Returns to College Education Reexamined:
Individual Treatment Effects, Selection Bias, and Sorting Gain

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Abstract

Using Taiwanese data collected in the early 2000s, we address the question of whether or not higher earnings observed for college graduates over high school graduates are caused by college education *per se* or the selection of persons into college who would gain more from their college education. We estimate and compare results from the Mincer-type productivity model and a selection model of "essential heterogeneity" proposed by Heckman, Urzua, and Vytlacil (2006). Specifically, we borrow Heckman, Urzua, and Vytlacil's approach of estimating the "marginal treatment effect" (MTE) under assumptions for local instrumental variables (LIV). The empirical results obtained from the semiparametric LIV estimation reveal that there is substantial individual heterogeneity in the Taiwanese data, and there is a negative selection bias and a positive sorting gain. Our results show TT > ATE > TUT. The negative selection bias implies that persons who attend college would make low-income high school graduates, while the positive sorting gain suggests that the principle of comparative advantage is also at work.

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1. Introduction

The earnings premium for college graduates over high school graduates in the labor market is well documented. Why do the college-educated earn more? There are a number of possible explanations. One is a pure productivity story: college education raises an individual's human capital and thus improves productivity, which, in turn, leads to a significant increase in earnings. Another explanation is one of selection: the type of persons who select (or are selected) into college has traits and characteristics – both observable and unobservable – that make them earn more in the labor market. In this paper, we reassess the causal effects, particularly heterogeneous effects, of college education on earnings, using data from recent Taiwanese surveys in the early 2000s for young workers aged 25-34.

As in most studies of the economic returns to education, we begin with the classic "Mincer equation" as a point of departure. The "Mincer equation" is just a simple linear regression of logged earnings on schooling and a separable quadratic function in work experience (Mincer 1974). The equation can be easily estimated via ordinary least squares (OLS) regression with observed data. While simple, the coefficient of the education variable in the Mincer equation has the desirable property of being easily interpretable as the rate of economic return to schooling. However, the causal interpretation of the "Mincer coefficient" of education relies on a number of strong assumptions that are unlikely to hold true. For example, it has long been recognized that if some unobserved factor, such as ability, are both correlated with schooling choice and affect earnings, the OLS estimator of the return to schooling will be biased (Griliches 1977). Based on notions of comparative advantage, Willis and Rosen (1979) also argue that persons may self-select into college versus non-college educational levels based on their anticipated economic benefits from their educational decisions. More recently, Heckman and his associates (e.g., Heckman, Lochner, and Todd 2006) challenge an assumption underlying the Mincer model that the causal effects of education are homogeneous, and propose methods that help examine heterogeneous effects at the individual level.

In this paper, we borrow the recent work of Heckman and his associates to separate biases from the conventional Mincer model into a selection bias and a sorting gain. We rely on the methodological approach developed by Heckman and Vytlacil (1999, 2001, 2005) and Heckman, Urzua, and Vytlacil (2006) that allows the researcher to estimate the "marginal treatment effect" (MTE) under assumptions for local instrumental variables (LIV). This methodological approach has been implemented in studies of Carneiro and Heckman (2002) and Heckman and Li (2004).

Our empirical work consists of several steps. We first follow the literature of educational stratification (e.g., Shavit and Blossfeld 1993; Shavit, Arum, and Gamoran 2007), using ascriptive characteristics Z to predict one's propensity of receiving four years' college education and thereby obtain the propensity score. For this study, we treat this set of variables (Z) as instrumental variables (IV), which are assumed to affect earnings only indirectly by affecting college attendance. To the extent that this IV assumption is not true in practice, our results would be subject to alternative explanations. However, under the provisional IV assumption, this approach allows us to examine heterogeneous treatment effects at different levels of unobserved selectivity.

Next, capitalizing on the nonlinear relationship between the propensity score and logged earnings, we use the propensity score as a local instrumental variable (LIV) of marginal treatment effects (MTE, i.e., treatment effect at the margin). Through the marginal treatment effect, we gauge the average treatment effect (ATE, i.e., the effect of randomly assigning a person with observed characteristics X to college), the treatment effect for the treated (TT, i.e., the effect of treatment on those who go to college compared with what they would experience without going to college), and the treatment effect for the untreated (TUT, i.e., the effect of treatment on those who do not go to college compared with what they would experience with the treatment). We finally decompose the conventional bias (i.e., the difference in magnitude between OLS and ATE estimators) into two components: the selection bias (i.e., the mean bias of selection on observed characteristics in the absence of college education) and the sorting gain (i.e., the average additional college premium for persons who attend college relative to that for persons who do not attend college).

Our empirical results obtained from the Heckman-type semiparametric approach (LIV) of estimation reveal that there is substantial individual heterogeneity in the Taiwanese data. We know that TT overweights the ATE for persons who are more likely to attend college, whereas TUT overweights the ATE for persons who are less likely to attend college. The shape of the estimated MTE yields the result that TT > ATE > TUT. All in all, there is a negative selection bias and a positive sorting gain. The negative selection bias implies that persons who attend college would make poor high school graduates, while the positive sorting gain suggests that the principle of comparative advantage is at work. These findings for Taiwan in the early 2000s are consistent with the conclusions of Heckman and Li (2004) for the young people (aged 21 to 36) of urban China in 2000.

In the remainder of the paper, we first discuss the productivity explanation and selection explanation through a selective review of the literature. We then present analytical models considered in our framework for causal inference, along with the rationale for using them. After an illustration of methods and data used in this analysis, we report the empirical findings. We finally conclude with discussions.

2. Explanations for Economic Returns to College Education

One of the best-established empirical findings in social science research is that more educated people attain higher earnings in the labor market (Card 1999; Glewwe 2002), irrespective of gender (McCall 2000). Nevertheless, the nature of connection between education and earnings has long been a subject of debate. A widely held view in both economics and sociology argues that schooling causally affects earnings positively, as part of human capital that raises a worker’s productivity. Critics however contend that the documented relationship is not necessarily causal.[1] For example, individuals with certain traits and characteristics – such as high ability or advantaged family background – may attain more schooling and would attain higher earnings in the absence of higher levels of education. In this contrarian view, it is the selection in the allocation of educational resources and economic rewards that matters. Below, we briefly review the two competing explanations.

The Productivity Explanation

One prevailing explanation for the positive relation between education and earnings views education as a source of marketable skills. It is commonly believed that the economic value of schooling lies in the human capital it instills in students. Higher education, in particular, provides students with skills that are valued and rewarded in the labor market. The thesis of industrialism, for example, suggests that educational systems are a rational mechanism for training workers (e.g., Blau and Duncan 1967; Treiman 1970). School systems expand in modern society to meet the increased need for a trained labor force, and this expansion, in turn, leads to a more meritocratic allocation of both schooling and economic rewards. In industrialized societies where high economic reward is allocated to those jobs requiring high degrees of skill, educational credentials represent a type of "capital" – be it human capital or status capital[2] – that allows individuals to "buy" their way into more lucrative jobs. Accordingly, individuals invest in university education, for which the earnings premium represents a justifiable return to a prior investment.

The productivity explanation is best provided by Becker's (1964) human capital theory,

[1] Critics of the causality argue that some portion of the schooling-earnings relationship is spurious, but disagree as to how much; see Card (1995; 1999) for a survey of the economic literature.

[2] Conflict and reproduction theorists have long challenged the common argument that advances in technology and the upgrading of the occupational structure have resulted in a need for higher level of skill and training that education is said to supply (e.g., Boudon 1974; Collins 1979). They argue that the critical role played by education in industrialized societies is not to provide training but to preserve the status culture. Educational credentials serve as a signal, and employers select those job candidates whom they believe will fit best into the status culture of the elite. Thus, the schools are used to control membership in economic institutions. As a result, educational systems may expand without increasing the equality of educational opportunity, nor fostering the meritocratic allocation of economic rewards.

which offers an economic conceptual apparatus for explaining why earnings inequality is a necessity in an economy where some activities require more costly investments than others. In this theory, differential wages are assumed to result in large part from differences in the amounts of human capital possessed by workers over the life cycles, as human capital determines productivity. Thus, human capital theory explains earnings disparities between college graduates and high school graduates as attributable to their differences in productive capacity. Becker emphasizes that if one views higher education as an investment, then persons decide whether or not to invest in it in the expectation of maximizing a positive return on their investment.

Mincer's (1974) pioneering work provided an elegant way to empirically estimate the return to schooling within the human capital framework. He developed a "standard" human capital earnings function, using OLS regressions with logged earnings as the dependent variable and years of schooling as a primary independent variable, along with years of work experience, and squared years of work experience. The Mincer coefficient of the return to education is actually just some average percentage difference in mean earnings for each additional year of schooling. Mincer showed that this is the private rate of return to the investment in a year of schooling, if forgone earnings are the only cost of school attendance. The Mincer equation has been "one of the great success stories of modern labor economics" (Willis 1986: 526); numerous articles have been published using it as an empirical tool (Heckman, Lochner, and Todd 2006).

Two issues arise with the Mincer model. The first is the "ability" problem: unobserved heterogeneity in ability may cause a bias in the return estimated via the Mincer model. It has been suggested that part of the observed positive correlation between education and earnings is due to a shared source of individual variability – ability. For example, Griliches (1977) argued that if schooling and ability are positively correlated, then a measure of the return to schooling that ignores the ability variable will be biased upward by the product of this correlation and the regression coefficient of ability on schooling. Nevertheless, he also entertained a model with a negative correlation between schooling and ability. Thus, how unobserved ability may cause a bias to the Mincer return remains an open question.

The Selection Explanation

Alternatively, the positive association between education and earnings can be attributable to the "self-selection" problem: some individuals choose to go to college and others do not. Resources and incentives are two major determinants of college attainment (Buchmann and DiPrete 2006). We know that the family plays an important role in shaping educational opportunities of its members. The economist's view is that college attendance is the result – at least in part – of optimizing behavior by agents (i.e., individuals and their families) within a certain opportunity set and based on some anticipated return to schooling (Willis and Rosen 1979). If the full opportunity set cannot be observed and opportunities vary across agents, then observed data are systematically censored and there is no guarantee that the Mincer coefficient will accurately reflect the causal effect of schooling of any individual in the population (Willis 1986). The self-selection problem is intimately tied to the ability bias problem, but more serious and more complicated. Whereas conventional conceptualization of the ability bias is concerned with heterogeneity in an individual's ability to earn money in the labor market without additional education (i.e., a pre-treatment predictor), self-selection is caused by individual heterogeneity in returns to education that is unknown to the researcher but may be partially known to the agent. Thus, self-selection cannot be addressed by measures of ability as a pre-treatment covariate in empirical studies (Carneiro and Heckman 2002).

A basic assumption of the selection explanation is that those with the highest returns may be most likely to take part in the "treatment" of attending college. This assumption suggests that the average student going to college may have higher earnings than the marginal student who is indifferent about going vs. not going to college (see, e.g., Heckman and Vytlacil 1999; Card 2001). Estimating the marginal return for a latent group at margin represents a difficult empirical task.

It was Roy (1951) who provided a prototypical model of selection for a two-sector choice. The Roy model posits that self-selection due to comparative advantage in skills reduces earnings differences by sector relative to those that would result if workers were randomly assigned to the sectors. The importance of Roy's work was not widely recognized by economists until the 1970's (Neal and Rosen 2000) and not implemented in empirical work until Willis and Rosen (1979).

Willis and Rosen (1979) extended the Roy model to allow for endogenous skill acquisition through education. Their empirical work revealed that expected lifetime earnings gains influence the decision to attend college: those who did not attend college would have earned less than observably similar people who did attend, while those who attended college would have earned less as high school graduates than observably similar people who stopped after high school. Willis and Rosen regarded this positive sorting – which, in their interpretations, is equivalent to positive selection bias – in both groups as no "ability bias" in the American data used. They said that the ability bias might actually be zero or even negative because quitting school early was indicative of good earnings prospects.

While separating those who attend college from those who do not, Willis and Rosen assumed homogeneous education effects within a sector. The pioneering work by Heckman and Robb (1985) established the importance of heterogeneous treatment effects. Responding to this new emphasis, Bjorklund and Moffitt (1987) modified the then "standard" selection model by allowing "heterogeneity of rewards" in the model for the effects of education and other economic activities on earnings. They argued that such heterogeneity creates a new form of selection bias, namely, sorting on the gain, which is distinct from sorting on the level. And they demonstrated how to use a selection model to identify the marginal gain to persons induced into a treatment status by a marginal change in the cost of treatment. Bjorklund and Moffitt (1987) thus introduced the parameter of *marginal treatment effect* into the literature in a parametric context. Later, Imbens and Angrist (1994) showed how to identify a discrete approximation to this parameter as a local average treatment effect (LATE) using the instrumental variable (IV) approach.

The Roy model has been further clarified and extended by Heckman and his associates (e.g., Heckman and Honoré 1990). This body of recent work (e.g., Heckman and Vytlacil 1999, 2000, 2005; Carneiro and Heckman 2002; Carneiro, Hansen, and Heckman 2003; Heckman and Li 2004; Heckman, Urzua, and Vytlacil 2006) extends the "marginal treatment effect" approach to a semiparametric context with a local instrumental variable (LIV), which is essentially the propensity score for treatment consisting of at least some instrumental variables. Heckman (2001a, 2001b) argues that returns to college education should be conceptualized as heterogeneous at the individual level, with an emphasis on unobservables: due to unobserved heterogeneity, observationally identical people make different schooling choices and earn different wages, and hence there should be a wide range of causal effects of college education for different members in a population. Furthermore, Heckman and his associates (cited above) present new methods that model the "essential heterogeneity" in responses to schooling, i.e., persons select into college based on their own idiosyncratic return (conditional on observed characteristics). They also show that biases from the Mincer model can be separated into a bias due to selection into college and a sorting gain to college attendees.

To conclude, the conventional Mincer-type productivity model assumes that agents making different schooling choices are *ex ante* identical. Thus, there is a single effect of schooling. In contrast, the Heckman-type selection model assumes not only individual heterogeneity but that people act on it when making schooling choices. Consequently, persons who receive the treatment into college are those who get more out of it than persons who do not. In what follows, we apply methodologies developed by Heckman, Urzua, and Vytlacil (2006) to recent survey data in Taiwan in order to ascertain the selection bias component and the sorting gain component in the relationship between college education and earnings in the Taiwanese context.

3. Analytical Models and Rationale

In this paper, we borrow the language in the causal inference literature and estimate the causal effect of four-year college education on earnings. Treating four-year college education as treatment and high-school education as control, we ask the question: What would be the economic outcome if a given person received the treatment (i.e., attained university education) compared to the case where the person had not received the treatment (i.e., stopped education after high school or equivalents)? Of course, this counterfactual question is impossible to answer at the individual level, as a person is observed either to have received college education or not. Thus, attempts to answer this causal question empirically always invoke statistical analyses of observational data under some assumptions. Such attempts, called *statistical approaches to causal inference,* can only be made at an aggregate level (Holland 1986).

<u>*The Conventional Mincer-type Model*</u>

The conventional Mincer-type model treats the return to education to be invariant, although we can also reinterpret it as a weighted average of heterogeneous treatment effects (Angrist and Krueger 1999). The earnings equation takes the form:

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

where Y_i is earnings in the logarithm form; i (= 1, …, n) is subscript for persons; D_i is a dummy variable representing whether or not the person receives four years' college education (D_i = 1 if yes; D_i = 0 otherwise); β is the return to college education, after controlling for the effects of X_i, a vector of other earnings determinants including constant, gender, years of Mincer experience (defined as age – years of schooling – 6), and Mincer experience-squared; γ is a vector of coefficients; U_i is the disturbance component of log earnings which includes such unobserved factors such as ability, effort, and market luck.

It is hardly a new hypothesis but an empirical regularity established around the world that $\beta > 0$; see, e.g., Psacharopoulos (1985) for international comparisons. The real question of social science interest is this: Does the magnitude of β estimated in equation (1) accurately reflect the causal effect of college education on earnings? There can be two potential sources of bias (Heckman, Lochner, and Todd 2006): (1) D_i is correlated with U_i (i.e., if high-ability people choose to go to college, then there is the problem of ability bias); and (2) β is correlated with D_i (i.e., whether or not schooling decisions are made with expected gain β, resulting in a sorting gain). As mentioned earlier, a long-nagging concern in the literature is that high-ability people would go to college and would attain higher earnings even if they had not received college education. In such a case, the schooling-earnings connection may be a mirage; it is just a reflection of the fact that high-ability people are rewarded with an earnings premium for their (unobservable) innate skills in the labor market. Another possibility is that high ability is associated with advantaged family background. The result is that the Mincer coefficient may be biased due to the omission of ability or family background. In our study, we are limited by lack of an ability measure. We can, however, retain the assumption that ability is unobservable and test whether, after the inclusion of the background variable in the model, there is still some evidence of self-selection.

The Heckman-type Selection Model

To test whether those who receive college education are those who benefit more from it, we employ a Heckman-type two-stage selection model that consists of two equations: an earnings outcome equation and a treatment selection equation. We assume that there are two mechanisms involved in the determination of college attendance: (1) social selection, that is, inequality of educational opportunities due to ascribed characteristics such as family origins; and (2) individual heterogeneity such as high – or lack of – ability (i.e., a concept covering intelligence, aspiration, and effort). While the latter is unobservable, the former can be captured by the propensity score, which is defined as the conditional probability of receiving the treatment given a set of observed pretreatment variables (Rosenbaum and Rubin 1983). A key unverifiable assumption is that at least some observed background variables can serve as instrumental variables (IVs) in order to identify the effects of the unobserved component.

We then follow recent work of Heckman and his associates – e.g., Heckman and Vytlacil (1999, 2001, 2005), Carneiro and Heckman (2002), Heckman and Li (2004), and Heckman, Urzua, and Vytlacil (2006) – and revise the model of equation (1) to allow for self-selection based on individual idiosyncratic returns. The revised model can be expressed in the random coefficient form as:

$$Y_i = \beta_i D_i + \gamma X_i + U_i \, , \tag{2}$$

where β_i represents the *heterogeneous* return to college education, which varies among persons; D_i is an *endogenous* dummy variable denoting whether or not the treatment of four years' college education is assigned to person *i*; other notations remain the same.

With respect to the endogeneity in education, 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. The assumption of optimizing behavior implies that agents would "rationally" choose college graduation over high school graduation when economic benefits can be anticipated from this choice. Nevertheless, the anticipated gain to a particular person from college education is unknown. In this model, the "latent" gain is assumed to be determined by comparing the person's propensity of receiving college education and his/her unobserved heterogeneity in the treatment selection equation.

To be more specific, the following decision rule is used to predict the binary selection into college:

$D_i = 1$ if $D_i^* > 0$; $D_i = 0$ otherwise,

$$D_i^* = P_i(Z_i) - U_{Di} \qquad (3)$$

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" of receiving college education, which is a linear function of Z_i, a vector of observed exogenous covariates like gender, ethnicity, family background, and birth cohort; U_{Di} is the unobserved individual heterogeneity. Note that the propensity score $P_i(Z_i)$ can be estimated by a probit or logit model.

Within this framework, $P_i(Z_i)$ and U_{Di} in the schooling choice equation (3) may be interpreted as observed and unobserved costs of education, respectively; see Carneiro and Heckman (2002) for details. The higher the propensity score $P_i(Z_i)$, the more advantaged the family background, thus the lower the observed costs of education, and the larger the person's educational opportunity. By contrast, the larger the unobserved individual heterogeneity U_{Di}, the larger the unobserved costs of education, and hence the less likely it is that the person receives college education. If $P_i(Z_i) = U_{Di}$, then person i is assumed to be indifferent between treatment or not.

We use this schooling decision rule to break the earnings equation (2) into two switching equations representing the two potential selection outcomes (Y_{0i}, Y_{1i}) for each person i:

$$Y_{0i} = \gamma_0 X_i + U_{0i} \qquad \text{if } D_i = 0 \qquad (4a)$$

$$Y_{1i} = \gamma_1 X_i + U_{1i} \qquad \text{if } D_i = 1 \qquad (4b)$$

where $E(U_{0i} \mid X_i) = 0$ and $E(U_{1i} \mid X_i) = 0$ in the population. The individual-level treatment effect is $\Delta_i = Y_{1i} - Y_{0i} = (\gamma_1 - \gamma_0) X_i + (U_{1i} - U_{0i})$. However, recall that Y_1 cannot be observed for those who do not go to college ($D_i = 0$), while information on Y_0 is missing for those who attain college education ($D_i = 1$). The individual treatment effect is thus 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 casual effects; see

Heckman (2005a, 2005b) and Sobel (2005) for exchanges in ideas regarding the scientific model of causality.

Following Heckman, Urzua, and Vytlacil (2006), we can also combine the two equations in a single-equation form with a switching weight:

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i}, \text{ and } U_i = D_i U_{1i} + (1 - D_i) U_{0i}. \tag{5}$$

Using equations (4a), (4b), and (5), we can rewrite equation (2) as:

$$Y_i = \beta_i D_i + \gamma_0 X_i + U_{0i}, \text{ where } \beta_i = (\gamma_1 - \gamma_0) X_i + (U_{1i} - U_{0i}). \tag{6}$$

Note that in general X contains the predictor for the intercept term, 1. When 1 is the only predictor, $\beta_i = (\gamma_1 - \gamma_0) + (U_{1i} - U_{0i})$. Individual heterogeneity either in observed term $(\gamma_1 - \gamma_0)X_i$ or in unobserved term $(U_{1i} - U_{0i})$ gives rise to the heterogeneity in β_i in the population even after controlling for X. Thus, the return to college education (conditional on X) is a random variable with a distribution. There may be sorting on the gain. The sorting gain is the mean gain of the unobservables for those who receive college education, which is defined as $E[(U_1 - U_0) | X, D = 1]$ and equal to TT minus ATE, where TT = $E(Y_1 - Y_0 | X, D = 1)$ is the treatment on the treated, and ATE = $E(Y_1 - Y_0 | X)$ is the average treatment effect that records the average gain of moving a randomly selected person from “0” to “1”, conditional on X.

To conclude, according to Heckman (2001b), TT and ATE may be the same under one of the two conditions: (1) $U_{1i} = U_{0i}$ so $\Delta_i = \Delta$; and (2) $E(U_{1i} - U_{0i} | \mathrm{X}, D_i = 1) = 0$. Condition (1) implies no response heterogeneity given X, and hence there is a common effect given the same observed covariates. This is the homogeneous case presented in the Mincer Model. In such a model, selection bias arises for TT (= ATE) if $E(U_i | X, D_i = 1) \neq 0$. Condition (2) says that college attendees do not select into college based on gains from it. In such a case, outcomes may differ among persons with identical X characteristics, but *ex ante*, there is no perceived heterogeneity, and thus TT = ATE. In contrast, if $E(U_{1i} - U_{0i} | X, D_i = 1) \neq 0$ (which means that persons select into college based on their own gains), then TT ≠ ATE. In this case, again, selection bias arises for TT if $E(U_{0i} | X, D_i = 1) \neq 0$. In the presence of heterogeneity and selection, the use of conventional methods (such as OLS or IV) fails to identify the treatment effects of concern. We next illustrate the methods used in this analysis.

4. Methods

The fundamental reason why a simple Mincer model may yield biased estimate is that college education is not randomly assigned, so that the treated (i.e., college-educated) group and the untreated (control) group may systematically differ in important ways other than in observed pre-treatment covariates. These differences may exhibit complex correlations with the outcome variable, making it difficult to ascertain the average causal effect of the treatment.[3] If the average differences between treated and untreated groups can be fully captured by observed pre-treatment covariates, we can use the conditional probability of receiving the treatment given a set of observed pretreatment variables (namely, the propensity score) to account for such differences. While Rosenbaum and Rubin (1983) establish the central role of the propensity score in matching models, Heckman (1980) and Heckman and Robb (1985, 1986) establish the central role of the propensity score in selection models. Recent work by Heckman and Vytlacil (1999) shows that the propensity score also plays a central role in instrumental variable estimation of treatment effects even when unobserved selection bias and sorting effect are present. In this analysis, we use a new semiparametric approach (and software) developed by Heckman, Urzua, and Vytlacil (2006) to estimate the heterogeneous returns to college education via the method of local instrument variables (LIV).

Our empirical work involves two stages, the second of which consists of several steps. In the first stage, we predict a persons' probability of selection into four years' college education by following the literature of educational stratification (e.g., Shavit and Blossfeld 1993; Shavit, Arum, and Gamoran 2007). We use ascriptive characteristics Z (e.g., gender, ethnicity,

[3] To solve this problem several approaches have been adopted in the literature, including matching models, selection models, and instrumental variable models.

birth cohort, parental education, growing-up place prior to age 15, and some two-way interaction terms) as predictors in the treatment selection equation. The propensity score $P(Z) = Pr(D = 1| Z)$ is estimated by a probit model.

The propensity score $P(Z)$ is then used as a local instrumental variable (LIV) of marginal treatment effects in the second stage of the analysis, in which the nonlinear relationship between the propensity score and logged earnings can be written as:

$$E\left(Y \middle| X = x, P\left(Z\right) = p\right) = \gamma_0 x + \left[\left(\gamma_1 - \gamma_0\right)x\right]p + K\left(p\right) \tag{7}$$

where p is a particular evaluation value of the propensity score and

$$K\left(p\right) = E\left(U_1 - U_0 \middle| D = 1, P\left(Z\right) = p\right)p\,. \tag{8}$$

The marginal treatment effect – defined as the average effect of treatment given the unobserved characteristics in the decision rule of schooling choice – plays a fundamental role in the identification and estimation of treatment effects of concern. Note that the marginal treatment effect (MTE) has two interpretations. First, the MTE defined as $E(\Delta \mid X, U_D)$ is the expected effect of treatment conditional on observed characteristics X and conditional on U_D, the unobservables from the first stage decision rule. That is:

$$MTE\left(X_i = x, U_{Di} = u_D\right) = E\left(\Delta_i \middle| X_i = x, U_{Di} = u_D\right) = \left(\gamma_1 - \gamma_0\right)x + E\left(U_{1i} - U_{0i} \middle| U_{Di} = u_D\right). \tag{9}$$

In such a case, the parameter of local average treatment effect (LATE) is a version of MTE. LATE defined as $E[(Y_1 - Y_0) | D(z) - D(z') = 1]$ is the average treatment effect for individuals whose treatment status is influenced by changing an exogenous regressor included in the treatment equation.

Alternatively, we can also interpret the MTE as the mean gain in terms of Δ (= $Y_1 - Y_0$) for persons with observed characteristics X who would be indifferent between treatment or not if they were exogenously assigned a value of Z, say z, such that $U_D(z) = u_D$. Heckman and Vytlacil (1999, 2005) show that the MTE can be identified by taking derivatives of E(Y | Z = z) with respect to P(z). This derivative Δ^{MTE} is called the local instrumental variable (LIV).

$$MTE\left(X_i = x, U_{Di} = P_i = p\right) = LIV\left(X_i = x, P_i = p\right) = \frac{\partial E\left(Y_i \middle| X_i = x, P_i = p\right)}{\partial p} \tag{10}$$

$$\Delta^{LIV}\left(x, u_D\right) = \left.\frac{\partial E\left(Y \middle| X = x, P(Z) = p\right)}{\partial p}\right|_{p=u_D} = \Delta^{MTE}\left(x, u_D\right) \tag{11}$$

From this, we observe that the estimation of MTE involves the partial derivative of the expectation of the outcome Y (conditional on $X = x$ and $P(Z) = p$) with respect to p. This is the method of local instrumental variables introduced in Heckman and Vytlacil (2001). For the model of essential heterogeneity, Heckman, Urzua, and Vytlacil (2006) consider a linear and separable version of the form:

$$\left.\frac{\partial E\left(Y \middle| X = x, P(Z) = p\right)}{\partial p}\right|_{p=u_D} = \left(\gamma_1 - \gamma_0\right)x + \left.\frac{\partial K(p)}{\partial p}\right|_{p=u_D} \tag{12}$$

and it requires the utilization of nonparametric techniques to estimate the last term $\frac{\partial K(p)}{\partial p}$. That is to say, within their semiparametric approach the LIV estimator of the MTE is ultimately computed as

$$\Delta^{LIV}\left(x, u_D\right) = \left(\widehat{\gamma_1 - \gamma_0}\right)' x + \left.\widehat{\frac{\partial K(p)}{\partial p}}\right|_{p=u_D} = \widehat{MTE}\left(x, u_D\right), \tag{13}$$

and is evaluated over the set of p’s contained in P.

All treatment parameters of concern can be identified by using weighted averages of the MTE. Heckman, Urzua, and Vytlacil (2006: 396) show that:

$$\text{ATE}(x) = E\left(Y_1 - Y_0 \middle| X = x\right) = \int_0^1 \Delta^{\text{MTE}}\left(x, u_D\right) du_D$$

$$\text{TT}(x) = E\left(Y_1 - Y_0 \middle| X = x, D = 1\right) = \int_0^1 \Delta^{\text{MTE}}\left(x, u_D\right) w_{\text{TT}}\left(x, u_D\right) du_D$$

$$\text{TUT}(x) = E\left(Y_1 - Y_0 \middle| X = x, D = 0\right) = \int_0^1 \Delta^{\text{MTE}}\left(x, u_D\right) w_{\text{TUT}}\left(x, u_D\right) du_D$$

$\text{IV}_J(x) = \int_0^1 \Delta^{\text{MTE}}\left(x, u_D\right) w_{\text{IV}}^J\left(x, u_D\right) du_D$, given instrument J

$$\text{OLS}(x) = \int_0^1 \Delta^{\text{MTE}}\left(x, u_D\right) w_{\text{OLS}}\left(x, u_D\right) du_D$$

where the weights are

$$w_{\text{ATE}}(x,u_D)=1$$

$$w_{\text{TT}}(x,u_D)=\left[\int_{u_D}^{1} f(p|X=x)\,dp\right]\frac{1}{E(P|X=x)}$$

$$w_{\text{TUT}}(x,u_D)=\left[\int_{0}^{u_D} f(p|X=x)\,dp\right]\frac{1}{E((1-P)|X=x)}$$

$$w_{\text{IV}}^{J}(x,u_D)=\left[\int_{u_D}^{1}\left(J(Z)-E(J(Z)|X=x)\right)\int f_{J,P|X}(j,t|X=x)\,dt\;dj\right]\frac{1}{\text{Cov}(J(Z),D|X=x)}$$

$$w_{\text{OLS}}(x,u_D)=1+\frac{E(U_1|X=x,U_D=u_D)\,w_1(x,u_D)-E(U_0|X=x,U_D=u_D)\,w_0(x,u_D)}{\Delta^{\text{MTE}}(x,u_D)}$$

where f is a density function.

We finally follow the work of Heckman and Li (2004) and decompose the conventional bias (i.e., the difference in magnitude between OLS and ATE estimators) into two components: the selection bias (i.e., the mean bias of selection based on observed characteristics in the absence of treatment) and the sorting gain (i.e., the mean difference in the return to college education between persons who went to college and persons who did not).

$$\begin{aligned}
&\text{Sorting Gain}+\text{Selection Bias}\\
&=E(U_1-U_0|X,D=1)+\left[E(U_0|X,D=1)-E(U_0|X,D=0)\right]\\
&=\left[E(U_1|X,D=1)-E(U_0|X,D=1)\right]+\left[E(U_0|X,D=1)-E(U_0|X,D=0)\right]\\
&=E(U_1|X,D=1)-E(U_0|X,D=0)\\
&=\text{Bias arising in the OLS estimate}
\end{aligned}$$

5. Empirical Results

5.1 Data and the Propensity Score

This analysis is based on data from the Taiwan Social Change Survey (TSCS), which is a series of island-wide surveys conducted by the survey office at Academia Sinica. TSCS is an ongoing project designed to create data sets on the main themes of Taiwan's changing society; see http://www.ios.sinica.edu.tw/sc1/ for details of the surveys. For this analysis we use the

TSCS data collected during the period of 2001 to 2003. We limit our focus on the young entrants (aged 25-34 when surveyed) to the labor market, who reported non-zero earnings and who attained at least 12 years of schooling (i.e., high school or higher). Our analysis is thus based on the information ascertained from 1,439 workers born between 1967-1978, who provided complete information on earnings, education, and parental education, among other things.

Table 1 presents descriptive statistics of most of the variables used in the analysis. As shown in the table, 28.2% of the analysis sample went to college/university after high school graduation, and their average monthly earnings (nt$45,000) is significantly higher than that of workers who stopped after high school or equivalents (nt$35,092). We observe that 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 non-college-educated workers. Parental education is used as an important indicator of family socioeconomic background.[4]

(Table 1 about here)

We start our analysis with estimating the probability of receiving four years' college education for every observation in the analysis sample, using a probit model. The model and coefficient estimates are presented in Table 2. The last column of the table gives the mean marginal effect for each explanatory variable *Z*. The marginal effects derived from a probit model, $\Pr\left(D=1|Z\right)=\Phi\left(\delta' Z\right)$, is of the form:

$$\text{Marginal Effects} = \frac{\partial \Pr\left(D=1|Z\right)}{\partial Z} = \phi\left(\delta' Z\right)\delta$$

where δ is the coefficients estimated in the probit model, $\Phi(\bullet)$ is the standard normal distribution and $\phi(\bullet)$ is the standard normal density. Figure 1 depicts the density function

[4] Due to data limitations, unfortunately, we are unable to consider father's occupation or family income in this analysis.

for the estimated propensity score of college attendance for the treated group and the untreated group, respectively. It is the support of $P(Z)$ that helps identify the treatment effect of concern in this analysis.

(Table 2 and Figure 1 about here)

5.2. Results of OLS Regressions Predicting Logged Earnings

Next, we gauge the returns to college education. We first estimate a standard Mincer earnings equation which includes in the model only Mincer experience, Mincer experience squared, and gender as explanatory variables, in addition to a dummy variable indicating whether or not the respondent receives four year's college education. Table 3 presents the OLS coefficients estimated for the total analysis sample and for men and women, separately. All the coefficients reported in the table are statistically significant at the level of $\alpha = .05$. The OLS estimate of the mean return to four-year college attendance is 38% for Taiwan's young entrants to the labor market in the early 2000s. The estimate for females (44.5%) is significantly higher than that for males (32.4%), indicating that college credentials are more important for women than for men in the pursuit of labor market achievements.

(Table 3 about here)

5.3. Results of the Heckman-type Selection Model

We next employ the Heckman-Urzua-Vytlacil semiparametric approach of estimation via the method of local instrumental variables (LIV), using the probability of receiving college education as the instrument. Results presented in this session are obtained from local linear regressions with Gaussian Kernel and cross-validation optimal bandwidth.

Figure 2 plots the estimated marginal treatment effect as a function of unobserved heterogeneity U_D in the schooling choice equation.[5] As we can see in the figure, the relationship between the MTE and U_D is nonlinear with many curves. Overall speaking, the

[5] The curved line plotted in the figure has a few blanks in the right tail, because the MTE cannot be estimated at points where the support of P(Z) is short.

MTE declines with increasing unobserved component in the schooling choice equation. Recall that within this framework, the higher the unobserved individual heterogeneity U_D, the higher the unobserved costs of attending college, thus the lower the probability of attending college. Accordingly, the declining pattern of MTE with U_D means that those who have the highest probability of going to college (i.e., those who are most advantaged in social selection) have the largest marginal returns; by contrast, those who have the least probability of going to college (i.e., those who are disadvantaged in educational attainment due to ascribed characteristics Z) have the lowest marginal returns. The declining MTE in U_D not only confirms heterogeneity in the return to college education for Taiwan but suggests that the average college attendee earns more than the marginal participant in Taiwanese higher education. In such a case, the homogeneity assumption does not fit our data, and neither does the conventional approach.

(Figure 2 about here)

Figure 3 depicts the estimated weights used to gauge treatment parameter ATE, TT, and TUT. As shown in the figure, ATE weights MTE evenly. But, TT overweights the ATE for persons with low values of U_D, who, *ceteris paribus*, are more likely to attend college. By contrast, TUT overweights the ATE for persons with high values of U_D, who are less likely to attend college. And hence, TT > ATE > TUT, in light of the shape of MTE and the shape of the weights.

(Figure 3 about here)

5.4. Gender Differences

Table 4 contains the estimated coefficients γ_0 (i.e., high school) and $\gamma_1 - \gamma_0$ (i.e., college vs. high school) of observed characteristics X, using the semiparametric approach of estimation. Inspection of the table reveals that when the propensity of going to college is taken into account, gender differences in γ_0 and $\gamma_1 - \gamma_0$ are both significant. As we can see in the table, men are advantaged over women in earnings among high school graduates, with an estimate of 36.4%, whereas there is a male disadvantage among college graduates (-5.8%). Thus, the coefficient of earnings premium for college graduates over high school graduates for males, as opposed to females, is negative (-42.2%). This finding implies that going to college is an important channel for women to achieve in the labor market and to overcome their disadvantages associated with their gender. The gender issue seems interesting, and hence we continue to estimate the gender-specific marginal treatment effects.

(Table 4 about here)

Figure 4 presents results obtained from estimating the Heckman-type selection model on men and women, separately. Inspection of the figure reveals that while the shapes of weights for men and women are similar to each other (and to those shown in Figure 3), the shape of the MTE differs between men and women.

(Figure 4 about here)

To be more precise, we observe that patterns of the MTE as a function of unobserved heterogeneity in the treatment selection equation differ between men and women. While the relationship between the MTE and U_D is nonlinear for both genders, this relationship is opposite for men and women. Among men the MTE is highest for those who are less likely to attend college. Among women, on the contrary, the MTE is highest for those who are more likely to attend college. In short, the general pattern that the MTE is declining in U_D reported earlier for the total sample does not appear when we estimate the model separately for males and females.

5.5. Summary: Selection Bias and Sorting Gain

To summarize the empirical findings, Table 5 presents comparisons among various treatment parameters of interest. Table 5 also reports the IV estimates, appropriately weighted for the entire distribution of U_D (see Heckman, Urzua, and Vytlacil 2006). A few findings emerge from the table.

(Table 5 about here)

First of all, when men and women are pooled together, the ATE estimate (38.8%) is close to the OLS estimate (38.0%). It seems that the bias in the Mincer coefficient is not serious (-0.8%). Nevertheless, this happens to be true because a relatively large negative selection bias (-20.4%) is compensated by a positive sorting gain for college attendees (19.6%), which is approximately of the same size in magnitude. The negative selection bias implies that persons who attend college would make low-income high school graduates, while the positive sorting gain confirms a purposive sorting into college on the basis of economic returns from college education.

Second, TT > ATE > TUT. The treatment effects of going to college on those who go and on those who do not go are 58.3% and 30.4%, respectively. Besides, the IV estimator is 48.7% and larger than ATE. This pattern is different from the case presented by the homogeneous model in which $U_1 = U_0$ and thus IV = ATE = TT. It is clear that IV is upward biased owing to heterogeneity and selection bias.

Third and finally, gender differences in the earnings premium for college graduation over high school graduation are statistically significant, after the propensity of receiving college education has been taken into account. Nevertheless, the patterns of gender differences are complicated. Generally speaking, the principle of comparative advantage can apply to both men and women. There are positive sorting gains for college attendees of each sex.

6. Conclusion and Discussions

Both economists and sociologists have had a long-standing interest in estimating the causal effect of education on labor market outcomes such as earnings. While there is a consensus in the relevant literature that higher education is associated with higher earnings, there are, however, disagreements over the nature of this observed relationship and the proper way to precisely estimate the true magnitude of the causal effect of education on earnings. In this paper, we test and distinguish between the Mincer-type productivity model and the Heckman-type selection model of "essential heterogeneity."

Our empirical findings indicate that the average treatment effect (ATE) of four years of college attendance (the earnings premium resulting from randomly selecting someone to go to university) is 38.8% for the young labor force of Taiwan, whereas the OLS (using the Mincer model) and IV (using the propensity score as an instrumental variable) estimators are 38.0% and 48.7%, respectively. Compared with Heckman and Li's (2004: 166) estimates for the young people (aged 21 to 36) of urban China in 2000 – which are 43% (ATE), 29% (OLS), and 56% (IV), respectively – our result is consistent with theirs in that IV > ATE > OLS. The OLS method produces a small downward biased estimate of ATE, whereas the conventional IV approach yields an upward biased estimate of ATE. In addition, our estimates of the treatment effect on the treated (TT) and on the untreated (TUT) are 58.3% and 30.4%, respectively, which are close to those reported in Heckman and Li (2004: 166) for urban China: 51% and 36%, respectively. Finally, both studies find that there is a negative selection bias and a positive sorting gain. On the one hand, persons who attend college would make low-income high school graduates; the estimated selection bias (of -22% for China, and of -20% for Taiwan) is important in estimating the economic return to schooling. On the other hand, the principle of comparative advantage is also at work; the estimated sorting gain is 19.6% for Taiwan and 8% for Urban China, respectively.

Although our results are similar to those of Heckman and Li (2004), the two studies are different in a few aspects of model specifications. For example, Heckman and Li use parental income as a key variable, both as proxy of ability in wage equation and as part of the treatment selection equation. By contrast, we retain the assumption of unobservable ability throughout the analysis and do not use a proxy of ability. Future studies would benefit from using rich data sets in which not only parental income but direct measures of intelligence (e.g., IQ) and achievement aspirations are available, such as the use of the Wisconsin longitudinal data.

A well-known tenet of status attainment research is that education is a crucial intervening link between the social background of individuals and their later socioeconomic achievements. In a stylized form of path analysis, parental education is assumed to affect one's educational attainment, which, in turn affects one's occupational attainment and earnings (Blau and Duncan 1967; Sewell and Hauser 1975). In this study, we consider parental education an important indicator of family socioeconomic background that directly affects the attainment of college education and only indirectly influences labor force outcome through college education. Thus, both father's and mother's years of schooling are part of the schooling selection equation, but there is no background variable in the earnings equation.

Finally, we find that patterns of gender differences are interesting but complicated. Because our analysis of women's earnings is restricted to samples of working women, this restriction may be likely to confound the observed gender differences in the relationship between marginal treatment effect and unobserved heterogeneity. Future research on gender comparisons in earnings should pay closer attention to potential selectivity in female labor force participation.

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Table 1. Variables and Descriptive Statistics

Independent Variables	Total (N = 1,439) Mean	SD	Treated Group (N = 406) Mean	SD	Untreated Group (N = 1,033) Mean	SD
4 years' college attendee (= 1, if yes)	.282		1.000		.000	
Monthly earnings	37,887	24,134	45,000	25,225	35,092	23,112
Log of earnings	10.419	.477	10.614	.437	10.343	.471
Mincer experience (= Age - years of schooling - 6)	9.585	3.504	6.892	2.892	10.644	3.138
Male (= 1, if yes)	.548		.532		.555	
Parental education						
Father's years of schooling	8.520	3.843	10.399	4.084	7.781	3.478
Mother's years of schooling	6.630	3.583	8.180	3.951	6.021	3.232
Ethnicity						
Hokkien (= 1, if yes)	.735		.704		.747	
Hakka (= 1, if yes)	.138		.128		.141	
Mainlander (= 1, if yes)	.120		.165		.102	
Aborigine (= 1, if yes)	.008		.002		.010	
Residence prior to age 15						
Major city (= 1, if yes)	.226		.281		.204	
Not major city (= 1, if yes)	.559		.493		.585	
Not in Taiwan (= 1, if yes)	.007		.005		.008	
Missing data (= 1, if yes)	.208		.222		.203	
Birth cohort						
1967 (= 1, if yes)	.023		.015		.026	
1968 (= 1, if yes)	.055		.054		.055	
1969 (= 1, if yes)	.093		.091		.094	
1970 (= 1, if yes)	.099		.076		.107	
1971 (= 1, if yes)	.093		.096		.092	
1972 (= 1, if yes)	.106		.118		.102	
1973 (= 1, if yes)	.113		.108		.114	
1974 (= 1, if yes)	.099		.108		.095	
1975 (= 1, if yes)	.083		.084		.083	
1976 (= 1, if yes)	.113		.126		.108	
1977 (= 1, if yes)	.076		.062		.082	
1978 (= 1, if yes)	.047		.062		.041	

Table 2. Estimated Probit Model for College Attainment (N = 1,439)

Independent Variables	Coefficient	SE	Mean Marginal Effect
Intercept	-1.618*	.345	—
Parental education			
Father's schooling	.072*	.027	.024
Mother's schooling	-.028	.033	-.009
Gender (relative to female)			
Male	.071	.205	.023
Ethnicity (relative to Hokkien)			
Hakka	.261	.339	.090
Mainlander	-.288	.380	-.087
Aborigine	-.574	.529	-.151
Residence prior to age 15 (relative to not in major city)			
Major city	.168	.267	.056
Not in Taiwan	.074	.483	.025
Missing data	.080	.098	.027
Birth cohort (relative to 1967)			
1968	.315	.310	.111
1969	.269	.292	.094
1970	.040	.294	.013
1971	.292	.292	.102
1972	.281	.289	.098
1973	.210	.289	.072
1974	.231	.290	.080
1975	.150	.297	.051
1976	.272	.288	.094
1977	.084	.300	.028
1978	.318	.316	.112
Two-way interaction terms			
Father's schooling * Mother's schooling	.004	.003	.001
Father's schooling * Gender	.005	.026	.002
* Hakka	-.093*	.041	-.030
* Mainlander	-.048	.033	-.016
* Major city	-.016	.031	-.005
Mother's schooling * Gender	-.004	.027	-.001
* Hakka	.093*	.046	.030
* Mainlander	.130*	.041	.042
* Major city	.040	.034	.013
Gender * Major city	-.386*	.181	-.114
* Hakka	-.303	.226	-.091
* Mainlander	-.202	.243	-.062
Hakka * Major City	.414	.374	.150
Mainlander * Major City	-.244	.267	-.074

* Significant at the level of α = .05.

Table 3. OLS Regressions Predicting Logged Earnings

Independent Variables	Total	Male	Female
Intercept	10.048*	10.258*	10.088*
	(.044)	(.062)	(.056)
4 years' college attendee	.380*	.324*	.445*
	(.029)	(.044)	(.038)
Mincer experience	.021*	.027*	.013*
	(.004)	(.005)	(.005)
Experience squared	-.006*	-.006*	-.004*
	(.001)	(.001)	(.001)
Male (= 1, if yes)	.242*		
	(.023)		
R^2	.169	.086	.186
N	1,439	789	650

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

Table 4. Estimated Coefficients Using Local Linear Regression with Gaussian Kernel and Optimal Bandwidth

Independent Variables	High School (γ_0)	College vs. High School ($\gamma_1 - \gamma_0$)
1. Total (N = 1,439)		
Mincer experience	.011	-.036
	(.008)	(.030)
Experience squared	.000	-.016*
	(.002)	(.006)
Male (= 1, if yes)	.364*	-.422*
	(.046)	(.137)
2. Male (N = 789)		
Mincer experience	.019	-.043
	(.011)	(.040)
Experience squared	-.001	-.014*
	(.003)	(.007)
3. Female (N = 650)		
Mincer experience	-.006	-.011
	(.010)	(.035)
Experience squared	.003	-.018*
	(.002)	(.008)

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

Table 5. Comparisons of Different Treatment Parameters

Parameter	Total (N=1,439)	Male (N=789)	Female (N=650)
1. OLS	.380*	.324*	.445*
	(.029)	(.044)	(.038)
2. IV	.487*	.282*	.602*
	(.092)	(.142)	(.136)
3. ATE	.388*	.306*	.602*
	(.180)	(.144)	(.144)
4. TT	.583*	.309*	.610*
	(.226)	(.156)	(.167)
5. TUT	.304	.308	.598*
	(.233)	(.162)	(.163)
6. Bias = OLS − ATE	-.008	.018	-.157
7. Selection bias = OLS − TT	-.204	.015	-.165
8. Sorting gain = TT − ATE	.196	.003	.008

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

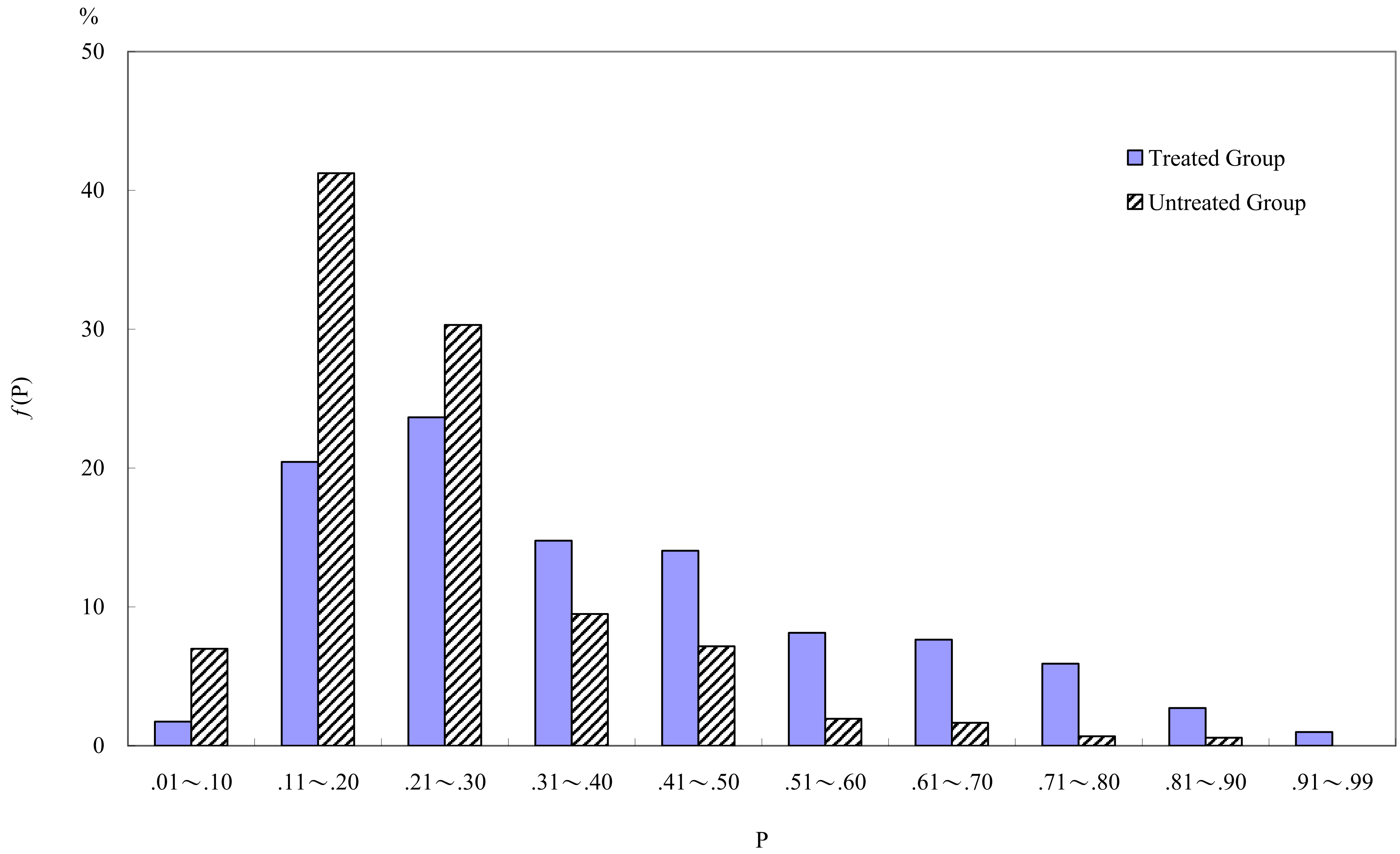

Figure 1. Density of Estimated Propensity Score $\Pr\left(D=1\right)$

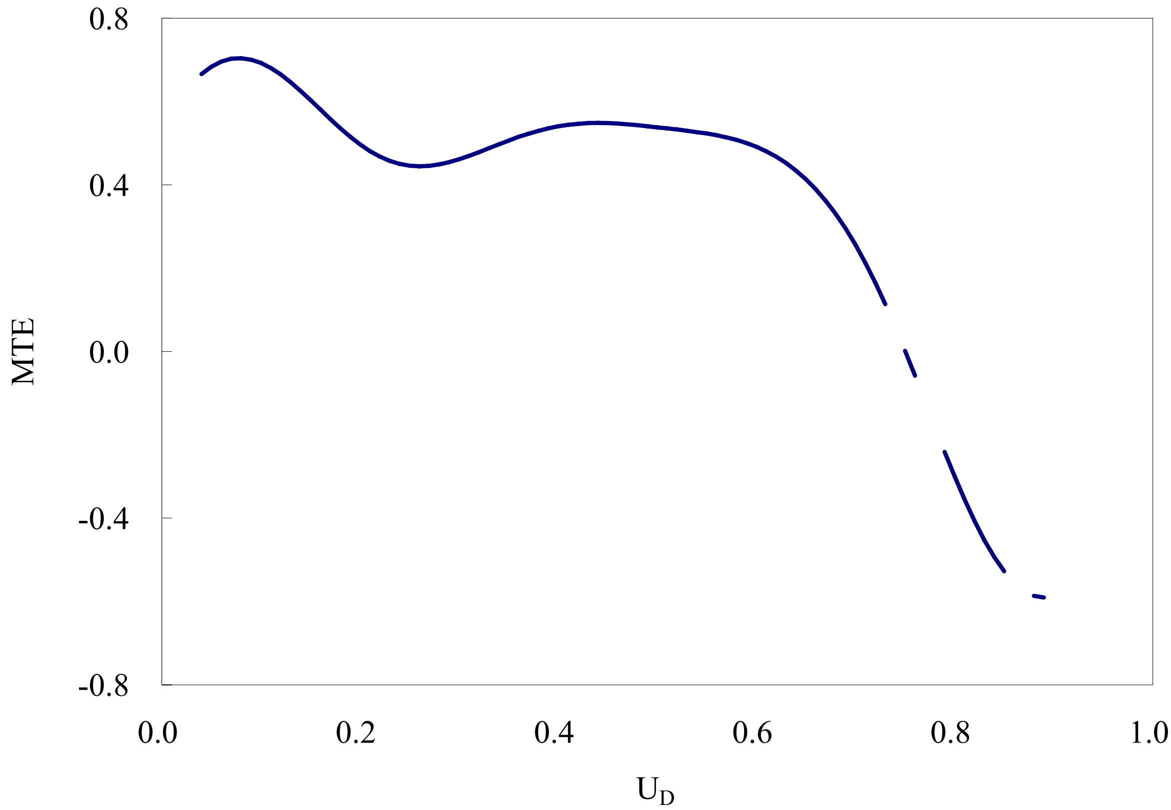

Figure 2. Marginal Treatment Effect as a Function of Unobserved Heterogeneity U_D

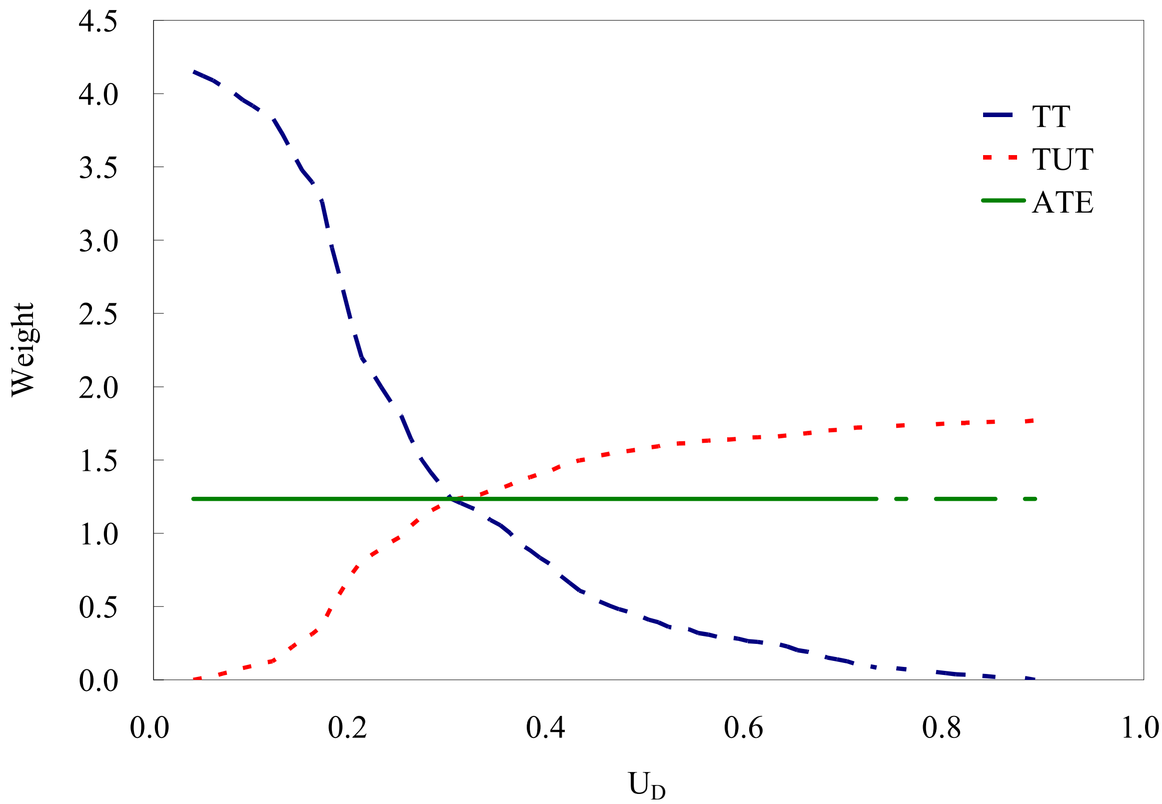

Figure 3. Weights of Treatment Parameters

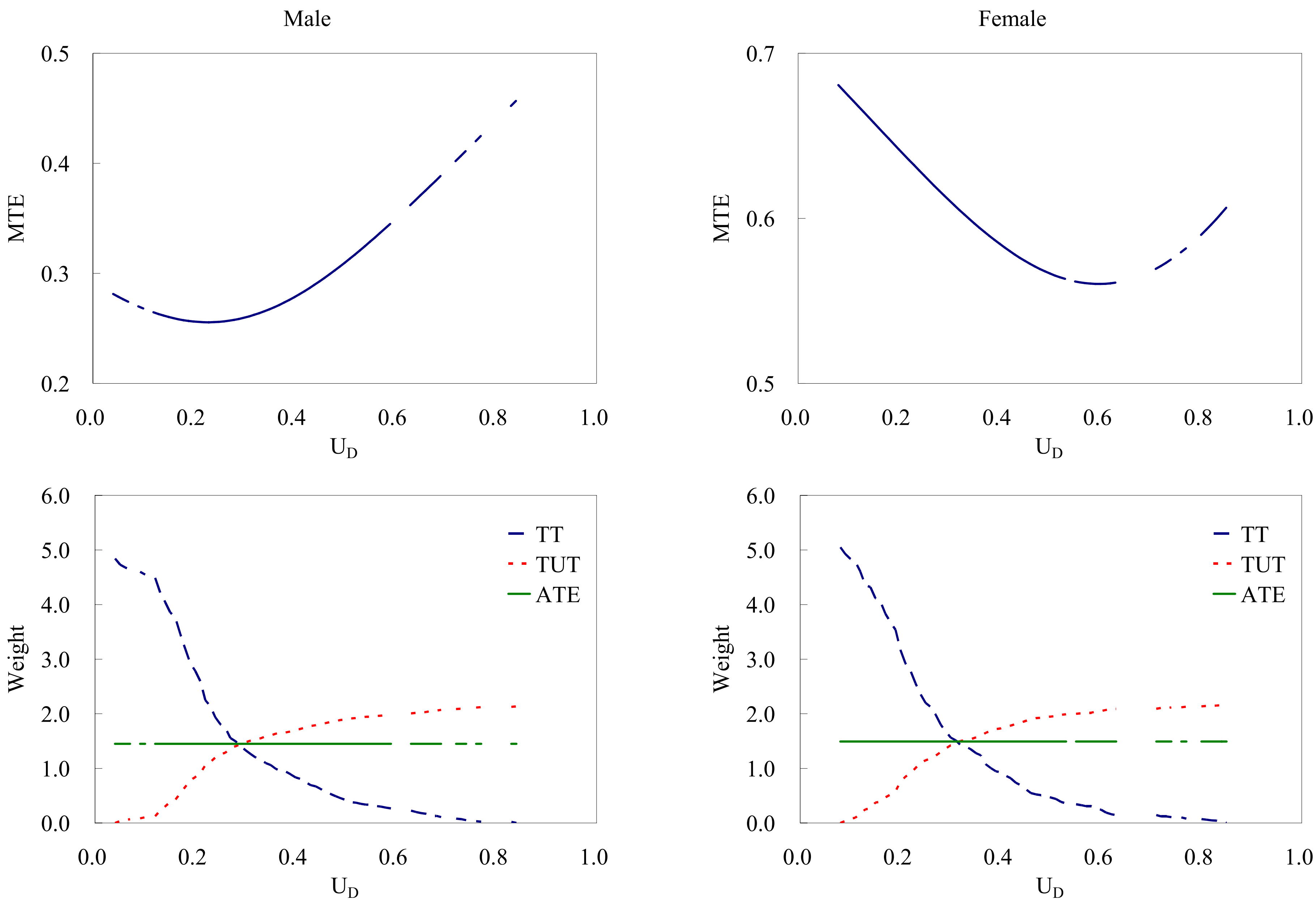

Figure 4. Gender-specific MTE and Weights as a Function of Unobserved Heterogeneity U_D