the years 1990 to 1995 into the earlier period, and data collected in years of 2005 to 2011 into the later period. Data for the earlier period are derived from eleven TSCS surveys (1990–I, 1991–I, 1991–II, 1992–I, 1992–II, 1993–I, 1993–II, 1994–I, 1994–II, 1995–I, and 1995–II). The older sample pertains to 3,341 respondents (1,867 males and 1,474 females) in birth cohorts of 1956 to 1970. For the later period, I use data from ten TSCS surveys (2005–I, 2005–II, 2006–I, 2007–I, 2007–II, 2008–II, 2009–I, 2010–I, 2011–I, and 2011–II), plus the 2005 SSM survey and the 2009 PSFD "new" survey. The younger sample includes 5,749 respondents (3,081 males and 2,668 females) in birth cohorts of 1971 to 1986.

In addition to birth cohort, time period, and gender (scored 1 if female; 0 if male), the following variables are used in the empirical analysis:

College education. This analysis is concerned with whether or not the respondent received a four-year college education after completing secondary education. The binary treatment into college education is indicated by a dummy variable scored 1 if the highest level of education attained by the respondent is a four-year college education or higher (that is, 16 years of schooling at least), and 0 if otherwise (that is, 12–15 years of schooling).

Earnings. The surveys asked information on respondents' average monthly earnings using a closed-form question with categories that truncated the highest earnings at NTD$200,000 in the earlier surveys and at NTD$300,000 in the later surveys. In the outcome equation, earnings are measured in the (natural) log form.

Parental education. Father's and mother's education are measured by their highest completed levels of education. Educational categories are recoded into years of schooling: no education = 0; self-study or incomplete primary education = 3; primary education = 6; lower secondary education = 9; upper secondary education = 12; junior college = 13 to 15; bachelor's degree = 16; master's degree = 18; doctoral degree = 20. Parents' years of schooling are used in this analysis as key indicators of family background. There are no better measurements available; only a few surveys asked information on father's occupation, and almost no survey collected information on family income at the time when the respondent was about to enter college.

Mincer experience. The survey data are short of a direct measure of labor force experience. This analysis uses Mincer's definition of labor force experience, which is measured as age minus years of schooling minus six. A separable quadratic function in labor force experience is also included in the outcome equation.

Tuition. Similar to the work of Carneiro et al. (2011), this analysis uses tuition and fees for public university at 17 as an instrument variable (IV), which may affect college attendance, but does not affect potential earnings directly. Data for tuition and fees are derived from official statistics reported in Government Gazette (1974–1993) and Department of Statistics, the Ministry of Education (1994–2011).

VI. Results

A. Descriptive Statistics

Table 1 presents descriptive statistics of major variables by time period. In this analysis, 48.5 percent of the samples in the younger cohorts received at least a four-year college education (46 percent for males; 51 percent for females), much higher than the corresponding figure (18.3 percent) for the older cohorts (19 percent for males and 18 percent for females). Trends in the average earnings reported in

Table 1: Descriptive Statistics for Major Variables by Period

	Earlier Period (N=3,341)		Later Period (N=5,749)	
Variables	Treated (18.3%)	Untreated (81.7%)	Treated (48.5%)	Untreated (51.5%)
Years of schooling	16.317	12.691	16.459	12.846
	(.731)	(1.079)	(.896)	(1.001)
Monthly earnings	40,556	34,016	40,483	34,578
	(25,977)	(24,361)	(25,115)	(22,129)
Father's schooling	9.879	7.075	10.166	8.003
	(4.434)	(3.842)	(3.515)	(3.123)
Mother's schooling	6.498	4.419	8.828	6.803
	(4.144)	(3.458)	(3.391)	(3.100)
Mincer experience	7.443	10.832	6.326	10.696
	(2.859)	(3.030)	(2.328)	(2.885)
Female (%)	42.8	44.4	49.0	44.0

Note: Numbers in parentheses are standard deviations.

the table for the treated group (decreasing) and the untreated group (increasing) seem opposite, but, actually, neither trend is statistically significant (at the level of $\alpha=0.05$). These findings imply that the wage level for young workers did not significantly rise over the past two decades. Neither did the gap in earnings increase between the college-educated workers and the non-college-educated workers. Table 1 also shows that the college-educated workers are more likely to come from better-educated families, with both father's and mother's average years of schooling significantly higher than those of the non-college-educated workers. This pattern holds for both men and women.

B. Returns to College Education under the Assumption of Homogeneity

Table 2 presents the estimated effects of college education on earning, separately by time period and gender, through regression analyses under the assumption of homogeneity. As shown in the table, I consider two different sets of (X) covariates: (1) parental education, as emphasized in the sociological literature; and (2) the Mincer variables, as often used in the economic literature. Two findings emerge in Table 2. First, temporal change in the estimated college effect—be it negative or positive in sign—is not statistically significant in all the models tested. Thus, there

Table 2: Effects of College Education on Logged Earnings under the Assumption of Homogeneity

Control Variables (X)	Men			Women			Gender Difference	
	Earlier Period (N=1,867)	Later Period (N=3,081)	Temporal Change	Earlier Period (N=1,474)	Later Period (N=2,668)	Temporal Change	Earlier Period (N=3,341)	Later Period (N=5,749)
0. None	.125***	.080***	−.045	.280***	.263***	−.017	.155**	.183***
	(.030)	(.019)	(.036)	(.034)	(.019)	(.039)	(.045)	(.027)
1. Parental education	.119***	.082***	−.037	.232***	.230***	−.001	.112*	.148***
	(.031)	(.020)	(.037)	(.035)	(.020)	(.041)	(.047)	(.029)
2. Mincer variables	.267***	.326***	.059	.325***	.364***	.039	.058	.038
	(.032)	(.023)	(.040)	(.037)	(.024)	(.044)	(.049)	(.033)
3. Parental education and Mincer variables	.255***	.317***	.063	.283***	.340***	.056	.029	.022
	(.033)	(.023)	(.040)	(.038)	(.024)	(.045)	(.050)	(.034)

Note: Numbers in parentheses are standard errors; * $p<.05$, ** $p<.01$, *** $p<.001$ (two-tailed tests).

is no evidence of a significant change in the returns to college education over time, consistent with the OLS findings reported in Tsai and Xie (2008) for trend between the early 1990s and the early 2000s. Second, the estimated college effect is larger for women than for men (in Models 0 and 1 of Table 2), but once controlling for work experience, gender difference in the college effect is negligible (in Models 2 and 3).

C. Estimating Propensity Score

In this analysis, I estimate the propensity of receiving college education—that is, $P(Z)$—for every observation sample, using probit models and a set of Z variables. Besides gender, I use father's and mother's years of schooling, their interaction term, tuition for public university at 17, and dummy variables for birth cohorts to predict college attendance, as shown in Table 3. I find that the estimated tuition effects are significantly positive in the later period, regardless of pooling men and women together or separating them. This finding seems unique, as tuition effects are found to be negative in the United States (Carneiro et al., 2011) and insignificant in the Netherlands (Canton and de Jong, 2005). In Taiwan, a low-tuition policy based on Sun Yat-Sen's ideology had been implemented since 1945, with the explicit aim of reducing class inequality in educational attainment. Over recent decades, especially in the later period, the rising levels of college tuition and the increasing rates of college enrollment are moving in the same direction. To detrend the effects, I have included many cohort dummies in the probit analysis so that the potential problem

Table 3: Estimated Probit Models for College Attendance

	Men				Women			
	Earlier Period (N=1,867)		Later Period (N=3,081)		Earlier Period (N=1,474)		Later Period (N=2,668)	
Independent Variables (*Z*)	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	−1.083**	.342	−1.650***	.309	−.906	.518	−1.612***	.329
Father's schooling (FS)	.028	.015	.056**	.018	.072***	.020	.015	.019
Mother's schooling (MS)	−.058*	.022	−.005	.021	.052	.030	.012	.022
FS * MS	.009***	.002	.005*	.002	.001	.003	.007**	.002
Tuition (in thousands NTD)	−.013	.031	.029**	.011	−.078	.044	.022*	.010
Birth cohort (relative to 1956)								
1957	−.212	.329	—	—	−.476	.480	—	—
1958	.048	.315	—	—	−.988*	.472	—	—
1959	−.006	.289	—	—	−.623	.421	—	—
1960	−.152	.285	—	—	−.707	.409	—	—
1961	−.081	.264	—	—	−.476	.378	—	—
1962	−.168	.237	—	—	−.473	.335	—	—
1963	−.052	.244	—	—	−.118	.333	—	—
1964	−.165	.260	—	—	−.214	.348	—	—
1965	.019	.267	—	—	.027	.358	—	—
1966	−.058	.270	—	—	.035	.363	—	—
1967	−.144	.295	—	—	.339	.384	—	—
1968	−.116	.319	—	—	.037	.415	—	—
1969	−.327	.372	—	—	.161	.427	—	—
1970	—	—	—	—	—	—	—	—
Birth cohort (relative to 1971)								
1972			−.268	.212			.397	.233
1973			−.113	.185			.049	.211
1974			−.038	.188			.087	.202
1975			−.355	.187			.121	.196
1976			−.310	.195			−.082	.194
1977			−.214	.184			.089	.187
1978			−.217	.204			.029	.200
1979			−.230	.231			.092	.218
1980			−.519*	.262			.000	.241
1981			−.523	.303			.151	.278
1982			−.397	.317			.116	.288
1983			−.599	.355			.194	.324
1984			−.542	.393			.072	.353
1985			−.571	.435			.215	.401
1986			—	—			—	—

Note: Numbers in parentheses are standard errors; * $p<.05$, ** $p<.01$, *** $p<.001$ (two-tailed tests).

of spurious causality can be avoided. Results indicate that when higher education becomes more and more accessible, the higher the economic cost of college education, the higher the likelihood of college attendance. This pattern holds for both men and women. It seems safe to say that while most Taiwanese parents aspire for a university education for their children, nowadays, the more the parents can afford the rising costs of higher education, the more likely their children are to obtain at least a college diploma.

D. Testing for Negative Social Selection on Observables

To test for the negative selection hypothesis in sociology, I estimate treatment effects specific to six propensity score strata (see Appendix Table A2), and then detect the pattern of effects across strata with a hierarchical linear model (HLM). Table 4 reports the main results obtained from the SM-HTE approach—that is, HLM estimates of level-2 slope—which are used to decide which selection pattern (positive or negative) is observed for which period. As shown in the table, the slope estimates are all negative in the models tested, among which Model 1 represents social selection based on family background, a main focus in this part of the analysis. Thus, there is evidence for the negative pattern of social selection proposed by sociologists.

Fig. 2 depicts HLM results of economic returns to college for the two periods using Model 1, separately by gender. The downward linear plot depicted in the figure shows that the treatment effects decline with the propensity stratum rank, suggesting that individuals who are less likely to attend college according to their observed attributes actually would benefit more from college than individuals who are more likely to attend college. This finding is consistent with the work of Tsai and Xie

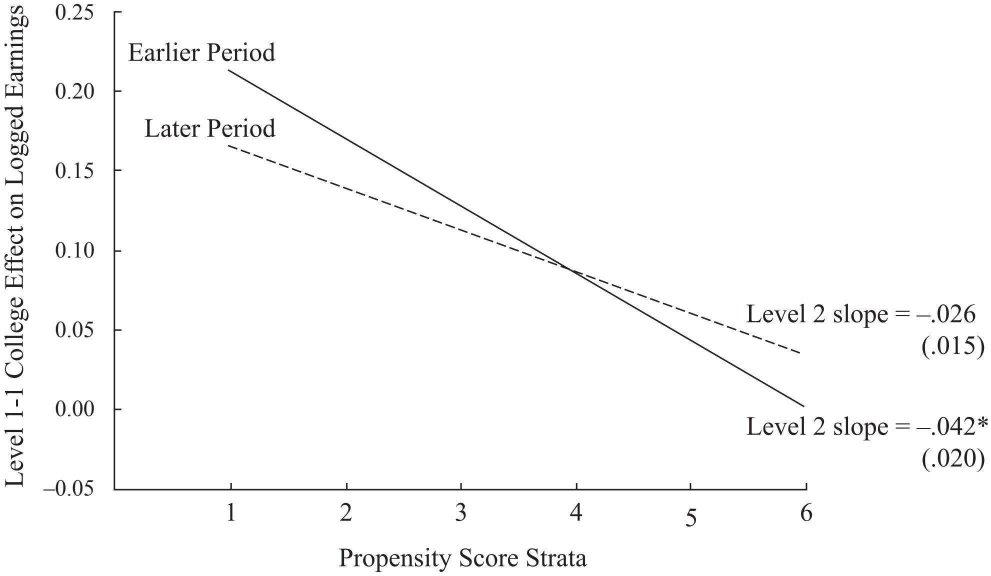
Table 4: SM-HTE Estimates of Level-2 Slope

Covariates (X)	Earlier Period (N=3,341)	Later Period (N=5,749)
0. Constant only	−.051***	−.035***
	(.011)	(.005)
1. Parental Education	−.042**	−.036***
	(.015)	(.010)
2. Mincer variables	−.030*	−.005
	(.015)	(.012)
3. Parental Education and Mincer variables	−.041*	−.009
	(.019)	(.017)

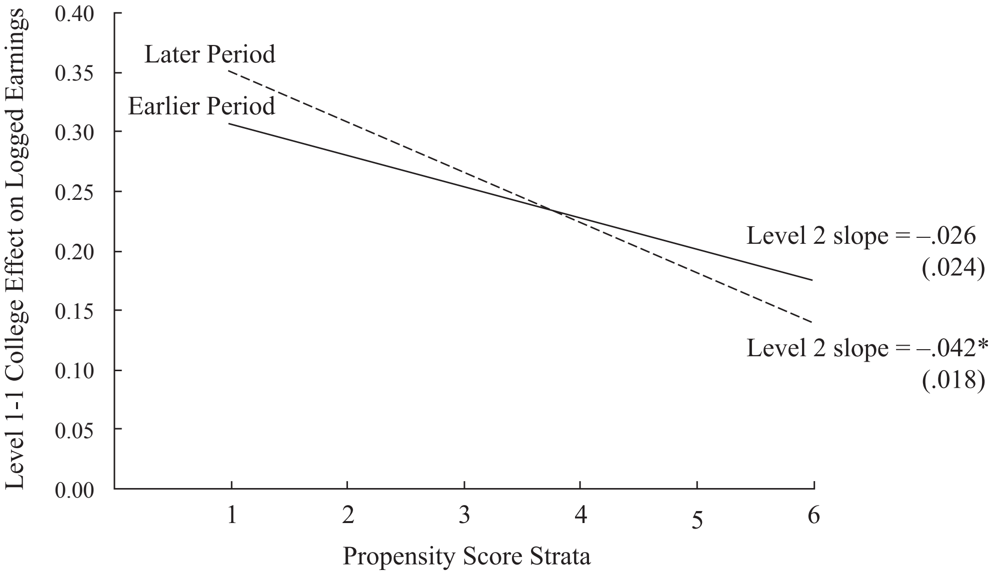
Note: Numbers in parentheses are standard errors; * $p<.05$, ** $p<.01$, *** $p<.001$ (two-tailed tests).

Fig. 2: HLM of Economic Returns to College by Period and Gender

A. Men



B. Women



Note: Numbers in parentheses are standard errors; *significant at the level of α=.05.

(2008), in which two different time periods (1991–1993 and 2001–2003) are examined. Fig. 2 also reveals gender similarity in this finding, although the observed negative pattern of selection is more profound among men in the early 1990s, whereas it is more profound among women in the late 2000s. Overall, it appears that educational expansion did not disrupt pattern of social selection based on family background in a dramatic way.

E. Testing for Positive Self-Selection on Unobservables

To test for positive self-selection, I follow Heckman's econometric approach and use his software to gauge various population-level treatment effect parameters that are relevant to policy evaluation, through estimating treatment effects for those who are just at the margin of receiving treatment. In this part of the analysis, I include parental education in the model mainly as Z covariates, along with the other Z variables listed in Table 3, and use the Mincer variables as X covariates, similar to the work of Tsai and Xie (2011). But, different from that work, this analysis uses tuition as the instrument. I depict the density function for the estimated propensity score of college attendance for the treated group and the untreated group, respectively, in Appendix Fig. A1, using total analysis samples in each period examined. It is the support of $P(Z)$ that helps identify the treatment effects of concern. A few cases are lost due to lack of a common support. In what follows, I first give a general picture of temporal change, and then proceed to gender-specific results.

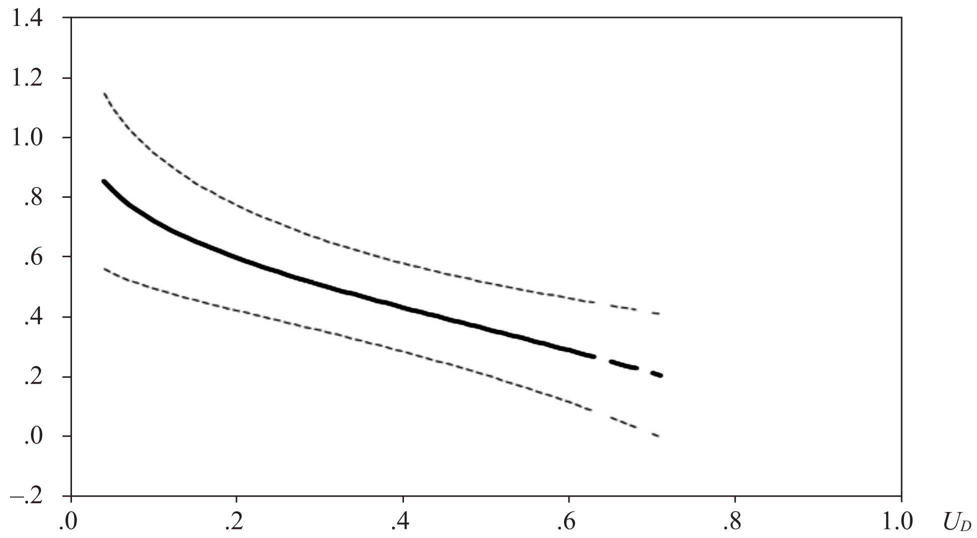
E.1. Estimating Marginal Treatment Effects

Marginal treatment effect (MTE) can be estimated as a function of the unobserved component U_D in the schooling choice equation, using a parametric or semiparametric approach. The parametric approach estimates the marginal treatment effect under the assumption of a joint trivariate normal distribution for errors in a switching regression setup—the two error terms in the earnings equation (equation 3) under the two treatment regimes, and the error term in selection (equation 5). The semiparametric approach does not invoke this assumption. Because I am concerned that the data used may be too thin to support the semiparametric approach (especially for the earlier period), in the following I mainly rely on the parametric results to assess the impact of educational expansion. Those who are interested in the semiparametric results may contact the author.

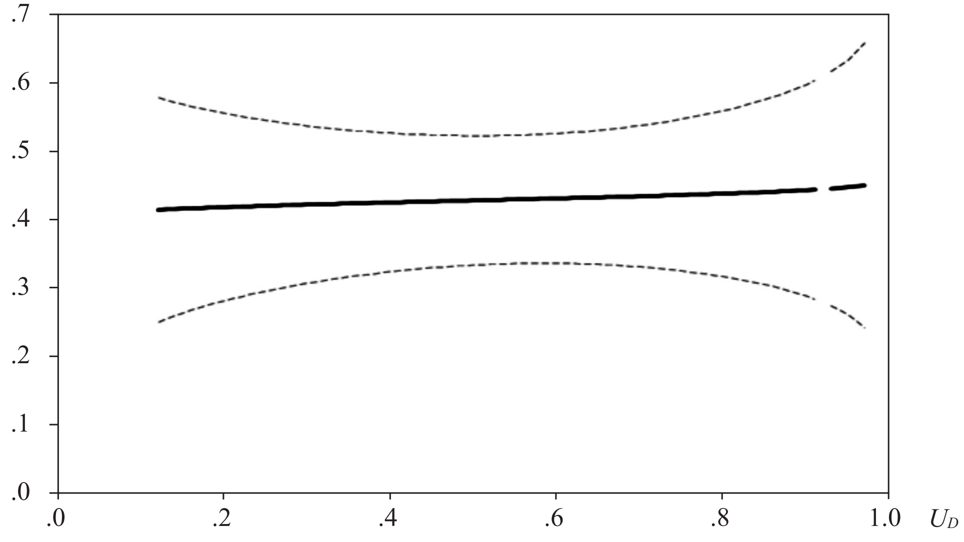
Fig. 3 plots the estimated marginal treatment effect (MTE) as a function of the unobserved component U_D in the schooling choice equation, along with their 95% confidence intervals. Note that the lines plotted in Fig. 3 have a few blank areas, because the MTE cannot be estimated at points where the support of $P(Z)$ is weak. The figure shows a declining pattern of MTE with U_D for the earlier period. Recall

Fig. 3: MTE as a Function of Unobserved Heterogeneity (U_D) by Period

A. Earlier Period



B. Later Period



that within this econometric framework, the higher the unobserved U_D, the higher the unobserved cost of attending college, and thus the lower the probability of attending college, everything else being equal. Accordingly, the declining pattern of MTE with U_D means that those who have the highest latent tendency of going to college (i.e., those who are most likely to attend college, all else equal) have the largest marginal returns. By contrast, those who have the least likelihood of going to college have the lowest marginal returns. This finding is consistent with the positive selection hypothesis proposed by economists. Nevertheless, the shape of the MTE for the later period appears rather flat, revealing a profound change over time.

E.2. Assessing the Impact of Educational Expansion

To facilitate evaluation of policy impact, it is useful to summarize individual-level MTE estimates into summary quantities of interest for a population or subpopulations, using weights given by Heckman, Urzua, and Vytlacil (2006) for such quantities. I depict in the Appendix (Fig. A2) the estimated weights from the data used for the average treatment effect (ATE), the average treatment of the treated (TT), and the average treatment effect of the untreated (TUT). Table 5 reports the parametric estimates of these treatment effect parameters for the two periods, along with the conventional OLS and IV estimators obtained from the same data. Table 5 also presents the estimates of different types of selection bias. Significance tests for differences between any pair of parameter estimates of concern are carried out by using a bootstrapping method.

Table 5: Estimates of Treatment Parameters for Two Periods

Parameter	Earlier Period (N=3,337)	Later Period (N=5,741)	Temporal change
ATE	.475*	.430*	−.045
	(.076)	(.048)	(.090)
TT	.702*	.420*	−.282*
	(.106)	(.057)	(.121)
TUT	.412*	.438*	.026
	(.076)	(.055)	(.097)
OLS	.289*	.343*	.054
	(.025)	(.017)	(.030)
IV (Tuition)	.554*	.426*	−.128
	(.083)	(.051)	(.097)
Bias=OLS−ATE	−.187*	−.087	
	(.080)	(.051)	
Ability bias=OLS−TT	−.413*	−.077	
	(.109)	(.060)	
Sorting gain=TT−ATE	.226	−.010	
	(.130)	(.075)	

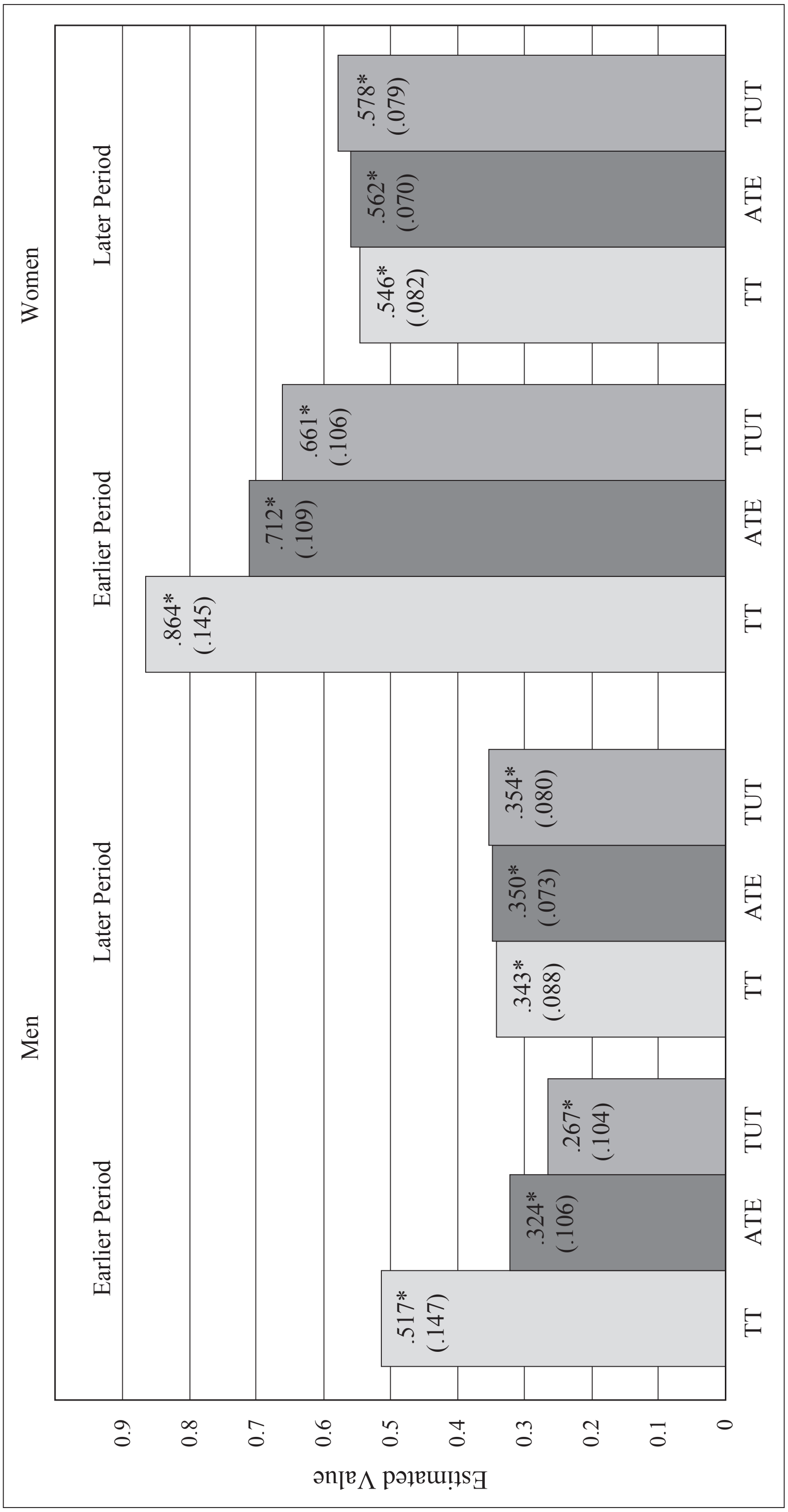
Note: Bootstrapped standard errors (in parentheses) are presented below the correspondent Parameters (250 replications); * Significant at the level of $\alpha=.05$.

Four findings emerge in Table 5. First, the pattern of heterogeneous returns to college education has changed over time. A positive selection pattern of TT > ATE > TUT can be observed for the earlier period, whereas there is a negative selection pattern of TUT > ATE > TT for the later period. Second, temporal change in the treatment effect is most profound in the case of TT, indicating that college graduates experienced a significant decline in returns to college education between the early 1990s and the late 2000s. It is thus evident that college education has been devalued in the labor market, as a result of educational expansion. Third, ability bias is more profound in the earlier period, when the mean probability of receiving a college education is much lower and heterogeneity in returns to college education is more obvious, as opposed to the later period. Fourth, although both sorting biases are not statistically significant, the observed sorting pattern switches from a sorting gain in the earlier period to a sorting loss in the later period.

E.3. Gender Differences

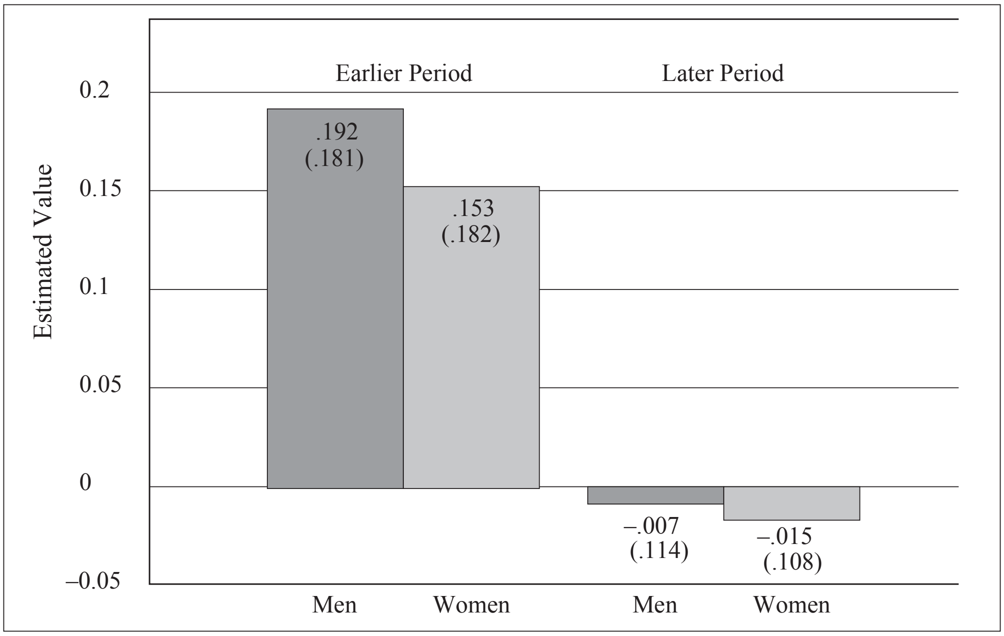
I finally depict the gender-specific results in Fig. 4 (estimates of three population-level treatment effect parameters), Fig. 5 (estimates of sorting gain or loss), and Fig. 6 (estimates of ability bias). Inspection of these figures reveals four findings. First, college treatment effects are generally larger among women than among men, indicating that college credentials are more important for women than for men in the pursuit of labor market achievements. Second, with respect to the earlier period, the observed pattern of TT > ATE > TUT holds for both men and women, with a sorting gain that appears to be larger among men than among women. Third, with respect to the later period, although the pattern of TUT > ATE > TT can be observed for both men and women, the estimated treatment effects are actually homogeneous between the treated and the untreated, with a small extent of sorting loss. Fourth, regardless of which period is examined, ability bias—which is negative in sign—is more profound for women than for men. Ability bias was thought to be always positive (Griliches, 1977). However, recent economic studies have shown that this type of selection bias may be negative, if comparative advantage is operative (e.g., Carneiro and Heckman, 2002). Thus, the results imply that Taiwanese women's processes of status attainment are more influenced by the unmeasured (ability) variables than are their male counterparts'.

Fig. 4: Estimates of Population-Level Treatment Effect Parameters by Period and Gender



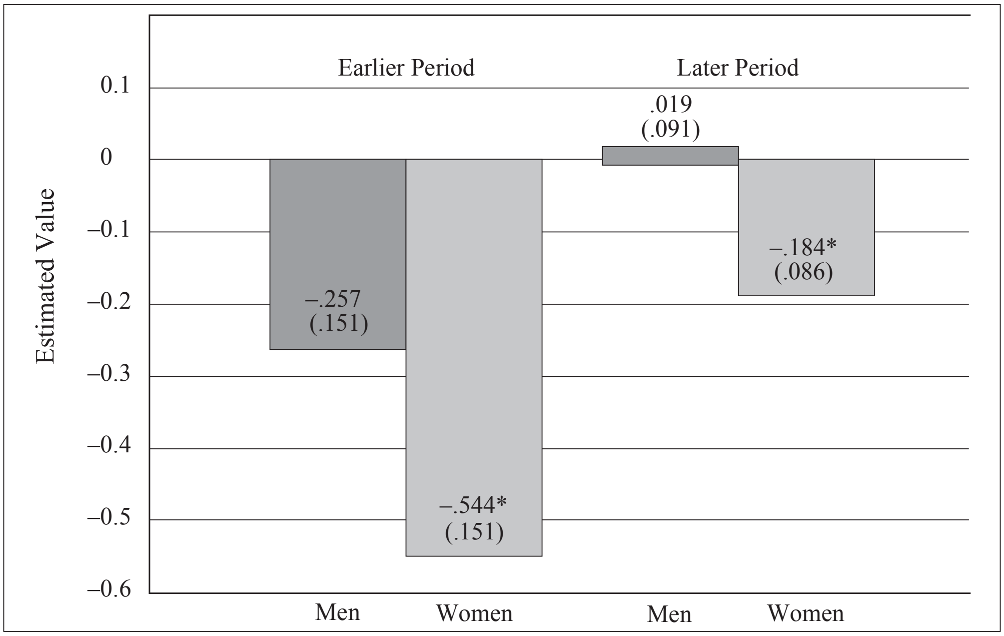
Note: Numbers in parentheses are standard errors; * significant at the level of $\alpha = .05$.

Fig. 5: Estimates of Sorting Gain or Loss by Period and Gender



Note: Numbers in parentheses are standard errors.

Fig. 6: Estimates of Ability Bias by Period and Gender



Note: Numbers in parentheses are standard errors; * Significant at the level of α = .05.

VII. Discussion and Conclusion

A. Interpretations of Results

The central result of this study is that a negative pattern of social selection based on family background and positive pattern of self-selection based on the principle of comparative advantage are not two mutually exclusive patterns of selection. Both patterns emerge in the Taiwanese data collected in the early 1990s, indicating that the two selection hypotheses are not necessarily incompatible. The interpretation of this result lies in the fact that ascription inequality due to parental education is not the only form of inequality involved in the process of educational and socioeconomic achievements. Besides family background, there are many other forces driving socioeconomic success, including those confounders that are measureable but omitted in this analysis due to data limitations (academic performance in high school, significant other's influence, and aspiration), and those drivers that are essentially unobservable (inner ability, expected utility of college education, and efforts).

Generally speaking, in the presence of class inequality in schooling attainment, students from advantaged backgrounds are better prepared by their families for scholastic competition, which may facilitate them to get ahead in both school and the labor market. Along this line of sociological thinking, Brand and Xie (2010) suggest that college graduates from lower classes are either more selective or uniquely driven by the economic rationale, and thereby they receive a higher college premium in the labor market, as opposed to their counterparts from upper classes. In this revisit, again, I find evidence in support of negative social selection. Nevertheless, sharing a structural position in class competition for higher education does not guarantee that people will have the same ability, or respond to college education in the same way. Once selection on unobservables is taken into account, there is evidence for positive sorting-gain selection, implying that self-selection into college based on comparative advantages was a basic logic of rational human action in the early 1990s. Thus, it is possible for empirical studies to provide evidence to support both the negative selection hypothesis in sociology and the positive selection hypothesis in economics, even though the two selection hypotheses have different implications for social scientists and policy makers.

Regarding the impact of educational expansion, the findings are more complicated. Brand and Xie (2010: 294) speculate that if educational expansion results in a larger number of college goers who are otherwise unlikely to attend college, unobserved selectivity due to economic incentive may go down, which could lead to a flat pattern of selection across propensity strata. This speculation is not empirically tested in Brand and Xie's article. In this revisit, when using Xie's statistical method, I find that the observed pattern of social selection based on parental education remains negative, even given a large increase in the supply of college graduates to the labor market caused by rapid expansion of college education. On the other hand, when using Heckman's econometric approach, I do find a new homogeneous pattern emerging in Taiwan, instead of the earlier pattern of heterogeneity in returns to college education. The new pattern emerges as a consequence of a significant decline in the treatment effects for the treated over the last two decades. There are signs of a sorting loss, in the face of negative selection based on observed family background. This finding seems interesting especially because results from conventional methods (OLS and IV) tell us that "the college effect" remains stable over time.

B. Implications of Results

Overall, the empirical results have three implications for future research. First, this study shows that negative selection is the dominant pattern, as far as social selection based on family background is concerned. Such may be the case because class inequality in schooling attainment is ubiquitous. Traditionally, sociologists are particularly concerned with the issue of how structural forces channel individuals into diverging pathways of socioeconomic achievements, with persisting attention on structural constraints and normative challenges facing socially disadvantaged groups. Focusing on ascribed class inequality, negative selection hypothesis conveys an inspiring message, especially for those in lower socioeconomic backgrounds who are swimming upstream, regarding how their efforts will be rewarded in the future, as long as they keep studying diligently and working hard. Could this encouraging message be well received around the world? To provide an answer to this question, carrying out international comparative studies would be helpful.

Second, this study demonstrates that self-selection into college is more widespread in the time of demand (for college education) exceeding supply, especially when class inequality in educational attainment is severe and rules (exams) governing college attendance are rigorous. Educational expansion may decrease educational selectivity by family background, and thus disrupt the pattern of self-selection. However, the expansion of college education also involves change in the nature of college, that is, change in the treatment. In Taiwan, the treatment used to be an elite education, and now it is massive, less challenging, more practical, and vocational. Future studies should pay more attention on how change in the treatment effect would result from change in the treatment.

The third implication is methodological. Sociologists widely acknowledge that unobserved selectivity matters for causal inference with observational data, but they rarely model it directly. This study suggests that empirical studies taking the selection issue seriously would benefit from employing Heckman's advanced econometric approach, as it allows researchers to explicitly account for selection on unobservables. This suggestion may be particularly important for sociological research using country-specific data which are poor in measurements of variables relevant to socioeconomic attainment. Selection on unobservables should be foreseen, especially in the situation of data limitations. After all, it is the selection on unobservables that gives rise to policy evaluation problems (Heckman, 2001a; 2001b; 2005a; 2005b).

C. Limitations

I cannot claim that the findings of this study are typical of contemporary societies, as Taiwan's recent experience of educational expansion was situated in its peculiar and changing political economy. As is well known, economic returns to college education vary with institutional and market context. Also, educational policy impacts are sensitive to national context. In the era of globalization, educational expansion and technological upgrading are two intertwining forces driving economic growth. Economic development is typically accompanied by an increase in college-educated workforce as well as a rise in returns to college education (Goldin and Katz, 2008). This stylized fact, nevertheless, does not describe the case of Taiwan at the turn of the 21st century. Contrary to the increasing trend in the rate of returns to schooling (OLS estimates) between 1980 and 1990 (Chan et al., 1999; Tsai and Mai, 1998), since 1990 there has not emerged a significant rise—some even suggested a decline—in returns to higher education (Chuang and Lai, 2010; Tsai and Xie, 2008; Yang et al., 2011). Why is this the case? This article provides evidence for the negative impact of the supply-driven change. Nevertheless, the demand-driven change may also exert an impact on college treatment effects.

As early as the 1960s, Taiwan was tied closely to the world market, making remarkable "growth with equity" in the 1970s. The state initially pursued an industrial strategy based on export of labor-intensive products, and later shifted to the strategy of exporting high value-added goods based on capital- and knowledge-intensive production. In Taiwan, as in many larger societies, skilled-biased technological change—particularly the advent of computerized technologies—favors highly skilled and more highly educated workers over low-skilled and less-educated workers, which should drive up the wage premium for college education. Nowadays, in order to survive and compete in the world market, Taiwan's economy continues to move toward more sophisticated industry, in which human capital raises productivity and earnings. Nevertheless, Taiwan's economy unexpectedly shrank in the late 2000s, with slow growth rates, rising unemployment rates, and increasing income inequality over recent years. How the decline in the economy may play a part in the decline in the college treatment effect for college graduates is an important issue, yet it is beyond the scope of this study.

The empirical part of this study has three limitations. First, as mentioned earlier, this analysis used data collected from different surveys. There may be a problem with the representativeness of the pooled data. It would be better for future research to use a singular data set with a large number of samples representative of birth cohorts under study, if such a data set is available. Second, multiple years of survey data were used in this analysis. There may be some changes in price level over time, and hence it would be better if earnings and tuition had been deflated by the consumer price index (CPI) in advance. Third, the effect of tuition on the propensity of receiving college education is positive in the later period examined. This finding is counter-intuitive, as it is opposite to the direction in sign (negative) predicted in American studies (e.g., Carneiro et al., 2011). If possible, future research should try with other measures related to tuition, or use other IVs that might fit the purpose better than tuition. The above three shortcomings remain to be improved or overcome in future research.

D. Conclusion

To conclude, both sociologists and economists are concerned with the causal relationship between education and earnings, but they disagree over the pattern of selection in heterogeneous returns to college education. Sociologists argue that there is a negative selection bias involved, such that those who are most likely to benefit from college education are least likely to attend college. Economists argue that those who attend college are most likely to benefit from it. This article moves beyond such a conflicting contrast, showing that the contradictions between negative selection hypothesis in sociology and positive selection hypothesis in economics are related to the contradictions between selection on observables and selection on unobservables in causal inference, which are at the heart of the contradictions between the two disciplines in the diverging developments of advanced counterfactual analyses of college treatment effects.

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Appendix

Table A1: Samples Aged 25-34 by Birth Cohort and Survey Year

	Survey Year												
	Earlier Period						Later Period						
Birth Cohort	1990	1991	1992	1993	1994	1995	2005	2006	2007	2008	2009	2010	2011
1956	34												
1957	33	34											
1958	32	33	34										
1959	31	32	33	34									
1960	30	31	32	33	34								
1961	29	30	31	32	33	34							
1962	28	29	30	31	32	33							
1963	27	28	29	30	31	32							
1964	26	27	28	29	30	31							
1965	25	26	27	28	29	30							
1966		25	26	27	28	29							
1967			25	26	27	28							
1968				25	26	27							
1969					25	26							
1970						25							
1971							34						
1972							33	34					
1973							32	33	34				
1974							31	32	33	34			
1975							30	31	32	33	34		
1976							29	30	31	32	33	34	
1977							28	29	30	31	32	33	34
1978							27	28	29	30	31	32	33
1979							26	27	28	29	30	31	32
1980							25	26	27	28	29	30	31
1981								25	26	27	28	29	30
1982									25	26	27	28	29
1983										25	26	27	28
1984											25	26	27
1985												25	26
1986													25

Table A2: Frequency Counts and Estimated College Effect per Propensity Score Stratum

Total							
Earlier Period (N = 3,341)				Later Period (N = 5,749)			
P-Score	D = 0	D = 1	Estimated College Effect	P-Score	D = 0	D = 1	Estimated College Effect
[.000, .103]	579	51	.323 (.069***)	[.000, .297]	707	205	.254 (.042***)
[.103, .125]	558	66	.203 (.063**)	[.297, .384]	673	377	.241 (.033***)
[.125, .141]	434	70	.190 (.064**)	[.384, .466]	552	437	.219 (.029***)
[.141, .185]	426	89	.225 (.061***)	[.466, .561]	515	478	.132 (.030***)
[.185, .275]	415	102	.099 (.052)	[.561, .675]	312	524	.112 (.035**)
[.275, 1.00]	317	234	.072 (.048)	[.675, 1.00]	200	769	.102 (.045*)
N =	2,729	612		N =	2,959	2,790	

Note: Numbers in parentheses are standard errors; * p < .05, ** p < .01, *** p < .001 (two-tailed tests).

Men							
Earlier Period (N = 1,867)				Later Period (N = 3,081)			
P-Score	D = 0	D = 1	Estimated College Effect	P-Score	D = 0	D = 1	Estimated College Effect
[.000, .114]	390	47	.228 (.070**)	[.000, .305]	484	152	.126 (.045*)
[.114, .135]	378	48	.114 (.070)	[.305, .393]	385	224	.172 (.044***)
[.135, .168]	298	51	.152 (.085)	[.393, .479]	309	241	.123 (.039**)
[.168, .250]	230	54	.135 (.075)	[.479, .574]	270	247	.085 (.045)
[.250, .365]	131	65	.076 (.081)	[.574, .700]	137	262	.114 (.057*)
[.365, 1.00]	90	85	−.040 (.092)	[.700, 1.00]	72	298	−.013 (.079)
N =	1,517	350		N =	1,657	1,424	

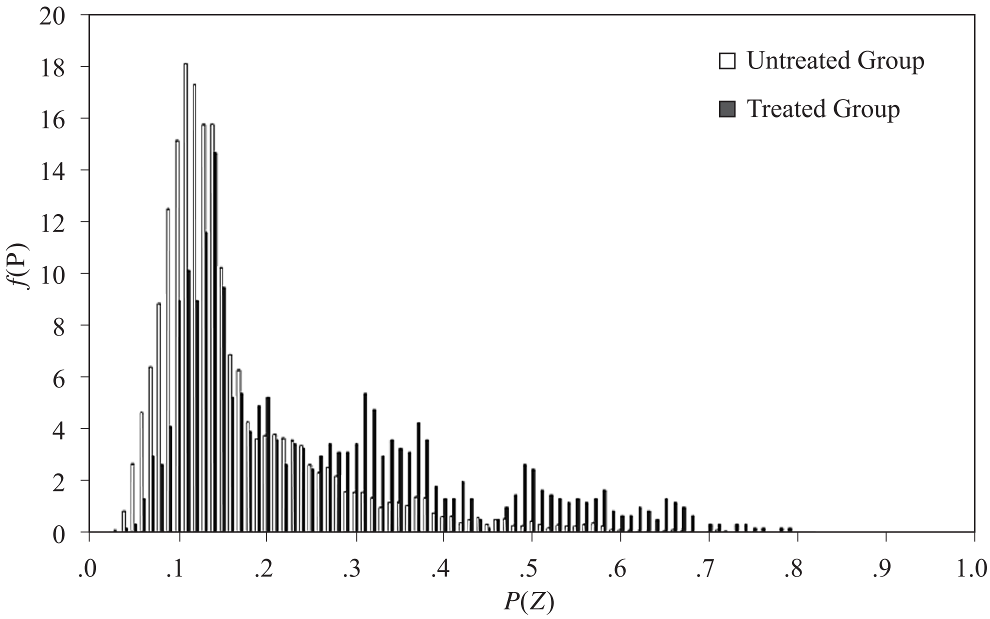
Note: Numbers in parentheses are standard errors; * p < .05, ** p < .01, *** p < .001 (two-tailed tests).

Women							
Earlier Period (N = 1,474)				Later Period (N = 2,668)			
P-Score	D = 0	D = 1	Estimated College Effect	P-Score	D = 0	D = 1	Estimated College Effect
[.000, .073]	266	12	.473 (.142**)	[.000, .335]	414	143	.380 (.053***)
[.073, .129]	261	33	.216 (.092*)	[.335, .425]	304	183	.327 (.047***)
[.129, .172]	253	38	.217 (.083**)	[.425, .525]	223	211	.261 (.046***)
[.172, .240]	187	52	.261 (.080**)	[.525, .630]	177	225	.130 (.040**)
[.240, .350]	145	57	.229 (.077**)	[.630, .755]	133	297	.178 (.044***)
[.350, 1.00]	100	70	.155 (.083)	[.755, 1.00]	51	307	.242 (.084**)
N =	1,212	262		N =	1,302	1,366	

Note: Numbers in parentheses are standard errors; * p < .05, ** p < .01, *** p < .001 (two-tailed tests)

Fig. A1: Density of Estimated Propensity Score *P(Z)* by Period

A. Earlier Period



B. Later Period

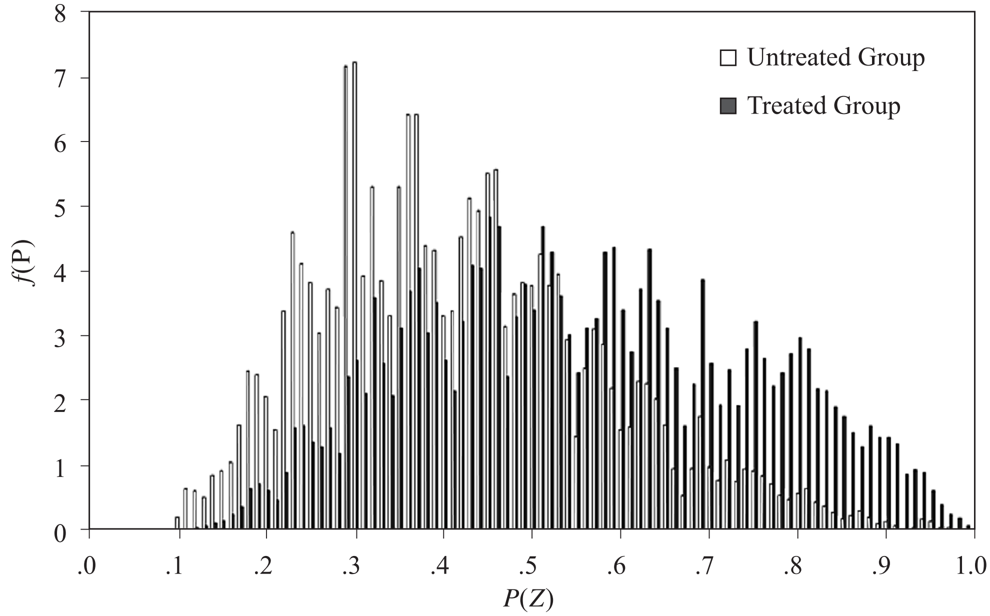
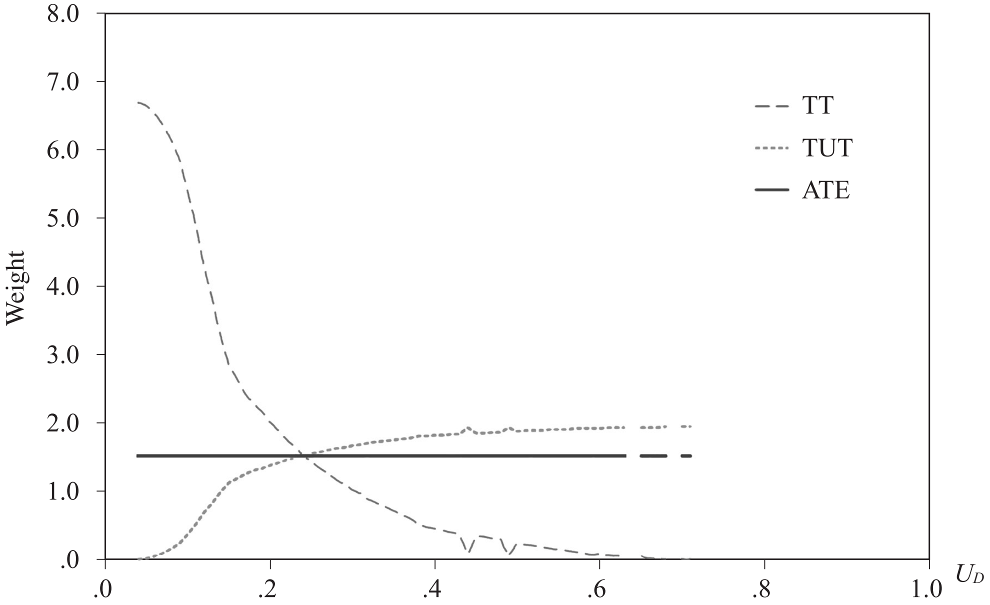
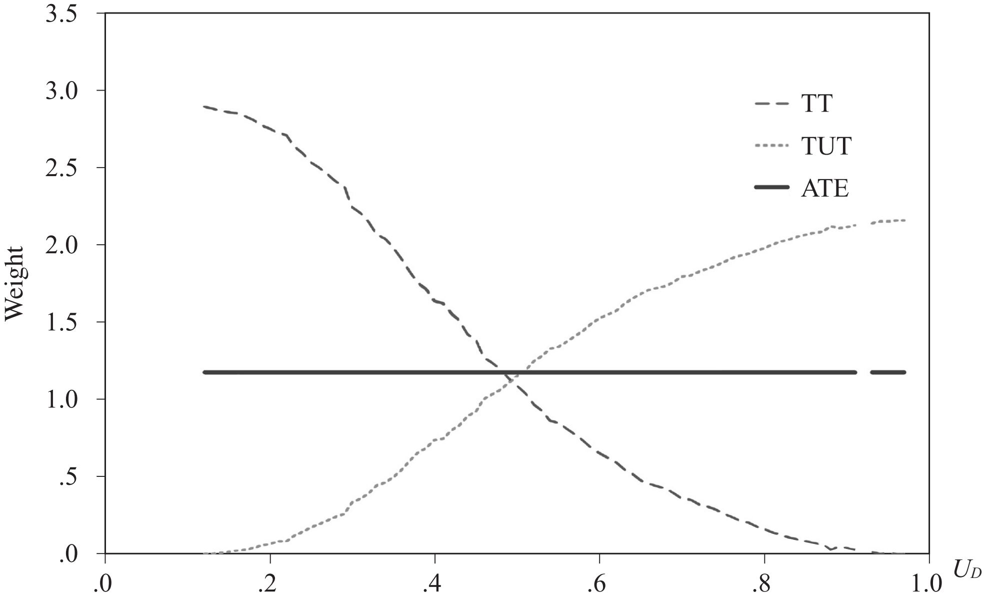


Fig. A2: Weights of Treatment Parameters by Period

A. Earlier Period



B. Later Period



再論大學教育之異質回報的選擇性

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摘　要

社會學家認爲大學教育之異質性經濟回報是負向選擇的結果：最不可能上大學者，其回報最高。經濟學家則主張正向選擇：回報愈高者，愈可能上大學。本文說明：這兩個假設之所以看似矛盾對立，和「可觀察變數的選擇性」與「不可觀察變數的選擇性」之差別，息息相關。臺灣之實徵分析結果顯示：在九〇年代初期，基於家庭背景的「負向社會選擇」與基於比較優勢原則的「正向自我選擇」可以並存，並非彼此互斥。然而，近二十年來大量擴展高等教育的結果，晚近的回報已顯著不如早期，自我選擇的分類收益有由正轉負的跡象，但負向的社會選擇依然如故。

關鍵字：社會選擇、自我選擇、分類收益、大學教育回報、反事實（擬眞）分析