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Measuring the Effects of Schooling on Wages for a Young Sample from Rural Guatemala

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...for the laborer is worth his wage.

—Luke 10:7

Abstract

In order to measure the intrinsic effect of schooling on wages for adolescents and young adults from four villages in Rural Guatemala, this paper estimates different wage specifications that have been suggested in the human capital literature. Successively accounted for are potential sources of bias in the estimated coefficient of schooling, such as those arising from self-selectivity in the wage-earning sample and from the omission of innate ability, family background, and the quality of schooling from the set of wage determinants. The results show that when these potential sources of bias are treated, the rate of return to schooling is about 5.9 percent for the population of adolescents and young adults in these villages.

I. Introduction

The relationship between educational attainment and earnings has been one of the most widely studied and intensely debated subjects in economics. In this literature, perhaps the central issue has been what to make of the universally observed correlation between these two factors. The mainstream view, as described by human capital theory (Maglen 1990), maintains (a) that there is a direct causal effect running from schooling to wages and (b) that this causality is due to increases in productivity that education confers on the more schooled workers. But this contention is challenged by competing theoretical explanations. The screening model, for instance, claims that the correlation is simply a spurious statistical artifact that arises because education serves as a signal for innate ability, which is the primary determinant of productivity. On the other hand, the credentialist hypothesis, while allowing that there may be an underlying relationship between schooling and wages, argues that this arises instead from the licensing or certifying function that education performs.

On empirical grounds, the impact of schooling on wages, as estimated by the standard human capital earnings functions, has been called into question as well. Griliches and Mason (1972) and Behrman and Birdsall (1983), for instance, point out that the estimates of the standard human capital wage equation may be spurious because important variables that are correlated with education, such as innate ability, family background, and the quality of education, are left unspecified.

Using data on adolescents and young adults from four rural villages in Guatemala, this study attempts to measure the intrinsic effect of schooling on wages by estimating different wage specifications that have been suggested in the human capital literature. The wage regressions successively account for potential sources of bias in the estimated coefficient of schooling, such as those arising from self-selectivity in the wage-earning sample and from the omission of innate ability, family background, and the quality of schooling from the set of wage determinants. The regression results show that when these

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potential biases are treated, the rate of return to schooling is about 5.9 percent for the population of adolescents and young adults in these villages.

Following recent studies (Glewwe 1991; Boissiere *et al.* 1985) which have attempted explain the underlying correlation between education and wage rates through the cognitive outcomes of schooling, this paper also estimates wage equations with cognitive test scores as the indicator of human capital. In these wage equations, when schooling is not specified as a regressor, test scores on numerical aptitude, though not test scores on vocabulary and reading ability, turn out to be weakly significant. When both schooling (to measure the noncognitive returns to education) and the cognitive test scores are included in the set of wage regressors, none of the human capital regressors is significant perhaps because the specification, with its longer list of explanatory variables, demands more from the data set. To verify that schooling does affect cognitive outcomes, the paper also regresses cognitive test scores on schooling (and other variables). The results confirm that schooling is a very significant determinant of cognitive outcomes.

This study is organized as follows: In the next section, a short exposition of modern human capital theory is provided, and important issues surrounding the estimation of the wage function are discussed. Screening and credentialism are also summarized in a subsection. Certain aspects of data collection and some features of the data set are then discussed in the third section. In the fourth, the regression results are reported, and their limitations and implications are discussed in the fifth section. The sixth section summarizes the regression results and concludes the chapter.

II. Human Capital Theory: A Short Exposition

The idea that people invest in themselves in order to enhance their productivity capacity is as old as the classical economists. In *The Wealth of Nations* (1776, pp. 203–204), Adam Smith had written:

> [T]he wages of labour vary with the easiness and cheapness, or the difficulty and expense of learning the business.
>
> When any expensive machine is erected, the extraordinary work to be performed by it before it is worn out, it must be expected, will replace the capital laid out upon it, with at least the ordinary profits. A man educated at the expense of much labour and time to any of those employments which require extraordinary dexterity and skill, may be compared to one of those expensive machines. The work which he learns to perform, it must be expected, over and above the usual wages of common labour, will replace to him the whole expense of his education, with at least the ordinary profits of an equally valuable capital. It must do this, too, in a reasonable time, regard being had to the very uncertain duration of human life, in the same manner as to the more certain duration of the machine.
>
> The difference between the wages of skilled labour and those of common labour is founded upon this principle.

Prior to the 1950s, however, the work of human capital was directed at estimating the worth of the capital resident in men.[1] In his survey of this literature, Kiker (1966) notes that economists and statisticians during this period developed methods based one of two approaches: the cost of production method calculated the outlays incurred in the *production* of a human being, net of basic needs and expressed in real terms, while the earnings approach estimated the discounted value of a person's stream of lifetime labour income. The formulas derived were then used to estimate the value of a person's life (in order to assess compensatory damages for injury or death in court cases), the hidden

[1] Indeed, the very first attempts at this predates even Adam Smith himself, and the credit probably goes to Sir William Petty for his work around 1691 (Kiker 1966).

costs of war and migration (in the form of human capital losses), and even the wealth of nations.

In contrast, the modern vision of human capital theory is a theory of earnings. Following a discounted earnings approach, it maintains that differences in earnings—or wages, which is less affected by variations in the supply of labour—are due mainly to differences in education and training, because the more schooled as well as the more highly trained individuals are also the more productive workers.

Generally attributed to Becker (1962, 1975) and Mincer (1958, 1962, 1974), modern human capital theory, like its old versions, had a strong empirical emphasis from the start. Becker's work was motivated by the observation that the sustained increases in real per capita income since the 1800s could not be explained by the simple accounting of units of physical capital accumulated and man-hours of labour expended (Schultz 1988; Becker 1962, 1975); whereas Mincer's sought to explain why personal income had a skewed distribution when ability or intelligence was supposedly normally distributed (Mincer 1958, 1974). But perhaps the primary contribution of modern human capital theory has been that it provided (and continues to provide) the estimation of generic wage functions with a theoretical framework as well as a regression specification, thus spawning a vast empirical literature in its wake.

Briefly, the human capital argument went as follows: Treated solely as an investment activity, schooling has opportunity costs in the form of foregone earnings and direct costs, such as school fees. Thus, a wealth-maximizing individual who opts to stay in school for an additional year must be compensated with higher annual earnings over his working life. But in a competitive economy (at long run equilibrium), higher earnings can only be obtained with higher productivity, since workers are paid the value of their marginal product. Therefore, if workers with more schooling have higher earnings, *ceteris paribus*, it can only be because they are also more productive.

From this basic paradigm, Mincer (1974) developed what has come to be known as the standard human capital wage function. This has the form

$$\ln w_i = \alpha_0 + \alpha_1 S_i + \alpha_2 X_i + \alpha_3 X_i^2 + \varepsilon_i \tag{1}$$

where $\ln w_i$ is the natural logarithm of the wage of the ith individual in the population, S_i is the number of years he has spent in school, X_i is his years of work experience, and ε_i is the disturbance term reflecting the impact of other factors. The coefficient α_1 is interpreted as the private internal rate of return to an additional year of schooling, and experience is hypothesized to have a concave profile so that $\alpha_2 > 0$ and $\alpha_3 < 0$.

Equation (1) is a specification that pragmatically integrates Becker's and Mincer's theories of investment in education and post-school training and some of the implications of the dynamic human capital models (See Ben-Porath [1967], Haley [1973], and Wallace and Ihnen [1975], for example) within an econometric framework using cross-section data. To see this, one need only derive (1), which in discrete time may be done as follows:

Let E_t denote earning capacity, let Y_t stand for disposable income or earnings net of the costs of investment in human capital, and let I_t be the investment costs—all in period t. Assume that there is a base level of earnings, $E_0 = Y_0$, paid to workers with no schooling and experience. Then, earning capacity in year 1 may be given as

$$E_1 = Y_0(1 + r_0 k_0) \tag{2}$$

where $k_0 = I_0/E_0$ is the proportion of earning capacity spent on investment in human capital in year 0 and r_0 is the rate of return on investment.

Based on (2), earning capacity in year 2 may be derived as

$$E_2 = E_1(1 + r_1 k_1) = Y_0(1 + r_0 k_0)(1 + r_1 k_1) \tag{3}$$

and earning capacity in year t as

$$E_t = Y_0 \prod_{i=0}^{t-1}(1 + r_i k_i) \approx Y_0 \exp\Big(\sum_{i=0}^{t-1} r_i k_i\Big) \tag{4}$$

since $e^{r_i k_i} \approx (1 + r_i k_i)$.

Assuming that (a) $k_i = 1$ and $r_i = r_S$ for $i = 0, \ldots, S-1$, or during the period when schooling is pursued full-time, and (b) $r_j = r_w$ and $k_j = a - bj$ for $j = 0, \ldots, x-1 (x = t - S)$, during the working period,[2] the logarithmic transformation of (4) may be given as

$$\begin{aligned} \ln E_t &= \ln Y_0 + r_S S + r_w \sum_{j=0}^{x-1}(a - bj) \\ &= \ln Y_0 + r_S S + r_w a x - r_w b \frac{x(x-1)}{2}. \end{aligned} \tag{5}$$

By definition, actual (observed) earnings is the proportion of earning capacity that is not invested in the accumulation of human capital, *i.e.*,

$$Y_t = E_t(1 - k_t) \approx E_t e^{-k_t} \tag{6}$$

where $k_t = 1$ for $t = 0, \ldots, S-1$ and $k_t = a - bj$ for $j = 0, \ldots, x-1 (x = t - S)$. Hence, (5), the (unobserved) earning capacity equation, may be expressed in terms of the following observed net income function

$$\ln Y_t = (\ln Y_0 - a) + r_S S + \left(r_w a + b + \frac{r_w b}{2}\right) x - \frac{r_w b}{2} x^2. \tag{7}$$

Equation (7) is the natural logarithm of earnings function for a single individual at period t of his life cycle. If taken for a cross-section sample of persons at a point in time (with working hours held constant so that w_t is a fixed proportion of Y_t, (7) is equivalent to (1) without the error term ε_i: $\alpha_0 = \ln Y_0 - a$, $\alpha_1 = r_s$, $\alpha_2 = r_w a + b + r_w b/2$, and $\alpha_3 = -r_w b/2$. Note that the derivation has also shown that (a) α_1 is the private rate of return to education and (b) the signs of the experience coefficients give it a concave profile.

A key point not often duly noted, however, is that in (1) it is assumed that the rate of return to schooling is an exogenous parameter for the individual. If it is, then the individual's marginal internal rate of return equals his average rate of return, and as a wealth-maximizing person, he would be indifferent between alternative levels of educational investments. But if so, this further implies that the overall distribution of schooling is unaffected by individual decisions, so that schooling itself may be treated as an exogenous variable.[3] Thus, it is under the assumptions that the rate of return to schooling is fixed for the individual and that ε_i is a normally and independently

[2] A declining post-schooling k_t is one of the results derived from life cycle models of optimal human capital accumulation.

[3] Indeed, Willis (1986) argues that an exogenous rate of return is inconsistent with the wealth-maximizing framework and that under such an assumption Mincer's standard wage equation is more properly interpreted as a statistical earnings function that relates the joint distributions of the observed variables (schooling and age) and unobserved individual-specific factors, on the one hand, to the distribution of observed earnings, on the other. Schultz (1988), however, points out that it has been the simplifying convention to treat the level of schooling completed as being determined by the parents so that it is independent of the individual's choice set as an adult.

distributed (NID) random variable with mean zero and variance σ_ε^2 that it is usually deemed feasible to apply ordinary least squares (OLS) on cross-section data to estimate the coefficients of schooling and experience in (1).

Nonetheless, the OLS-estimated coefficients of the wage equation may still be subject to biases—because of omitted variables and measurement errors. The omitted variables problem arises because systematic differences in wages may not be fully explained by schooling and work experience. Other factors may exert independent effects on wage rates as well. If these factors are also correlated with schooling (and work experience), their absence in the set of wage determinants would violate the assumption of orthogonality between the regressors and the error term, *i.e.*, $E(S_i\varepsilon_i) \neq 0$.

On the other hand, the errors-in-variable problem issues from the question of how appropriate schooling is (rather than some test of cognitive skills) as the measure of human capital. Seen merely as an input in the production of human capital, school attendance may be regarded as an indicator that is measured with (random) error. As such, its estimated coefficient, when interpreted as the rate of return to human capital, would be biased toward zero. Consequently, recent studies (Glewwe 1991; Boissiere *et al.* 1985) suggest that the rate of return to schooling on wages be decomposed into the contribution of cognitive skills on wages (which is to be taken as the rate of return to human capital) and the influence of school attendance on the acquisition of cognitive skills.

For developing country samples, one other potential source of bias stems from endogenous sample selection. This problem arises because people in developing countries are able to select themselves into the wage- and nonwage-earning subsamples. In particular, when an individual decides to become a wage-earner, it is likely that the factors that influence his choice—his personal characteristics, his present versus future circumstances (and his rate of time preference), and the resources available to him—are also the same ones that determine his wage. If these factors are unobserved, then their effects would be subsumed in the error term of the wage equation (for the subsample of individuals who report earning a wage). This error term possibly would be correlated with the wage regressors, and the expected value of this error term would be nonzero. As Heckman (1976, 1979) has shown, the consequence of all these—*i.e.*, of failing to control for endogenous sample selection—is that a bias similar to that of an omitted variable is induced in the coefficient estimates of the included (wage) regressors. (The technical details are provided in the Appendix.)

To deal with these potential sources of bias, a more completely specified structural model of wage determination needs to be written out. One such specification is

$$\ln w_i = \beta_0 + \beta_1 K_i + \beta_2 X_i + \beta_3 X_i^2 + \beta_4 A_i + \beta_5 B_i + u_i \qquad \text{if } I_i = 1 \tag{8}$$

$$I_i = \begin{cases} 1 & \text{if } Z_i\tau + v_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where K_i is the human capital stock of individual i, A_i is his innate ability, and B_i his family background; Z_i represents a set of instruments which determine selection into or out of the sample of wage-earners; and u_i and v_i are assumed to be NID disturbance terms with means zero and variance matrix

$$\Omega = \begin{bmatrix} \sigma_u^2 & \\ \sigma_{uv} & 1 \end{bmatrix}.$$

In this revised model the estimation problems have been handled as follows: Ability and family background have been added to the list of wage determinants in (8), where S_i has also been replaced by K_i as the human capital variable. Endogenous self-selection (into or out of the wage subsample) has been taken into account by the probit equation (9), with the estimation of the wage equation now made contingent on the observation that the individual has opted to be in the wage regime, *i.e.*, $I_i = 1$.

To calculate the rate of return to schooling as well as to control for the effects of school quality in this revised model, a human capital production function has to be specified. Positing the inputs to include the years of schooling, S_i, the quality of education, Q_i, innate ability, A_i, and family background, B_i, the production function may be written as

$$K_i = K(S_i, Q_i, A_i, B_i). \tag{10}$$

The impacts of schooling and school quality can then be derived by the application of the chain rule: The rate of return to schooling may be calculated as $\partial \ln w_i/\partial S_i = (\partial \ln w_i/\partial K_i)(\partial K_i/\partial S_i)$, whereas the impact of school quality on the natural logarithm of wages would be $\partial \ln w_i/\partial Q_i = (\partial \ln w_i/\partial K_i)(\partial K_i/\partial Q_i)$.

Equations (8), (9), and (10) thus make up an expanded human capital wage model that addresses the major estimation problems that have been raised in the literature. They form the structural backbone of the regressions reported in this study.

Two Competing Hypotheses: The Screening and Credentialist Models

As mentioned in the Introduction, screening and credentialism suggest different interpretations to (as well as policy implications for) the relationship between schooling and wages. The screening model (Arrow 1973; Spence 1973, 1976) claims that education does not necessarily enhance productivity. Instead, it may provide a signal about a worker's innate ability, which is posited to be the primary determinant of productivity. Suppose employers use education to sort out prospective employees, so that high- (low-) ability individuals as signalled by their educational attainment receive higher (lower) wage offers. Then, assuming that the marginal cost of schooling (or the probability of graduating, in Arrow's model) also depends on ability, wealth-maximizing job applicants would choose to obtain the schooling level that maximizes the return on their acquisition of the signal. True screening (or complete filtering, in Arrow's terminology) occurs when the outcome of screening process is a separating equilibrium. Workers are assigned to tasks that are commensurate to their ability and are paid accordingly. Consequently, when innate ability is unobserved or ignored, as in standard human capital theory, an identification problem ensues: It cannot be determined whether wages are rewarded according to the innate ability of workers or to their acquisition of the schooling signal.

Credentialism, on the other hand, is a generic term that is used to describe wage structures in which education performs a certifying or licensing function for certain jobs or occupations. One view of credentialism (Taubman and Wales 1974) holds that it is discrimination based on educational attainment. According to this view, credentialism occurs when minimal educational qualifications are imposed as job requirements so that workers who are otherwise qualified (*i.e.*, they possess the requisite skills to do the job) may nevertheless be barred from competing for lack of appropriate educational credentials.

The common feature of credentialist models, however, is that the wage schedule is set according to the educational credentials of the workers. Note that the same condition is actually true of the screening model, except that there education merely serves as a screening device and the worker's innate ability or productivity is what is really being rewarded. Thus, credentialism may be categorized as a special case of the screening model which is realized when a pooling equilibrium obtains (See Spence [1976], for example). Because the signal conveyed by education is unclear and employers are unable to discern the workers' types, the link to productivity or innate ability is broken, and wages are really paid according to educational qualification.

The screening and credentialist models are important alternative explanations to the link between wages and schooling because, if the educational system merely performs a screening or certifying function, schooling would be an expensive social exercise. Other sorting procedures, such as intelligence or aptitude tests, administered either by the government or a few private firms would be far more efficient.

This completes the exposition on human capital theory and the discussion of the major issues relevant to the estimation of generic wage equations. In the next section, important features of the data set and the variables are pointed out to lay the groundwork for the presentation of the regression results.

III. Data Set and Variables

The data come from four rural, *Ladino* (Spanish speaking, of *mestizo* heritage) communities located in the department of *El Progreso* in East Central Guatemala. Three of the villages—*San Miguel Conacaste, San Juan,* and *Santo Domingo Los Ocotes*—are located in the mountainous region near the Motagua Valley, an area that is dotted with smallholder households who largely perform subsistence farming. The other village—*Espíritu Santo*—is located in the lowlands near the Motagua River where agricultural production is organized by *fincas* (large, commercial farms), making poor households more dependent on wage labor (Chung, 1992).

The surveys of the villages were undertaken by the *Instituto de Nutrición de Centroamérica y Panamá* (INCAP) during the course of two research projects. Conducted from January 1969 to September 1977, the initial project was an intensive longitudinal study of the effects of undernutrition on the mental development and physical growth of preschool children. A unique feature of the research design was that nutritional supplements were given free, on demand, to all children seven years or younger as well as to all pregnant women and lactating mothers. In two villages (one large and one small), *fresco*, a low-calorie drink was used to supplement the normal diet; in two other villages (again one large and one small) *atole*, a high-protein, high-calorie drink was provided.[4] To follow up on the effects of the nutritional supplementation in adolescence and early childhood, the second study was carried out in 1987–1988.[5] The data set generated for the wage regressions come mostly from this latter study.

Table 1 presents all the variables used in the regressions. Also provided in the table are the means, standard deviations, and ranges of these variables—for the whole sample and for the subsample of wage-earners. Two features of the data set are worth noting. First, of the 676 individuals on whom complete information was available, only 153 or 22.6 percent reported ever receiving wages during the survey period. Second, the sample is made up of adolescents and young adults; their ages range from 11.5 to 26.6 years. This restricted age composition imposes the limitation that the full stretch of the concave age-earning trajectory that is meant to be captured by the experience coefficients in the wage equations is not observed in the sample. Moreover, it is not even likely that the peak earning years of individuals are covered by the survey period. All this means that there may be less variability in wages and years of experience than in a more age-dispersed sample. On the other hand, the restricted age range offers the advantage that the opportunities faced by individuals in the sample may be less dissimilar than in cross-section data with a wider spread in ages.

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[4] *Santo Domingo Los Ocotes* and *Espíritu Santo* are the large and small *fresco* villages; *San Miguel Conacaste* and *San Juan* are the large and small *atole* villages.

[5] This study was a collaborative project involving Stanford University; University of California, Davis; Cornell University; and INCAP. It was supported by NIH grant HD22440. The principal investigator was Reynaldo Martorell.

In the data set, wage is the mean daily wage rate, weighted by days worked at each job and expressed in *quetzales*.[6] The values of this wage variable are derived from self-reported wage rates per payment period, average days worked per week, and the number of months worked in 1988, which were collected (separately for men and women by different questionnaires) as part of the information on retrospective life histories up to that time. For each job reported,[7] the wage over the payment period is converted to daily wage rate as follows:

$$w_{k_i} = \begin{cases} w^h_{k_i} l^h_{k_i} & \text{if the wage is paid hourly,} \\ w^d_{k_i} & \text{if the wage is paid daily,} \\ w^w_{k_i}/l^w_{k_i} & \text{if the wage is paid weekly,} \\ w^f_{k_i}/(2l^w_{k_i}) & \text{if the wage is paid fortnightly,} \\ w^m_{k_i}/(4l^w_{k_i}) & \text{if the wage is paid monthly,} \\ w^a_{k_i}/(52l^w_{k_i}) & \text{if the wage is paid annually.} \end{cases}$$

where w_{k_i} is the ith individual's daily wage rate in his k_ith job; $w^j_{k_i}$ is his wage rate over payment period j (j stands for h if the wage is paid hourly, d if daily, w if weekly, f if fortnightly, m if monthly, and a if annually); $l^h_{k_i}$ is the number of hours worked per day; and $l^w_{k_i}$ is the average number of days worked per week. Labor supply in days worked at each job in 1988 is generated as $l_{k_i} = 4.3125 l^w_{k_i} m_{k_i}$, where m_{k_i} is the number of months the ith individual worked at his k_ith job in 1988. The weighted mean of daily wage rates for each wage-earner in the sample is then derived as

$$\bar{w}_i = \frac{\sum_{k_i=1}^{K_i} w_{k_i} l_{k_i}}{\sum_{k_i=1}^{K_i} l^{k_i}},$$

where $\bar{w}_i$ is the weighted mean of daily wage rates for the ith individual in the sample and K_i is the number of jobs he reported having in 1988.

Schooling is the self-reported highest grade attained. As in many human capital studies, experience is defined as *age less schooling less age at school entry*, where *age at school entry* in Guatemala is 7 years old.

Scores in various tests were used in the regressions as measures of intelligence and cognitive ability. As in Glewwe (1991) and Boissiere *et al.* (1985), performance in (the first three scales of) Raven's Progressive Matrices served as the proxy variable of intelligence or innate ability.[8] Quantitative aptitude was measured by a 41-item numeracy test, which included questions probing number and price comprehension, queries on the proper ordering of sequences, and problems requiring simple arithmetic calculations. Three tests of verbal proficiency were used: a 19-item test of reading comprehension that was developed at INCAP, the reading comprehension module of the Interamerican Reading Series, and the vocabulary module of the same series, both of which had 40 items each.[9] These verbal aptitude tests were administered to persons who had either completed sixth grade or passed a literacy screening test. Those who failed were not allowed to continue and were given a score of zero in these tests.

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[6] At the same time of the survey, the exchange rate was Q2 : \$1.

[7] Many persons in the sample practice different occupations over the year.

[8] Raven's Progressive Matrices is a test of abstract or non-verbal reasoning ability, which tonsists of five scales of 12 items each. Data from the pilot test revealed very low variances for the fourth and fifth scales, however, so that only the first three scales were administered to the whole sample.

[9] The Interamerican Reading Series is a standardized battery of verbal proficiency tests that were originally developed for Spanish-speaking children in Texas. But it has since been used by other researchers in Guatemala. For a detailed description of the tests, see Pollitt *et al.* (1992).

IV. Regression Results

Tables 2 to 6 present the regression results of different specifications of the wage equation as potential sources of bias are successively accounted for. Table 2 reports the coefficient estimates of the standard human capital wage function, Table 3 the parameter estimates of the sample selection corrected standard wage equation, Table 4 the estimates of the coefficients of the wage equation in which the direct effects of innate ability and family background on wages are controlled for, Table 5 the estimates of the wage determinants when cognitive skills are substituted for schooling as the measures of human capital, and Table 6 the results of the specification testing whether schooling retains an independent effect even when cognitive skills, innate ability, and family background are already included as regressors.

Finally, to verify that schooling does enhance cognitive skills, this paper also estimates an equation corresponding to (10) in the structural model. Its coefficient estimates are reported in Table 7.

The Standard Wage Equation

Table 2 presents the parameter estimates of Mincer's standard wage equation for the subsample of wage-earners. It shows that the average rate of private return to an additional year spent in school is 6.0 percent and significant at two-tailed $\alpha = 0.05$. The coefficients of *experience* have the expected signs. They yield a rate of return of 3.8 percent to an additional year of experience (calculated at the subsample mean). Both coefficients are not significantly different from zero, however, perhaps because of the restricted age range of the sample. Negative and significant, the coefficient of *female* indicates that the wages of women are, on average, a staggering 66.4 percent below the men's. Finally, the coefficients of the *village dummies* are statistically insignificant, implying that the wage patterns are not substantially different across villages.[10]

Is there Sample Selectivity?

The estimates reported in Table 2 may be biased because individuals may have been endogenously sorting themselves into the wage- and nonwage-earning activities. To control for self-selection in the wage subsample, the paper specifies a probit equation and the wage equation is cast as being conditional on whether the individual reported receiving wages during the survey period. The two-equation model is then estimated using Heckman's two-step procedure and maximum likelihood (ML).[11] The results of both methods of estimation are presented in Table 3.

Before turning to the regression results, however, a cautionary word must be said about the states differentiated by the dependent variable of the probit model. The distinction is between the wage-earning and nonwage-earning states, rather than between employment and unemployment. In particular, included among the nonwage-earners are the self-employed, the students who do not seek employment (and are thus not part of the labor force), and the unemployed. The wage earners may be full- or part-time workers, students, or self-employed persons for the better part of their time. The data set simply could not support making finer classifications.

Who then are the wage-earners? The columns of Table 3 showing the coefficient estimates of the probit equation disclose that wage earners are likely to be more schooled as well as the more experienced members of their peer groups. In particular, *experience* has a (concave) quadratic impact on the probability of an individual's being a wage-earner. Gender does not affect the probability of having a wage paying job. Among the village populations, only the residents of *Espíritu Santo* have a greater tendency to

[10] Alternatively, the village dummy coefficients may be perceived as reflecting differences in the quality of schooling between *Santo Domingo*, the control village, and the three other villages. But as will be seen below, this interpretation does not seem to be the case here.

[11] The structural model and the two estimation methods are briefly described in the Appendix.

go into the wage-earning occupations than inhabitants of the larger, more established community of *Santo Domingo*. Members of larger households are more likely to seek wage jobs, while members of households with the relatively larger farm holdings are less likely to do so (although its ML-estimated coefficient is not significant at two-tailed $\alpha = 0.10$), probably opting to work on the family farm instead. Finally, the *amount of income transfers received by an individual's household*, although having the expected negative sign, does not have a significant impact on whether or not he participates in the wage labor market.

As for the selectivity-corrected standard wage equation, the results of both Heckman's 2-step procedure and the method of maximum likelihood show that only *female* has retained significance.[12] With the coefficient estimates applying not just to the wage-earners but to the village populations, the rates of return to schooling and experience have decreased slightly. The premium to schooling has dropped to 5.2 percent and is not quite significant even at two-tailed $\alpha = 0.10$ for Heckman's procedure, and is only 4.4 percent and insignificant in the ML method. The proportionate increase in wages due to additional year of work experience (calculated at the sample mean of experience for wage earners) is between 2.3 percent (for ML) and 3.1 percent (for Heckman's), although still insignificant. The wages of women are about 65 percent below those of men's. This suggests that although women enjoy equal access to wage paying jobs (since *female* is not significant in the probit equation), they have limited opportunities for being hired to the high paying jobs. Finally, observe that $\hat{\sigma}_{uv}$ the covariance of the disturbance terms of the probit and wage equations, which is the coefficient of the inverse Mills' ratio in Heckman's procedure, is estimated to be negative, as is $\hat{\rho}$ the correlation coefficient of the error terms in the ML method. If truly significantly different from zero, the negative signs of these parameters indicate that the mean of the natural logarithm of wages that is conditional on the decision to enter a wage occupation ($\mathrm{E}[\ln w_i \mid I_i = 1]$) is lower than for the population as a whole. In other words, the negative signs of these parameters imply that the wage-earners as a group do not enjoy any comparative advantages in the wage-earning occupations.

Incorporating Innate Ability and Family Background

The estimates reported in Tables 2 and 3 are fairly standard empirical results of the standard wage equation. The estimated rates of return to schooling are lower than those reported for Latin America,[13] but this is possibly due to errors arising from the generation of data on daily wage rates across different types of labor contracts and given the transitory nature of (wage) work for rural residents, so that wages are usually a poor proxy for the value of the marginal product of labor in rural regions of developing countries (Haddad and Bouis 1991).

Even these low estimates, however, may be biased upward because innate ability and family background, two presumably important determinants of educational attainment, may themselves have direct, positive effects on wages. To control for the independent impact of innate ability on wages, the *score on Raven's progressive matrices* is added to the set of wage regressors. To capture the effects of family background, *grades passed by both parents* are used as proxy measures. Table 4 shows the parameter estimates of this new specification.

For the probit model, the results are not much different from those reported in the previous table. The coefficients of *highest grade attained*, *experience* and its square,

[12] This may be the effect of imprecise estimation due to ill-conditioning since the determinants of the standard wage equation are highly collinear—the village dummies are necessarily so and experience is operationalized as a function of schooling—and the size of the subsample of wage-earners is quite small.

[13] Psacharopoulos (1985) reports that the private rate of return to schooling in Latin America, considering all levels of education, is 14 percent.

household size, farm size (though again only in Heckman's procedure), and *residence in Espíritu Santo* remain significant and retain their signs; whereas none of the new variables turns out to be significant, implying that innate ability and family background do not affect the individual's decision to seek a wage paying job.

On the other hand, the regression results for the wage equation are somewhat different from those of the previous specifications. Higher rates of return to schooling and experience are now obtained. The return to each additional year of schooling is 5.9 percent, and significant at two-tailed $\alpha = 0.10$ for Heckman's procedure and just below significance for the ML estimate. For *work experience*, the return to an additional year (at the subsample mean of wage-earners) is 3.5 percent, although in both methods of estimation the experience coefficients are not significant. In addition, the gap in the wage rates of men and women has narrowed slightly to 63.3 percent. The *village dummy coefficients*, although still insignificant, are now slightly lower. Compared to their peers from *Santo Domingo*, *San Miguel Conacaste* and *Espíritu Santo* residents have wages that are, respectively, 4.4 and 10.7 percent lower, while inhabitants of *San Juan* are paid daily wages that are 8.3 percent higher. Finally, the selectivity parameters ρ and σ_{uv} remain negative and statistically insignificant from zero, implying that selection into the wage-earning sample is a random process.

Turning to the newly introduced variables, observe that *Raven's test* and *father's education* both have expected positive impacts on the natural logarithm of wages, although their coefficients are insignificant. The *education of the mother*, however, is estimate to have a large negative effect—and significant at 90% confidence interval in Heckman's procedure. This counterintuitive result may be due to the following relationships: Since more educated women have higher aspirations for their children, for given levels of ability, their offspring tend to complete higher grade levels. For their educational attainments, however, the children of more educated mothers would be less productive and therefore earn lower wages.

Wages, Cognitive Skills, and Intelligence

Another, perhaps even more fundamental issue concerns the appropriateness of using schooling as the human capital variable. Relative to the theoretical construct *human capital, highest grade attained* may be viewed as an indicator that is measured with error, so that its coefficient estimate, if interpreted as the return to human capital, would be biased toward zero. To circumvent these errors-in-variable problem, recent studies (Boissiere *et al.* 1985; Glewwe 1991) specify cognitive outcome measures, such as scores on tests of verbal ability and numeracy, as the true measures of human capital. In this revised specification, school attendance is no longer included as a determinant because it is assumed that wages and schooling are only indirectly linked through the process of acquisition of cognitive skills.

A bonus of this formulation is that it may also be used to test the validity of the screening hypothesis (See Glewwe [1991]). If education merely serves as a screening device for innate ability or motivation and does not enhance the productivity of workers, then the coefficient of Raven's matrices, but not those of the cognitive tests, would be positive and significant. If education performs a partial screening function, then the coefficients of Raven's matrices and the profiicency tests would all be positive and significant.

The parameter estimates of this wage-cognitive skills-innate ability specification are reported in Table 5, which is presented in three parts, corresponding to the three different tests of verbal ability that were available. Table 5a shows the results of the specification using the INCAP-*developed reading test scores*, Table 5b the results of the specification using the *scores on the reading comprehension module of the Interamerican Series*, and Table 5c the results of the specification using the *Interamerican Series vocabulary scores*.

Once again, the results for the probit equation, which are reported in columns 1 and 3 of Table 5, are very similar to those of the previous tables. The quadratic *experience* terms exert a very significant positive, though declining impact on the likelihood of an individual's supplying his hours in the wage labor market. Among the inhabitants of the three villages, only *Espíritu Santo* residents have a greater tendency than *Santo Domingo* villagers to render wage labor. The *size of the household* and *of the household farm* are the instrumental variables that register significant effects in the probit equation, although again *farm size* loses significance in the ML estimates. Family background, innate intelligence, and gender do not affect the probability of an individual's being a wage-earner.

Of the verbal proficiency and numeracy tests that replaced educational attainment in the current specification, only the *Interamerican Vocabulary Test* turns out to be significant; it has a positive coefficient in the probit equation of Table 5c, which implies that having a good command of words increases the likelihood of getting a wage-earning job.

The results for the wage equation, which are reported in the second and fourth columns of Table 5, show that *female* is the only consistently significant determinant of the logarithm of wages. In the results of the 2-step procedure, the *numeracy test* is significant in the specifications in which *reading skill* is the measure of verbal competence, and *mother's education* is significant in the specifications using the INCAP *reading test* and the *Interamerican Vocabulary Test*. The significance of the *numeracy test* but not of *Raven's matrices* suggests that there is some validity to the revised human capital model (and that screening may be absent). Advancement in wage jobs is due in part to proficiency in mathematics, not innate intelligence. Finally, the covariance and correlation terms of the errors of the probit and wage equations are once again negative but close to zero.

Incidentally, notice that although the coefficients of *experience* have the expected signs and are still insignificant, its rate of return (calculated at its mean for wage-earners) has dropped to about 1.7 to 2.0 percent in this specification. This suggests a left-out variable effect: omitting schooling leads to a *downward* bias in the estimated coefficient of *experience* because of the negative covariance between schooling and experience in the sample.[14]

Testing for an Independent Schooling Effect

What is the impact of schooling when placed alongside measures of intelligence and cognitive ability? This final specification may be regarded as the expanded human capital model in which the coefficient of schooling may be interpreted as the rate of return to the noncognitive aspects of education (including its credentialist function).

Table 6, which adopts the same reporting scheme as Table 5, presents the regression results of this expanded wage model. As far as the significance of the coefficients is concerned, the results of the probit model are no different from those presented in Tables 3 and 4. Schooling and experience retain very significant effects on the likelihood of entry into the wage-earning occupations—even when the cognitive outcomes of schooling are already controlled for. Similarly, in Heckman's procedure, *household* and *farm size* have significant impacts, though in opposite directions (with the significance of farm size fading in ML, however). Again, gender, parents' education, and income from non-labor sources apparently do not identify who the wage-earners are. As for the test scores, none ever turns out to be significant.

In the wage equation, the rate of return to (the noncognitive aspects of) schooling is measured to be between 4.5 percent and 5.9 percent, but is never significant. Instead, the natural logarithm of wages is significantly determined by the gender dummy variable and mother's education, though the latter is significant only in Heckman's procedure. The wages of women are, on average, between 59.7 percent and 61.2 percent less than

[14] The limited range of ages in the sample has the effect that, on average, more time devoted to schooling means less time spent in the workplace.

those of the men. Each grade passed by the mother causes her children's wages to grow by 7.0 to 7.4 percent less.

Does Schooling Affect Cognitive Skills?

However one interprets the results of the wage regressions, it remains relevant to ask if schooling contributes to the acquisition of such cognitive skills as reading comprehension and verbal and quantitative proficiency. After all, education is not simply a pure investment good but may have considerable *non-income* returns as well, such as in the form of lower mortality and morbidity rates for children of more educated mothers and a more cohesive society as a concomitant effect of higher literacy rates.

Table 7 reports the OLS-estimated coefficients of the determinants of cognitive skills (which corresponds to (10) in the structural model). Note that a flexible functional form, borrowed from Glewwe (1991), is specified. Quadratic forms are given to *age*, *schooling*, and *Raven's test*. Interaction terms among these variables are provided as well. The product of Raven's matrices and schooling tests whether the more innately intelligent learn more per grade attended, while that of Raven's matrices and age controls for the possibility that the more intelligent simply learn more each year. The interaction term between age and schooling is intended to capture variations in the quality of learning across different age cohorts, while geographical variations in learning quality are meant to be reflected in the village dummy variables.[15] A dummy variable, *female*, is included to reflect gender differences in the acquisition of cognitive skills. The effects of family background are meant to be captured by the schooling of both parents.

Looking across the columns in Table 7, notice that the quadratic coefficients of age and Raven's matrices do not turn out to be significant in all four equations. With the exception of the products of years schooling and age as well as years of schooling and Raven's matrices in the numeracy test, all other interaction terms are insignificant. For the tests of verbal aptitude, the absence of an age effect may be taken to mean that retention of reading and vocabulary skills is fairly strong. For the numeracy test, however, the significant negative interaction coefficient of schooling and age indicates that competence in numeracy declines with age. In other words, either the teaching of arithmetic or the mathematical aptitude of the younger cohorts of students has improved over time. As for the coefficient estimates of Raven's test, their utter lack of significance in the verbal aptitude tests implies that innate or nonverbal reasoning ability does not have an independent effect on the development of verbal and reading skills. On the other hand, the significant negative coefficient of the interaction term between years schooling and Raven's matrices is an unexpected result. It implies that people who did well in Raven's matrices had poorer scores in the numeracy test—and progressively so with each additional year of school.[16]

The coefficients of highest grade attained and its square turn out to be significant in all four regressions. Their signs reflect a concave shape, although the magnitudes of the coefficients (including those of the significant interaction terms for the numeracy test) indicate that the peaks of the schooling profiles occur nearly at or beyond the maximum value of highest grade attained in the sample.[17] Thus, the net impact of schooling on

[15] The coefficients of the village dummies and the interaction term between age and schooling ought to reflect the quality of instruction. However, because of the nutritional intervention introduced by the first INCAP project, they may also reflect the impact of the type of nutritional supplement made available to the village residents as well as the cohort effects of the supplement on the cognitive abilities of village residents.

[16] A possible reason for this result is that Raven's test may have been too difficult while the numeracy test may have been too easy for the test takers, as may be gleaned from the descriptive statistics, particularly the means, of the variables in Table 1.

[17] The schooling profiles achieve their maximum value at 12.7, 16.7, 14.0, and 9.4 grades of education completed for the reading test, the Interamerican reading test, the Interamerican vocabulary test, and the numeracy test, respectively.

the test scores is never negative,[18] although the concavity of the profiles suggest that the marginal effect of schooling on verbal and arithmetic ability becomes progressively weaker with each additional grade level.

Comparing the test results by geographical area, observe that the residents of the *atole* villages of *San Miguel Conacoste* and *San Juan* consistently outscore the inhabitants of *Santo Domingo*. On the other hand, the performance of *Espíritu Santo* residents do not significantly differ from those of people from *Santo Domingo* except in the Interamerican reading test where they are estimated to have significantly lower scores.[19] These results imply that the distinction in village-based quality differences (in either the learning capacity of students or the instruction provided by the schools) has more to do with the type of nutritional supplement than with village size. In particular, the *atole* village residents did better than their *fresco* counterparts.

The significant positive coefficient of the sex dummy variable in the Interamerican Test Series indicates that the verbal proficiency of women is better than the men's.

Finally, the educational attainment of mother exerts a significant impact on their children's Interamerican Series test scores, This is yet another piece of evidence showing that the schooling of women (more than the men's) has important effects on how well the household fares and particularly on the *quality* and welfare of the children.

V. Discussion and Critique

How are the results of the preceding section to be interpreted? Are they to be taken at face value? Recall that the econometric estimation proceeded against rather severe limitations. The data set is ill-suited for the estimation of Mincer's wage equation. First, the ages of the individuals in the sample only ranges from 11.5 to 26.6 years instead of being dispersed over the entire life cycle. This restricted age distribution implies that (a) the age-wage profile which Mincer's equation seeks to capture is not fully reflected in the sample; (b) relatively few wage-earners would be identified, since people may not have completed their schooling, many individuals may be self-employed as is prevalent in less developed regions, and unemployment may be more widespread in rural areas; (c) the variability of wage rates and experience would not be as much as in a more dispersed sample; and (d) the wages reported are likely to be below the peak wages for given educational attainment.

Second, wages may themselves be poor proxy measures of the value of the marginal product of labor in rural regions of developing countries due to measurement errors arising from the variety of labor contracts and the transitory nature of wage work in these areas.

Third, there are problems associated with the schooling variable used. Highest grade attained is afflicted with nonrandom measurement error because it totally ignores wastage in school attendance. Since drop out and repetition rates are quite high in developing countries and in the study villages in particular (Pollitt 1990), the true costs of education are underestimated with the highest grade attained as the indicator of schooling so that, in turn, the private rate of return is overestimated. Moreover, this measurement error is passed along to the experience variable, since experience is merely generated as a *residual* of age and years in school.

A fourth problem is that the data of the variables specified in the wage equations are ill-conditioned. Regression diagnostics revealed that the test scores are collinear, as are schooling and experience as well as the village dummies. Presumably, these collinearities

[18] Even for the numeracy test, it takes more than 18 grades passed (with the Raven's test and age evaluated at their sample means) for education to have a negative net effect.

[19] These results thus indicate that the coefficients of the villages in the wage equations do not reflect similarities in school or learning quality but in wage patterns, as pointed out in a previous footnote.

are pervasive in human capital data sets, which makes it important to have very large observations on which to do the estimations. Unfortunately, with only 153 wage observations throughout the four study villages, the parameters of the wage equations may not have been estimated with precision.

Given all these reasons, it is not surprising that the wage determinants are all virtually insignificant, particularly in the ML estimations.

Relative to the broader canvas of the human capital literature, the regression results reported here bring to mind many of the same issues raised by the previous studies. In particular, the result that Raven's matrices never turned out to be significant does not reject the screening model. It only serves to underscore the catch in incorporating ability measures in the wage equation: As Griliches (1977) decries, if the coefficient of ability is found significant, it is said to be due to the correlation of ability with unobservable variables, such as the quality of schooling or the quality of the home environment; if insignificant, ability is said to be measured with error.

As for the *cognitive ability as human capital* equation, it may have the same problem regarding the appropriateness of the variables used as measures of human capital as the standard Mincerian equation. Perhaps reading, writing, and numeracy are the rudimentary skills required by all jobs in urban, more developed settings; whereas in rural, less developed areas, these skills are not as well accepted as signals of productivity. Perhaps jobs in the study villages still do not require literacy and numeracy skills—hence their being only slightly significant in the wage specifications—and the indicators of productivity are much more varied and specific to the occupations of the wage-earners. As Arrow (1973, pp.214–215) points out, "[T]here is considerable evidence in direct studies of productivity ... that ability to pass tests is [only] weakly related to ability to perform specific productive tasks [and it] is only the latter ability that is relevant." Moreover, it may be that schooling itself is regarded as a signal of productivity, not because students are taught how to read and write in school, but because they are inculcated with the mores and ethics that are important to the wage occupations. And perhaps "employers know that education is a signal, that there are other attributes of individuals [besides literacy or numeracy] that partially determine productivity, and that these are being captured in the signal" (Spence, 1976, p.53). Unfortunately, as ever finer cuts are made to distinguish the many facets of educational outcomes, it becomes increasingly difficult to get statistically significant and meaningful results, particularly with samples from developing countries, because of the heavier demands the specification makes on the data set in terms of the (sub)sample size and the number of variables, and because of problems with the applicability of less generalizable model assumptions and with the operationalization of nebulous theoretical constructs.

VI. Summary of the Regression Results

The problems with the data set and variables as well as with the regression specifications notwithstanding, several results stand out, which may be summarized as follows: First, educational attainment is a very significant predictor of wage-earners. The results of the probit model consistently show that the more schooled people are more likely to be involved wage-earning activities. Moreover, schooling is an important determinant of wages. Given all the measurement errors and ill-conditioning of the variables in the data set, schooling surprisingly turns out to be significant or almost significant at two-tailed $\alpha = 0.10$ in two of the four wage equations in which it is specified as a regressor. The rate of return to schooling, inclusive of its cognitive and noncognitive aspects, is reported in Table 4 to be 5.9 percent for the population of adolescents and young adults in the four rural Guatemalan villages. And it must not be forgotten that schooling is found to exert very strong effects on the acquisition of cognitive skills (Table 7) and that numeracy skill turns out to be weakly significant when test scores are used as measures of human capital (Tables 5a and 5b).

Second, experience is derived to have a concave profile in both the probit and wage equations across different specifications. The coefficients of experience are consistently very significant in the probit model, but do not turn out to be significant in the wage equation, perhaps because of the restricted age range of the sample.

Third, the wages of women are estimated to be between 59.6 percent and 66.4 percent lower than those of the men, indicating that women in the sample have limited opportunities in getting the high paying wage jobs.

Fourth, mother's education is measured to have a large, unexpected, and (in Heckman's procedure) significant impact on the logarithm of wages. It is suggested that this result may be because more educated workers who have more educated mothers may not be as able as similarly educated workers with less educated mothers who may have had lower aspirations for their schooling. On the other hand, a result that is more in keeping with the findings of other studies is that mother's education is shown to have a positive and significant effect on her children's verbal skills as measured by the Interamerican Test scores.

Fifth, among the test measures employed, only the Interamerican Vocabulary Test turns out to be significant as a predictor of who the wage-earners are, and only the numeracy test is a significant determinant of the logarithm of wages. These results suggest that cognitive skills perhaps do affect wages, if only weakly, in rural populations of developing countries.

Sixth, the size of the household and the area of the household farm are the two instrumental variables of the probit equation that significantly help to sort out the wage-earners from the nonwage earners (although farm size turns out to be significant only in Heckman's procedure and is never significant at two-tailed $\alpha = 0.10$ in ML). As expected, the larger the size of his household, the higher the probability that an individual is wage-earner; the bigger the household farm, the less likely it is that the individual would seek a wage paying job.

Seventh, the wage-earners are more likely to come from *Espíritu Santo*, even though the wage patterns in the four villages are not significantly different from each other and residents of the *atole* villages consistently outscored the *fresco* villagers in the cognitive tests.

Finally, the sample selectivity parameters are estimated to be close to zero and not significantly different from it in all specifications. One interpretation of this result is that increments to wages (or opportunities for advancement in the wage occupations) may be a process that is independent of the decision to be a wage-earner, although, obviously, selectivity depends on the states that are being distinguished, and the fact that the nonwage-earning state includes the self-employed, the unemployed, and the full-time students probably muddles the effect of selectivity on the wage equation.

Appendix
Correcting for Sample Selectivity

This section briefly describes the estimation methods that were used to treat sample selectivity in the wage-generating functions. The structural model of wage determination may be written as follows:

$$\ln w_i = X_i\alpha + u_i \qquad \text{if } I_i = 1 \tag{A.1}$$

$$I_i = \begin{cases} 1 & \text{if } Z_i\tau + v_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{A.2}$$

where $\ln w_i$ is the natural logarithm of wages of the ith individual in the sample, X_i is a vector of exogenous variables affecting wages, Z_i represents a set of exogenous variables which determine selection into or out of the sample of wage earners, and u_i and v_i are normally and independently distributed (NID) disturbance terms with means zero and variance matrix

$$\Omega = \begin{bmatrix} \sigma_u^2 & \\ \sigma_{uv} & 1 \end{bmatrix}.$$

Applying OLS on the subsample of wage earners would yield biased estimates because $E(u_i) \neq 0$ and u_i is likely to be correlated with X_i as a result of the censoring of $\ln w_i$ when $w_i \leq 0$. Two procedures that correct for this potential source of bias are Heckman's two-step procedure and the method of maximum likelihood.

Heckman's procedure

The two-step procedure proposed by Heckman (1976; 1979) is based on the observation that if OLS estimation of (A.1) could be performed *conditional on the sample selection rule* I_i in (A.2), the estimates derived would be asymptotically consistent, if inefficient. More formally, the procedure relies on the following insight: Observe that

$$\begin{aligned} E(\ln w_i \mid I_i = 1) &= X_i\alpha + E(u_i \mid I_i = 1) \\ &= X_i\alpha + \sigma_{uv}\lambda(-Z_i\tau) \end{aligned}$$

since

$$\begin{aligned} E(u_i \mid I_i = 1) &= E(u_i \mid v_i > -Z_i\tau) \\ &= \int_{-\infty}^{\infty}\int_{-Z_i\tau}^{\infty} u_i \frac{f(u_i, v_i)}{\int_{-Z_i\tau}^{\infty} f(v_i)dv}\, dv\, du \\ &= \frac{1}{1-\Phi(-Z_i\tau)}\int_{-Z_i\tau}^{\infty}\left[\int_{-\infty}^{\infty} u_i f(u_i \mid v_i)du\right] f(v_i)\, dv \\ &= \frac{1}{1-\Phi(-Z_i\tau)}\int_{-Z_i\tau}^{\infty} \sigma_{uv} v_i f(v_i)\, dv \\ &= \sigma_{uv}\lambda(-Z_i\tau), \end{aligned}$$

and

$$\begin{aligned} \mathrm{Var}(\ln w_i \mid I_i = 1) =\ & \mathrm{Var}(u_i \mid v_i > -Z_i\tau) \\ =\ & E_{u_i \mid v_i > -Z_i\tau}[u_i - E_{u_i \mid v_i > -Z_i\tau}(u_i)]^2 \\ =\ & E_{u_i \mid v_i > -Z_i\tau}(u_i)^2 - \sigma_{uv}^2\lambda(-Z_i\tau)^2 \\ =\ & \sigma_u^2(1-\rho^2) + \sigma_{uv}^2(-Z_i\tau)\lambda(-Z_i\tau) + \sigma_{uv}^2 - \sigma_{uv}^2\lambda(-Z_i\tau)^2 \\ =\ & \sigma_u^2[1 - \rho^2\delta(-Z_i\tau)] \end{aligned}$$

where

$$\lambda(-Z_i\tau) = \frac{\phi(-Z_i\tau)}{1-\Phi(-Z_i\tau)},$$
$$\rho(-Z_i\tau) = \sigma_{uv}/\sigma_u,$$
$$\delta(-Z_i\tau) = \lambda(-Z_i\tau)[\lambda(-Z_i\tau) - (-Z_i\tau)],$$

and $f(\cdot)$ and $\phi(\cdot)$ denote the density functions of the normal and standard normal random variable, respectively, while $\Phi(\cdot)$ represents the standard normal cumulative distribution function.

Thus, another way of viewing the censoring problem of (A.1) is as an omitted variable issue: a specification error is committed when λ_i is not included in the set of regressors.

To correct for this source of estimation bias, the wage equation may be rewritten as:

$$\ln w_i = X_i\alpha + \sigma_{uv}\lambda(-Z_i\tau) + \varepsilon_i \tag{A.3}$$

where $E(\varepsilon_i) = 0$ and $Var(\varepsilon_i) = \sigma_u^2[1 - \rho^2\delta(-Z_i\tau)]$.

A problem remains because λ_i is unobservable. But Heckman noted that the ratio $\hat{\lambda}_i$ can be generated using the estimated parameters of the probit equation (A.2). Thus, after $\hat{\lambda}_i$ is conveniently substituted into (A.3), OLS would be a consistent estimator of the revised wage equation. It should be noted, however, that OLS is an inefficient estimator both because ε_i is heteroscedastic and $\hat{\lambda}_i$ is estimated.

Maximum Likelihood

Unlike Heckman's single equation approach, the method of maximum likelihood involves the simultaneous estimation of the structural parameters of a system of equations. It does so by maximizing the value of the model's log-likelihood function, which is derived below for the sample selection wage model.

The equations (A.1) and (A.2) have the following likelihood function:

$$\begin{aligned} L &= \prod_{i=0}^{n}\Big[\Pr(I_i=0)\Big]^{1-I_i}\left[\Pr(I_i=1)\int_{-Z_i\tau}^{\infty}\frac{f(u_i,v_i)}{\int_{-Z_i\tau}^{\infty}f(v_i)\,dv}\,dv\right]^{I_i} \\ &= \prod_{i=0}^{n}\Big[\Phi(-Z_i\tau)\Big]^{1-I_i}\left[\int_{-Z_i\tau}^{\infty}f(v_i\,|\,u_i)\,dv\,f(u_i)\right]^{I_i} \end{aligned}$$

where $u_i = \ln w_i - X_i\alpha$.

Since $(v_i\,|\,u_i)$ is a univariate NID random variable with mean $(\sigma_{uv}/\sigma_u^2)u_i$ and variance $[1-(\sigma_{uv}/\sigma_u^2)]$, this implies that

$$\int_{-Z_i\tau}^{\infty} f(v_i\,|\,u_i)\,dv = 1 - \Phi\left[\frac{-Z_i\tau - (\sigma_{uv}/\sigma_u^2)u_i}{\sqrt{1-(\sigma_{uv}/\sigma_u)^2}}\right].$$

On the other hand,

$$\begin{aligned} f(u_i) &= \frac{1}{\sqrt{2\pi}\sigma_u}\exp\left(\frac{-1}{2\sigma_u^2}u_i^2\right) \\ &= \frac{1}{\sigma_u}\phi\left(\frac{u_i}{\sigma_u}\right). \end{aligned}$$

Therefore, the log-likelihood function of (A.1) and (A.2) comes down to

$$\ln L = \sum_{i=0}^{n}\left\{(1-I_i)\ln\Phi(-Z_i\tau) + I_i\left\{\ln\left[1-\Phi\left(\frac{-Z_i\tau-(\sigma_{uv}/\sigma_u^2)u_i}{\sqrt{1-(\sigma_{uv}/\sigma_u)^2}}\right)\right] + \ln\phi\left(\frac{u_i}{\sigma_u}\right) - \ln(\sigma_u)\right\}\right\}.$$

Maximizing this log-likelihood function with respect to α, τ, σ_u, and σ_{uv} yields unbiased and efficient estimates of the parameters of the structural wage model.

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Table 1. Descriptive Statistics of Variables

Variables	Descriptions	Whole Sample				Wage Earners			
		Mean	Standard Deviation	Minimum Value	Maximum Value	Mean	Standard Deviation	Minimum Value	Maximum Value
Wage	Weighted average daily wage rates (in					5.68	4.00	0.21	25.00
Highest Grade Attained	Self reported highest grade attained	4.39	2.69	0.00	13.00	4.92	2.86	0.00	13.00
Raven's Test	Raven's Progressive Matrices test score	10.84	4.20	0.00	27.00	11.29	4.68	3.00	27.00
Reading Test	INCAP-developed reading test score	11.17	7.33	0.00	19.00	12.25	7.55	0.00	19.00
Interamerican Reading Test	Interamerican reading test score	11.98	8.12	0.00	35.00	12.63	8.39	0.00	34.00
Interamerican Vocabulary Test	Interamerican vocabulary test score	18.23	12.59	0.00	39.00	20.11	13.12	0.00	39.00
Numeracy Test	Numeracy test score	31.84	8.60	0.00	41.00	33.01	8.78	6.00	41.00
Age	Age as of January 1, 1989	17.43	3.38	11.51	26.63	18.60	2.94	11.64	23.99
Experience	Age-Highest Grade Attained-7	6.04	4.07	0.04	16.99	6.68	3.82	0.16	16.99
Female	1=female; 0 otherwise	0.49	0.50	0.00	1.00	0.47	0.50	0.00	1.00
Father's Grade Attainment	Grades passed by father as of 1974	1.30	1.62	0.00	6.00	1.14	1.50	0.00	6.00
Mother's Grade Attainment	Grades passed by mother as of 1974	1.07	1.41	0.00	6.00	1.12	1.36	0.00	6.00
Household Size	Number of household members in 1977	8.87	3.52	1.00	19.00	9.66	3.44	2.00	19.00
Size of Household Farm	Land area of household farm (in *manzanas*)	1.51	2.76	0.00	18.61	1.06	1.78	0.00	7.56
Income Transfers	Non-labor income (in *quetzales*)	74.67	196.42	0.00	1144.00	55.71	164.26	0.00	1144.00
Santo Domingo	1=resident of large, *fresco* village; 0 otherwise	0.23	0.42	0.00	1.00	0.23	0.42	0.00	1.00
San Miguel Conacaste	1=resident of large, *atole* village; 0 otherwise	0.25	0.43	0.00	1.00	0.21	0.41	0.00	1.00
Espiritu Santo	1=resident of small, *fresco* village; 0 otherwise	0.20	0.40	0.00	1.00	0.25	0.43	0.00	1.00
San Juan	1=resident of small, *atole* village; 0 otherwise	0.32	0.46	0.00	1.00	0.31	0.47	0.00	1.00
Number of Observations		676				153			

Table 2. Standard Wage Equation

Variables	
Constant	1.19507
	3.762**
Highest Grade Attained	0.06006
	2.360**
Experience	0.06448
	1.220
Experience Squared	-0.00195
	-0.631
Female	-0.664
	-5.946**
San Miguel Conacaste	-0.03773
	-0.237
Espiritu Santo	-0.04355
	-0.275
San Juan	0.08282
	0.581
R^2	0.285
Adjusted R^2	0.250
Log of Likelihood Function	-144.819
Number of Observations	153

T-statistics are reported below the coefficient estimates.
**-significant at 95% confidence interval;
* -significant at 90% confidence interval.

Table 3. Standard Wage Equation Corrected for Sample Selectivity

Variables	Heckman's 2-Step Procedure		Maximum Likelihood	
	Probit Equation	Wage Equation	Probit Equation	Wage Equation
Constant	-3.06386	1.43297	-3.03410	1.67101
	-8.680**	2.392**	-7.754**	2.209**
Highest Grade Attained	0.13531	0.05220	0.13477	0.04436
	5.111**	1.574	4.780**	1.360
Experience	0.21998	0.04589	0.22064	0.02761
	4.251**	0.776	4.030**	0.324
Experience Squared	-0.00735	-0.00115	-0.00746	-0.00037
	-2.271	-0.395	-2.286**	-0.075
Female	-0.01018	-0.65751	-0.00912	-0.64926
	-0.089	-6.506**	-0.075	-4.490**
San Miguel Conacaste	-0.02902	-0.02464	-0.02483	-0.01051
	-0.171	-0.128	-0.139	-0.068
Espiritu Santo	0.33127	-0.05977	0.33110	-0.07611
	1.924*	-0.381	1.808*	-0.373
San Juan	0.13821	0.08510	0.13522	0.08640
	0.864	0.529	0.779	0.575
Household Size	0.08039		0.07803	
	4.729**		4.356**	
Size of Household Farm	-0.05551		-0.05637	
	-1.937*		-1.612	
Income Transfers	-0.00044		-0.00048	
	-1.322		-1.397	
$\sigma_{u\varepsilon}$ (coefficient of the Inverse Mills' Ratio)		-0.10467		
		-0.469		
σ_{u}				0.64233
				8.923**
ρ				-0.32782
				-0.748
R^2	0.096	0.286		
Adjusted R^2		0.246		
Percent Correct Predictions		77.515		
Log-Likelihood Function	-326.217	-144.733	-470.881	
Number of Observations	676	153	676	

T-statistics are reported below the coefficient estimates. For the 2-step estimated wage determinants, these are computed from robust White standard errors.
** significant at 95% confidence interval
* significant at 90% confidence interval

Table 4. Incorporating Innate Ability and Family Background

Variables	Heckman's 2-Step Procedure		Maximum Likelihood	
	Probit Equation	Wage Equation	Probit Equation	Wage Equation
Constant	-3.09270	1.20934	-3.09169	1.22044
	-8.138**	1.905*	-7.488**	1.62**
Highest Grade Attained	0.12866	0.05905	0.12864	0.05868
	4.495**	1.696*	4.106**	1.589
Experience	0.21876	0.05245	0.21875	0.05161
	4.197**	0.860	3.982**	0.57
Experience Squared	-0.00741	-0.00127	-0.00742	-0.00123
	-2.287	-0.429	-2.291**	-0.235
Raven's Test	0.00343	0.01113	0.00331	0.01111
	0.234	0.882	0.213	0.878
Father's Grade Attainment	-0.05470	0.04223	-0.05454	0.04250
	-1.428	1.068	-1.340	0.890
Mother's Grade Attainment	0.05495	-0.06989	0.05522	-0.06992
	1.279	-1.876*	1.130	-1.274
Female	-0.00204	-0.63305	-0.00258	-0.63274
	-0.017	-6.456**	-0.021	-4.053**
San Miguel Conacaste	-0.01921	-0.04496	-0.01702	-0.04439
	-0.112	-0.232	-0.090	-0.258
Espíritu Santo	0.40588	-0.10660	0.40754	-0.10760
	2.274**	-0.591	2.075**	-0.520
San Juan	0.14772	0.08283	0.14893	0.08286
	0.918	0.506	0.838	0.511
Household Size	0.08295		0.08257	
	4.829**		4.526**	
Size of Household Farm	-0.05564		-0.05630	
	-1.927*		-1.600	
Income Transfers	-0.00046		-0.00047	
	-1..360		-1.304	
σ_{uv} (coefficient of the Inverse Mills' Ratio)		-0.05251		
		-0.221		
σ_{u}				0.61677
				17.711**
ρ				-0.09326
				-0.190
R^2	0.104	0.305		
Adjusted R^2		0.251		
Percent Correct Predictions		77.959		
Log-Likelihood Function	-324.609	-144.677	-467.286	
Number of Observations	676	153	676	

T-statistics are reported below the coefficient estimates. For the 2-step estimated wage determinants, these are computed from robust-White standard errors.
**-significant at 95% confidence interval;

Table 5a. Cognitive Skills as Human Capital

Variables	Heckman's 2-Step Procedure		Maximum Likelihood	
	Probit Equation	Wage Equation	Probit Equation	Wage Equation
Constant	-2.93768	1.06597	-2.93139	1.09106
	-6.807**	1.637	-6.305**	1.407**
Reading Test	0.01735	0.00720	0.01739	-0.00729
	1.366**	1.650	1.256	-0.435
Numeracy Test	0.01101	0.01804	0.01100	0.01797
	1.029	1.683*	0.941	1.549
Experience	0.20011	0.04219	0.19999	0.04029
	3.890**	0.729	3.732**	0.442
Experience Squared	-0.00790	-0.00180	-0.00791	-0.00171
	-2.442**	-0.602	-2.448**	-0.714
Raven's Test	0.00879	0.01283	0.00866	0.01275
	0.591	0.913	0.555	1.077
Father's Grade Attainment	-0.04813	0.05017	-0.04795	0.05077
	-1.273	1.272	-1.164	0.977
Mother's Grade Attainment	0.06913	-0.06122	0.06914	-0.06142
	1.636	-1.648*	1.443	-1.201
Female	-0.02077	-0.65216	-0.02126	-0.65136
	-0.179	-6.700**	-0.176	-4.476**
San Miguel Conacaste	-0.09628	-0.04494	-0.09395	-0.04305
	-0.568	-0.232	-0.506	-0.253
Espiritu Santo	0.45205	-0.07892	0.45401	-0.08167
	2.539**	-0.427	2.256**	-0.390
San Juan	0.08025	0.07008	0.08107	0.07058
	0.503	0.425	0.458	0.430
Household Size	0.07954		0.07912	
	4.649**		4.354**	
Size of Household Farm	-0.04845		-0.04880	
	-1.712*		-1.431	
Income Transfers	-0.00057		-0.00058	
	-1..683*		-1.650*	
$\sigma_{\varepsilon v}$ (coefficient of the Inverse Mills' Ratio)		-0.05553		
		-0.228		
σ_{ε}				0.61943
				17.216**
ρ				-0.10890
				-0.211
R^2	0.089	0.300		
Adjusted R^2		0.240		
Percent Correct Predictions		77.811		
Log-Likelihood Function	-330.332	-144.159	-473.489	
Number of Obsevations	676	153	676	

T-statistics are reported below the coefficient estimates. For the 2-step estimated wage determinants, these are computed from robust-White standard errors.

**-significant at 95% confidence interval;

Table 5b. Cognitive Skills as Human Capital

Variables	Heckman's 2-Step Procedure		Maximum Likelihood	
	Probit Equation	Wage Equation	Probit Equation	Wage Equation
Constant	-3.01938	1.06263	-3.01379	1.07247
	-7.066**	1.606	-6.514**	1.372
Interamerican Reading Test	0.00846	-0.00669	0.00851	-0.00670
	0.763	-0.690	0.692	-0.448
Numeracy Test	0.01620	0.01784	0.01618	0.01780
	1.608	1.728*	1.461	1.613
Experience	0.20234	0.03981	0.20226	0.03908
	3.931**	0.682	3.791**	0.432
Experience Squared	-0.00816	-0.00168	-0.00817	-0.00165
	-2.526**	-0.556	-2.545**	-0.306
Raven's Test	0.00901	0.01364	0.00887	0.01360
	0.601	0.941	0.565	1.148
Father's Grade Attainment	-0.04674	0.05052	-0.04655	0.05076
	-1.237	1.298	-1.129	1.000
Mother's Grade Attainment	0.06790	-0.05903	0.06794	-0.05910
	1.597	-1.546	1.402	-1.147
Female	-0.02233	-0.64670	-0.02290	-0.64638
	-0.191	-6.700**	-0.187	-4.633**
San Miguel Conacaste	-0.10294	-0.03519	-0.10083	-0.03440
	-0.605	-0.179	-0.540	-0.202
Espiritu Santo	0.47300	-0.08423	0.47506	-0.08529
	2.670**	-0.458	2.361**	-0.403
San Juan	0.07485	0.07923	0.07562	0.07944
	0.470	0.468	0.426	0.489
Household Size	0.08055		0.08018	
	4.712**		4.429**	
Size of Household Farm	-0.04967		-0.05000	
	-1.753*		-1.459	
Income Transfers	-0.00055		-0.00056	
	-1.635*		-1.604*	
$\sigma_{\varepsilon u}$ (coefficient of the Inverse Mills' Ratio)		-0.05821		
		-0.242		
σ_{ε}				0.61901
				17.259**
ρ				-0.10145
				-0.200
R^2	0.089	0.301		
Adjusted R^2		0.241		
Percent Correct Predictions		77.811		
Log-Likelihood Function	-330.986	-143.137	-474.123	
Number of Obsevations	676	153	676	

T-statistics are reported below the coefficient estimates. For the 2-step estimated wage determinants, these are computed from robust-White standard errors.
**-significant at 95% confidence interval;

Table 5c. Cognitive Skills as Human Capital

Variables	Heckman's 2-Step Procedure		Maximum Likelihood	
	Probit Equation	Wage Equation	Probit Equation	Wage Equation
Constant	-2.86160	1.13189	-2.85363	1.16775
	-6.650**	1.779*	-6.124**	1.547
Interamerican Vocabulary Test	0.01535	-0.00036	0.01537	-0.00054
	2.086**	-0.058	1.938*	-0.051
Numeracy Test	0.00709	0.01415	0.00709	0.01414
	0.693	1.403	0.621	1.247
Experience	0.20325	0.03978	0.20319	0.03695
	3.947**	0.680	3.783**	0.404
Experience Squared	-0.00772	-0.00145	-0.00773	-0.00131
	-2.388**	-0.485	-2.401**	-0.245
Raven's Test	0.00568	0.01229	0.00551	0.01221
	0.378	0.862	0.349	1.023
Father's Grade Attainment	-0.04819	0.05072	-0.04789	0.05161
	-1.271	1.319	-1.156	0.977
Mother's Grade Attainment	0.06020	-0.06186	0.06022	-0.06206
	1.412	-1.659*	1.249	-1.189
Female	-0.05194	-0.65470	-0.05248	-0.65306
	-0.442	-6.591**	-0.426	-4.500**
San Miguel Conacaste	-0.13638	-0.04382	-0.13351	-0.04048
	-0.797	-0.222	-0.712	-0.234
Espiritu Santo	0.45944	-0.08739	0.46153	-0.09153
	2.584**	-0.480	2.285**	-0.428
San Juan	0.06102	0.07059	0.06196	0.07162
	0.381	0.425	0.349	0.432
Household Size	0.08016		0.07960	
	4.679**		4.385**	
Size of Household Farm	-0.04917		-0.04962	
	-1.734*		-1.457	
Income Transfers	-0.00057		-0.00059	
	-1.697*		-1.685*	
$\sigma_{\epsilon u}$ (coefficient of the Inverse Mills' ratio)		-0.06797		
		-0.282		
σ_u				0.62161
				15.531**
ρ				-0.13785
				-0.271
R^2	0.093	0.299		
Adjusted R^2		0.239		
Percent Correct Predictions		78.107		
Log-Likelihood Function	-329.062	-143.300	-472.359	
Number of Observations	676	153	676	

T-statistics are reported below the coefficient estimates. For the 2-step estimated wage determinants, these are computed from robust-White standard errors.
**-significant at 95% confidence interval;
*-significant at 99% confidence interval

Table 6a. Testing for an Independent Schooling Effect

Variables	Heckman's 2-Step Procedure		Maximum Likelihood	
	Probit Equation	Wage Equation	Probit Equation	Wage Equation
Constant	-3.09863	0.96944	-3.09175	0.98725
	-7.071**	1.457*	-6.409**	1.294
Reading Test	-0.00035	-0.01358	-0.00030	-0.01355
	-0.025**	-1.162	-0.020	-0.781
Numeracy Test	0.00006	0.01367	0.00005	0.01369
	0.005	1.290	0.004	1.078
Experience	0.21885	0.05549	0.21882	0.05411
	4.189**	0.926	3.919**	0.579
Experience Squared	-0.00742	-0.00177	-0.00743	-0.00171
	-2.278**	-0.611	-2.247**	-0.313
Raven's Test	0.00347	0.00928	0.00332	0.00925
	0.231	0.687	0.207	0.723
Father's Grade Attainment	-0.05472	0.04740	-0.05455	0.04785
	-1.426	1.199	-1.330	0.889
Mother's Grade Attainment	0.05496	-0.07366	0.05525	-0.07371
	1.279	-1.988**	1.121	-1.332
Highest Grade Attained	0.12921	0.05425	0.12910	0.05353
	3.358**	1.387	3.093**	1.012
Female	-0.00179	-0.61246	-0.00230	-0.61196
	-0.015	-6.599**	-0.019	-3.602**
San Miguel Conacaste	-0.01884	-0.03086	-0.01633	-0.02994
	-0.109	-0.161	-0.085	-0.172
Espiritu Santo	0.40594	-0.08278	0.40791	-0.08440
	2.260**	-0.455	2.009**	-0.413
San Juan	0.14806	0.07027	0.14932	0.07026
	0.913	0.430	0.825	0.428
Household Size	0.08296		0.08251	
	4.805**		4.454**	
Size of Household Farm	-0.05568		-0.05639	
	-1.923*		-1.592	
Income Transfers	-0.00046		-0.00047	
	-1.341*		-1.299*	
$\sigma_{\varepsilon\varepsilon}$ (coefficient of the Inverse Mills' Ratio)		-0.05853		
		-0.248		
σ_{u}				0.61353
				16.521**
ρ				-0.10882
				-0.211
R^2	0.104	0.314		
Adjusted R^2		0.249		
Percent Correct Predictions		77.959		
Log-Likelihood Function	-324.609	-141.699	-466.307	
Number of Obsevations	676	153	676	

T-statistics are reported below the coefficient estimates. For the 2-step estimated wage determinants, these are computed from robust-White standard errors.
**-significant at 95% confidence interval;

Table 6b. Testing for an Independent Schooling Effect

Variables	Heckman's 2-Step Procedure		Maximum Likelihood	
	Probit Equation	Wage Equation	Probit Equation	Wage Equation
Constant	-3.18996	0.92582	-3.18359	0.93345
	-7.314**	1.340	-6.573**	1.204
Interamerican Reading Test	-0.01191	-0.01445	-0.01182	-0.01441
	-0.947	-1.272	-0.858	-0.932
Numeracy Test	0.00401	0.01373	0.00400	0.01373
	0.377	1.366	0.339	1.148
Experience	0.21983	0.05280	0.21978	0.05223
	4.208**	0.870	3.973**	0.565
Experience Squared	-0.00765	-0.00160	-0.00765	-0.00158
	-2.348**	-0.545	-2.341**	-0.295
Raven's Test	0.00490	0.01092	0.00475	0.01090
	0.324	0.782	0.299	0.964
Father's Grade Attainment	-0.05642	0.04774	-0.05628	0.04793
	-1.468	1.225	-1.376	0.905
Mother's Grade Attainment	0.05859	-0.06974	0.05894	-0.06975
	1.357	-1.838**	1.175	-1.274
Highest Grade Attained	0.14538	0.05931	0.14518	0.05898
	3.660**	1.396	3.433**	1.101
Female	0.01752	-0.59861	0.01695	-0.59664
	0.148	-6.040**	0.135	-3.839**
San Miguel Conacaste	0.01196	-0.00910	0.01409	-0.00875
	0.068	-0.047	0.072	-0.050
Espiritu Santo	0.39660	-0.09067	0.39882	-0.09126
	2.206**	-0.507	1.967**	-0.445
San Juan	0.16508	0.09050	0.16624	0.09046
	1.011	0.533	0.913	0.564
Household Size	0.08293		0.08252	
	4.806**		4.478**	
Size of Household Farm	-0.05579		-0.05638	
	-1.922*		-1.586	
Income Transfers	-0.00045		-0.00046	
	-1.305*		-1.251	
σ_{w} (coefficient of the Inverse Mills' Ratio)		-0.05737		
		-0.243		
σ_{e}				0.61227
				17.226**
ρ				-0.09932
				-0.195
R^2	0.105	0.251		
Adjusted R^2		0.249		
Percent Correct Predictions		77.515		
Log-Likelihood Function	-324.161	-141.490	-465.652	
Number of Obsevations	676	153	676	

T-statistics are reported below the coefficient estimates. For the 2-step estimated wage determinants, these are computed from robust-White standard errors.

**-significant at 95% confidence interval;

*-significant at 90% confidence interval.

Table 6c. Testing for an Independent Schooling Effect

Variables	Heckman's 2-Step Procedure		Maximum Likelihood	
	Probit Equation	Wage Equation	Probit Equation	Wage Equation
Constant	-3.02602	1.04650	-3.01067	1.14188
	-6.908**	1.581	-6.197**	1.527
Interamerican Vocabulary Test	0.00477	-0.00436	0.00482	-0.00450
	0.583	-0.721	0.554	-0.407
Numeracy Test	-0.00278	0.01073	-0.00280	0.01099
	-0.259	1.051	-0.232	0.871
Experience	0.21797	0.04795	0.21811	0.04040
	4.183**	0.796	3.935**	0.432
Experience Squared	-0.00727	-0.00124	-0.00731	-0.00092
	-2.236**	-0.429	-2.229**	-0.171
Raven's Test	0.00243	0.00989	0.00213	0.00096
	0.160	0.715	0.132	0.766
Father's Grade Attainment	-0.05446	0.05000	-0.05408	0.05250
	-1.419	1.305	-1.317	0.944
Mother's Grade Attainment	0.05249	-0.07168	0.05291	-0.07197
	1.216	-1.925**	1.069	-1.307
Highest Grade Attained	0.11906	0.04844	0.11883	0.04492
	3.025**	1.258	2.819**	0.876
Female	-0.01584	-0.60956	-0.01657	-0.60626
	-0.133	-6.225**	-0.132	-3.695**
San Miguel Conacaste	-0.03994	-0.02595	-0.03616	-0.02050
	-0.228	-0.133	-0.187	-0.116
Espiritu Santo	0.40664	-0.09972	0.40872	-0.10899
	2.265**	-0.557	2.014**	-0.519
San Juan	0.13656	0.07211	0.13755	0.07228
	0.836	0.436	0.762	0.435
Household Size	0.08270		0.08165	
	4.793**		4.398**	
Size of Household Farm	-0.05521		-0.05630	
	-1.910*		-1.589	
Income Transfers	-0.00047		-0.00050	
	-1.383*		-1.378	
$\sigma_{\epsilon w}$ (coefficient of the Inverse Mills' Ratio)		-0.07681		
		-0.324		
σ_{ϵ}				0.62116
				12.401**
ρ				-0.19685
				-0.396
R^2	0.104	0.310		
Adjusted R^2		0.245		
Percent Correct Predictions		77.959		
Log-Likelihood Function	-324.439	-142.126	-466.557	
Number of Observations	676	153	676	

T-statistics are reported below the coefficient estimates. For the 2-step estimated wage determinants, these are computed from robust-White standard errors.
**-significant at 95% confidence interval;
* -significant at 99% confidence interval.

Table 7. Determinants of Cognitive Test Scores

Variables	Reading	Interamerican Reading	Interamerican Vocabulary	Interamerican Numeracy
Constant	-10.40690	-8.18319	-14.09360	9.11747
	-2.107**	-1.493	-1.688*	1.492
Age	0.42035	0.48638	0.65615	-0.13619
	0.767	0.800	0.709	-0.201
Age Squared	-0.00712	-0.01507	-0.02208	0.01381
	-0.452	-0.862	-0.829	0.709
Highest Grade Attained	4.21064	3.88024	6.29159	5.88113
	9.747**	8.097**	8.615**	11.002**
Highest Grade Attained Squared	-0.16578	-0.11609	-0.22406	-0.21183
	-6.551**	-4.135**	-5.237**	-6.765**
Raven's Test	0.44429	0.07035	0.10253	0.45238
	1.556	0.222	0.212	1.280
Raven's Test Squared	-0.00094	0.00721	-0.00245	-0.00903
	-0.116	0.806	-0.180	-0.905
Raven's Test * Age	-0.00175	0.00563	0.02348	0.02339
	-0.129	0.373	1.022	1.391
Raven's Test * Highest Grade	-0.02983	-0.01583	-0.00301	-0.04759
	-1.483	-0.709	-0.089	-1.912*
Highest Grade Attained * Age	-0.02341	-0.02160	-0.04191	-0.07918
	-1.014	-0.843	-1.074	-2.771**
Female	0.33838	1.45964	2.28065	-0.26475
	0.965	3.754**	3.849**	-0.610
San Miguel Conacaste	1.97601	3.06807	5.55995	1.53305
	3.838**	5.372**	6.388**	2.406**
Espiritu Santo	0.74174	-1.08510	-0.01828	-0.45361
	1.366	-1.801*	-0.020	-0.675
San Juan	1.60107	2.15747	3.90629	2.40865
	3.402**	4.133**	4.910**	4.136**
Father's Grade Attainment	-0.00869	-0.14564	-0.07180	-0.00886
	-0.076	-1.154	-0.365	-0.063
Mother's Grade Attainment	0.10281	0.38376	0.61971	0.08507
	0.797	2.681**	2.841**	0.533
R^2	0.642	0.641	0.653	0.602
Adjusted R^2	0.634	0.633	0.645	0.593
Log-likelihood Function	-1957.98	-2028.04	-2312.85	-2101.94
Number of Observations	676	676	676	676

T-statistics are reported below the coeficient estimates.
**-significant at 95% confidence interval;
* -significant at 90% confidence interval.