E C O N O M I C S B U L L E T I N

Is the earnings−schooling relationship linear? a semiparametric analysis

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Abstract

Using data from Labor Force Surveys (LFS), this study implements additive models to analyze the impact of schooling on wages. It also uses the Sperlich, Tjostheim and Yang (2002) test to validate the existence of interaction terms. Results confirm that the earnings−schooling relationship exhibits convexity. However, the degree to which the said relationship is convex is materially affected by the presence of the interaction component in the additive wage function.

Financial and administrative support from the Japan International Cooperation Agency (JICA) and Japan International Cooperation Center (JICE) are gratefully acknowledged. I would also like to thank Professor Kimio Morimune and the associate editor for invaluable comments.
Citation: Dacuycuy, Lawrence, (2005) "Is the earnings−schooling relationship linear? a semiparametric analysis." *Economics Bulletin*, Vol. 3, No. 37 pp. 1−8
Submitted: May 20, 2005. **Accepted:** July 28, 2005.
URL: http://www.economicsbulletin.com/2005/volume3/EB−05C10007A.pdf

1. Introduction

Much of returns to education studies remain in the parametric paradigm wherein a given structure is assumed to capture the marginal effects of education. In an original empirical setting, the wage function is linear in schooling (Mincer, 1974). Clearly, the parametric structure acts to restrict the shape of the earnings–schooling relationship.

In the literature of human capital, examining the earnings–schooling relationship is important. Bjorklund and Kjellstrom (2002) analyzed how deviations from assumptions in Mincer's model would affect the interpretation of returns to schooling vis–a–vis internal rates of return. Part of their methodology involves practical estimation methods like Box–Cox variable transformation and the use of dummy variables to account for each year in the worker's schooling profile. Investigating such relationships also allows the researcher to ascertain trends in returns over time which yields important inferences used to prove or disprove theories on the behavior of the labor market (Psacharopoulos, 1989).

Deviating from the usual parametric methodology, Linton and Nielsen (1995) estimated additive effects of schooling and experience using CPS data. The effect of schooling is linear, consistent with the common Mincerian specification. However, there are studies that indicate that the relationship is convex. Lemieux (2002) noted that the earnings–schooling relationship may be convex, implying that returns to schooling may indeed increase at an increasing rate.

While we do not compute for the internal rate of return, the principal task of this paper is to relax the parametric structure by employing semiparametric additive models in order to examine the marginal effect of schooling on earnings. Since the introduction of the interaction term materially influences the shape of the earnings–schooling relationship, we will also employ the Sperlich, Tjostheim and Yang (1998) test to verify the statistical significance of the interaction component. To our knowledge, no additive models have been applied to analyze earnings–schooling relationships in the Philippines.

The remainder of the paper is as follows: Section 2 provides a brief introduction to semiparametric additive models and the test for the significance of the interaction component. Section 3 details the data used. Results are analyzed in section 4, followed by concluding remarks.

2. Semiparametric additive modeling

In a parametric model, the marginal effects of education are determined by an assumed functional relationship between earnings and years of schooling and more often than not, this relationship is specified as a linear one. To relax a somewhat rigid parametric structure, we can employ semiparametric additive models.

Define the conditional mean function of wages as

$$E[w_i|x_i] = h(x_{1i}, x_{2i}) \tag{1}$$

where x_{1i} denotes schooling, x_{2i} experience and w_i the natural logarithm of wages. Equation 1 is also called a statistical earnings function (Willis, 1986; Bjorklund and Kjellstrom, 2002). The most widely used functional form for the conditional moment $E[w_i|x_i]$ is $y_i = \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{2i}^2$ which is known as the Mincerian quadratic equation. This functional assumption corresponds to the maintenance of assumption 3 in Bjorklund and Kjellstrom. The said assumption implies that $\frac{\partial E[w|x]}{\partial x_1}$ is not a function of x_2.

Note that when the quadratic specification is used, the relationship between wages and schooling is linear in both parameter and variable while wages are quadratic in experience. An alternative semiparametric strategy is to avoid the parameterization of the various relationships. In this case, the estimating equation becomes

$$E[w_i|x_i] = \mu + f_1(x_{1i}) + f_2(x_{2i}) \tag{2}$$

wherein both components f_1 and f_2 are estimated via marginal integration and μ, the constant term. To elucidate, let $E[w_i|x_i] = m(x)$. Thus, $m(x) = \mu + f_1(x_{1i}) + f_2(x_{2i})$. By the assumption of location normalization, $\int f_k(x_{ki})q(x_{ki})dx_{ki} = 0$, wherein k indices the functional components x_1 and x_2. To get the estimator of $f_1(x_{1i})$, integrate $m(x)$ with respect to x_2. This yields the following equation:

$$\int m(x)q(x_2)dx_2 = 0 + \int f_1(x_1)q(x_2)dx_2 \tag{3}$$

which upon manipulation, we arrive at the fundamental form for estimating the nonparametric function. Thus, the marginal integration based estimator is written as $\int \hat{m}(x)\hat{q}(x_2)dx_2$, where $\hat{m}$ is the kernel estimator of m and $\hat{q}$ is the weight function. From this basic structure, it is possible to make estimates more efficient by using a procedure in Linton (1997) that makes use of backfitting techniques. Since x_1 and x_2 are correlated, more efficient estimates for f_1 and f_2 are arrived at by computing for the partial residuals $U_{1i} = w_i - \hat{f}_2(x_{2i}) - \hat{\mu}$ and $U_{2i} = w_i - \hat{f}_1(x_{1i}) - \hat{\mu}$ and applying a smoothing technique like kernel–based methods on U_{1i} and U_{2i}.

When joint effects of schooling and experience are deemed feasible, one may modify the quadratic specification by including an interaction term. This is tantamount to a relaxation of assumption 3 in Bjorklund and Kjellstrom, wherein $\frac{\partial E[w|x]}{\partial x_1}$ becomes a function of x_2. This allows the introduction of a first order interaction component. The additive model is now augmented by an interaction function which is written as

$$E[w_i|x_i] = \mu + h_1(x_{1i}) + h_2(x_{2i}) + h_{12}(x_{1i}, x_{2i}) \tag{4}$$

For the interaction component, Sperlich et al defined the estimator for h_{12} as $1/n \sum_{i=1}^{n} \hat{m}(x_1, x_2, x_{12i})$, where x_{12i} contains the interaction component. For each of the individual functional components, the estimating equation is given by $h_k = 1/n \sum_{i=1}^{n} \hat{m}(x_k, x_{-ki})$, where x_{-ki} contains variables other than x_k. Both $\hat{m}(x_k, x_{-ki})$ and $\hat{m}(x_1, x_2, x_{12i})$ are known as pre-estimators which can be estimated using local polynomial smoothers. Using results from the said preestimators, one may now apply marginal integration techniques to get the functional estimates.

The resulting estimates in both additive models refer to marginal covariate effects. Ascertaining the correct model may be done by testing for the existence of the interaction functional component. If the interaction component is insignificant, then the relevant estimating equation is equation 2. This may be carried out using the methodology described in Sperlich, Tjostheim and Yang (2002).

In the test by Sperlich et al, the interaction function is estimated via marginal integration. Another procedure calls for the estimation of the mixed derivative but we choose to implement the former. The test functional is written as

$$T_n = nh \int \hat{h}_{12}^2 \varphi(x_{1i}, x_{2i}) d(x_{1i}) d(x_{2i}) \tag{5}$$

where $\hat{h}_{12}$ is the estimated interaction component, h the bandwidth parameter and φ is a nonnegative weight function. Though the nonparametric test statistic has a limiting normal distribution, the bootstrap procedure is superior to asymptotic order expansion in the case of limited sample size.

3. Data

The data come from Philippine labor force surveys (LFS) undertaken in 1994 and 1995. The LFS is a representative multi - stage survey that is used primarily to gather wages and other data pertinent to the labor market. Following the Mincerian tradition, experience is defined as age–schooling–6 and years of schooling are computed using education codes furnished by the National Statistics Office (NSO). We limit our sample to working male individuals in the Bicol region, one of the Philippines' poorer regions. Based on some descriptive statistics, the mean years of schooling in 1994 was 8.16 and slightly improved to 8.35 in 1995. In the estimation samples, there are 663 and 772 males in 1994 and 1995, respectively.

4. Results

To aid comparisons, we estimated simple wage functions using ordinary least squares. The first specification estimated is the quadratic Mincerian model, after which, the said specification is slightly modified to account for the interaction component. Based on the coefficient of schooling in the Mincerian equation, the returns to schooling was 0.025 in 1994 and 0.029 in 1995 for the model that incorporates an interaction term. The said figures do not account for the role of experience. When the interaction term is excluded, the coefficient of schooling registered 0.077 in 1994 and 0.093 in 1995. The results imply that the inclusion of the interaction component is critical in quantifying the returns to schooling. The drawback of the Mincerian specification, however, lies in the fact that it is not possible to discern the returns at specific levels of education. This is accounted for by the estimation of additive models.

Figures 1 and 2 show that the marginal effects of schooling from 1994 to 1995 are nonlinear. The results appear to support the parametric findings, in that, when the interaction term is neglected, the estimates appear to be more convex than when it is incorporated, indicating that the presence of interaction effects introduces material changes to the additive model estimates.

Based on figure 1, rapidly increasing returns are evident for workers with more than 7 years of schooling. On the other hand, decreasing returns are observed for workers with less than 7 years of schooling, in some cases, 6 years. When considered as a dimension of skill, these schooling differences could amount to a widening wage gap between 1994 and 1995. This would then have a positive impact on wage inequality.

Figure 2 indicates that increasing returns are observed even for workers with poor educational profile,thereby negating the earlier observation that decreasing returns occur within the 0–7 interval. The marginal effects across years appear to converge at higher schooling intervals and diverge at lower schooling intervals. Judging from the slopes, we see that the most steep belongs to highly educated workers.

To determine the significance of the interaction component, we have implemented the Sperlich, Tjostheim and Yang test. In the said test, the null hypothesis states that the interaction component does not exist. Conversely, in the alternative hypothesis, the interaction component is statistically significant. It is noted that the null hypothesis may or may not be rejected depending on the chosen level of significance. For the additive model estimate in 1994, the null hypothesis is only rejected at the 20% level of significance while in 1995, the null hypothesis is accepted at the 1% and 5% levels of significance.

5. Concluding remarks

This paper has demonstrated the value of additive modelling in uncovering hidden structures that simply cannot be captured by a parsimonious parametric model. The econometric exercise pointed to the nonlinearity of the earnings–schooling relationship. However, as in the parametric model, the slope of the earnings–schooling relationship hinges on the significance of the interaction term. When the interaction term is included, the profile appears to be increasing and when excluded, the profile exhibits marked convexity. The convexity of the marginal effects lends support to the contention that increasing returns to schooling may be realized. This observation may prove useful in understanding the effects of educational returns to wage inequality. However, as encountered in the empirical literature on wage function estimation, the addition of interaction terms potentially alters the estimates. The tests indicate that the relevant additive model in 1994 is the model without interaction effects while the model with an interaction component may be more relevant for the 1995 data.

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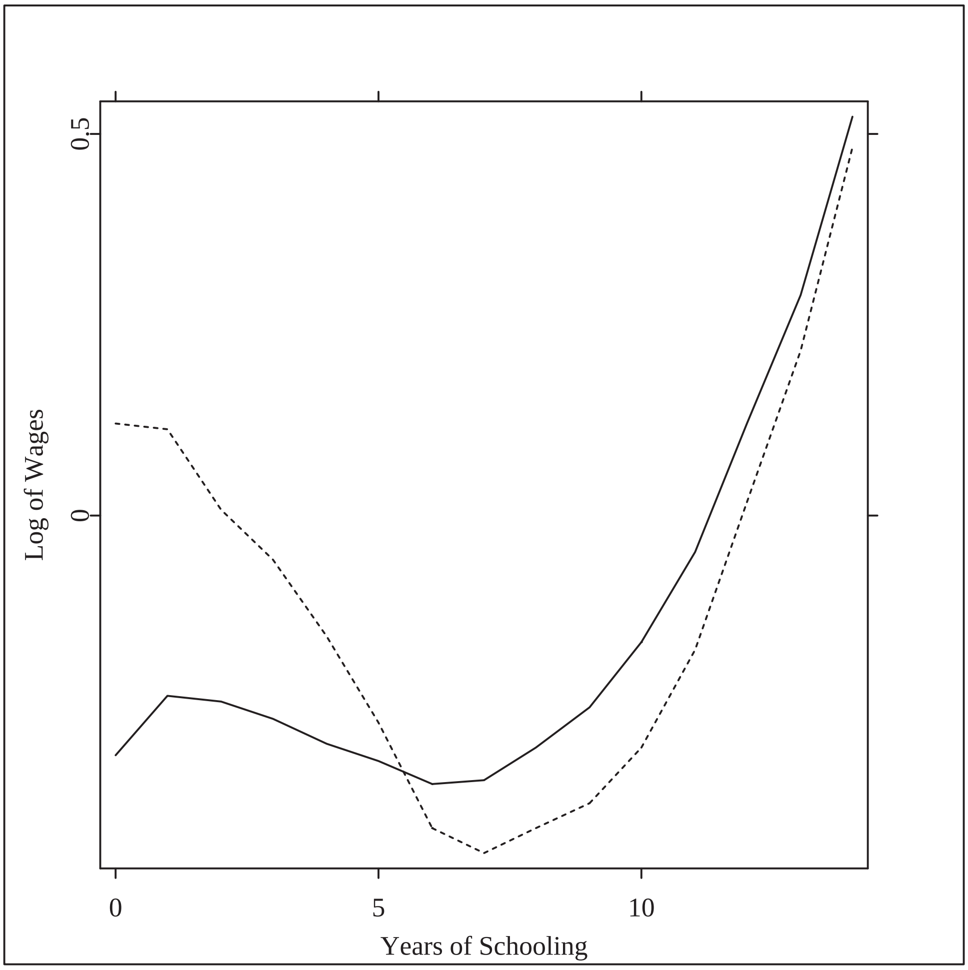

Figure 1: Additive model estimates of the effects of schooling,
Note: 1994 (solid line); 1995 (broken line)

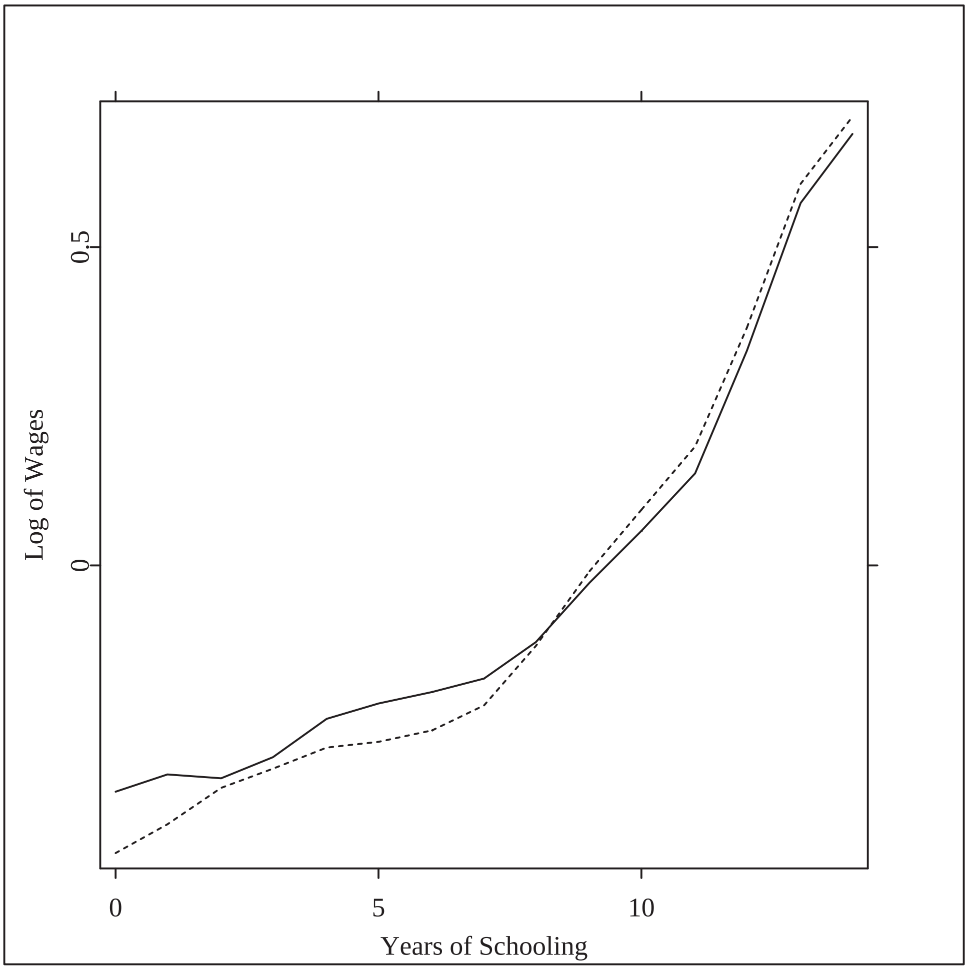

Figure 2: Additive model with interaction estimates of the effects of schooling
Note: 1994 (solid line); 1995 (broken line)