

ESTIMATING RETURNS TO EDUCATION IN OFF-FARM ACTIVITIES IN RURAL ETHIOPIA

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ABSTRACT

I have used an extended version of Mincer's original model to estimate the returns to schooling in rural Ethiopia. In a first step, a multinomial logit model is applied to distinguish between four groups of people, (1) full-time farmers, (2) part-time farmers and part-time wage workers, (3) part-time farmers and part-time traders and (4) full-time non-farmers. In a second step, a correction for sample selectivity is made using the Lee-Heckman method and the returns are estimated. The results show that returns on schooling are high in group (4) and lower in groups (2) and (3). Entry in well-paid jobs is constrained for non-educated people. Women are particularly well represented in the third group but strongly underrepresented in the fourth group. The estimation shows overall that education is a worthwhile investment in rural Ethiopia and the fact that households underinvest in education can be attributed to the lack of resources at the household level.

1. INTRODUCTION

Ethiopia has one of the lowest enrolment rates in the world. Only 20% of all school-aged children in rural Ethiopia are going to school. The causes for this low degree of participation in schooling are to be found at the level of the household, the provider as well as the labour market.¹ In this paper, I want to take a close look at one aspect of the problem. I address the question whether or not education is a worthwhile investment in rural Ethiopia. Can we make general statements about the return to education or is the return conditional on entry in certain jobs? This research follows up on previous research where I examined the determinants of household schooling decisions. Lack of resources at the household level is one of the major reasons why children are not attending school in rural Ethiopia.²

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The organization of the paper is as follows. After a review of the literature on education, returns and off-farm activities, I present the Mincerian model, the occupational choice model and the Lee-Heckman correction method for sample selectivity. Section four of the paper gives descriptive statistics and section five discusses the econometric specification. I present estimation results in part six and a conclusion at the end of the paper.

2. REVIEW OF THE LITERATURE

Many studies report parental education as an important determinant of child schooling. Strauss and Thomas (1995) for example refer to a number of studies where a positive relation is found between parental and child schooling. An explanation for this positive relation is found in two papers by Appleton and Mackinnon (1993). These authors call this effect the intergenerational transmission of education and they give several reasons for it: (1) educated parents have the skills to help children in homework, (2) educated parents are mostly richer and can devote more resources to education than other parents, (3) educated parents stimulate and motivate their children strongly, (4) educated parents derive more direct utility from their child's education and will therefore devote more resources to education, (5) educated parents expect a higher return from investment in education and will therefore invest more, and (6) educated parents have access to more accurate information.

Psacharopoulos (1985) reports high returns on primary and secondary education in African countries. He summarised estimates of returns to education for 60 different countries in the 1970s. Developing countries had a return of 15 percent on average per year of education, whereas the average for high-income countries was 9 percent per year. The first explanation for these high returns is just the law of supply and demand. Wages for schooled workers (and therefore returns) are high because they reflect the relative scarcity of human capital.

The methodological problem here is that if education is correlated with family background, then returns to education are overestimated, because part of the return has to be devoted to family background characteristics. Lam and Schoeni (1993) for example report that returns to schooling fall by one-third when parental schooling is added to wage equations. The authors interpret this as evidence that parental characteristics represent unobservable worker attributes. Direct effects of parental schooling on wages are substantial according to Lam and Schoeni, but well below the returns to a worker's own schooling. Schooling as well as unobservable characteristics can also be important determinants of entry in the paid labour force.

Most of the recent works on returns to education in developing countries correct for selectivity in the labour force. Alderman, Behrman, Ross and Sabot (1996) for

example perform a joint maximum likelihood estimation of the wage relation and of current wage-labour participation as a comparison between wages and the returns to alternative activities in rural Pakistan. The returns to alternative time use, in turn, are affected in part by a set of variables that do not enter directly into the wage relation, so they permit identification of the selectivity control in the wage equation. As Krishnan (1996) points out, the problem is to find identifying instruments for this selection equation, since many of the variables which determine earnings are also likely to determine entry in the paid labour force. To do the selectivity-correction correctly, an equation explaining the probability that a person is in a particular group is specified, using land, livestock and other variables in the selection equation and making sure that at least one of these variables differs from the variables used in the wage equation.

Heckman and Hotz (1986) estimated earnings equations for Panamanian males and found also that estimated returns to the worker's own schooling drop by about one-third when father's and mother's education is included in the regression. Controlling for a large set of family background variables, Lam and Schoeni (1983) estimated a return on schooling of over 10 percent per year using Brazilian data. They pay attention to the problem of measurement error and suggest that the decline in returns to schooling by introducing family background characteristics may be explained by measurement error in schooling. The decline in rate of return to schooling can therefore be overestimated, too.

In this paper, the researcher focuses on the economic return of human capital investments, being entry in the labour market and earnings. Schooling also has social returns, which are however difficult to quantify. A good example of a social return is found in Dercon (1996). He reports a strong health effect of female education on children: mothers who had primary education will seek medical treatment for their child in case of illness much more than uneducated mothers, namely 25% more. Dercon and Krishnan (1996) found intergenerational social effects of education: the father's education had a strong effect on his son's behaviour towards the use of contraception. This however, demands a long planning horizon, probably too long for poor people.

If education is important for entry in the labour market, then parents have an incentive to invest in child schooling. One therefore expects that parents have a reason to send their child to school even when direct economic returns from this investment are low. The economic return from schooling is the difference in wages between educated and non-educated workers. There are two main explanations for these wage differentials in the literature. The first one is the pure human capital thesis that wages reflect marginal productivity and that education increases a worker's productivity. The second is the screening hypotheses which argues that education serves as a screen for unobserved innate characteristics. In this case we should observe a 'diploma

effect¹: completing primary and secondary education should increase income significantly. I will test these hypotheses by using dummies for educational levels in one regression and number of years in school in another regression.

The focus on off-farm activities in this paper is partly justified by data limitations (see further on) but also because several authors point out the importance of off-farm work for the diversification of income in rural households. Reardon (1997) gives an interesting summary of recent findings. The simple average share of income earned in off-farm activities over 25 studies of African households is 45%. He also finds evidence showing the poor distribution of off-farm earnings in rural areas. Richer households earn substantial income in off-farm self-employment and hire in (poorer) farm labourers to work on their farms. Reardon interprets these findings as (at least rough) evidence for entry barriers and labour market segmentation in rural Africa.

3. OUTLINE OF THE MAIN MODEL

3.1. Mincer's Model

One of the main contributions of human capital theory is the relation made between earnings, costs and rates of return. According to Becker (1993) the most important single determinant of the amount invested in human capital may well be its profitability or rate of return¹. Both he and Mincer (1974) develop a model that relates earnings, opportunity costs and investment in education. Becker derives his model by taking differences in earnings of an individual that invested in education and an individual that not invested in education. Mincer uses earnings ratio's between these two individuals. I will follow Mincer's approach since his model leads directly to a specification that can be estimated and where the coefficient of schooling can be interpreted as the rate of return on investment in schooling.

Mincer's basic model goes as follows:

let Y_s be the annual earnings of an individual with s years of schooling

let V_s be the present value of an individual's lifetime earning

let n be the fixed span of earning life (the cost of schooling must be recouped during a fixed period)

let δ be the discount rate

let d be the difference in the years of schooling

let K be the earnings ratio

$$V_s = Y_s \sum_t (1/1 + \delta)^t, \text{ when the process is discrete} \quad [1.1]$$

$$V_s = Y_s \int_0^{n+s} e^{-\delta t} dt = Y_s / \delta (e^{-\delta s} (1 - e^{-\delta n})), \text{ when the process is continuous and} \quad [1.2]$$

$$V_{s-d} = Y_{s-d} \int_0^{n+s-d} e^{-\delta t} dt = Y_{s-d} / \delta (1 - e^{-\delta n}) e^{-\delta(s-d)} \quad [1.3]$$

Solving for $K_{s,s-d}$ from the equalisation of present values, we get⁴

$$K_{s,s-d} = Y_s / Y_{s-d} = e^{-\delta(s-d)} / e^{-\delta s} = e^{\delta d} \quad [1.4]$$

We see that K , the earnings ratio, does not depend on the levels of schooling nor on the length of earning life.

$$\text{Now we define, } K_{s,0} = Y_s / Y_0 = K_s. \quad [1.5]$$

$$\text{According to equation (1.4) } K_s = e^{\delta s} \quad [1.6]$$

In logarithms, this means

$$\ln Y_s = \ln Y_0 + \delta s \quad [1.7]$$

Equation [1.7] shows a relationship between earnings and years in school whereby δ is the rate of return of investment in schooling. δ shows the percentage increase in wage when schooling is prolonged by 1 year. It is a percentage increase because $\ln Y = dY/Y = (Y_2 - Y_1) / Y_1$. The percentage increase in earnings are strictly proportional to the absolute difference of the time spent in school.

Equation [1.7] is the basic Mincerian earnings equation. One can estimate it in a semi-log formulation with the log of earnings as the dependent variable and years of schooling as the independent variable.

Mincer formulated his model originally under the assumption of perfect credit markets, meaning that individuals face the same interest rate. Furthermore he assumes that interest rates and discount rates are the same. His model can thus be written in the following way:

$$\ln Y_s = \ln Y_o + rs \quad [1.8]^5$$

There are four major problems with this approach. The first is the assumption of perfect credit markets which are hardly found in developing countries. The second that it is far from obvious that rural people adopt their preferences (discount rate) to market conditions (interest rate)⁶. This is only the case in a highly integrated labour market. Third, all other factors affecting earnings are summarised in $\ln Y_o$. And fourth, all years of schooling have the same return to the individual, as if the first year of primary schooling gives the same return as the third year. The first two remarks will be discussed in the empirical part of this paper. The model is extended to deal with the third remark and the fourth problem is discussed at the end of this section.

A first extension of the model in [1.8] is done by including years of labour market experience and its square as independent variables. People namely do not stop the learning process once they finish schooling, they also develop skills while working. According to human capital theory, this enhances the productivity of the workers. We also include the square of the years of experience to capture the non-linear effect of experience.

This gives the following model,

$$\ln Y_s = \ln Y_o + rs + b_1 \text{exp} + b_2 (\text{exp})^2 \quad [1.9]$$

Following Lam and Schoeni (1993), we also extend the model with family background variables. The real equation is thus

$$\ln Y_s = \ln Y_o + rs + b_1 \text{exp} + b_2 (\text{exp})^2 + c_1 \cdot FB \quad [1.10]$$

where FB is the unobserved family background of a child. Assume now that family background and schooling are positively correlated, then we have a missing variable problem in [1.8]. Returns on education are overestimated because earnings are also determined by FB. In the extreme case, both schooling and earnings are entirely determined by FB which makes the content of formal education useless for economic life.

Mincer makes the assumption that all years of education have the same return. Several authors however report high marginal returns to primary education and low marginal returns to secondary education. Psacharopoulos (1994), using the Mincerian

method, reports a marginal return to completed primary education of over 40%. In order to pick up a different effect from primary and secondary education, dummy variables for education are introduced. When a person has completed primary education, the dummy is one. The same counts for other levels of education. In this way, one can measure the additional effect of having completed junior and secondary education. In the approach chosen here, the secondary education variable for example catches the marginal effect of having completed secondary education. Most pupils indeed stop education in the age between 12 and 15. One can ask the question if it is worth continuing for the secondary school level? Does this level of schooling add a return? When not, it is economically rational to quit school after junior or primary school.

This model can be written as follows:

$$\ln Y_i = \ln Y_o + a_1 \cdot pr + a_2 \cdot jun + a_3 \cdot sec + b_1 \exp + b_2 (\exp)^2 \quad [1.11]$$

One can argue that a separate variable for the number of years in primary school and a number of years in secondary school should be introduced. In this way, the difference in the marginal effect of each year of primary and each year of secondary education on the wages can be determined.

3.2. A Model of Occupational Choice

The schooling variable in Mincer's model only captures the direct effect of schooling on wage. From previous studies we know that schooling also has an indirect effect, namely it is one of the determinants of entry into an occupation. In order to account for this, we have to construct a choice model where a set of independent variables determine the kind of occupation that an individual is engaged in.

According to Dercon and Krishnan (1995), the characteristics of individuals explain the kind of economic activity these individuals choose. In a paper on income portfolios in Tanzania and Ethiopia, Dercon and Krishnan explain this as follows:

certain activities will offer higher returns to households with particular skills, ability or composition than to households without such advantages. However, some activities will require substantial investment, so that poorer or credit constrained households will not be able to enter them. In fact, skill or ability constraints may be sufficient to exclude certain households from particular activities. Comparative advantage and entry constraints will not just help to explain differences in portfolios within particular areas or villages, but also across areas or countries. Access to public infrastructure

such as market places and roads, proximity to towns, common property resources such as forest, and other public goods will also contribute to the different portfolio patterns across regions.

From the work of Bevan and Pankhurst (1996) we know that there is a clear division of labour between the sexes in rural Ethiopia. Women are responsible for domestic work (cooking, cleaning, looking after the small children, repairing clothes, looking after elderly and ill people) and for light agricultural work and income generating activities. While the shadow price of labour for males and boys is determined by the cultivated area of land per capita, the shadow price of female labour is determined by the size of the household. In large households, therefore, little time is left for a woman to be engaged in paid activities, since her labour is valued high in the household.

And, in many villages, traditional income generating activities (weaving, tanning, pottery) have been looked down on. Nevertheless and in spite of their domestic work, women are active in trading at market places and in selling agricultural products in Africa. Women allocate their time in such a way that they combine their work at home with their work for pay.

These kinds of problems require the use of a multinomial model. A multinomial logit model determines the probability of ending up in one occupation or, a category of occupations. The model is a natural extension of the binary logit model. The categories in the dependent variable are discrete, nominal or unordered.

Let us first look at the binary choice model.⁷

The probability of having $y = 1$ instead of zero can be written as follows.

$$\text{Prob}\{y = 1\} = G(x_k, \beta) \quad [2.1]$$

where G is a functional form containing the vectors x and β . Usually, the functional form is restricted to

$$G(x_k, \beta) = F(x_k' \beta) \quad [2.2]$$

where F is a cumulative distribution function.

It is possible to derive a binary choice model using a latent variable presentation of the model.

$$y^* = \sum_k \beta_k + \varepsilon \quad [2.3]$$

where y^* is an unobserved latent variable and ε symmetrically distributed with zero mean and cumulative distribution function $F(\varepsilon)$. What we observe is a dummy variable y , a realisation of a binomial process, defined by

$$y = 1 \quad \text{if } y^* > 0 \quad \text{and } y = 0 \quad \text{otherwise.}$$

Therefore,

$$\begin{aligned} \text{Prob}(y = 1) &= \text{Prob}\left(\sum_k \beta_k + \varepsilon > 0\right) \\ &= \text{Prob}\left(\varepsilon > -\sum_k \beta_k x_k\right) \\ &= 1 - F\left(-\sum_k \beta_k x_k\right) \end{aligned} \quad [2.4]$$

The specific functional form of F depends on the assumptions that one makes concerning the distribution of ε . In case of the binary logit model, we assume that ε follows a logistic distribution. This distribution is almost similar to the standard normal distribution but instead of a variance of 1 it has a variance of $\pi^2/3$.

In that case,

$$\text{Prob}(y = 1) = L\left(\sum_k \beta_k x_k\right) = \frac{e^{\sum_k \beta_k x_k}}{1 + e^{\sum_k \beta_k x_k}} \quad [2.5]$$

The model in [2.5] is the binary logit model, and it represents the probability of the event occurring ($y = 1$).⁸

The multinomial logit model is a straight forward extension of the model in [2.5]. The multinomial model estimates the effects of explanatory variables on a dependent variable with unordered response categories. The equation

$$\text{Prob}(y = j) = \frac{e^{\sum_k \beta_k x_k}}{1 + \sum_j e^{\sum_k \beta_k x_k}} \quad [2.6]$$

is referred to as the multinomial logit model. In this model, the choice probabilities are dependent on individual characteristics only. The model estimates relative probabilities, defined relative to the base group (the full-time farmers in my analysis). The number of parameters to be estimated is equal to the number of individual characteristics multiplied by the number of possible choices minus one. Each of our adults will fall into one of the 4 categories with probabilities given by [2.6]. The subscript j indicates that there are $J-1$ sets of β estimates.

3.3. Lee-Heckman Correction for Selectivity

At the time of a survey, many people are not engaged in paid labour. With 'paid work' I mean an activity for which the labouring person receives an amount of money or an amount in kind. The majority of the rural working population does not participate in paid work. They are full-time farmers or domestic workers. Because it is very difficult to value domestic work and farmers' output, rates of return on education are typically only measured for persons doing paid work. In this case, we have a sample-selection problem, some people are 'selected' into the paid labour force and other people not.

In a wage-equation, sample-selectivity can in fact be seen as an omitted variable problem. The researcher believes that his estimated returns are biased because something is missing in the equation. It is the same story as we had before. In section 3.1, we wondered if parental education had an influence on earnings. If this is the case, returns on education are overestimated when parental education is left out of the equation.

The sample-selectivity problem is a problem of omitted variables: something affects the earnings of a person, and this is not captured by the variables already in the equation. This problem can be solved by first explaining the reason why some people are 'selected' into the paid labour force. This information is then used to eliminate the potential bias in the estimation of the private returns to schooling. When participation is positively related to human capital variables, the coefficients on the human capital variables in the OLS wage equations - not corrected for selectivity - are likely to be biased.

The conventional sample selection model has the following form. [3.1]

$$y_i^* = x_i\beta + \varepsilon_i, \quad \text{with } i \text{ from } 1 \text{ to } n, \text{ with } n \text{ the number of cases in the sample}$$

$$d_i^* = z_i\gamma + v_i, \quad \text{with } i \text{ from } 1 \text{ to } n$$

$$d_i = \text{Iif } d_i^* > 0; \cdot d_i = 0 \quad \text{otherwise}$$

$$y_i = y_i^* \cdot d_i;$$

where y_i^* is a latent endogenous variable and y_i the observed variable; d_i^* is a latent variable with associated indicator function d_i reflecting the selection equation. ε_i and v_i are zero mean terms with $E(\varepsilon_i/v_i) \neq 0$. We make the assumption (assumption 1) that ε_i and v_i are independently and identically distributed $N(0, \Sigma)$,

$$\text{where } \Sigma = \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon v} \\ \sigma_{\varepsilon v} & \sigma_v^2 \end{pmatrix}$$

OLS estimation of β over the subsample n corresponding to $d_i = 1$ will lead to inconsistent estimates due to the correlation between x_i and ε_i .

Different procedures are used in empirical work, but two-step estimation is the most common approach. I will use the parametric two-step estimation like Heckman did (1976, 1979).⁹

Our primary equation of interest is

$$y_i = x_i \beta + \varepsilon_i, \quad \text{with } i \text{ from } 1 \text{ to } n \quad [3.2]$$

Knowing that $E(\varepsilon_i/x_i, d_i = 1) \neq 0$, the method proposed by Heckman (1976) is to overcome this misspecification through the inclusion of a correction term which accounts for $E(\varepsilon_i/z_i, d_i = 1)$.

To employ this approach, we take the conditional expectation of [3.2] in order to get

$E(y_i/z_i, d_i = 1) = x_i \beta + E(\varepsilon_i/z_i, d_i = 1)$; i from 1 to n . From bivariate normality it follows that $E(\varepsilon_i/z_i, d_i = 1) = E(\varepsilon_i/v_i) = (\sigma_{\varepsilon v} / \sigma_v^2) / v_i$. This can be proved.

Using assumption 1 and the formula for the conditional expectation of a truncated random variable we note that

$$E(\varepsilon_i/z_i, d_i = 1) = (\sigma_{ev}/\sigma_v^2) \left[\phi(-z_i\gamma) / (1 - \Phi(-z_i\gamma)) \right] \quad [3.3]$$

where Φ denotes the cumulative distribution function of the standard normal distribution. Lee (1983) has shown that this also works in case of a logistic distribution. This is what I need, because I am using a (multinomial) logit model.

In [3.3] we replace ϕ by l and Φ by L , L being the cumulative distribution function of the logistic distribution. The second term on the right hand side of the equation in [3.3] is known as the inverse Mills ratio.

Thus, the two-step procedure suggested by Heckmann first estimates γ over the entire N observations and then constructs an estimate of the inverse Mills ratio. One can then consistently estimate the parameters by OLS over the n observations reporting values for y_i by including

$$E(\varepsilon_i/z_i, d_i = 1) = (\sigma_{ev}/\sigma_v^2) \lambda_i \quad \text{as an additional regressor in} \quad [3.2].$$

$$= (\sigma_{ev}/\sigma_v^2) \int v_i l(v_i) dv$$

We estimate

$$y_i = x_i\beta + \mu \lambda_i + \eta_i \quad [3.4]$$

by OLS. The t-test on the null hypothesis $\mu=0$ is a test of $\sigma_{ev} = 0$ and represents a test of sample selectivity bias. In equation [3.4], one clearly views the problem as a problem of omitted variables. Least squares regressions of y on x and λ would produce consistent estimates, but if λ is omitted, the specification error of an omitted variable is committed. If λ is observed, OLS estimates are consistent but inefficient. The disturbance η is heteroscedastic.¹⁰

4. DESCRIPTION OF THE DATA

In the beginning of the nineties, Ethiopia entered a process of profound transformation. The Centre for the Study of African Economies at Oxford University and the Department of Economics at Addis Ababa University decided to do a large scale rural household survey as a follow up of a survey done by the International Food

Policy Research Institute in 1989. The sample consists of 1477 rural households in 15 areas of Ethiopia. No attempt has been made to have a representative sample of rural Ethiopia. According to Dercon and Krishnan (1995), the geographical spread however is likely to provide a very relevant picture of rural Ethiopia. Random sampling is applied in each site and the number of households interviewed in each site was proportional to the population of the region relative to the national population.

This paper uses data from the first round of this survey, concentrating on the parts in the survey where questions on off-farm activities were asked. Information on education was taken from the second round, conducted a few months later, since it was more detailed than the education part in the first round. In the survey, enumerators asked how many days the respondent had worked for pay in the last four months. We do not have information on hours worked per day or on hourly earnings. This could cause biases in estimation because not all people work for pay the same number of hours per day. This may not be important in a regulated, industrialised country, but it is important in rural Ethiopia, where much of the employment is informal and highly variable in hours worked. Individuals who work many hours a day will - *ceteris paribus* - have higher daily earnings.

A comparison of the earnings per day between men and women shows that men earn much more than women. It is however risky to attribute this to discrimination in the labour market, since we only have information on days worked. We know, that women do a lot of household work on a daily basis and it is therefore very likely that they work less hours a day for pay than men do. This is not observable from the data on earnings since we only asked for daily earnings. Of course, it is possible that there is a high degree of variance in the hours worked between men too. To avoid possible distortion we will conduct separate wage equations for men and women after correcting for selectivity.

We also asked what pay the respondent received for his/her labour. This pay could be expressed in kind or in cash. The pay in kind was converted to kilograms and valued at the local price (also expressed per kg of course) for that commodity. In case of payment both in cash or in kind, both were added up. In case of more than one off-farm activity, the earnings of all activities were summed. Then, all earnings were divided by the numbers of days worked, which gave average earnings per day. Since prices and crops differ substantially according to villages, this calculation was performed separately for all villages.¹¹

For the dependent variable, the log of earnings per month is used. One cannot take total earnings in these four months as dependent variable, because in that case earnings are also determined by the number of days worked. It may be that earnings per day and number of days worked for pay are determined by the same variables.

Table 1 shows an example of this problem: more educated people seem to supply more labour. If they earn more in these four months, this can be due to their education, but also because they have worked more.

Table 1. Days Worked for Pay (averages) during Last Four Months by Level of Education

	Level of Education			
	No education	Max. primary school	Max. high school	Max. university
Days worked	40.23	37.86	48.48	96.50

In order to control for days worked, it is necessary to take earnings per day as a basic variable. I assume daily earnings to be independent of number of days worked¹². There are 1224 individuals in the sample who reported to do off-farm work. 912 also gave us the pay they got for their work. I will use these 912 persons to do the regressions.

I first discuss descriptive statistics of participation in paid work in rural Ethiopia. One can distinguish four groups in rural Ethiopia when it comes down to paid work. We have 3097 individuals (>14 years) who are either farmers or domestic workers and who are not engaged in any kind of off-farm activity. These people are full-time working at home or on their farm. They do not participate in paid work. A second group consists of 802 individuals whose main activity is also farming or doing domestic work, but next to that, they participate in off-farm activities. These people are part-timers, viz. they devote some of their working time at home or on their own farm and other time working for pay. These paid activities can be very diverse: working on someone else's farm, food-for-work, domestic servant, unskilled labour, collecting and selling firewood, trading grain or other crops, trade in livestock.

Because of the diversity of the economic activities and the theoretical explanation of Dercon and Krisnan (page 7), the group of 802 people is split into two groups: a group of 294 people working on the farm (or at home) and doing part-time wage labour and another group of 508 people doing part-time farm work and part-time income earning activities. Table 2 shows that people in wage-labour have lesser land endowments and livestock than people in income earning activities. They also live further away from town. From Bevan and Pankhurst (1996) we also know that in the rural areas wage-labour is looked down on.

Table 2. Second and Third Group Compared

	Farmer and wage-labourer	Farmer and Income earning activities
Size of the household	6.31	6.20
Age in years	37.00	36.00
Land endowment	1.00	3.06
Value of livestock	906.70	2818.80
No. of years at school (excluding nursery)	4.02	3.55
Distance to town in km	11.97	8.65

Table 3. Part-time Farmers/Part-time Wage Workers are Involved in:

	Frequency	Percent
Farm worker	65	22.1
Labour sharing	11	3.7
Labourer (skilled)	16	5.4
Unskilled worker	39	13.3
Domestic servant	8	2.7
Food-for-work	137	46.6
Other	17	6.1
Total	294	100.0

Table 4. Part-time Farmers/Part-time Income Earning Activities are Involved in:

	Frequency	Percent
Weaving/Spinning	71	14.0
Handicraft	49	9.6
Trade in grain, Sales	92	18.1
Trade in livestock	27	5.3
Transport	7	1.4
Collecting and selling wood,	237	46.7
Other	15	2.4
Total	508	100.0

The main activity of the fourth group of people is not farming, nor working at home. They are full-time engaged in paid work. They are teachers, factory workers, mechanics, administrators, traders, ...etc.

Table 5. Full time Off-farm Workers are Involved in:

	Frequency	Percent
Manual worker	39	9.2
Weaver	12	2.8
Craftworker/potter	39	9.2
Foodseller (Tella)	37	8.8
Driver/Mechanic	10	2.4
Skilled (factory) worker	17	4.0
Teacher	18	4.3
Party official/Administrator	17	4.0
Soldier	30	7.1
Trader	125	29.6
Other	78	18.1
Total	422	100.0

Table 6. Earnings in Birr, Males and Females

		Per Month	
		M	F
Farmer and Wage-earners	Min	7.61	10.69
	Max	1139.00	416.00
	Mean	108.60	82.53
Farmer and Income earning activities	Min	1.83	1.67
	Max	2083	1000.00
	Mean	177.80	98.53
Non-Farmer	Min	15.63	8.33
	Max	2075.00	958.30
	Mean	234.40	77.04

Table 6 shows the earnings-profile of people doing off-farming activities in rural areas of Ethiopia. From these three groups, part-time wage-earners have the lowest incomes and non-farmers the highest. Men earn more than women, especially when they are full-time non-farmers.

5. ECONOMETRIC SPECIFICATION

5.1. Estimating Mincer's Model

I will first estimate the model as specified by equations [1.8], [1.9] and [1.10] for the entire sample, not corrected for sample selectivity in one of the off-farm groups. This estimation allows us to get a first look at the effects and to compare later with more advanced estimations. I repeat the regression, but this time, I use dummy variables for education.

5.2. Specification of the Occupational Choice Model

The decision to participate in wage labour or to exercise another non-farming economic activity is influenced by a number of factors. The land endowment of the head of the household, to start with, has an important influence on the labour decisions of all household members. If your household head owns a farm in rural Ethiopia, it is likely that you work on the farm. In order to avoid an endogeneity problem, I left out all heads of households from the estimation. Labour has a different shadow price for every household depending on the land endowments and the number of household members. When cultivated land is large compared to household members, the likelihood of working off-farm is expected to decrease because the labour is needed on the own farm, and members of the household have a higher reservation wage. When cultivated land is small compared to household members, the shadow price of labour is lower and the probability to do off-farm work is likely to increase. In this case, farming may not yield enough output for the household to survive in which case off-farm work gives a supplementary income.¹³

The independent variables in the multinomial logit model determine the relative probability of ending up in one of the three mentioned groups: part-time farmers and wage-labourers, part-time farmers and income generating activities and non-farmers. The group of full-time farmers or domestic workers is the baseline group.

I used the size of the household, the occupation of the household head, the level of education of the household member, the value of the livestock of the household, the area of cultivated land per capita, the presence of an all-weather road and the distance to the nearest town as independent variables in the multinomial logit estimation. The parameters in this model are estimated using maximum likelihood.

I expect a positive relation between schooling and the chance to do off-farm work. It is often said that educated persons don't want to be a farmer anymore. But one can wonder if educated persons have parents that are farmers. What I mean is that I also expect a positive relation between the head of the household being a non-farmer and the probability of household members of being in the fourth group, namely the non-farmers. Children from non-farming households have a comparative disadvantage in farming.

The value of the livestock is introduced as a proxy for wealth in rural Ethiopia. Wealthier households are expected to be well-represented in income generating activities (group 3). Most of these activities namely demand collateral or assets. The proximity of roads and towns is expected to increase the probability of choosing wage labour because they reduce transportation costs and increase the demand for wage labour.

I will estimate the returns on investment in education for the three groups doing off-farm work separately. Moreover, as we noticed before, women work fewer hours for pay than men do and since we only have data on daily earnings, I estimate wage regressions for women and men separately to avoid potential bias.

5.3. Lee-Heckman Specification

If one wants to estimate returns to education, one has to take account of the selection bias in paid labour. The idea is that if people in the labour force, be it part-time or full-time workers, are non-random samples of the population, the observed earnings distribution gives a non-random picture of the real distribution, thereby causing biased OLS estimates of the Mincerian log-earnings function. The purpose therefore is to estimate returns on education corrected for the selectivity bias in paid labour.

We estimate equation [3.4]

$$y_i = x_i\beta + \mu\lambda_i + \eta_i$$

by OLS. The t-test on the null hypothesis $\mu=0$ is a test of $\sigma_{\eta\lambda} = 0$ and represents a test of sample selectivity bias.

6. ESTIMATION RESULTS

6.1. First Estimation

Regression 1 shows the results of four specifications. One has to be careful with the interpretation of the results. Since the sample is not corrected for selectivity into the paid labour force, returns to education will be biased.

Every year of schooling seems to give an additional income of 4.7%. The coefficient of the schooling variable is significant at the 1% level. When returns are this high, households have a strong incentive to send children to school and to keep them in school. We nevertheless observe a very low enrolment rate, which means that either the Mincerian specification overestimates the returns on schooling or that households are constrained. In the latter case, households cannot send children to school, even if they wanted to.

The two age variables, measuring labour market experience have the expected sign but are not significant. Other things being equal, your monthly earnings drop by 20% when you are female. In the specification with dummies, only the dummy for primary education is significant. Completion of primary school gives a return of 27%.

In the third specification, father's education is added based on the arguments of Lam and Schoeni. Father's education does not prove to be significant and the coefficients of our schooling variable does not lower because of the introduction of this new variable. This could be an important result, since several papers (e.g. Lam and Schoeni (1993)) report strong effects of parental education on earnings of children. However, making use of father's education in the regression is difficult because there is very few variation across the sample. 87 percent of the fathers have no education and 8 percent of the data are missing which leaves only 5 percent of the data set to provide variation. The researcher therefore refrains to use this variable in the following regressions. Moreover, the adjusted R^2 shows an extremely small value, which further weakens the regression.

Regression 1
Comparisons of Rates of Return to Education Across Different Specifications of the wage Function

Variables used	Basic Mincerian method	Basic Mincerian method	Lam and Schoeni	Lam and Schoeni
Intercept	4.07 (10.5)	4.242 (11.12)	4.07 (10.52)	4.24 (11.1)
Number of years in school	0.047 (3.86)		0.047 (4.04)	
Primary ed.		0.27 (1.7)		0.26 (1.6)
Junior ed.		0.33 (1.53)		0.34 (1.57)
Secondary ed.		0.082 (0.25)		0.08 (0.25)
age in years	0.015 (0.73)	0.009 (0.47)	0.015 (0.073)	0.009 (0.47)
age square	-0.0009 (-0.36)	-0.0002 (0.91)	-0.0003 (-1.6)	-0.0002 (-0.99)
sex dummy	-0.23 (-2.07)	-0.212 (-1.882)	-0.215 (-1.9)	-0.21 (-1.86)
Father's ed.			-0.0002 (-0.4)	-0.0002 (-0.37)
Adjusted R^2	0.05	0.05	0.048	0.05
F-stat	6.09 (0.00)	4.5 (0.00)	4.9 (0.00)	3.88 (0.00)

Note: These regressions are not corrected for selectivity into the paid labour force. Monthly earnings used as dependent variable.

Up to here, the variable measuring the numbers of years in school has shown to be significant in our wage-regressions. From the dummy-variables used, only the primary school dummy was significant (at the 10% level). The two other education dummies are not significant. These results however, are not conclusive enough to favour the human capital interpretation of schooling (knowledge learned in school enhances one's productivity which is rewarded with higher wages) against the screening hypotheses. In the latter case we would expect a diploma-effect: employers use diploma's as screens for unobservable abilities. Schooling as such would not have a productivity-increasing effect. Our results indicate that the return on completed primary education is not very different from the return per year over six years. Moreover, since the dummy for primary education also is significant, we cannot opt for one of the two theories. The test is performing well for the primary education variables, but we have to keep in mind that the test is not corrected for sample selectivity and that it remains a rather weak test. In order to falsify one of the theories, the researcher has to have firm level data indicating the way employers hire and reward people.

6.2. Estimation of Labour Market Participation

6.2.1. Results of the Multinomial Logit

		Regression 2a			
Dependent Variable(KEUS)		For Men		For Women	
Number of Observations		Occupational Choice		Occupational Choice	
Iterations Completed		2044		2277	
Log Likelihood Function		9		14	
Restricted Log Likelihood		-1784.04		-1442.62	
Chi-squared		-2108.13		-1707.94	
Degrees of Freedom		648.19		530.62	
Significance Level		27		27	
		0.00		0.00	
Variable	Coefficient	Sig.	Coefficient	Sig.	
Part-time Wage Workers					
Constant	-2.04	0.00	-5.47	0.00	
HHSIZE	-0.06	0.03	-0.10	0.05	
DUMFARM	-0.17	0.65	-0.71	0.08	
PRIMC	0.28	0.38	-10.86	0.97	
JUNC	-0.54	0.30	0.69	0.10	
HIGHC	0.77	0.39	-0.62	0.10	
LIVVAL	-0.00	0.00	-0.00	0.04	
CULTCP	-1.03	0.01	-5.54	0.00	
ALLWROAD	0.88	0.00	2.32	0.00	
TOWNKM	0.12	0.00	0.28	0.00	
Part-time Income Generating Activities					
Constant	-1.47	0.00	-2.53	0.00	
HHSIZE	-0.07	0.00	-0.10	0.00	
DUMFARM	0.30	0.49	0.23	0.45	
PRIMC	0.44	0.11	0.37	0.43	
JUNC	0.26	0.49	-0.87	0.27	
HIGHC	-0.54	0.50	-11.88	0.98	
LIVVAL	0.00	0.17	0.00	0.11	
CULTCP	0.90	0.00	1.35	0.00	
ALLWROAD	-0.45	0.00	0.663	0.00	
TOWNKM	-0.03	0.12	0.02	0.17	
Full-time Non-farmers					
Constant	-0.09	0.82	-0.33	0.34	
HHSIZE	0.05	0.04	0.02	0.38	
DUMFARM	-3.08	0.00	-1.81	0.00	
PRIMC	0.53	0.09	-0.36	0.53	
JUNC	0.36	0.38	0.49	0.52	
HIGHC	2.36	0.00	0.49	0.52	
LIVVAL	-0.00	0.04	-0.00	0.01	
CULTCP	-2.21	0.00	-1.65	0.01	
ALLWROAD	0.93	0.00	0.53	0.01	
TOWNKM	-0.05	0.01	-0.07	0.00	

VARIABLES USED

HHSIZE is the size of the household, DUMFARM head of the household is farmer or not, PRIMC completed primary education or not (same for JUNC and HIGHC), LIVVAL value of livestock, CULTCP cultivated land per capita, ALLWROAD presence of an all-weather road or not, TOWNKM distance to nearest town.

The results in Regression 2a show the effect the independent variables have on the relative probability of being in one of the three groups. The results presented are not the marginal effects of each variable on this probability. I will only look at the sign and the size of the effect of each variable. Both men and women from larger households have a smaller chance of doing off-farm work than men and women from smaller households. This effect, however, only holds in the case of part-time work. If your head of the household is a farmer, it is very unlikely that you will be a full-time non-farmer. The dummy, which can be interpreted as a family background variable, namely shows a negative and very significant effect, both for males and females. The relative probability for females to be engaged in off-farm wage work for part of their time also decreases when the head is a farmer¹⁴. The author did not include father's education as a family background variable in the estimation because of the lack of variation of this variable in each of the subgroups and especially in one of the subgroups. Given the importance of agriculture, the occupation of the head of the household is probably a better family background variable.

The dummy variables for the educational level of the individuals are significant for entry in a full-time non-farming occupation. This is a strong result. One does not have to be educated in rural Ethiopia to do off-farm work for a part of one's time, but one does need to complete school if one wants to enter a non-farming economic activity as main occupation. This is clearly indicated by the significance of the dummies for education. However, the results on the education variables only hold for men. For females, the dummies for education are not significant. These effects indicate that men without schooling (especially without a degree) experience severe entry constraints in these full-time non-farming occupations.

The variable used as a proxy for wealth in the regression, the value of livestock is significant for male wage earners and non-farmers and for female wage-earners. This means that the relative probability of being in these jobs decreases when the value of livestock increases. In the case of wage-work, one can say that well-off people will not hire out their labour, they get higher returns in other activities. People with a lot of livestock, mostly also have a farm, which in turn reduces the relative probability of engagement in full-time off-farm work.

The variable measuring the opportunity cost of labour, cultivated land per capita, performs very well in the regression. From the theory, we expect a negative effect of

this variable on the relative probabilities: the larger the area cultivated relative to household members, the lower the relative probability of doing off-farm work. If labour is scarce on the farm, it has a high shadow price, which keeps the household members on the farm. In the regression, this proves to be true for both men and women in case of part-time wage work and full-time off-farm work. The relative probability of entering income generating activities however, increases when cultivated land per capita increases. One way to interpret this is that these people are relatively well-off, which means that they can hire in labour or rent out land and choose for themselves an activity with a higher return than the return they would get in farming.

In almost all cases, the presence of an all-weather road has a positive effect on the relative probability of off-farm work. Only once, in the case of males in income earning activities, does the presence of an all-weather road decrease the relative probability. In general however, accessible roads will enlarge one's opportunities to work outside the farm. In the case of wage labour for example, one can see the ease in which employees can be mobilised. Roads decrease transport costs both for goods and for persons. The effect of the distance to town is puzzling, since the sign of the coefficient differs according to sex and activity. Only in the case of females, the proximity of a town has a positive effect on the relative probability of doing full-time off-farm work. In all other cases proximity of a town has a negative impact.

6.2.2. Returns Not Corrected for Selectivity

Regression 2b: Mincerian wage regressions with monthly wage as dependent variable and years of schooling and years of experience as regressors for the three groups of people active in the paid labour force and for both sexes. Not corrected for selectivity.

For the men, schooling is significant in explaining wages of non-farmers and farmers who engage in income-generating activities and almost significant for part-time wage earners. With an extra year of education, the earnings of a non-farmer rises by 15 percent. For income generating activities, this is 4.5 percent and for wage earners 5%.

Referring to the outline of Mincer's original model on page four, we notice different values of r depending on the category one belongs to. It is thus not correct to interpret this r as a discount rate that applies to all people in rural Ethiopia in the same way. It is better to understand this r as the internal rate of return for investment in education depending on the kind of labour that one is involved in¹⁵. The results in Regression 2b, which are not yet corrected for selectivity, indicate that an extra year of education is more rewarding if you have a full-time non-farming job than when you are part-time farming, part-time non-farming. If these results are maintained in the regression which does correct for selectivity, this would be a clear indication of the

segmentation of labour markets in rural Ethiopia. A typical example would be the profession of teachers in Ethiopia. Teachers are paid according to standards set by the government. If you go 1 year to Teachers College after high school, you earn less than a person who went two or three years to Teachers College or who obtained an M.A.

	Part-time farmers part-time wage	Part-time farmers part-time income	Full-time non-farmers	
	man*	man	women	man*
Variables in				
Constant	6.092 (7.776)	3.764 (5.76)	4.35 (11.46)	3.49 (1.89)
number of	0.053 (1.701)	0.045 (2.669)	0.016 (0.33)	0.15 (3.74)
Age	-0.114 (-2.571)	0.041 (1.19)	0.008 (0.035)	0.0017 (0.144)
age	-0.0016 (2.847)	-0.0005 (-1.199)	0.0001 (0.32)	-0.00018 (-0.102)
Adj. R Square	0.085	0.034	0.02	0.254
F-stat	3.617	2.75		4.972

* not enough observations for regression for women

The age variables (used as proxies for experience) are significant in explaining the wages of men working part-time as wage labourers. The same variable is insignificant in explaining the earnings of a non-farmer and a person in an income generating activity. The sign of the age variable in the regression for wage-labour however, is negative. This unexpected result might be explained as follows in this kind of activities, productivity is not explained by experience (human capital accumulation on the job) but by physical strength (or physical ability). Since physical strength decreases with age, the coefficient on the age variable is negative.¹⁵ Although progressively improving, the R^2 is very low.

6.3. Returns Corrected for Selectivity

Regression 3

Mincerian wage regressions with monthly wage as dependent variable and years of schooling years of experience and father's education as regressors for the three groups of people active in the paid labour force and for both sexes. Corrected for selectivity.

Variables in the equation	Part-time farmers part time wage labour	Part-time farmers part-time income generating activities		Full-time non-farmers
	man*	man	women	man
Lambda	0.73 (2.59)	0.84 (2.84)	-0.10 (-0.31)	0.52 (1.74)
number of years in school	0.05 (1.30)	0.06 (3.25)	0.10 (2.12)	0.18 (4.02)
age	0.15 (5.26)	0.17 (6.58)	0.23 (9.02)	0.18 (4.21)
age squared	-0.00 (-4.03)	-0.00 (-6.03)	-0.00 (-7.11)	-0.00 (-2.65)
Adj. R Square	0.47	0.12	0.47	0.24

Not enough observations for regression for women. T-values in bracket.

Lambda, the inverse Mill's ratio is positive and significant for the men in all three groups. The null hypothesis of μ being zero has to be rejected, which means that we have a sample selectivity bias. Since Limdep software actually estimates $-\lambda$ there is a positive correlation between the unobserved variables in the wage equation and in the selection equation. People entering paid economic activities in rural Ethiopia are non-randomly selected in these activities. The direct returns are 5% per year in part-time wage work, 6% per year in part-time income generating activities and 18% per year in full-time non-farming economic activities.¹⁷

The age and age squared variables are very significant and with the expected sign. This is an improvement in comparison with Regression 2b (not corrected for selectivity) where the age variables are estimated insignificantly and with a non-expected sign. One can say that in the regression corrected for selectivity, the age variables are correctly estimated and the direct effect of the coefficient of age and age square on earnings immediately is the full effect since these variables do not turn up in the selection equation. With human capital theory, we can interpret these effects as the return to experience. Experience increases one's skill and productivity which is rewarded with higher earnings. At higher ages, when one grows older and becomes less productive, the effect of age on earnings decreases (coefficient of age square is negative).¹⁸ Depending on the group you are into, an extra year of experience increases your monthly earnings by 15, 17 or 18 percent.

For the women in income earning activities, there is no selectivity bias since λ is not significant. The direct return on education for these women is 10% per year. The age variables for women are also significant and have the expected sign.

7. CONCLUSION

In this paper, I tried to look at education in rural Ethiopia from the economist's point of view. I wanted to know if education is a worthwhile investment. Does education have an economic return in rural Ethiopia? If returns are substantial, parents have incentives to send children to school. For reasons outlined above, I limited the study to those persons working in off-farming economic activities.

From survey data and rural appraisals, we know that parents want to send their children to school, and parents have positive attitudes towards schooling. Only a small minority of parents is afraid that schooling will change the identity of a child. I did not study the curriculum of schools in rural Ethiopia. It is indeed quite likely that a number of factors situated at the level of the school influence enrolment. One could think of tuition, availability of books, quality of teaching staff, sizes of classes, etc. However, parents will judge all these factors and weigh them with the return they expect from education. I did not use expected return as a variable in my enrolment regression, since we have no data on the monetary expectations concerning child schooling in rural Ethiopia. I did calculate realised returns from off-farm activities. In order to do so, I estimated a multinomial logit model using several variables which determine the probability of entering a part-time or full-time non-farming economic activity. I applied the Lee-Heckman correction for sample selectivity in off-farm activities and found that the individuals working off-farm are a non-random sample of the adult population in our data-set. The probability of an individual entering a non-farming occupation as full-time economic activity increases when this person completed primary school and increases strongly when this person completed higher secondary education. The returns on education in these activities are 18% per year, but this percentage is an overestimation, since one still has to subtract the partial derivative of λ derived to schooling. It is sure however that education determines entry in these jobs and that the return on education is substantial. The return in part-time off-farm work is about 5%. From these results, one can conclude that there are strong economic incentives to invest in education. This means that the reasons for underinvestment in education (low rates of enrolment, not analysed in this paper, but substantiated in other research) are to be found at the household level, namely lack of resources to send children to school and at the market level, namely imperfectly working credit and labour markets. Households have difficulties to hire in labour to replace children on the farm and have difficulty or no access to credit to pay for child education (direct and opportunity costs). The segmentation of the labour market is also demonstrated by the different internal rates of return on education depending on the type of labour that one is doing.

Notes

- ¹ Collier, P., Dercon, S. and Mackinnon, J., *Ethiopian Social Sector Review (PER III)*, Oxford University, 1996.
- ² Verwimp, Ph., *Enrolment in rural Ethiopia*, Center for Economic Studies, Catholic University of Leuven, mimeo, 1996.
- ³ Becker, G.S., *Human Capital*, third edition, 1993, p.59.
- ⁴ If we equalise present values, we can find the ratio K , of annual earnings after s years of schooling compared to earnings after $(s-d)$ years of schooling.
- ⁵ This model, in its discrete form, can also be derived directly from
- $$Y_t = (1+r)^t Y_0 \quad \ln Y_t = \ln Y_0 + s \ln(1+r) = \ln Y_t = \ln Y_0 + rs$$
- ⁶ Meaning that r_i is likely to differ from r_j .
- ⁷ We will follow the approach taken in Liao, T.F., *Interpreting probability models*, Quantitative applications in the social sciences series, Sage publications, 1994.
- ⁸ An important issue in the use of multinomial logit models is the assumption of independence from irrelevant alternatives. This means that the ratio of choice probabilities of any two alternatives (in response categories) for a particular observation is not influenced systematically by any other alternatives.
- ⁹ This presentation is based on Vella, F., *Estimating Models with Sample Selection Bias : A Survey*, *The Journal of Human Resources*, vol 33, nr 1, Winter 1998, p.129
- ¹⁰ The proof for this can be found in Greene, 1993, p.707.
- ¹¹ To avoid very small numbers and to present nice-looking descriptive statistics, daily earnings were multiplied by 25, which gave the earnings per month. This does not mean that all individuals work 25 days a month. Here, one assumes that earnings per day are independent of number of days worked.
- ¹² If one would do a tobit analysis in order to explain the number of days a person worked for pay, number of days worked would of course be an essential variable.
- ¹³ In a paper on child labour (Addison, Bhalotra, Coulter and Heady, 1997) the authors found some empirical evidence that supports this theory. Landless households make less use of the labour of their children than households with land. Households with land use the labour of their children to work on the farm. This gives rise to the apparent paradox that child labour is greater in relatively better-off rural households. (Cain 1977, Stekes et al 1984, Fure 1983 and Vlassoff 1979).
- ¹⁴ This is different from our data on children (see enrolment estimation in Verwimp, Ph., C.E.S., mimeo) where we do have a lot of fathers who went to school and which reported this. About 400 children have educated fathers. Since in our present estimation, where we are dealing with adults, we need data on the educational level of their parents, where it is very likely that they did not go to school. However, if father's education is significantly determining enrolment and if one needs a degree to enter a full-time economic activity outside farming, father's education indirectly determines entry as well.
- ¹⁵ See our discussion on the discount rate, page four.
- ¹⁶ A possible way to test this hypothesis is to add a proxy for physical strength in the regression, for example the Quetelet Index (Body Mass Index (BMI)).
- ¹⁷ this β corresponds to the β in formula (a.2) in the appendix. I refer to the appendix for the discussion on the marginal effects.
- ¹⁸ The estimation, however, is not corrected for heteroscedasticity, which means that standard errors are biased.

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APPENDIX

There is a lot of discussion between scholars on the marginal effect of schooling. There are three ways to calculate marginal effects. The first way is the unconditional return on investment in education

$$\frac{\partial E(y_i^*)}{\partial x_i} = \beta. \quad [a.1]$$

It gives you the marginal return on 1 year of education without correcting for sample selectivity.

The second way corrects for this. The marginal effect on y in the observed sample consists of two components. There is the direct effect on the mean of y , which is β . In addition, if education variables appear in the selection equation, they will influence y through their presence in λ . The full effect of changes in schooling on y is

$$\frac{\partial E(y_i/y_i > 0)}{\partial x_i} = \beta + \mu \frac{\partial \lambda}{\partial z_i} \frac{\partial z_i}{\partial x_i} \quad [a.2]$$

because $z_i = f(x_i, t_i)$.

This gives the effect of schooling on earnings corrected for the fact that only members of a particular group are observed¹.

Since I use dummy variables for education in the selection equation, I should multiply the formula in (a.2) by approximately 1/6 for primary education, 1/2 for junior secondary education and 1/4 for higher secondary education.

The third way to calculate the marginal effect of schooling takes account of the probability to be a member of one of the three groups. β gives you the marginal effect of schooling on earnings for a person belonging to (= working in) one of three groups, but this effect must be multiplied with the probability of belonging to this group. Moreover, this probability changes itself with an extra year of education. The result is then the marginal return on investment in education, conditional upon entry in one of the three groups.

$$\frac{\partial E(y_i)}{\partial x_i} = \frac{\partial}{\partial x_i} [\text{prob}(g = a)E(y_i/g = a)], \quad \text{for } a \text{ is } 1 \text{ to } 4$$

$$= \left[\frac{\partial}{\partial x_i} (\text{prob}(g = a))E(y_i/g) \right] + \left[\text{prob}(g = a) \left(\beta + \mu \frac{\partial \lambda \partial z_i}{\partial z_i \partial x_i} \right) \right]$$

This formula gives the actual incentive to invest (or not) in education, since an individual does not know in which occupation he/she will work.