



Heterogeneity in returns to college education: Selection bias in contemporary Taiwan

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ABSTRACT

The causal impact of higher education on earnings may be heterogeneous across different members of a population. Using a newly developed instrumental-variable method in economics, we illustrate heterogeneous treatment effects of higher education on earnings resulting from sorting mechanisms that select individuals with certain unobserved attributes into college education. The setting of our empirical work is contemporary Taiwan – a transitional economy that has recently experienced a rapid expansion in higher education. We find distinct patterns by gender, with selection bias most clearly shown among women but not among men: the college return to earnings is on average greater for women who actually attended college than women who did not attend college.

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1. Introduction

One of the best-established empirical findings in social science research is that college graduates attain higher earnings in the labor market than do high school graduates (e.g., Morris and Western, 1999), irrespective of gender (Bobbitt-Zeher, 2007; Mare, 1995; McCall, 2000) or social context (Gerber and Schaefer, 2004; Glewwe, 2002). Nevertheless, the extent to which the observed association between higher education and earnings is actually causal has long been a subject of debate. A widely held view in both economics and sociology is that schooling causally affects earnings positively, as one part of human capital that raises a worker's skills and productivity (Becker, 1964; Blau and Duncan, 1967; Mincer, 1974). Critics, however, contend that the empirically documented relationship between the two is not necessarily causal, as some portion of the schooling-earnings relationship may be spurious (see, e.g., Card, 1995, 1999).

At issue is how much the commonly estimated “effect” of college education on earnings via a regression using survey data may be different from the “true” causal effect under a hypothetical scenario of random assignments. For a long while, it was commonly accepted that the former would be larger than the latter, because the typical person who chose to go to college would have relatively high earnings due to his/her higher unobserved personal endowments, such as mental ability and work ethic, whether or not s/he actually went to college. This is called the “ability bias,” which was thought to be always positive (Griliches, 1977; Hauser and Daymont, 1977).

Both the conventional estimation using regressions and the discussion of the ability bias in the earlier literature relied on an implicit assumption that the effect of education is homogeneous across different members in a population or a subpopulation of individuals with the same observed attributes, including status of college attendance (i.e., Willis and Rosen, 1979). However, this assumption is untenable, because individual-level heterogeneity is intrinsic to almost all social phenomena

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(Heckman, 2001a; Xie, 2007). That is to say, earnings return to higher education varies not only between those who attend and those who do not attend college but across individual members in a population. When the causal effect is heterogeneous, there is no such thing as the “true effect” of higher education. The best we can do is to estimate the weighted average treatment effect either for the entire population or for a subpopulation. When the effect is averaged for the entire population, it is called the average treatment effect (ATE). When the effect is averaged for the subpopulation of those who attended college, it is called the average treatment effect of the treated (TT). Likewise, when the effect is averaged for the subpopulation of those who did not attend college, it is called the average treatment effect of the untreated (TUT). When TT is greater than TUT, we say that there is a positive sorting (or a sorting gain); conversely, when TT is smaller than TUT, we can say that there is a negative sorting (or a sorting loss).

The consideration of heterogeneous treatment effects has been one of the great achievements in social science research (Heckman, 2001a). However, empirical investigation of heterogeneous treatment effects has been extremely difficult, as it places enormous demands on data that go far beyond what is needed under homogeneous regimes. Much previous work in sociology on heterogeneous treatment effects of higher education (e.g., Brand and Xie, 2010; Tsai and Xie, 2008) has relied on the ignorability assumption, i.e., it is assumed that those who attend college and those who do not are not systematically different conditional on observed covariates.¹ In this paper, using a newly developed instrumental-variable method in economics, we illustrate heterogeneous treatment effects of higher education on earnings resulting from sorting mechanisms that select individuals with certain unobserved attributes into college. The setting of our empirical work is contemporary Taiwan – a transitional economy that has recently experienced a rapid expansion in higher education. We find distinct patterns by gender, with selection bias clearly shown among women but not among men: the college return to earnings is on average greater for women who actually attended college than women who did not attend college.

2. Theoretical issues

That college graduates earn more than high school graduates in the labor market is well documented. There are many competing explanations for this well-established pattern. One major contender is a pure productivity story: college education raises an individual's human capital and thus improves his/her skills and productivity, which, in turn, leads to a significant increase in earnings. Another important explanation is one of selection: the types of persons who select (or are selected) into college have certain characteristics – both observable and unobservable – that enable them to earn more in the labor market. From this contrarian view, it is the selection in the allocation of educational resources and economic rewards that matters. Note that the interpretation that stresses the role of selection does not rule out productivity as a partial explanation for college premium, but it differs distinctly from the productivity story in causal interpretations.

The productivity explanation is best provided by Becker's (1964) human capital theory. Becker views college education as a form of investment and hypothesizes that a rational person (or family) would decide whether or not to invest in it depending on their expected return on the investment. This theoretical framework actually capitalizes on the heterogeneity of returns to college, as it underlies the individual-specific decision regarding college attendance. Within the human capital framework, Mincer (1974) develops a “standard” equation to empirically estimate the return to schooling, using OLS regressions 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. The Mincer equation has been “one of the great success stories of modern labor economics” (Willis, 1986, p. 526). Not until recently was the Mincer model seriously criticized, by Heckman et al. (2006).

The main competing explanation attributes the positive association between education and earnings to educational selectivity. As discussed earlier, a key idea underlying human capital theory is that some individuals benefit more from higher education than others. This idea is analogous to Roy's (1951) model of sorting gain selection due to comparative advantages. The importance of Roy's work was not widely recognized by economists until the 1970s (Neal and Rosen, 2000), and not implemented in empirical work until Quandt (1972), Heckman (1974), and Gronau (1974) provided the econometric foundations for estimating switching regression, selection model, and selectivity bias.

In this context, it is useful to distinguish two forms of selection bias. One form of selection bias assumes that persons with higher fixed endowments (such as innate ability) are more likely to attend college and also tend to have higher earnings. This form of selection is often called “ability bias.” Another form of selection bias assumes that persons who benefit the most from college educations 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 going (Card, 2001; Heckman and Vytlacil, 1999). This form of bias is called “sorting gain.”²

An influential study by Willis and Rosen (1979) considered heterogeneous returns to college, using a parametric two-sector selection model separating those who attend college from those who do not. Using a switching regression, Willis and Rosen 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 affecting the likelihood of college education. They found

¹ Holland (1986) provides a good introduction to the causal inference literature. See Sobel (1995), Winship and Morgan (1999), DiPrete and Gangl (2004), and Morgan and Winship (2007) for methodological discussions in sociology. For recent applications in sociological research, see Morgan (2001, 2004), Brand and Halaby (2006), Xie and Wu (2005), Tsai and Xie (2008), and Brand and Xie (2010).

² For more extensive discussions of these two sources of bias in sociological literature, see Brand and Xie (2010) and Winship and Morgan (1999).

evidence for this selection bias, 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.

Later, Heckman and Robb (1985) established the importance of heterogeneous treatment effects in more general terms. Responding to this new emphasis, Björklund and Moffitt (1987) modified the then “standard” selection model by identifying the marginal gain to persons induced into a treatment status by a marginal change in the cost of treatment. They 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). In a large body of work, Heckman and his associates (e.g., Carneiro et al., 2003; Carneiro and Heckman, 2002; Carneiro et al., forthcoming; Heckman and Li, 2004; Heckman et al., 2006a; Heckman and Vytlačil, 1999, 2000, 2005) have extended the “marginal treatment effect” framework to a semi-parametric approach, with the propensity score for treatment consisting of at least some instrumental variables. With an emphasis on rational choice, Heckman (2001a,b) argues that returns to college education should be conceptualized as heterogeneous at the individual level due to unobservables: observationally identical people not only possess different latent abilities but should also differ in reaping potential financial benefits from college education. Hence, the causal effect of college education varies across different members in a population, a phenomenon Heckman and Vytlačil (2001a,b) termed “essential heterogeneity.”

Conditional on covariates, is it possible that persons who go to college and persons who do not differ in ways that are unobservable to the researcher but result in heterogeneous effects of higher education on earnings? In what follows, we will apply the approach advocated by Heckman and his associates to illustrate the heterogeneous effects of higher education on earnings due to unobservable factors in Taiwan. First, however, we shall provide a brief introduction to the Taiwanese context.

3. The Taiwanese context

The Taiwanese educational system has a basic structure of 6–3–3–4 years of schooling, the first 9 years being compulsory. Students completing compulsory education take a competitive examination and are assigned to tracked high schools according to their examination scores. The transition from high school to university/college is also based largely on stringent examinations. Prior to 1995, 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, and those who failed the examination could retake it again in subsequent years. During the period of 1995–2002, certain departments in some universities were allowed to hold their own matriculation examinations and to recruit preferred students up to a certain proportion of the total intake (from 5% to 30%). Since 2002, almost all institutions of higher education have been granted the freedom to select preferred students up to a preferred proportion in spring first – using student’s performance in the nationwide “basic academic test” held in winter as a major qualification consideration – and then recruit the remainder intake in summer through the unified college entrance examination. In 2007, 87.8% of female and 87.6% of male high school graduates moved onto the tertiary level (Ministry of Education, ROC, 2008), making Taiwan one of the most highly educated societies in the world.

In Taiwan, educational expansion has resulted in a rapid increase in the supply of college-educated labor to the labor market in recent years. To meet the growing demand for skilled workers generated by rapid industrialization, national manpower planning has been part of the economic development plans implemented by the Taiwanese government since as early as the 1960s. Prior to the lifting of martial laws in 1987, higher education was highly centralized, and the “low-tuition” policy was enforced with an explicit purpose of reducing class inequality in educational opportunity by lowering the economic barriers to higher education. During the 1990s, the state exercised less and less control over educational policies. To meet the increasing social demand for its services, higher education has expanded rapidly since the 1990s. In 1990, there were 121 institutions of higher education with a total of 576,623 students; by 2007, the number of institutions was 164, serving 1,326,029 students. The expansion of higher education systems coincided with a period of declining gender and even some ethnic stratification, but accompanied by growing inequality in educational attainment between categories of parental education (Tsai and Shavit, 2007).

The expansion of higher education means a rapid increase in the proportion of a birth cohort who attains college education. Does this expansion result in the diluted value of higher education? Or, from the perspective of individuals, do persons who would otherwise not have attended college in the absence of the expansion benefit the same amount as those who would have attended college regardless of the expansion? This interesting research question has important implications for policies concerning higher education, as it informs the policy maker as to the potential social benefits of expanding higher education (Brand and Xie, 2010). In a previous study (Tsai and Xie, 2008), we adopted the same statistical methodology and reached essentially the same conclusion as Brand and Xie (2010): the average return to college education remained stable over the period from the early 1990s to the early 2000s, with individuals least likely to attend college based on observed attributes reaping the higher earnings returns from college education. One shortcoming of the studies of Brand and Xie

(2010) and Tsai and Xie (2008) is that they rely on the ignorability assumption that college education is unrelated to potential earnings conditional observed covariates. In this paper, we relax this assumption.

A note of caution is in order. In Taiwan, higher education refers to education provided by junior colleges, colleges, universities, and graduate schools. Junior colleges constitute the lowest tier of education at the tertiary level.³ In this study, we limit our focus to earnings disparities between college attendees and those whose highest educational level is high school or junior college.⁴ Clearly, this is an oversimplification. Nevertheless, by treating college education as a simple dichotomous treatment, this simplification allows us to borrow the literature on causal inference and to focus on the main points of the paper.

4. The theoretical model

We begin with a conventional Mincer-type model that treats the return to be homogeneous and college education exogenous (Mincer, 1974). For the i th person ($i = 1, \dots, n$), the earnings equation takes the form⁵

$$y_i = \beta d_i + \mathbf{x}'_i \lambda + u_i, \quad (1)$$

where y_i is the observed value of the outcome variable Y representing logged earnings; d_i is the observed value of a dummy variable; D representing whether or not the person attended college (1 if yes; 0 if no); β is the return to college attendance; \mathbf{x}_i is a vector of observed values for other earnings determinants \mathbf{X} , with λ as coefficients; u_i is the realization of the disturbance term U , encompassing such unobserved factors as ability, effort, and market luck. A necessary assumption for estimating β in Eq. (1) via ordinary least squares (OLS) is that U and D are independent, conditional on \mathbf{X} .

Now we can define more precisely what we mean by two potential sources of bias. These are two situations in which the assumption for identifying Eq. (1) via OLS fails to be true. The first source of bias occurs if D is correlated with U (e.g., high-ability people tend to go to college). The second source of bias occurs if β is heterogeneous at the individual level and is correlated with D (e.g., persons with high expected return β tend to go to college). The first is called the ability bias, a bias due to differences in pre-existing attributes (such as ability and work habits) between those who attend college and those who do not attend college. Even in the absence of college education, the two groups would still differ in their average earnings due to their differences in these relevant but unobserved attributes. The second is called the sorting gain, a bias due to the average difference in returns to high education between those who attend college and those who do not. Both types of biases are selection biases that may threaten the validity of causal inference with observational data (Campbell and Stanley, 1963). Of course, under randomization, both forms of bias average to zero. In general, however, they are two distinct forms of bias. In this paper, we aim to separate out the two forms of bias and thus demonstrate heterogeneous returns to education. Departing from Brand and Xie (2010) and Tsai and Xie (2008), our approach does not depend on the ignorability assumption.

In avoiding the ignorability assumption, we borrow the new approach developed by Heckman and his associates through the use of instrumental variables (Carneiro et al., 2003; Carneiro and Heckman, 2002; Carneiro et al., forthcoming; Heckman and Li, 2004; Heckman et al., 2006a; Heckman and Vytlačil, 1999, 2000, 2005). Our objective is mainly exploratory, contrasting this methodological approach with the earlier approach of Brand and Xie (2010) and Tsai and Xie (2008) under ignorability. For this reason, we build a simple model. Let us assume two groups of factors affecting college attendance: observed attributes due to family background (i.e., inequality of educational opportunities due to ascribed characteristics), and unobserved individual heterogeneity that is associated with the earnings in the two potential regimes of college education and non-college education. We know that family background plays an important role in shaping educational opportunities and educational expectations of its members. We include a number of family background variables in our model predicting college education, but we do not necessarily expect them to affect earnings directly. A key unverifiable assumption for our study is the assumption of exclusion restrictions of IV: the observed background variables serve as instrumental variables (IVs) in that they affect earnings only indirectly via higher education but do not affect potential earnings outcomes directly. We are not so naïve as to believe that this exclusion actually holds true in reality, just as we do not think that ignorability is likely true. Rather, we make this simplifying assumption to explore its empirical implications and compare the results to those under an alternative assumption of ignorability.

Consider a simple selection model that consists of three equations: earnings outcome equations under the two counterfactual regimes (for college education and non-college education) and a treatment selection equation. Using notations similar to those in Brand and Xie (2010) with superscripts denoting treatment regime, the model can be expressed as

$$y_i^0 = \alpha^0 + \mathbf{x}'_i \lambda^0 + u_i^0 \quad \text{if } d_i = 0 \quad (2a)$$

³ There are three types of junior colleges in Taiwan: 5-year junior colleges that admit graduates of junior-high schools; 2-year junior colleges that admit graduates of vocational high schools; and 3-year junior colleges that admit graduates of both academic and vocational high schools. In 2007, there were 149 universities and 15 junior colleges in Taiwan.

⁴ Due to data limitations, we do not distinguish between college attendance and college completion, i.e., we assume that all college attendees complete college. This assumption is largely true in Taiwan, with 9.1% of the drop-out rate (temporary: 4.8%; permanent: 4.3%) at the tertiary level of education; see http://www.edu.tw/EDU_WEB/EDU_MGT/STATISTICS/EDU7220001/service/sts4-2.htm.

⁵ Throughout the paper, we use upper-case English letters to denote variables, and corresponding lower-case English letters to denote their realized values.

$$y_i^1 = \alpha^1 + \mathbf{x}_i' \lambda^1 + u_i^1 \quad \text{if } d_i = 1 \quad (2b)$$

u_i^0 and u_i^1 are error terms for the i th person, realizations of random variables U^0 and U^1 . We assume $E(U^0|\mathbf{X}) = 0$ and $E(U^1|\mathbf{X}) = 0$ in the population. This setup changes Eq. (1) so that returns to college education are explicitly person-specific, because

$$\beta_i = y_i^1 - y_i^0 = \alpha^1 - \alpha^0 + \mathbf{x}_i'(\lambda^1 - \lambda^0) + (u_i^1 - u_i^0). \quad (3)$$

Note that the treatment effect β depends on covariates \mathbf{X} .

Although a person may experience two potential outcomes, in practice only one of them is realized (or can be observed). Therefore, the two equations can be combined in a single-equation form with a switching weight:

$$y_i = d_i y_i^1 + (1 - d_i) y_i^0 \quad (4)$$

We now specify a selection model into college education. Let t_i be the latent tendency to attend college:

$$t_i = \mathbf{z}_i' \gamma - v_i \quad (5a)$$

$$d_i = 1 \quad \text{if } t_i > 0 \quad (5b)$$

$$d_i = 0 \quad \text{if } t_i \leq 0 \quad (5c)$$

Here, \mathbf{z}_i is a vector of observed values of \mathbf{Z} , variables that predict the treatment probability, γ is a vector of coefficients, and v_i is the realized value of the disturbance term V . In practice, \mathbf{Z} includes all predictors of treatment probability, including \mathbf{X} . Assuming that V is independent of each other (i.e., over i) and follows a normal distribution, we obtain a standard probit model, so that

$$p(d_i = 1 | \mathbf{z}_i) = \Phi(\mathbf{z}_i' \gamma),$$

where $\Phi(\cdot)$ is the cumulative normal distribution that transforms the index function, $\mathbf{z}_i' \gamma$, into a probability (Powers and Xie, 2008, Chapter 3).⁶ Note that, without loss of generality, we can take advantage of the monotonic property of $\Phi(\cdot)$ for the following:

$$t_i > 0 \iff \gamma' \mathbf{z}_i > v_i \iff \Phi(\mathbf{z}_i' \gamma) > \Phi(v_i) \quad (6)$$

We now denote $\Phi(\gamma' \mathbf{z}_i)$ by $P(\mathbf{Z} = \mathbf{z}_i)$, and $\Phi(v_i)$ by u_{Di} . $P(\mathbf{Z} = \mathbf{z}_i)$ represents the i th person's "propensity score" of receiving college education due to \mathbf{Z} ; u_{Di} is the i th person's realized value of U_{Di} , unobserved individual-level resistance to receiving college education now normalized between 0 and 1.

Within this framework, $P(\mathbf{Z})$ and U_D may be interpreted respectively as the inducement and the resistance to college education. The higher the propensity score $P(\mathbf{Z})$, the more inducement to college education because of \mathbf{Z} . By contrast, the larger the unobserved component U_{Di} , the larger the unobserved resistance to college education, and the less likely it is that the person will receive college education, everything else being equal. Eq. (6) states that for a person of strong resistance, it takes a strong inducement due to \mathbf{Z} to enter college. If $P(\mathbf{Z}) = U_D$, a person is indifferent concerning whether to go or not go to college.

A fundamental question in a causal analysis of the effect of education on earnings is concerned with whether or not the unobserved component of the college-going equation, i.e., U_D , can be assumed to be independent of U^1 and U^0 . When this is satisfied (after we control for observed covariates), it is called "ignorability." Under the ignorability assumption, college attendance is uncorrelated with potential earnings conditional on the propensity score.⁷ In this case, various methods are available for drawing inferences about the causal effects of education (see Blundell et al., 2005; DiPrete and Engelhardt, 2004; DiPrete and Gangl, 2004; Morgan and Harding, 2006). Examples of estimating heterogeneous education effects under the ignorability assumption are studies by Brand and Xie (2010) and Tsai and Xie (2008), both of which report a declining effect of education on earnings as a function of the propensity score, suggesting that individuals less likely to attend college according to their observed attributes actually would benefit more from college than individuals more likely to attend college.

However, there is no good reason why the ignorability assumption should be accepted in practice. It is quite possible that the unobserved component, U_D , is correlated with β . For example, Heckman et al. (2006a) argue that β should be a negative function of U_D , as those who benefit the most from higher education are most likely to enroll in college. Departing from other sociological studies on heterogeneous returns to higher education, most notably Brand and Xie (2010) and Tsai and Xie (2008), we seriously explore implications when the ignorability assumption does not hold true, capitalizing on a semi-parametric instrumental variable (IV) estimation method developed by Heckman et al. (2006a,b). We now turn to a discussion of the method.

⁶ The normal distribution assumption is not necessary here, and distribution would work here. However, the normality assumption greatly simplifies the model for a parametric specification discussed later.

⁷ Rosenbaum and Rubin (1983) establish the central role of the propensity score in matching models, whereas Heckman (1980) and Heckman and Robb (1985, 1986) establish the central role of the propensity score in selection models. 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 (Heckman and Vytlačil, 1999).

5. Statistical methods

We conduct our analyses separately by gender. The core analysis of our work involves three stages. In the first stage, we follow the literature of educational stratification (e.g., Hauser and Andrew, 2006; Mare, 1980; Shavit et al., 2007; Shavit and Blossfeld, 1993), using selected ascriptive characteristics as IVs (ethnicity, birth cohort, parental education, growing-up place prior to age 15, and some interaction terms) to predict a persons' probability of attaining college/university education, versus high-school/junior-college education, thereby deriving an individual-specific estimated propensity score. To qualify as instrumental variables (IVs), variables must affect earnings only indirectly by affecting the likelihood of college attendance.

While we cannot verify this IV assumption empirically, there are good reasons for assuming the variables are plausible instruments for our study. Unlike in many other societal contexts, ethnicity in Taiwan for the most part refers to various social groups, who came to Taiwan at historically different times (Gates, 1981). While there are notable differences in social status (Tsai, 1992) and political opinions by ethnicity in Taiwan (Hsieh, 2005), researchers have not provided a good theoretical argument suggesting that ethnicity affects earnings directly (e.g., Bishop and Chiou, 2004; Vere, 2005). Similarly, although generations of sociologists (e.g., Blau and Duncan, 1967; Hauser et al., 1983; Hout, 1988; Hout and DiPrete, 2006; Sewell et al., 1970) have long identified parental education and place of growing up as important determinants of educational attainment, there is no good argument for treating them as direct determinants of earnings. In their original work, Heckman and his associates also treated similar variables as instrumental variables. For example, the study by Heckman et al. (2006a) uses the number of siblings and mother's education as instruments.⁸ See Card (1999) for a review of the literature using family background variables as instrumental variables. However, even if our IV assumption does not hold true in practice, our study is still worthwhile, as the exercise would allow us to compare varying heterogeneous effects estimated under the IV assumption to results under an alternative assumption – the ignorability assumption (Brand and Xie, 2010). At the minimum, our work serves as an empirical demonstration of the approach advocated by Heckman and his associates.

In the second stage, we use the method of Heckman et al. (2006a,b) and estimate treatment effects of college education on earnings at different levels of U_D – i.e., at different latent levels of resistance to college education. This is called the “marginal treatment effect” (Björklund and Moffitt, 1987), or MTE. We can define MTE as $E(\beta|\mathbf{X}, U_D)$, as the expected treatment effect conditional on \mathbf{X} and U_D . That is:

$$\text{MTE}(\mathbf{X} = \mathbf{x}, U_D = u_D) = E(\beta|U_D = u_D) = (\alpha^1 - \alpha^0) + \mathbf{x}'_i(\lambda^1 - \lambda^0) + E[U^1 - U^0|U_D = u_D] \quad (7)$$

In this setup, a local average treatment effect (LATE), the average treatment effect for individuals whose treatment status is altered by an IV, is actually a discrete form of MTE.

If the treatment effect is homogeneous with respect to U_D , we would observe a flat line of MTE as a function of U_D . Whether MTE decreases or increases with U_D informs us whether β is positively or negatively associated with the latent tendency of college attendance, conditional on \mathbf{X} .

Once MTE is known, we can derive all treatment parameters of concern as weighted averages of MTE.⁹ In the third stage, we decompose the conventional bias (i.e., the difference in magnitude between OLS and ATE estimators) into two components: the ability bias (i.e., the mean bias of selection 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). From Eqs. (2)–(4), we can show the key role played by the propensity score in determining logged earnings:

$$\begin{aligned} E[Y|\mathbf{X} = \mathbf{x}, P(\mathbf{Z}) = p] &= \alpha^0 + (\alpha^1 - \alpha^0)p + \mathbf{x}'\lambda^0 + [\mathbf{x}'(\lambda^1 - \lambda^0)]p + E[U^0|\mathbf{X} = \mathbf{x}, P(\mathbf{Z}) = p] \\ &+ E[U^1 - U^0|\mathbf{X} = \mathbf{x}, D = 1, P(\mathbf{Z}) = p]p, \end{aligned} \quad (8)$$

where p is a particular evaluation value of the propensity score. Below, we briefly describe two procedures of estimating MTE used in our study.

As shown by Heckman et al. (2006a), the presence of essential heterogeneity, or a covariation of β and U_D , is tantamount to a nonlinear relationship between the conditional expectation of Y and the propensity score $P(\mathbf{Z})$. Thus, a useful test for whether or not β and U_D are correlated is to examine whether or not the conditional expectation of Y is linear in $P(\mathbf{Z})$.

5.1. Estimating MTE under the parametric approach

This approach uses the parametric form of the marginal treatment effect under the assumption of joint normality for the error terms. In particular, the following assumption is added to the model:

$$(U^0, U^1, V) \sim N(0, \Sigma) \quad (9)$$

⁸ Heckman and Vytlačil (2001b) explored distance to college, the number of unemployment rate at age 18, and a state-level tuition variable but decided to rely on number of siblings as their primary instrumental variable. Heckman and Li (2004) use parental education and year of birth. Carneiro et al. (forthcoming) use as instruments presence of a college at 14, local log earnings at 17, local unemployment rate at 17, and tuition in 4 year public colleges at 17.

⁹ Theoretically, there are many alternative ways to derive weights in order to construct alternative summary measures of treatment effects (Heckman and Vytlačil (2001b)). For this paper, we borrow formulas from Heckman et al. (2006a) in deriving TT and TUT.

where Σ represents the variance and covariance matrix of the trivariate standard normal distribution. In Σ , we denote by σ_V^2 the variance of V , σ_0^2 the variance of U^0 , and σ_1^2 the variance of U^1 , $\sigma_{V,0}$ the covariance between U^0 and V , $\sigma_{V,1}$ the covariance between U^1 and V , and $\sigma_{0,1}$ the covariance between U^0 and U^1 . Heckman et al. (2006b) show that under this parametric assumption, MTE can be written as:

$$\text{MTE}(U_D = u_D) = (\alpha^1 - \alpha^0) + \mathbf{x}'(\lambda^1 - \lambda^0) + \left(\frac{\sigma_{V,1} - \sigma_{V,0}}{\sigma_V} \right) \Phi^{-1}(u_D). \quad (10)$$

We follow the algorithm described in Heckman et al. (2006b) in estimating MTE under the parametric approach.

5.2. Estimating MTE under the semi-parametric-LIV approach

One of the shortcomings of the parametric assumption is the requirement that the three disturbance terms U^0 , U^1 , V form a trivariate normal distribution, shown in Eq. (9). To overcome this restriction, we also borrow a semi-parametric estimation method developed by Heckman and his associates. This method capitalizes on the fact that the expected value of Y depends on the propensity score $P(\mathbf{Z})$ so that $P(\mathbf{Z})$ serves as a local instrumental variable (LIV).

Heckman and Vytlacil (1999, 2001a, 2005) show that MTE can be identified by taking derivatives of $E(Y|\mathbf{Z} = \mathbf{z})$ with respect to $P(\mathbf{z})$, all conditional on \mathbf{X} :

$$\text{MTE}(U_D = p, \mathbf{X} = \mathbf{x}) = \text{LIV}[p, \mathbf{x}] = \frac{\partial E[Y|P(\mathbf{Z}) = p, \mathbf{X} = \mathbf{x}]}{\partial p}. \quad (11)$$

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 $P(\mathbf{Z}) = p$) with respect to p . In the situation of a homogeneous treatment effect, MTE is a constant, and the expectation of the outcome Y is a linear function of p .

5.3. Using MTE to derive overall treatment effects

Under both semi-parametric-LIV and parametric approaches, all treatment parameters of concern can be identified by using weighted averages of MTE. Heckman et al., (2006a, p. 396) show that

$$\text{ATE}(x) = E(Y_1 - Y_0|X = x) = \int_0^1 \Delta^{\text{MTE}}(x, u_D) du_D \quad (12)$$

$$\text{TT}(x) = E(Y_1 - Y_0|X = x, D = 1) = \int_0^1 \Delta^{\text{MTE}}(x, u_D) w_{\text{TT}}(x, u_D) du_D \quad (13)$$

$$\text{TUT}(x) = E(Y_1 - Y_0|X = x, D = 0) = \int_0^1 \Delta^{\text{MTE}}(x, u_D) w_{\text{TUT}}(x, u_D) du_D \quad (14)$$

where the weights are

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

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

$$w_{\text{TUT}}(x, u_D) = \left[\int_0^{u_D} f(p|X = x) dp \right] \frac{1}{E((1 - P)|X = x)}$$

where f is the density function of p .

5.4. Ability bias and sorting gain

Finally, we decompose the conventional bias (i.e., the difference in magnitude between OLS and ATE estimators) into two components: the ability bias (i.e., the mean bias of selection in the absence of treatment) and the sorting gain (i.e., the mean difference due to heterogeneous returns to college education). Note that the total amount of bias for ATE can be decomposed this way:

$$E(U_1|D = 1) - E(U_0|D = 0) = E(U_1 - U_0|D = 1) + [E(U_0|D = 1) - E(U_0|D = 0)].$$

That is,

$$\text{Total bias} = \text{Sorting gain} + \text{Ability bias}.$$

Table 1
Variables and descriptive statistics.

| Independent variables | Male | | | | Female | | | |
|--|---------|--------|-----------|--------|---------|--------|-----------|--------|
| | Treated | | Untreated | | Treated | | Untreated | |
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Years of schooling | 16.591 | 1.012 | 12.827 | 1.037 | 16.395 | .834 | 12.938 | 1.080 |
| Monthly earnings | 46,863 | 29,051 | 41,318 | 27,484 | 41,272 | 17,822 | 29,879 | 16,819 |
| Log of earnings | 10.622 | .514 | 10.507 | .466 | 10.544 | .415 | 10.198 | .448 |
| Mincer experience = age-years of schooling-6 | 6.872 | 3.011 | 10.699 | 3.083 | 6.896 | 2.829 | 10.573 | 3.167 |
| Father's years of schooling | 10.176 | 4.156 | 7.721 | 3.522 | 10.427 | 3.887 | 7.714 | 3.470 |
| Mother's years of schooling | 8.058 | 4.000 | 5.999 | 3.395 | 8.247 | 3.934 | 5.895 | 3.189 |
| <i>Ethnicity</i> | | | | | | | | |
| Hokkien (=1, if yes) | .739 | | .743 | | .704 | | .745 | |
| Hakka (=1, if yes) | .124 | | .140 | | .128 | | .127 | |
| Mainlander (=1, if yes) | .131 | | .104 | | .165 | | .111 | |
| Aborigine (=1, if yes) | .006 | | .013 | | .002 | | .017 | |
| <i>Residence prior to age 15</i> | | | | | | | | |
| Major city (=1, if yes) | .293 | | .239 | | .338 | | .232 | |
| Not major city (= 1, if yes) | .582 | | .649 | | .565 | | .652 | |
| Not in Taiwan (=1, if yes) | .000 | | .004 | | .005 | | .015 | |
| Missing data (=1, if yes) | .124 | | .107 | | .091 | | .101 | |
| <i>Birth cohort</i> | | | | | | | | |
| 1966 (=1, if yes) | .026 | | .018 | | .020 | | .026 | |
| 1967 (=1, if yes) | .034 | | .035 | | .010 | | .036 | |
| 1968 (=1, if yes) | .045 | | .054 | | .037 | | .060 | |
| 1969 (=1, if yes) | .054 | | .071 | | .079 | | .065 | |
| 1970 (= 1, if yes) | .064 | | .104 | | .052 | | .082 | |
| 1971 (=1, if yes) | .099 | | .087 | | .077 | | .098 | |
| 1972 (=1, if yes) | .090 | | .086 | | .104 | | .082 | |
| 1973 (=1, if yes) | .086 | | .116 | | .109 | | .100 | |
| 1974 (=1, if yes) | .090 | | .081 | | .086 | | .098 | |
| 1975 (=1, if yes) | .094 | | .099 | | .086 | | .094 | |
| 1976 (=1, if yes) | .107 | | .082 | | .128 | | .084 | |
| 1977 (=1, if yes) | .077 | | .072 | | .074 | | .073 | |
| 1978 (=1, if yes) | .079 | | .053 | | .059 | | .048 | |
| 1979 (=1, if yes) | .032 | | .022 | | .049 | | .034 | |
| 1980 (=1, if yes) | .024 | | .022 | | .030 | | .021 | |
| Sample size (N) | 467 | | 1115 | | 405 | | 953 | |

Data source: 2000–2005 Taiwan Social Change Survey (TSCS).

6. Empirical results

6.1. Data source and variables

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 the Academia Sinica. TSCS is an ongoing project designed to collect social and economic data on contemporary Taiwan (see <http://www.ios.sinica.edu.tw/sc/> for details of the surveys). For this study, we use the TSCS data collected during the period from 2000 to 2005.¹⁰ We limit our focus to young entrants (ages 25–34 when surveyed) to the labor market who attained at least 12 years of schooling (i.e., high school or higher). After the restriction, our analytical sample consists of 2940 respondents (1582 males and 1358 females) born between 1966 and 1980, who provided information on earnings, education, family background, gender, and birth year.

Table 1 presents measurements and descriptive statistics for most of the variables used in the analysis. The share of college attendees in the sample is about the same for men (29.5%) and for women (29.8%). For both men and women, the average earnings of college attendees (i.e., the “treated” group) are significantly higher than those of high school graduates (i.e., the “untreated” group). Although men’s earnings are significantly higher than those of women for both groups, the gender gap is much smaller among college attendees (nt\$5591) than among high school graduates (nt\$11,439). We observe that, irrespective of gender, college attendees are much more likely to come from well-educated families, with both father’s and mother’s average years of schooling significantly higher than those in the untreated group. It is well known and commonly accepted that parental education is an important indicator of family socioeconomic background.¹¹ Besides these

¹⁰ TSCS uses two different types of questionnaire each year. We use data derived from surveys 2000 (I and II), 2001 (I), 2002 (I and II), 2003 (I and II), 2004 (I) and 2005 (I and II), as they provide information useful for this analysis.

¹¹ Due to data limitations, unfortunately, we are unable to consider father’s occupation or family income in this analysis.

Table 2
Estimated probit model for college attendance.

| Independent variables | Male (N = 1582) | | | Female (N = 1358) | | |
|--|--------------------|------|----------------------|---------------------|------|----------------------|
| | Coefficient | SE | Mean marginal effect | Coefficient | SE | Mean marginal effect |
| Intercept | -.887 [*] | .302 | - | -1.211 [*] | .334 | - |
| Father's schooling (FS) | .061 [*] | .027 | .020 [*] | .047 | .028 | .016 |
| Mother's schooling (MS) | .003 | .032 | .001 | -.066 | .037 | -.022 |
| <i>Ethnicity (relative to Hokkien)</i> | | | | | | |
| Hakka | -.262 | .619 | -.083 | -1.338 | .915 | -.293 |
| Mainlander | .622 | .509 | .231 | -.524 | .872 | -.151 |
| Aborigine | -.250 | .377 | -.078 | -.915 | .508 | -.210 |
| <i>Residence prior to age 15 (relative to not in major city)</i> | | | | | | |
| Major city | .164 | .437 | .056 | -.762 | .534 | -.221 |
| Not in Taiwan | - | - | - | -.505 | .444 | -.140 |
| Missing data | .165 | .114 | .057 | -.164 | .139 | -.052 |
| <i>Birth cohort (relative to 1966)</i> | | | | | | |
| 1967 | -.272 | .295 | -.084 | -.686 | .394 | -.177 |
| 1968 | -.376 | .280 | -.113 | -.130 | .315 | -.042 |
| 1969 | -.586 [*] | .272 | -.164 [*] | .430 | .297 | .156 |
| 1970 | -.728 [*] | .266 | -.196 [*] | -.061 | .302 | -.020 |
| 1971 | -.323 | .260 | -.100 | .023 | .291 | .008 |
| 1972 | -.378 | .262 | -.114 | .279 | .290 | .098 |
| 1973 | -.629 [*] | .259 | -.177 [*] | .213 | .286 | .074 |
| 1974 | -.347 | .262 | -.106 | -.041 | .290 | -.013 |
| 1975 | -.537 [*] | .260 | -.155 [*] | -.060 | .293 | -.020 |
| 1976 | -.303 | .261 | -.094 | .291 | .287 | .103 |
| 1977 | -.386 | .267 | -.116 | .031 | .298 | .010 |
| 1978 | -.262 | .271 | -.082 | .222 | .311 | .078 |
| 1979 | -.330 | .320 | -.100 | .291 | .322 | .104 |
| 1980 | -.461 | .328 | -.133 | .229 | .360 | .081 |
| <i>Interaction terms</i> | | | | | | |
| FS * MS | .003 | .003 | .001 | .008 [*] | .003 | .003 [*] |
| FS * Hakka | -.013 | .072 | -.004 | .019 | .088 | .006 |
| FS * Mainlander | -.076 | .050 | -.026 | -.010 | .075 | -.003 |
| FS * Major city | -.021 | .048 | -.007 | .065 | .057 | .022 |
| MS * Hakka | .097 | .091 | .033 | .295 [*] | .134 | .098 [*] |
| MS * Mainlander | -.116 | .080 | -.039 | .160 | .129 | .053 |
| MS * Major city | -.045 | .062 | -.015 | .160 [*] | .074 | .053 [*] |
| Hakka * Major city | .421 | .355 | .155 | .270 | .365 | .096 |
| Mainlander * Major city | .227 | .259 | .081 | -.637 [*] | .272 | -.169 [*] |
| FS * MS * Hakka | -.007 | .008 | -.002 | -.014 | .010 | -.005 |
| FS * MS * Mainlander | .010 | .006 | .003 | -.004 | .010 | -.001 |
| FS * MS * Major city | .004 | .005 | .001 | -.011 | .006 | -.004 |

^{*} Significant at the level of $\alpha = .05$.

background variables serving as IVs in this study, we also include in our earnings equation standard covariates (X), such as experience and experience squared, with experience calculated via the Mincer (1974) method.

6.2. Propensity score estimation

We estimate the propensity of receiving college education for every observation in the analysis sample using a probit model, separately for men and women. The results are presented in Table 2. The last column of the table gives the mean marginal effect for each explanatory variable Z . We observe that the variables representing family socioeconomic background all have expected coefficients in the propensity score model that are consistent with the long-standing literature in the sociology of education (Boudon, 1974; Bowles and Gintis, 1976; Breen and Goldthorpe, 1997; Buchmann and DiPrete, 2006; Coleman, 1988; Jencks et al., 1972; Raftery and Hout, 1993; Sewell et al., 1970).

6.3. Tests on sorting gain using semi-parametric approach

If there is a sorting gain so that the return to college education varies systematically with the unobserved cost of (or resistance to) college education, the relationship between the propensity score and logged earnings should be nonlinear (Heckman et al., 2006a, p. 397). Thus, we test the sorting gain hypothesis by testing the linearity of the conditional expectation of Y in terms of $P(Z)$, i.e., $E(Y|P(Z) = p)$. Our results indicate that polynomial regressions are preferred over the linear regressions for both men and women.

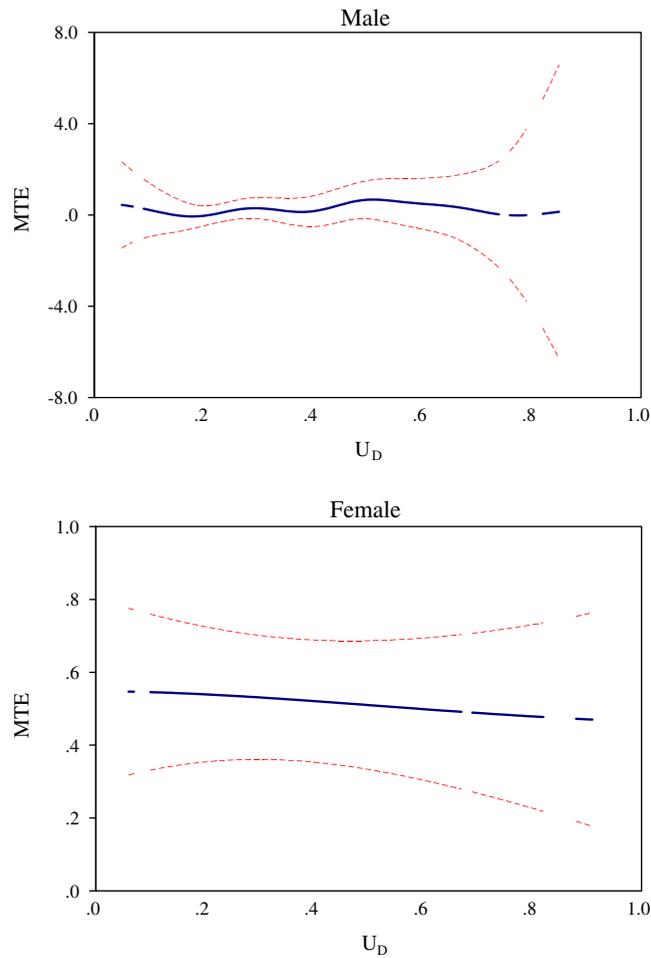


Fig. 1. MTE as a function of unobserved heterogeneity U_D : semi-parametric-LIV approach.

Thus, it is fruitful for us to employ the Heckman–Urzua–Vytlacil semi-parametric approach of estimation on our data, using the estimated probability of receiving college education as the instrument.

6.4. Gender-specific marginal treatment effects

We now proceed to estimate the gender-specific marginal treatment effects. We first continue the semi-parametric approach and estimate MTE as the derivative of the expected log earnings on the propensity to receive education, shown in Eq. (11). Fig. 1 presents the results, plotting the estimated marginal treatment effect as a function of the unobserved component U_D in the schooling choice equation, along with their 95% confidence intervals.

Inspection of Fig. 1 reveals that the confidence intervals are rather wide at the two ends (in particular, at the right end). Besides, the shape of MTE differs between men and women. While the estimated line for men is non-monotone, the one for women appears steadily declining.¹² Recall that within this framework, the higher the unobserved U_D , the higher the unobserved resistance to attending college, and thus the lower the probability of attending college, conditional on X . Accordingly, the declining pattern of MTE with U_D for women means that those who have the highest latent tendency of going to college (i.e., those who are most likely to attend college, everything else being equal) have the largest marginal returns. By contrast, conditional on X , persons who have the least likelihood of going to college have the lowest marginal returns. Women's declining pattern in MTE with U_D not only confirms heterogeneity in their returns to college education but also suggests that the average college attendee earns more than a marginal participant in Taiwanese higher education.

To facilitate interpretation, it is useful to summarize individual-level MTE estimates into summary quantities of interest for a population or subpopulations, using weights given by Heckman et al. (2006a) for such quantities. Fig. 2 depicts the estimated weights from our data for the average treatment effect (ATE), the average treatment of the treated (TT), and the average treatment effect of the untreated (TUT). As shown in the figure, the shapes of weights are similar between men and

¹² The line plotted in the figure has a few blank areas, because MTE cannot be estimated at points where the support of $P(Z)$ is weak.

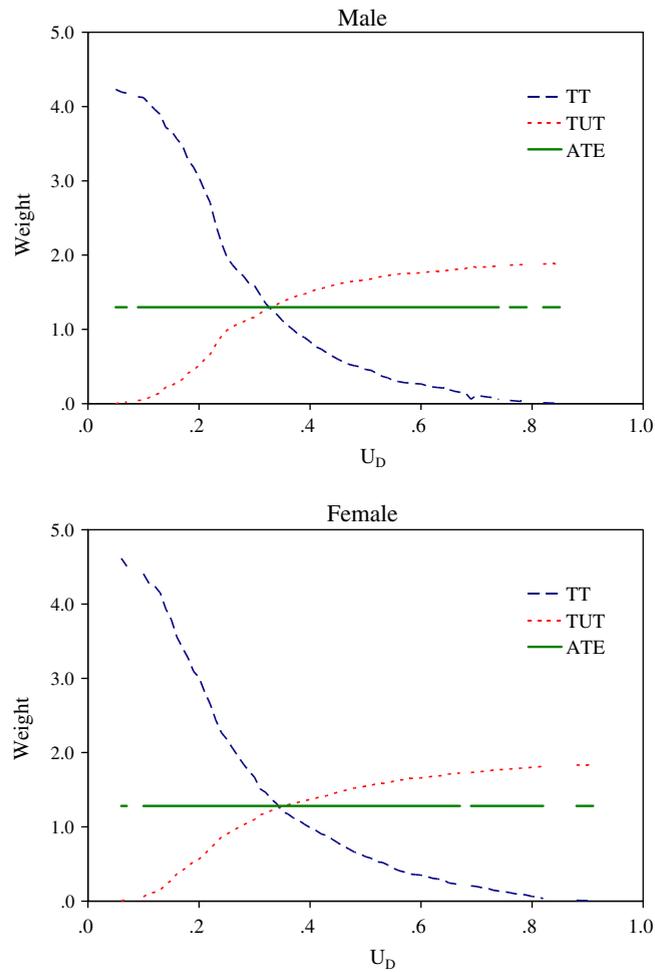


Fig. 2. Weights as a function of unobserved heterogeneity U_D : semi-parametric-LIV approach.

women: ATE weights MTE evenly, while TT overweights the ATE for persons with low values of U_D (who are more likely to attend college), and TUT overweights the ATE for persons with high values of U_D (who are less likely to attend college). Given the shape of MTE and the shape of the weights, it is easy to infer that $TT > ATE > TUT$, especially for women.

6.5. Results from the parametric approach

The analysis up to this point was carried out by using a semi-parametric approach. We have found a declining pattern of MTE for women in our data so that there is positive sorting gain for attaining college education. While our linearity test suggests that there is also essential heterogeneity for men, there is no clear pattern in the MTE results as to the direction of the sorting bias for men. We are concerned that our data may be too thin to support the semi-parametric approach. In this section, we report the results on essential heterogeneity using a parametric approach. This is accomplished by estimating the marginal treatment effect under the assumption of a joint trivariate normal distribution for errors in a switching regression setup (Quandt, 1972; Willis and Rosen, 1979) – the two error terms in the main earnings equations under the two treatment regimes in Eq. (5), and the error term in selection (Eq. (4)). Under this specification, we find that the linearity assumption is, again, rejected for both men and women.

6.6. Summary results

To summarize the results in the preceding analyses, we now compare, in Table 3, various estimated parameters of interest by different methods, along with the conventional OLS and IV estimators obtained from the same data. Again, we use weights of Heckman et al. (2006a). Three findings emerge from this approach.

First, the OLS results indicate that the average difference in earnings between college graduates and high school graduates is much more pronounced for women than for men. The OLS coefficient for college education is .260 for men, while the

Table 3

Comparisons of different treatment parameters: using two different estimation approaches.

| Parameter | Semi-parametric-LIV | | Parametric | |
|--------------------------|---------------------|-------------------|-----------------|-------------------|
| | Male (N = 1576) | Female (N = 1290) | Male (N = 1576) | Female (N = 1290) |
| 1. OLS | .260* (.030) | .416* (.030) | .260* (.030) | .416* (.030) |
| 2. ATE | .262 (.273) | .512* (.089) | .351* (.093) | .702* (.079) |
| 3. TT | .173 (.273) | .527 (.092) | .350* (.120) | .711* (.090) |
| 4. TUT | .301 (.374) | .506* (.096) | .352* (.094) | .698* (.085) |
| 5. IV | .270* (.112) | .520* (.086) | .353* (.096) | .706* (.078) |
| 6. Bias = OLS–ATE | –.002 (.275) | –.097 (.095) | –.091 (.097) | –.287* (.085) |
| 7. Ability bias = OLS–TT | .087 (.274) | –.112 (.097) | –.090 (.123) | –.296* (.095) |
| 8. Sorting gain = TT–ATE | –.089 (.387) | .015 (.128) | –.001 (.152) | .009 (.120) |

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

corresponding estimate is .416 for women. This finding is consistent with the literature, as women with little education have very low earnings (e.g., Gerber and Schaefer, 2004; Mare, 1995; Xie and Hannum, 1996).

Second, the pattern $TT > ATE > TUT$ holds for women using both the semi-parametric approach and the parametric methods. The main difference is that the parametric method yields statistically sharper results, as expected. This pattern indicates a negative ability bias and a positive sorting gain in the female sample. A negative ability bias means that women who attend college would make low incomes in the labor market if they did not make it to college. The finding of a negative “ability” bias is consistent with Willis and Rosen’s (1979) finding in the American context that college graduates would do poorly if they had not gone to college. The estimated amounts of the total bias and the ability bias under the parametric approach are larger than those under the semi-parametric approach, with the former attaining statistical significance.¹³ By comparison, among men both semi-parametric and parametric estimations yield a result that $TUT > ATE > TT$. This result seems at odds with that for women. However, the differences across these three estimates are small and statistically insignificant. There is not much evidence for selection bias for men in these data.

Third, even after we model selection bias using either the semi-parametric or the parametric approach, the treatment effect of college education on earnings is substantially larger for women than for men, no matter which estimation method we use. For example, the semi-parametric estimate indicates that the average treatment effect for women is 51.2% (about 14.6% annually with 3.5 more years of schooling, on average), much higher than the 26.2% for men (about 6.9% annually with 3.8 more years of schooling, on average). Again, the higher education returns for women should be interpreted as resulting from women’s severe disadvantage in the low-skill labor market rather than their advantage over men in the high-skill labor market (Xie and Hannum, 1996). It is possible that the overall higher return for women makes the sorting gain more salient for women than for men.

These results raise questions as to how to interpret the earlier results of Tsai and Xie (2008) and Brand and Xie (2010). Under the ignorability assumption, both of these studies report a pattern of declining earnings returns as a function of the propensity of college education, called “negative selection” by Brand and Xie (2010). However, the negative selection pattern identified in the two previous studies is merely descriptive, in the sense that it shows up in observed data, and thus subject to alternative interpretations. In the Xie and Wu (2005) paper that presented the kind of analysis later used by Tsai and Xie (2008) and Brand and Xie (2010), a negative selection pattern was interpreted in terms of differential selectivity. In our context of college education effect on earnings, differential selectivity may also be true: persons in low-propensity strata are attracted to college only with higher earnings gains (to overcome higher resistance) than persons in high-propensity strata.

Of course, we do not have the experimental data with which to evaluate the two different interpretations. Our study shows that whether we can accept the ignorability assumption may lead us to reach vastly different policy implications. If the ignorability assumption is to be accepted as true in reality, the negative selection identified by Tsai and Xie (2008) for Taiwan and by Brand and Xie (2010) for the U.S. means that marginal persons who currently do not attend college would have gained more from attending college than those already attending college. If the differential selectivity assumption is true, our study shows that marginal persons who do not attend college would gain less from college education than those who currently do, a finding consistent with those of Heckman and his associates (Carneiro and Heckman, 2002; Carneiro et al., forthcoming; Heckman, 2001a,b). We have found this sorting gain effect for women in Taiwan.

¹³ Yet, probably due to a moderate sample size, women’s sorting gain is not statistically significant, regardless of the estimation method used. In other words, we do not find strong evidence in support of the principle of comparative advantage at work in Taiwan.

7. Conclusion

Both economists and sociologists have had a long-standing interest in estimating the causal effects 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 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 results reveal substantial individual heterogeneity in the Taiwanese data, especially the female data. In Taiwan, as elsewhere (see, e.g., Gerber and Schaefer, 2004; Mare, 1995; Xie and Hannum, 1996), the gender gap in earnings is smaller among university degree holders, and as a result the returns to a university education are greater for women than for men. Not only do we find profound gender differences in the returns to schooling, we also find heterogeneity within the female sample. Among women, $TT > ATE > TUT$ with a positive sorting gain and negative ability bias. The downward biases in the Mincer coefficient for both ATE and TT are statistically significant. These results suggest that for women, not only do the treated group and the untreated group differ in unmeasured heterogeneity, but schooling choices are based on unobserved gains. There is a significant selection bias in terms of sorting gain.

A major limitation of the study is its reliance on a set of variables selected as instrumental variables – ethnicity, parental education, and growing-up place prior to age 15. It is assumed that these variables directly affect the attainment of college education and only indirectly influence earnings through college education. This assumption is not verifiable and can be false. However, under this assumption, our study demonstrates heterogeneous treatment effects due to unobserved factors. Not only does it show that the methodological work by Heckman and his associates can be used to enhance our methodological capability to detect heterogeneous treatment effects with observational data, but our results challenge the common interpretation of the findings reported previously in Tsai and Xie (2008) and Brand and Xie (2010) under the ignorability assumption: the marginal person who may be induced into seeking a college education may have lower, not greater, earnings return than the average person who already attends college.

Acknowledgments

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