DOCUMENT RESUME

ED 335 389		TM 017 004
AUTHOR	Glewwe, Paul	
TITLE	Schooling, Skills, and the Returns to Government Investment in Education: An Exploration Using Data from Ghana. Living Standards Measurement Study, Working Paper No. 76.	
INSTITUTION	World Bank, Washington, D. C.	
REPORT NO	ISBN-0-8213-1764-4; ISSN-0253-4517	
PUB DATE	91	
NOTE	69p.	
AVAILABLE FROM	The World Bank, Publications Department, 1818 H St., N.W., Washington, DC 20433 (Order Stock No. 11764, $6.95, Price Code 006).	
PUB TYPE	Reports - Evaluative/Feasibility (142)	
EDRS PRICE	MF01 Plus Postage. PC Not Available from EDRS.	
DESCRIPTORS	*Developing Nations; Economic Impact; *Educational Finance; Educational Policy; Educational Quality; Elementary Secondary Education; *Equations (Mathematics); Estimation (Mathematics); Federal Aid; Foreign Countries; *Government Role; Human Capital; Investment; *Mathematical Models; Outcomes of Education	
IDENTIFIERS	*Ghana; *Human Capital Theory; Return on Investment	

ABSTRACT

Investments in schooling are often regarded as essential for economic development, implying that such investments have high rates of return in developing countries. This paper examines the accuracy and usefulness of estimates of rates of return to formal schooling based on the standard human capital model of G. Becker and J. Mincer. Focus is on whether failure to account for differences in ability and school quality across a random sample significantly biases estimates of the private return to schooling derived from estimates of wage equations. This is done using an unusually rich data set from Ghana (over 4,700 households), which includes tests of ability and cognitive skills administered to 389 survey respondents. When years of schooling are used to measure the accumulation of human capital, there are virtually no returns to schooling in the private sector. Replacement of years of schooling by reading and mathematical ability does show positive returns to acquired skills, although these rates may be of little use to governments making schooling investment decisions because of the complexity of such decisions. Many government investments in education are designed to raise rates of return to schooling by raising school quality, but decisions by individuals assume that both rates of return and school quality are exogenous. Thirteen tables present data from the analyses. Four appendices provide supplemental data concerning the calculation of rates of return. (SLD)

SCOPE OF INTEREST NOTICE

The ERIC Facility has assigned this document for processing to: TM

In our judgment, this document is also of interest to the Clearinghouses noted to the right. Indexing should reflect their special points of view. SO

LSMS

Living Standards Measurement Study Working Paper No. 76

Schooling, Skills, and the Returns to Government Investment in Education

LSMS Working Papers

No. 6	*Household Survey Experience in Africa*
No. 7	*Measurement of Welfare: Theory and Practical Guidelines*
No. 8	*Employment Data for the Measurement of Living Standards*
No. 9	*Income and Expenditure Surveys in Developing Countries: Sample Design and Execution*
No. 10	*Reflections on the LSMS Group Meeting*
No. 11	*Three Essays on a Sri Lanka Household Survey*
No. 12	*The ECIEL Study of Household Income and Consumption in Urban Latin America: An Analytical History*
No. 13	*Nutrition and Health Status Indicators: Suggestions for Surveys of the Standard of Living in Developing Countries*
No. 14	*Child Schooling and the Measurement of Living Standards*
No. 15	*Measuring Health as a Component of Living Standards*
No. 16	*Procedures for Collecting and Analyzing Mortality Data in LSMS*
No. 17	*The Labor Market and Social Accounting: A Framework of Data Presentation*
No. 18	*Time Use Data and the Living Standards Measurement Study*
No. 19	*The Conceptual Basis of Measures of Household Welfare and Their Implied Survey Data Requirements*
No. 20	*Statistical Experimentation for Household Surveys: Two Case Studies of Hong Kong*
No. 21	*The Collection of Price Data for the Measurement of Living Standards*
No. 22	*Household Expenditure Surveys: Some Methodological Issues*
No. 23	*Collecting Panel Data in Developing Countries: Does It Make Sense?*
No. 24	*Measuring and Analyzing Levels of Living in Developing Countries: An Annotated Questionnaire*
No. 25	*The Demand for Urban Housing in the Ivory Coast*
No. 26	*The Côte d'Ivoire Living Standards Survey: Design and Implementation*
No. 27	*The Role of Employment and Earnings in Analyzing Levels of Living: A General Methodology with Applications to Malaysia and Thailand*
No. 28	*Analysis of Household Expenditures*
No. 29	*The Distribution of Welfare in Côte d'Ivoire in 1985*
No. 30	*Quality, Quantity, and Spatial Variation of Price: Estimating Price Elasticities from Cross-Sectional Data*
No. 31	*Financing the Health Sector in Peru*
No. 32	*Informal Sector, Labor Markets, and Returns to Education in Peru*
No. 33	*Wage Determinants in Côte d'Ivoire*
No. 34	*Guidelines for Adapting the LSMS Living Standards Questionnaires to Local Conditions*
No. 35	*The Demand for Medical Care in Developing Countries: Quantity Rationing in Rural Côte d'Ivoire*
No. 36	*Labor Market Activity in Côte d'Ivoire and Peru*
No. 37	*Health Care Financing and the Demand for Medical Care*
No. 38	*Wage Determinants and School Attainment among Men in Peru*
No. 39	*The Allocation of Goods within the Household: Adults, Children, and Gender*
No. 40	*The Effects of Household and Community Characteristics on the Nutrition of Preschool Children: Evidence from Rural Côte d'Ivoire*
No. 41	*Public-Private Sector Wage Differentials in Peru, 1985–86*
No. 42	*The Distribution of Welfare in Peru in 1985–86*

(List continues on the inside back cover)

Schooling, Skills, and the Returns to Government Investment in Education

An Exploration Using Data from Ghana

The Living Standards Measurement Study

The Living Standards Measurement Study (LSMS) was established by the World Bank in 1980 to explore ways of improving the type and quality of household data collected by statistical offices in developing countries. Its goal is to foster increased use of household data as a basis for policy decisionmaking. Specifically, the LSMS is working to develop new methods to monitor progress in raising levels of living, to identify the consequences for households of past and proposed government policies, and to improve communications between survey statisticians, analysts, and policymakers.

The LSMS Working Paper series was started to disseminate intermediate products from the LSMS. Publications in the series include critical surveys covering different aspects of the LSMS data collection program and reports on improved methodologies for using Living Standards Survey (LSS) data. More recent publications recommend specific survey, questionnaire, and data processing designs, and demonstrate the breadth of policy analysis that can be carried out using LSS data.

LSMS Working Paper
Number 76

Schooling, Skills, and the Returns to Government Investment in Education

An Exploration Using Data from Ghana

Paul Glewwe

The World Bank
Washington, D.C.

First printing March 1991

The complete backlist of publications from the World Bank is shown in the annual *Index of Publications*, which contains an alphabetical title list (with full ordering information) and indexes of subjects, authors, and countries and regions. The latest edition is available free of charge from the Publications Sales Unit, Department F, The World Bank, 1818 H Street, N.W., Washington, D.C. 20433, U.S.A., or from Publications, The World Bank, 66, avenue d'Iéna, 75116 Paris, France.

ISSN: 0253-4517

Paul Glewwe is an economist in the Welfare and Human Resources Division of the World Bank's Population and Human Resources Department.

Library of Congress Cataloging-in-Publication Data

Glewwe, Paul, 1958-
Schooling, skills, and the returns to government investment in education : an exploration using data from Ghana / Paul Glewwe.
p. cm.—(LSMS working paper, ISSN 0253-4517 ; no. 76)
Includes bibliographical references.
ISBN 0-8213-1764-4
1. Education—Economic aspects—Ghana. I. Title. II. Series.
LC67.G45G57 1991
338.4'337'09667—dc20 91-8098
CIP

ABSTRACT

Investments in schooling are often regarded as essential for economic development, which implies that such investments have high rates of return in developing countries. This paper examines the accuracy and usefulness of estimates of rates of return to formal schooling based on the standard human capital model of Becker and Mincer. Regarding accuracy, it investigates whether failure to account for differences in ability and school quality across a random sample significantly biases estimates of the private return to schooling derived from estimates of wage equations. This is done using an unusually rich data set from Ghana. When years of schooling are used to measure the accumulation of human capital, there are virtually no returns to schooling in the private sector Replacement of years of schooling by reading and mathematical ability does show positive returns to acquired skills. However, these rates of return may be of little use to governments when making schooling investment decisions because such decisions are much more complex than the investment decisions of individuals. In particular, many government investments in education are designed to raise rates of return to schooling by raising school quality, but decisions by individuals assume that both rates of return and school quality are exogenous.

ACKNOWLEDGEMENTS

The data used in this paper could not have been collected without the cooperation of Ghana's Ministry of Education and Culture and the Ghana Statistical Service, for which I am deeply grateful. Thanks also go to Nick Bennett of the World Bank for help and advice in the data collection.

Finally, I would like to thank Jere Behrman, Jacques van der Gaag, John Ham, Robert E. B. Lucas, George Psacharopoulos and David Ross for comments on earlier drafts of this paper. Of course, I alone am responsible for any shortcomings.

TABLE OF CONTENTS

LIST OF TABLES

I. INTRODUCTION

Education is a key factor in economic development. At the aggregate level, Lau, Jamison and Louat (1990) estimate that a one year increase in the average education level of the adult population can lead to increases of 3-5% in real GDP in East Asia and Latin America. From an individual point of view, investments in education could well be more profitable than other types of investments. Education is also promoted as a means of reducing inequality, of making other investments more productive, and as an avenue for social and political development (Haveman and Wolfe 1984). Yet recent concern about the quality of education in developing countries, particularly in Africa (World Bank, 1988), complicates the issue. In fact, a poor quality education could well be a poor investment.[1/]

Investments in education, like all investments, are largely evaluated in terms of their rates of return. Human capital theory provides a general methodology for estimating the rates of return to investments in education (Becker, 1975; Mincer, 1974). Application of this methodology to developing countries has produced apparent high rates of return which have been put forth as evidence of the need for giving priority to investments in education, particularly primary education, in developing countries (Psacharopoulos, 1985; World Bank, 1986).

This paper critically examines the extent to which rates of return to investments in education can be estimated using this methodology, with particular attention to the case where the quality of education may be

---

1/ Lau, Jamison and Louat found no relationship between adult education and real GDP in sub-Saharan Africa, which reinforces concern about the quality of education in Africa.

uneven. An unusually rich data set from Ghana, which includes tests of ability and cognitive skills administered to survey respondants, allows one to distinguish between the returns to years of schooling and the returns to human capital as measured by cognitive skills. It turns out that calculating rates of return to schooling investments is more complex than many applications of human capital theory seem to assume. Further, recommendations regarding which types of educational investments governments should undertake based on this methodology are inappropriate and potentially misleading.

The plan of the paper is as follows. Section II reviews the standard human capital theory underlying estimates of rates of return to investments in education, with particular attention to the impact of variation in ability, variation in skills attained and variation in school quality. Section III presents an econometric model to estimate private rates of return. Section IV uses household data from Ghana to demonstrate how "straightforward" application of human capital theory may lead to misleading results regarding the private returns to education. Section V examines specific hypotheses regarding the returns to investments in education in labor markets in Ghana. Section VI returns to the question of whether it is useful to estimate rates of return to education based on the standard human capital model, and Section VII concludes the paper.

II. RATES OF RETURN TO SCHOOLING INVESTMENTS: THE HUMAN CAPITAL MODEL AMONG OTHERS

The Human Capital Model. How can one estimate t..3 returns to investments in schooling? If one assumes that wage earners are paid their marginal product and that this marginal product rises as more human capital is accumulated, one might estimate private rates of return to additional years of schooling from wage data among persons who have different levels of education.[2/] The usual procedure is to assume that the logarithm of wages received by an individual i (w_i) is a function of the years of schooling (S_i) and years of experience (E_i) of that individual:

$$\ln(w_i) = f(S_i, E_i, u_i) \qquad (1)$$

$$\cong \alpha_0 + \alpha_1 S_i + \alpha_2 E_i + \alpha_3 E_i^2 + u_i$$

where the second line is a polynomial expansion of f that follows the common practice of dropping certain higher order terms and u_i represents other factors which affect wages but are assumed to be uncorrelated with schooling and experience.

One can then interpret α_1 as the private rate of return to schooling by appealing to the pioneering work on human capital by Becker (1975) and Mincer (1974). Their arguments for interpreting α_1 as the private rate of return to schooling are for the most part simply arguments for the functional

---

2/ Social rates of return, which adjust private rates by including costs of schooling borne by the government, will be discussed in section VI. That section will also discuss whether returns to additional years of schooling are appropriate tools for government investment decisions.

form given in (1).[3/] If one accepts that functional form (including the assumption on u_i) for any reason, empirical or theoretical, all one needs to assume further is that the cost of additional schooling is simply forgone wages, and then straightforward differentiation (or simple algebra) will yield α_1 as the private rate of return to schooling. Specifically, the annual private rate of return is the annual increase in income ($w_s - w_{s-1}$) divided by the cost of the investment (w_{s-1}):

$$\frac{w_s - w_{s-1}}{w_{s-1}} = \frac{w_s}{w_{s-1}} - 1 = \frac{e^{\alpha_0 + \alpha_1 S + \alpha_2 E_i + \alpha_3 E_i^2 + u_i}}{e^{\alpha_0 + \alpha_1 (s-1) + \alpha_2 E_i + \alpha_3 E_i^2 + u_i}} - 1 = e^{\alpha} - 1 \approx \alpha_1 \quad (2)$$

<u>Innate Ability and School Quality</u>. Estimating α_1 in (1) can be complicated by two potentially important factors: differences inn ability among individuals and differences in school quality, both among individuals and across time.[4/] To see this, modify model (1) to explicitly recognize that it is human capital, not years of school attendance, which makes workers more productive and thus leads to higher wages:

$$\ln(w_i) = g(H_i, E_i\ A_i, u_i) = \beta_0 + \beta_1 H_i + \beta_2 E_i + \beta_3 E_i^2 + \beta_4 A_i + u_i \quad (3)$$

where H_i is human capital accumulated by individual i, u_i is a random error term, and most higher order terms are omitted for expositional convenience. Differences in ability that may contribute directly (i.e. in addition to any

---

3/ For details see Appendix I.

4/ See Griliches (1977) for a discussion of the impact of ability on estimates of rates of return and Behrman and Birdsall (1983) on school quality.

indirect impact via human capital H) to increasing wages are captured in the ability variable A_i.

To see the effect of school quality on attempts to estimate the private returns to schooling using (1), it is useful to specify the process by which human capital is acquired. Assume that years of schooling, the quality of that schooling (Q), ability and family background characteristics (B) are the main factors which determine the acquisition of human capital:

$$H_i = h(S_i, Q_i, A_i, B_i, v_i) = \gamma_0 + \gamma_1 S_i + \gamma_2 Q_i + \gamma_3 A_i + \gamma_4 B_i + v_i \tag{4}$$

where quadratic and interaction terms are omitted for ease of exposition and v_i accounts for unmeasured factors which are not correlated with the other variables. If $\partial \ln(w_i)/\partial S_i$ can be interpreted as the private rate of return to schooling, then in the 2-equation system of (3) and (4) it is given by:

$$\partial w_i/\partial H_i \times \partial H_i/\partial S_i = \beta_1\gamma_1 \tag{5}$$

When does α_1 in equation (1) equal $\beta_1\gamma_1$? Substitute (4) into (3):

$$\ln(w_i) = \beta_0 + \beta_1(\gamma_0 + \gamma_1 S_i + \gamma_2 Q_i + \gamma_3 A_i + \gamma_4 B_i + v_i) + \beta_2 E_i + \beta_3 E_i^2 + \beta_4 A_i + u_i \tag{6}$$

$$= (\beta_0 + \beta_1\gamma_0) + \beta_1\gamma_1 S_i + \beta_1\gamma_2 Q_i + (\beta_1\gamma_3 + \beta_4)A_i + \beta_1\gamma_4 B + \beta_2 E_i + \beta_3 E_i^2 + (\beta_1 v_i + u_i)$$

The reduced form estimate in equation (6) is essentially (1) with additional variables for ability, school quality and family background. If any of the coefficients of these variables are non-zero and that variable is correlated with years of schooling (or experience), then estimates of (1) by OLS will suffer from omitted variable bias. It is likely that these variables are positively correlated with years of schooling, so that omitting them will tend to overestimate $\beta_1\gamma_1$ and thus overestimate the private returns to education. Note that the impact of ability works in two ways; even if it has no direct effect on wages (i.e. $\beta_4=0$) it may have an indirect effect by raising the amount of human capital attained for a given number of years (via γ_3) of schooling, which would still lead to omitted variable bias.

Other Schooling Models. The discussion so far assumes that the human capital model is the correct interpretation of positive correlation between schooling and wages. If wage employees were not paid their marginal products, or if schooling did not increase their marginal products, a private rate of return to schooling could be calculated but it would not represent the returns to investments in human capital. Two other models which purport to explain correlation between schooling and wages are the credentialist model (Spence, 1976) and the screening model (Arrow, 1973).

The former argues that workers may be paid on the basis of years of school attained or diploma held regardless of whether or not they are more productive workers. Of course, firms in the private sector which operate in this way are likely to have lower profits than firms which pay according to actual productivity of workers, and thus would tend to go out of business. However, government employers could conceivably pay workers according to a credentialist wage structure since they do not need to be profitable to survive. If credentialism exists in either sector one should find that years of schooling or diplomas obtained have a positive impact on wages even after one controls for human capital and ability. Thus if one adds years of schooling and dummy variables for diplomas obtained to equation (3) one would get a significantly positive coefficient (cf. Boissiere, et al, 1985).

The screening model argues that education does not necessarily impart productive skills to workers, but instead provides information by ranking workers according to their innate ability, which is the true productive asset which workers have. Employers can then judge the innate productivity of potential workers by observing their years of schooling, and although they will be paid according to their innate ability it may appear that human capital, as measured by schooling, is being rewarded. The best way to test this hypothesis is to examine the coefficients on ability and human capital in equation (3); if that on ability is significantly positive the screening model has some suppport, but otherwise its validity would be in doubt.[5]

5/ Entering an ability variable in equation (1) would be misleading because a positive effect of ability on wages may arise via the positive impact it has on human capital independent of schooling level [γ_3 in equation (4)] and consequently [$\beta_1\gamma_3$ in equation (6)] even if there is no direct effect of ability on wages (i.e. β_4 in equations (3) and (6) equals zero.

III. ESTIMATION

This section presents appropriate econometric methods for estimating equations (1) and (3) of Section II. The results will be presented in Section IV. In most developing countries many adults do not work in the wage sector. Thus estimates using ordinary least squares (OLS) may suffer from selectivity bias. Further, one would like separate estimates of returns to schooling for private wage earners and government wage earners, since perhaps only the former has a wage structure which reflects the impact of education on worker productivity, which is what government investment decisions must be based on. This suggests a model with three possible activities: wage employment in the private sector, wage employment in the government sector, and a residual category which includes self-employment and no employment. One observes wages for the first and second categories, but not the third.

It is convenient to model these labor market outcomes as the result of two binary events. The first divides individuals into those who work in the wage labor market and those who do not. For those in the former category, a second split is observed, separating those who work in the private sector from those in the public sector. This model can be expressed as follows:

$$\ln(w_g) = X_g\beta_g + u_g \qquad \text{government wage} \qquad (7)$$

$$\ln(w_p) = X_p\beta_p + u_p \qquad \text{private wage} \qquad (8)$$

$$I_1^* = Z_1\alpha_1 + v \qquad \text{govt. vs. private wage work} \qquad (9)$$

$$I_2^* = Z_2\alpha_2 + e \qquad \text{wage work vs. other activity} \qquad (10)$$

where Z_1 and Z_2 are vectors of exogenous variables (which may contain some or all of the variables in X_1 and X_2), and I_1^* and I_2^* are unobserved variables which correspond to observable indicator variables (I_1 and I_2) which take the value of 1 if the respective unobserved values are greater than or equal to zero and take the value of 0 if they are negative. I_2 (wage employment vs. other activity) is observed for the entire population, but I_1 (government vs. private wage work) is only observed if $I_2^* \geq 0$. Finally, w_g is only observed if $I_1^* \geq 0$ and $I_2^* \geq 0$ while w_p is only observed if $I_2^* \geq 0$ and $I_1^* < 0$.

The covariance matrix of this model can be written as:

$$\text{cov} \begin{vmatrix} u_g \\ u_p \\ v \\ e \end{vmatrix} = \begin{vmatrix} \sigma_g^2 & \sigma_{gp} & \sigma_{gv} & \sigma_{ge} \\ \sigma_{gp} & \sigma_p^2 & \sigma_{pv} & \sigma_{pe} \\ \sigma_{gv} & \sigma_{pv} & 1 & \sigma_{ve} \\ \sigma_{ge} & \sigma_{pe} & \sigma_{ve} & 1 \end{vmatrix} \tag{11}$$

The parameter σ_{gp} usually cannot be estimated because one rarely observes both wages for any individual. All other covariance parameters can be estimated. As long as all the variables in the vectors Z_1 and Z_2 are exogenous, both α_1 and α_2 are identified. In practice it is advisable to include variables in Z_1 which are not found in either X_1 or X_2 to assure identification of β_g and β_p. [6] Either a two-step procedure (cf. Poirier, 1980, and Fischer, Trost and Lurie, 1981) or a full maximum likelihood method can be employed. Both assume that the error terms in (11) are multivariate normal. The likelihood function used with the latter method is given in Appendix II.

6/ See Lee (1979) for issues of identification in a model which incorporates equations (7) - (9). Note that in the present paper no attempt is made to identify the structural probit in (9), i.e. the wage rates are not included as explanatory variables.

IV. PRIVATE RATES OF RETURN TO SCHOOLING IN GHANA

Section II cast some doubts on the estimates of the private returns to schooling based on equation (1). Although these and other caveats are well-known, many economists agree with Willis (1986, p. 590) that "the simple Mincer-type earnings function does a surprisingly good job of estimating the returns to education." This section uses an unusually rich data set from Ghana to systematically examine whether calculating private rates of return to schooling based on (3) and (4) give substantially different results than those based on (1). The data are from the second year of the Ghana Living Standards Survey (GLSS), which covered 3200 households from all regions of Ghana from October, 1988 to August, 1989. The GLSS data contain detailed information on many aspects of household conditions and activities in Ghana (cf. Glewwe and Twum-Baah, 1990). In this paper the GLSS data have been supplemented with three tests administered to household respondants between the ages of 9 and 55, inclusive. These data were collected for a subsample of 1586 households, thus comprising one half of the total sample of the second year of the GLSS.

The three tests covered abstract reasoning (Raven's Coloured Progressive Matrices), mathematics, and reading comprehension (in English). The last two were only administered to those persons who had completed at least three years of education and had passed simple screening tests (8 questions each) designed to prevent individuals with very low cognitive skills from taking the longer tests. Persons who failed the screening test or had less than 3 years of education were given a score of zero for the respective long test.[7]

7/ Some individuals who had less than 3 years of school but claimed to be able to read and/or write were given the reading and mathematics tests.

Conventional Estimates. To begin, several estimates of the earnings function given in equation (1) were computed.[8/] The variables are defined in Table 1 and the estimates are given in Table 2. Of all persons in the sample between 15 and 55 years, only 16% are wage workers. About 61% of these work for the government and the rest work in the private sector.

Beginning with the first column in Table 2, simple OLS estimates for all wage earners together yield fairly standard results. The private rate of return to education is 8-9% and the experience variables have the expected signs, although the statistical significance of the experience squared term is very weak (t-stat=-0.12). The rate of 8-9% is slightly below Psacharapolous' (1985, Table 3) general finding of 13% for Africa. Other things being equal, government jobs appear to pay more than those in the private sector, which is shown by the significantly positive dummy variable in column 2 of Table 2.[9/] Finally, in the third column of Table 2 a two-step estimator (cf. Heckman, 1979) controls for sample selectivity among wage earners as a whole. Note that private returns to schooling decline to less than 5% once selectivity is corrected, and it also appears that experience has no significant effect on

---

8/ In addition to the variables in (1), dummy variables are added for female wage earners and for residents of different geographic regions of Ghana (the omitted variable is the capital city, Accra). Removing female wage earners (25% of the sample) did not change the results noticeably - they were retained to maintain a larger sample size.

9/ In Ghana most government workers and some private sector employees receive compensation in the form of free goods and services, such as food, transportation and housing. The wage variable used here includes the monetary value of these goods and services.

TABLE 1: Variable Definitions and Means in Wage Equations

Durable	Mean	Std. Dev.	Definition
Wage	437.34	86.39	Hourly wage for main job during past 12 months, including value of payments in kind.
Years Schooling	9.59	5.08	Number of years of completed schooling.
Experience	18.33	11.05	Age - Years Schooling - 6.
Experience^2	457.75	509.52	Square of Experience.
Female	0.25	0.43	One for female, zero for male.
Government	0.61	0.49	One if government employee, zero otherwise.
Coast	0.27	0.44	One if resident of coastal area, zero. otherwise.
Forest	0.42	0.49	One if resident of forest area, zero otherwise.
Savannah	0.10	0.30	One if resident of Savannah, zero otherwise.

Note: Means and standard deviations are only for those individuals who are wage workers.

earnings. Further, women and residents of the forest or coastal areas seem to receive higher wages.[10/]

10/ These results are in most cases similar to those of Beaudry and Sowa (1989), who used the first year GLSS data. However, their paper suffers from several problems: 1. No attempt is made to control for sample selectivity; 2. Public and private sector workers are aggregated without testing for structural differences in wage determinants across these 2 sectors; and 3. They appear to include a large number of self-employed in their sample without realizing it.

TABLE 2: Earnings and Schooling in Ghana: Government and Private Wage Estimates

Variables	All Wage Earners OLS1	OLS2	2-step	Government OLS	Full ML	Private OLS	Full ML
Constant	2.9323	3.0187	3.7076	3.1606	4.2375	3.2720	3.9732
	(14.82)	(15.05)	(7.78)	(13.90)	(12.81)	(7.38)	(7.35)
Years Schooling	0.0851	0.0752	0.0483	0.0737	0.0380	0.0712	-0.0043
	(9.04)	(7.24)	(2.44)	(7.11)	(2.86)	(3.24)	(-0.14)
Experience	0.0216	0.0171	-0.0010	0.0216	0.0035	-0.0028	-0.0307
	(1.70)	(1.33)	(-0.06)	(1.65)	(0.21)	(-0.10)	(-0.85)
Experience^2	-0.0000	-0.0000	-0.0002	-0.0002	-0.0001	0.0005	0.0003
	(-0.12)	(-0.12)	(-0.74)	(-0.61)	(-0.36)	(0.78)	(0.36)
Female	0.1401	0.1098	0.2633	0.1928	0.0792	-0.0683	-0.2793
	(1.49)	(1.16)	(1.97)	(2.12)	(0.77)	(-0.33)	(-1.21)
Government	-	0.2105	0.2066	-	-	-	-
		(2.23)	(2.22)				
Coast	0.2365	0.2135	0.2338	0.1893	0.1142	0.2213	0.0193
	(1.96)	(1.77)	(2.22)	(1.56)	(0.72)	(0.90)	(0.06)
Forest	0.2392	0.2083	0.3405	0.2877	0.2022	0.0651	-0.2423
	(2.19)	(1.90)	(2.49)	(2.64)	(1.41)	(0.29)	(-0.86)
Savannah	0.1285	0.0524	0.1977	0.1500	-0.1258	-0.1398	-0.7020
	(0.83)	(0.33)	(1.09)	(1.04)	(-0.79)	(-0.36)	(-1.22)
Lambda	-	-	-0.3171	-	-	-	-
			(-1.59)				
σ_{uv}	-	-	-	-	-0.5102	-	-0.9514
					(-6.04)		(-4.07)
R^2 0.1860	0.1965	0.2014	0.2342	-		0.0904	-
Log Likelihood	-	-	-		-2396.97		-2396.97
Sample Size	389	389	389	237	237	152	152

Note: 1. t-statistics are in parentheses.

2. Variables included in the probit regressions (columns 3,5 and 7) but excluded in the wage regressions are marital status, family size, the three test scores, and a dummy variable which takes value of one if one's pa nt worked in a white collar job.

However, the assumption that wage determinants are identical in public and private wage employment in Ghana is doubtful.[11/] Further, estimates of returns to education should be done only for the private sector, since government pay scales may reward the educational attainment of workers in a manner only weakly related to their productivity (Psacharopoulos, 1986). The remaining columns of Table 2 estimate equation (1) separately for public and private sector employees. Turning first to the OLS estimates, the return to education is about 7% in both the public and private sectors. It is curious that experience in the public sector has a rather typical age-earnings profile, though with weak significance, while there is virtually no relationship between experience and wages in the private sector. It is also of interest that women who work in the public sector appear to have higher wages than otherwise identical males, but not so in the private sector Vijverberg and van der Gaag (1988) found a similar result in Côte d'Ivoire.

Maximum likelihood estimation of the full model (7)-(10) cannot reject the hypothesis that $\sigma_{ge} = \sigma_{pe} = \sigma_{ve} = 0$.[12/] Estimates of the full model are given in Appendix A. When maximum likelihood estimation of the simpler model (7)-(9) is used in both public and private sector regressions (columns 5 and 7, respectively), the returns to education drop to about 4% in the government and in the private sector they appear slightly <u>negative</u>, though

---

11/ The likelihood ratio test statistic for the hypothesis that the years schooling parameters are equal across the public and private sectors can be rejected only at the 75% significance level ($chi^2(1) = 1.57$). This low power reflects the small sample size. The identical test was performed for the 1st year of the GLSS data, whose large sample size includes 556 government workers and 426 private sector workers; the hypothesis is easily rejected at the 99.5% level of significance ($chi^2(1) = 11.22$).

12/ The test statistic for the likelihood ratio test was 1.78, which compares to a $chi^2(3)$ statistic of 7.81 at the 95% level of significance.

not significantly different from zero. The significantly negative covariance between the error terms in the wage equation and the probit in (8) indicates that the OLS estimates suffer from selectivity bias. Since it is private sector wages that are supposed to reflect worker productivity, one is led to the peculiar conclusion that there is no return to being educated in Ghana, except if one obtains a government job.[13/] This is a very different finding from what one would expect, or from what one obtains by estimating a simple OLS regression for both sectors combined (or separately) without controlling for selectivity. Controlling for selectivity also removes the significantly positive impact on government wages for female wage earners and residents of the forest region.

Intuitively, it is difficult to believe that there is no return to human capital in the private sector in Ghana, and studies of other developing countries also cast doubt on this finding (Psacharopoulos, 1985). One interpretation is that Ghana's education system has such low and uneven quality (cf. World Bank, 1989) that the omission of the school quality variable in (1) leads to biased results.[14/] One could also think of the problem as one of errors in variables (cf. Griliches, 1977); since the years of schooling variables measures human capital attained with a large amount of error, the parameter estimates on years of schooling are biased towards zero when interpreted as estimates of returns to human capital. How then can one estimate private rates of return to schooling for the general population? The

---

13/ It is also peculiar that there appears to be no returns to experience. This will be discussed in Section V.

14/ The World Bank report states that "... in many of the more remote areas, especially in the northern [i.e. Savannah] half of the country, the large majority (often more than 80%) of children completing grade 6, or even JSS1 [first year of secondary school], were completely illiterate."

following subsection calculates private rates of return to schooling using cognitive skills data available from Ghana.

Estimates Using Observed Cognitive Skills. Table 3 presents descriptive statistics for the variables needed to estimate (3), and Table 4 presents those estimates.[15/] Human capital (H_i) is measured by two variables, acquired reading and mathematics skills, while innate ability is measured by Progressive Matrices test.[16/] Years of schooling are omitted from these estimates as it is assumed that schooling contributes to wage rates only through the acquisition of cognitive skills. The validity of this assumption will be examined in Section V.[17/]

15/ Full maximum likelihood estimation of (7)-(10) could not reject the hypothesis that $\sigma_{ge} = \sigma_{pe} = 0$, but the assumption that $\sigma_{ve} = 0$ was rejected (cf. Appendix III). Since σ_{ve} probably has little effect on the wage equations (7) and III (8), maximum likelihood estimates of (7)-(9) were estimated. For comparison, Heckman's 2-step estimation is applied where the probits in (9) and (10) are estimated jointly (to allow for $\sigma_{ve} \neq 0$) but the Mills ratio is only calculated from the small probit (9), which is discussed briefly in Section V.

16/ For further information on the psychometric properties of this test, see Raven, et al (1984).

17/ Several specification tests were undertaken for equation (3) using Hausman's (1978) technique to test whether the mathematics and reading test scores are uncorrelated with the error term (i.e. exogenous). Instrumenting both variables simultaneously proved difficult because the instrumented math and reading test scores were highly correlated. Thus the tests were performed separately on the 2 test scores for the 2-stage estimators. For the private sector, one could not reject the hypothesis of no correlation for either test score, but for the government sector the hypothesis is rejected for both scores, which implies that the government wage is missspecified. However, the specification for the government sector in Section V below does not suffer from this problem. For details see Appendix IV.

TABLE 3: Means of Test Score and Other Variables by Wage Sector

Variable	Government Mean	Government Standard Deviation	Private Mean	Private Standard Deviation
Log (wage)	4.5275	0.6734	4.0564	1.0359
Years Schooling	10.4937	5.0687	8.1842	4.7750
Reading	15.1730	9.6309	9.8158	9.4241
Mathematics	11.9452	8.7808	7.6974	7.0730
Raven's Test	24.9873	7.6996	24.4803	6.9568
Experience	20.4304	11.2987	15.0526	9.8235
Experience^2	544.5232	553.4790	322.4474	397.5571
Female	0.2658	0.4427	0.2237	0.4181
Coast	0.2447	0.4308	0.3026	0.4609
Forest	0.4346	0.4968	0.4013	0.4918
Savannah	0.1308	0.3379	0.0592	0.2368
Sample Size	237		152	

Note: The maximum scores possible on the three tests are as follows: Reading - 29, Mathematics - 36, Raven's test - 36.

Turning first to the government sector, one sees that reading skills have no predictive power on wages but mathematics skills have a strong positive effect. Innate ability as measured by the Raven's test has no significant independent effect on wages, though it will be seen below that it has a strong effect on reading and mathematics scores. The experience variables still have weak statistical significance. Finally, the maximum likelihood estimates of the covariance term between the errors u_g and v is still significantly different from zero, indicating sample

TABLE 4: Wages and Cognitive Skills

Variable	Maximum Likelihood		2-Step	
	Government	Private	Government	Private
Constant	4.1582 (13.27)	3.8637 (7.36)	3.6898 (9.89)	3.9149 (7.73)
Reading	-0.0043 (-0.45)	0.0356 (1.68)	0.0033 (0.37)	0.0339 (2.09)
Mathematics	0.0260 (3.00)	0.0207 (0.85)	0.0342 (3.78)	0.0191 (0.95)
Raven Test	0.0074 (0.74)	-0.0202 (-1.07)	0.0003 (0.03)	-0.0202 (-1.23)
Experience	0.0075 (0.45)	-0.0142 (-0.40)	0.0169 (1.22)	-0.0180 (-0.62)
Experience^2	-0.0002 (-0.69)	0.0006 (0.71)	-0.0003 (-1.02)	0.0006 (0.92)
Female	0.0982 (0.99)	-0.0234 (-0.09)	0.1669 (1.86)	-0.0119 (-0.06)
Coast	0.0878 (0.53)	0.2179 (0.86)	0.1334 (1.15)	0.2231 (0.98)
Forest	0.2206 (1.41)	0.1733 (0.61)	0.3160 (2.75)	0.1743 (0.75)
Savannah	-0.0851 (0.51)	-0.0279 (-0.04)	0.1041 (0.63)	-0.0302 (-0.07)
σ_{uv}	-0.4705 (-5.71)	-0.1187 (-0.24)	-	-
Log Likelihood	-2389.65	-	-	-
Lambda	-	-	-0.0876 (-0.50)	0.1959 (0.54)
σ_{ev}	-	-	0.3349 (0.23)	0.3520 (0.15)
R^2	-	-	0.2809	0.1509
Sample Size	237	152	237	152

Note: 1. t-statistics are in parentheses.
2. Identify variables in the probit equation are years of schooling, marital status, family size, and a dummy variable taking the value of unity if the individuals mother or father was a white collar worker.

selectivity is still important for government workers. The 2-step estimator gives broadly similar results, except: 1. The parameter estimate for the mathematics test score is somewhat higher; 2. The coast dummy variable is significantly positive, and 3. The coefficient on the Mill's ratio is insignificant, indicating no selectivity.

The private sector estimates in Table 4 reveal that reading skills have a significant (10% and 5% levels of significance for maximum likelihood and 2-step estimators, respectively) and strongly positive effect on wages, while mathematical ability has a lower and statistically insignificant impact. Innate ability (Raven's score) has no significant independent impact on private sector wages, and has an unexpected negative sign. The experience variables are still insignificant and trace out an unexpected age-earnings profile; this will be taken up in Section V. Note also that the Savannah dummy variable decreases substantially in absolute value, which suggests that it indicated school quality in Table 2, since Savannah schools are generally of poor quality in Ghana (cf. World Bank, 1989). All these conclusions also hold using the 2-step estimator. Finally, the covariance term between the errors u_g and v declines dramatically and loses its statistical significance, indicating that this specification is little affected by problems of selectivity bias.

Given these effects of reading and mathematics skills on wages, what remains is to estimate the impact of a year of schooling on the acquisition of these skills by estimating the parameters in (4), which in turn can be used to calculate the returns to schooling as given in (5). Equation (4) asserts that attainment of skills depends on years of schooling, innate ability, schooling quality, and family background variables. Unfortunately, it is very difficult to get accurate information on schooling quality for people who have left

TABLE 5: Determinants of Cognitive Skills

Variable	Reading	Mathematics	Mean	Std. Dev.
Constant	1.7814	4.2348	1.0000	0.0000
	(1.97)	(5.71)		
Age	0.0473	-0.0248	24.5558	12.4953
	(1.31)	(0.84)		
Age ^{2}	-0.0003	0.0003	757.9333	729.7536
	(-0.48)	(0.79)		
Sex	-0.5400	-0.8661	0.5194	0.4997
	(-3.46)	(-6.78)		
Years Schooling	-0.3133	-0.2212	5.2329	4.6190
	(-3.79)	(-3.26)		
Years Schooling^2	0.0166	0.0205	48.7122	63.1658
	(3.49)	(5.26)		
Age & Years Schooling	0.0101	0.0057	131.6245	153.6734
	(5.78)	(3.95)		
Raven Test	-0.1654	-0.3308	19.4176	6.6958
	(-2.10)	(-5.13)		
Raven Test^2	0.0064	0.0096	421.8644	296.2742
	(3.18)	(5.80)		
Father's Year's Schooling	0.0152	0.0098	2.8890	5.0825
	(0.93)	(0.73)		
Mother's Year's Schooling	0.0039	-0.0126	0.9232	2.8627
	(0.14)	(-0.54)		
Coast	-1.5280	-0.8672	0.2534	0.4348
	(-5.07)	(-3.51)		
Forest	-2.2482	-1.[illegible]262	0.4711	0.4992
	(-7.83)	(-4.36)		
Savannah	-1.7442	-1.0581	0.1917	0.3937
	(-5.29)	(-3.91)		
Raven x Year's Schooling	0.0064	0.0096	119.9919	132.7214
	(3.18)	(6.99)		
Raven x Age	-0.0007	0.0003	485.5300	305.9524
	(-0.55)	(0.34)		
R^2	0.6815	0.6629		
Sample Size	3568	3568		

Note: t-statistics are given in parentheses.

school many years ago. The approach taken here is to capture the main differences in schooling quality by putting dummy variables for three of four geographic regions in Ghana (Accra being the omitted variable) to control for regional variation in school quality and by introducing an interaction term between age and years of schooling to capture variation in school quality over time. The family background variables used are mother's education, father's education, and a sex dummy variable to control for possible discrimination against girls in schooling attainment. Several quadratic and interaction terms are used to provide a relatively flexible functional form.

Ordinary least squares (OLS) estimates of the determinants of reading and mathematics skills are given in Table 5. Neither skill is significantly affected by age, which indicates that people's retention of skills is fairly strong as they grow older. There is a significantly negative female dummy variable, but the exact cause of this will not be examined here. Years of schooling has a strongly significant quadratic impact on reading and mathematics scores, the impact being stronger at higher levels of education.[18/] Interaction terms of school years with age and with the Raven's score imply that the impact of years of schooling is never negative. The significantly positive coefficient on the latter interaction term suggests that individuals with higher innate ability learn more for a given amount of time in school, and that on the former implies that persons who attended school many years ago learned more per year of school than persons attending today. This is consistent with claims that school quality declined substantially in Ghana in the 1970's and 1980's (cf. Keith, 1985).

[18/] One could argue that years of schooling is endogenous, (e.g. cognitive skills may determine entrance to higher levels of schooling), which would imply that the model being estimated is misspecified. This was tested using Hausman's (1978) technique. For the mathematics score regression, the t-statistic for the instrumented years of schooling variable (the key instruments were parents' years of schooling) was only 0.21, and the point estimate was very close to zero relative to the point estimate for the years of schooling variable. Similar results held for the reading score regressions (t-statistic was 0.76). For details see Appendix IV.

Generally speaking, innate ability as measured by the Raven's test is strongly positively correlated with attainment of skills.[19/] The quadratic specification shows an accelerated relationship, with only relatively low Raven's test scores (12 for reading and 16 for mathematics) showing a negative impact. In addition, the strong positive interaction effect of the Raven's test and years of schooling on cognitive achievement implies that for almost the entire sample the change in cognitive skills from an increase in innate ability is positive. Once one controls for innate ability, the impact of family background as measured by mother's and father's education is small and statistically insignificant (though parental education does have an indirect effect via its positive impact on years of schooling - cf. Appendix IV).

The regional dummy variables show strong variation in attainment of reading and mathematics skills across geographic regions in Ghana which lend themselves well to a school quality interpretation. The omitted region, the capital city Accra, has the best schools in Ghana, both public and private, while it is almost certain that the Savannah schools in Northern Ghana have the worst (cf. World Bank, 1989). On average, one could probably state that the schools in the Coastal areas are better than those in the Forest areas because the former schools have been in existence longer. The dummy variables for the two regressions in Table 5 support this ranking; all are strongly negative, with the Coast have the least negative coefficient and the Forest and Savannah areas competing for last place. For purposes of estimating the impact of years of schooling on the attainment of reading and mathematics skills, it may be reasonable to assert that specification error due to

---

19/ The Raven's Test score may well capture "motivation" and test-taking experience as well as innate ability. This is useful for the purpose at hand since one would want to control for these variables as well when estimating the impact of schooling on attainment of cognitive skills.

omitting variables of school quality has been avoided to a large extent.

To calculate γ_1 in equation (4) differentiate the specification given in Table 5 by years of schooling; the interaction and squared terms imply that the marginal effect of a year of schooling on reading and mathematics ability is a function of the years of schooling, the age of the person and the Raven's score. Table 6 shows different marginal impacts of schooling on these skills for different values of years of schooling and age, evaluated at the mean value of the Raven's score in the sample. Two conclusions stand out. First, the marginal impact of a year of schooling is much lower for younger people relative to older people; for both mathematics and reading skills the marginal effect for someone aged 55 is almost double that of a 10-year-old, again indicating that the quality of schooling has declined substantially in Ghana over the past 30 years. Second, for both reading and mathematics the impact of a year of schooling is stronger at higher levels of schooling, especially for reading skills, implying that primary education has a lower rate of return likelihood estimator. relative to higher levels of schooling.[20]

Table 7 calculates rates of return to schooling using a formula similar to that in equation (5), the only difference being that the separate impacts of reading and mathematics are summed. Since public sector wages show an insignificant and relatively small impact of reading ability on wages, that coefficient has been set to zero. For the private sector the mathematics score had a sizeable but insignificant effect on wages. The first estimates assume that the point estimate is accurate, while the calculations given in

---

[20] In Section V the calculations in Tables 6 and 7 are done so as to distinguish between different schooling levels. It will be seen that the stronger impact for higher levels of schooling does not hold for the highest levels of schooling.

TABLE 6: Marginal Impact on Math and Reading Skills from One Year of School

Mathematics

Age:		10	15	25	40	55
Years Schooling:	4	0.3316	0.3601	0.4171	0.5026	0.5881
	9	-	0.3886	0.4456	0.5311	0.6166
	13	-	-	0.4684	0.5539	0.6394

Reading

Age:		10	15	25	40	55
Years Schooling:	4	0.5918	0.6423	0.7433	0.8948	1.0463
	9	-	0.8083	0.9093	1.0608	1.2123
	13	-	-	1.0421	1.1936	1.3451

TABLE 7: Rates of Return to Schooling

Private Sector

Age:		10	15	25	40	55
Years Schooling:	4	2.79% (2.11%)	3.03% (2.29%)	3.51% (2.64%)	4.23% (3.19%)	4.94% (3.72%)
	9	-	3.68% (2.88%)	4.16% (3.24%)	4.88% (3.78%)	5.59% (4.32%)
	13	-	-	4.68% (3.71%)	5.40% (4.25%)	6.11% (4.79%)

Public Sector

Age:		10	15	25	40	55
Years Schooling:	4	0.86% (1.13%)	0.94% (1.23%)	1.08% (1.43%)	1.31% (1.72%)	1.53% (2.01%)
	9	-	1.01% (1.33%)	1.16% (1.52%)	1.38% (1.82%)	1.60% (2.11%)
	13	-	-	1.22% (1.60%)	1.44% (1.89%)	1.66% (2.19%)

Note: Figures in parentheses for the private sector assume that the impact of mathematics skills on wages in private sector equals zero, since it is not significantly different from zero. Figures in parentheses in the public sector assume that the 2-step estimator in Table 4 is more accurate than the maximum parentheses assume that the impact of mathematical ability on wages is zero.

Using the maximum likelihood estimates from Table 4 the private rates of return for one year of education in the private sector market in Ghana range between 2.8% and 6.1%, depending on the age and level of schooling. These are lower than the 7% figure given by the OLS estimates in Table 2 (column 6) but are higher than the complete lack of returns found in column 7 of Table 2. As one would expect from Table 6, the rates of return rise with age and decline with years of schooling. The former finding makes clear that the private returns to investment in schooling of 5-6% being reaped by those who attended school 30-40 years ago are not available to those who are attending school today, and the most plausible interpretation is that the quality of schooling today is markedly inferior to that attained in previous decades.[21/] Note that use of the human capital model in this manner produces private rates of return in the public sector that are much lower than in the private sector, regardless of whether the maximum likelihood or the 2-step estimates in Table 4 are used. However, this assessment is incomplete because there may be returns to schooling apart from those attained as returns to these skills if credentialism is operating in the public sector. This will be investigated in the next section.

21/ One might be tempted to ascribe this to some kind of cohort effect in the labor market, i.e. the older workers are getting higher returns to their human capital than the younger ones. Yet the specification of equation (3) forces the returns to human capital (as measured by mathematics and reading skills) to be the same for all workers. The "cohort effect" in Table 7 is due to the age-schooling interaction term in equation (4) which has absolutely nothing to do with labor market outcomes.

V: FURTHER EXAMINATION OF THE HUMAN CAPITAL MODEL IN GHANA

Is There Evidence of Screening or Credentialism? As pointed out in Section II, the screening model of education assumes that education simply serves as a "screen" or indicator of innate ability (or motivation), and does not in and of itself produce skills which make workers more productive. If this were true, one would expect that the Raven's test and not the reading or mathematics tests would have a strong and significant effect on wages in the private sector, and perhaps in the public sector as well. If it were partially true, then perhaps both the Raven's test and the other tests would have significantly positive effects on wages. However, the results in Table 4 indicate that neither is the case; the coefficients on the Raven's test are not significantly different from zero. Yet, this does not mean that innate ability has no effect on wages; the results from Table 5 indicate that it does so indirectly because it enables individuals to aquire more mathematics and reading skills. This result is essentially the same as that of Boissiere, Knight and Sabot (1985), who examined urban workers in Kenya and Tanzania.

The credentialist model hypothesizes that persons who have high credentials, as measured by years of schooling or attainment of diplomas, receive higher wages because they have those diplomas, not because they have acquired human capital skills. To test this hypothesis, the model in equation (3) was estimated adding the years of schooling variable and dummy variables for diplomas obtained. There is evidence that equation (3) without these variables is misspecified for the government sector (cf. footnote 17). The results are presented in Table 8 using both maximum likelihood estimation of (7)-(9) and the 2-step estimator based on the bivariate probit estimate of

TABLE 8: Testing for Credentialism

Variable	Maximum Likelihood Government	Maximum Likelihood Private	2-Step Government	2-Step Private
Constant	3.1172	4.1098	3.9034	3.9036
	(7.63)	(6.53)	(11.04)	(4.43)
Years Schooling	0.0340	-0.0452	0.0122	0.0250
	(1.81)	(-1.05)	(0.68)	(0.71)
Middle School Cert.	0.0384	-0.2852	0.0389	-0.1998
	(0.34)	(-1.11)	(0.41)	(-0.91)
O-Level Dipl.	0.0343	-0.0683	0.0308	0.0286
	(0.16)	(-0.16)	(0.18)	(0.08)
Teacher Training	0.4817	-	0.5064	-
	(2.67)		(3.29)	
Higher Degree	-0.2722	-0.6448	-0.2302	-0.4677
	(-1.18)	(-0.60)	(-1.04)	(-0.71)
Reading	0.0014	0.0276	-0.0015	0.0399
	(0.12)	(1.35)	(-0.19)	(2.57)
Mathematics	0.0340	0.0066	0.0244	0.0246
	(3.34)	(0.28)	(2.78)	(1.55)
Raven Test	-0.0075	0.0001	-0.0062	-0.0288
	(-0.76)	(0.01)	(-0.69)	(-1.20)
Experience	0.0202	-0.0396	0.0136	-0.0048
	(1.24)	(-1.07)	(1.02)	(-0.17)
Experience^2	-0.0001	0.0004	-0.0002	0.0006
	(-0.29)	(0.46)	(-0.83)	(0.78)
Female	0.1697	-0.2599	-0.0062	0.0108
	(1.74)	(-0.96)	(-0.05)	(0.05)
Coast	0.1563	0.0368	-0.0205	0.3212
	(0.93)	(0.12)	(-0.05)	(1.15)
Forest	0.3040	-0.0762	0.0562	0.3295
	(1.80)	(-0.26)	(0.36)	(0.96)
Savannah	0.2687	-0.5271	-0.1517	0.2450
	(1.29)	(-0.92)	(-0.69)	(0.42)
σ_{uv}	0.2840	-0.9541	-	-
	(1.80)	(-3.84)		
Log Likelihood	2377.02	-	-	-
Mills Ratio	-	-	-0.7261	-0.1516
			(-1.60)	(-0.31)
σ_{ve}	-	-	0.8895	
			(-9.91)	
R^2	-	-	0.3626	0.1599
Sample Size	237	152	237	152

Note: None of the private sector workers had a teacher training degree.

(9) and (10).[22] For the private sector both estimators given the same results; neither years of schooling nor any of the diploma variables have significant explanatory power beyond that provided by test scores, which implies that credentialism is not operating in that sector. In the public sector there is clear evidence of credentialism - maximum likelihood estimation shows a significantly positive coefficient on the teacher training degree and an almost significantly positive one on the schooling variable, while the 2-step estimator shows a significant positive effect of the teacher training degree only. This supports the hypothesis that credentialism is operating in the public sector in Ghana.

How Are Workers Allocated Between the Public and Private Sectors? The estimation strategy presented in Section III requires the estimation of 2 probit models, one which divides wage workers from all other individuals and the other which divides government and private wage workers. Though they are not the main focus of attention in this paper some comments can be made. The results of the former probit are given in Appendix III. Individuals who are more educated, both in terms of years of schooling and reading ability, are more likely to have wage occupations. The same is true of mathematics and innate ability as measured by the Raven's score, but these two parameters are not significantly different from zero. Women are less likely to take wage occupations than men. Finally, the three regions outside of Accra have fewer wage work opportunities and thus their residents are less likely to be working in the formal sector.

[22] The 4 diploma variables are Middle School Leaving Certificate (Grade 10), O-Level Diploma (Grade 15), Teacher Training A or B (15+3, or 10+4, respectively) and a fourth variable including all higher degrees.

Table 9 presents three sets of probit estimates on the separation of wage earners into government and private sector workers. The dependent variable takes the value of one if the individual works for the government. The three different estimates represent maximum likelihood estimation of (7)-(10), of (7)-(9), and of (9)-(10), the last of which is used in the 2-step procedure, in columns 1, 2 and 3, respectively. All three estimations show that persons with relatively high innate ability, as measured by the Raven's score are less likely to work for the government, and that persons living outside Accra (particularly in the Forest and Savannah areas) are more likely to work for the government. The latter finding simply reflects the fact that most wage employment outside of Accra is government employment. The former result is interesting because it indicates that more talented (in terms of innate ability and perhaps motiviation) persons avoid government employment, but puzzling because the wage equations did not reveal any separate impact of Raven's test scores on wages. Perhaps it reflects a taste factor in that more able and motivated persons prefer private sector work for reasons other than higher pay, or it may indicate that government hiring practices discriminate against individuals who have higher levels of innate ability.

Other results from Table 9 show weaker significance, depending on the estimation technique used. First, there is some support for the hypothesis that people with more schooling tend to have government jobs, which provides some support for the credentialist hypothesis. Second, persons with higher mathematics ability are more likely to work in the public sector, which is consistent with the finding that such skills are rewarded more in that sector than in the private sector. Third, the evidence on reading scores suggests some tendancy toward government jobs, but this does not fit well with the findings above that only the private sector rewards reading ability. Finally, note that there is some evidence that married individuals and persons with

TABLE 9: Government Employment vs. Private Sector

	4-equation model	3-equation model	2-equation model
Constant	0.2925	-1.9189	-2.6196
	(0.45)	(-3.54)	(-1.77)
Sex	0.6476	0.4304	0.2642
	(1.68)	(1.99)	(0.48)
Years Schooling	0.0389	0.0976	0.1212
	(1.37)	(3.46)	(3.18)
Raven Test	-0.0435	-0.0490	-0.0463
	(-3.40)	(-2.96)	(-2.01)
Reading Test	0.0078	0.0284	0.0301
	(0.58)	(1.78)	(1.84)
Mathematics Test	0.0190	0.0339	0.0338
	(1.22)	(1.78)	(1.84)
Experience	-0.0135	0.0315	0.0489
	(-0.52)	(1.03)	(0.98)
Experience^2	0.0009	0.0005	0.0003
	(1.82)	(0.82)	(0.28)
Coast	0.0433	0.0389	0.0319
	(2.23)	(1.64)	(1.01)
Forest	0.0770	0.0692	0.0536
	(4.36)	(3.28)	(1.16)
Savannah	0.1226	0.1326	0.1134
	(4.33)	(4.01)	(1.88)
Married	0.1313	0.2547	0.4072
	(0.95)	(1.42)	(1.85)
Family Size	0.0616	0.0401	0.0066
	(2.41)	(1.37)	(0.14)
Parent's Occupation	0.2395	0.2512	0.3020
	(1.09)	(0.95)	(1.08)
Sample Size	389	389	389

Note: The logarithms of the likelihood functions for all three models are not comparable since they include different numbers of equations. The log likelihood for the 4-equation model is given in Appendix A, while that for the 3-equation model is in Table 4. The log likelihood for the 2-equation model is -967.14.

---

large families are more likely to work in government jobs, which may reflect a perception that such jobs are more stable.

Does Experience Matter in Ghana? The human capital model of Becker and Mincer hypothesizes that wage earners will receive higher wages as they gain more years of experience because they accumulate more human capital as they are working, a process known as post-school investment.[23/] At some point a peak is reached as it becomes no longer profitable to accumulate addition human capital near the end of one's working life. Most wage regressions on survey or census data show such an earnings-age profile, but these data from Ghana do not. It could be that in the public sector wage scales are rigid in a way which prevents this from happening, but it is difficult to understand why this comes about in the private sector. Several hypotheses were checked with the data but failed to provide returns to experience: 1. Limiting the regressions to men only; 2. Using job specific experience rather than a general experience variable; and 3. Using a different, larger data set from Ghana (the 1987-88 GLSS data set which includes 982 wage workers including ... from the private sector).

This may be due to a prevalence of occupations for which prospect for on-the-job accumulation of human capital are weak. It is not clear th the occupations of the 152 private sector workers in the sample, as seen in Table 10, are ones for which post-schooling investments can greatly enhance marginal productivity. Further, the sizeable deterioration of the Ghana economy in the 1970's and early 1980's (cf. Glewwe and Twum-Baah, 1990) may have brought a situation where past investments in specific types of human capital have yielded few returns. These two arguments are admittedly speculative; full consideration of returns to experience is beyond the scope of this paper.

23/ The model assumes that learning on the job takes time away from product work, and thus lowers wages. Alternatively, one could assert "learning by doing," so that wages are not lowered as human capital is accumulated.

TABLE 10: Occupation of Private Sector Wage Earners

Transport Operators	6.4%
Fisherman	6.4%
Construction Workers	5.7%
Wholesale or Retail Trade	7.6%
Other Service Workers	5.1%
Farm Workers	4.5%
Painters	3.8%
Electrical Workers	3.2%
Food Service Workers	2.5%
Production Workers	2.5%
Workers in Religion	2.5%
Other Occupations	27.4%
Occupation Not Elsewhere Classified	19.1%

Rates of Return to Education by Schooling Level As pointed out in Section II, one can estimate private rates of return by different levels of schooling. This would involve estimating separate γ's in (4) for each level of schooling. Although the estimates of the impact of schooling on skill attainment (Table 6) and rates of return (Table 7) done in Section IV provide indirect information on the likely impact of different levels of schooling, it is useful to do so directly as well.

Table 11 presents estimates of the determinants of cognitive skills similar to those presented in Table 5 except that schooling and its square have been replaced by 4 variables which represent years of schooling at 4 different schooling levels: primary (grades 1-6), middle (grades 7-10), secondary (grades 11-17) and post-secondary (18 or more). Ghana is rather unusual in that 17 years of education are needed for entering post-secondary education. Most of the non-schooling variables display the same effect as in Table 5. When examining the coefficients of the schooling level variables the four schooling levels must be examined along with years of schooling interaction terms; e.g. the returns to primary school are not necessarily negative because one must add the age/years schooling and Raven/years schooling interaction terms. This is done in Table 12, which calculates the marginal impact of a year of schooling on mathematics and reading achievement.

Turning first to the mathematics, a year of primary schooling seems to have the lowest marginal impact while a year of middle schooling appears to have the highest. The impact of secondary and post-secondary schooling have intermediate effects. Notice also that those who attended school many years ago seem to have learned more for each year of schooling, especially at the primary level. The reading scores tell essentially the same story, except that it is necessary to comment on the very low impact at the primary level for those aged 10 and 15, and the negative impact at the post-secondary level. Turning to the former, it is worth keeping in mind that recent policy changes have put somewhat more emphasis on learning to read in African languages at the very first grades, which may partially explain why primary achievement in English is lower now than it was for those who attended schools many years ago. Still, children do study English at the higher level of the primary grades, and it appears they are not learning it (cf. World Bank, 1989). Also, English is much more widely used in Ghana as a written language than are the written forms of the various African languages, and thus reading [illegible] 11: **Determinants of Cognitive Skills with Separate Effects by Level of Education**

[illegible]able	Mathematics	Reading	Mean	Std. Deviation
[illegible]stant	5.1069	5.0970	1.000	0.0000
	(7.50)	(6.43)		
[illegible]	-0.0559	-0.0827	24.5558	12.4453
	(-2.14)	(-2.72)		
[illegible]^2	0.0008	0.0012	757.9333	729.7536
	(1.85)	(2.41)		
[illegible]s Primary	-0.3239	-0.7627	3.5723	2.5723
	(-4.48)	(-9.07)		
[illegible] Middle	0.4665	1.1434	1.3417	1.7627
	(4.33)	(9.12)		
[illegible]s Secondary	0.1189	0.0649	0.3010	1.1953
	(0.93)	(0.42)		
[illegible]rs Post-Sec.	-0.1041	-2.6871	0.0179	0.2443
	(-0.34)	(-7.51)		
[illegible]ather's Year's Schooling	0.0075	0.0085	2.8890	5.0825
	(0.56)	(0.55)		
[illegible]other's Year's Schooling	-0.0109	0.0107	0.9232	2.8627
	(-0.47)	(0.40)		
[illegible]	-0.8851	-0.6330	0.5194	0.4997
	(-6.97)	(-4.28)		
[illegible]	-0.9445	-1.6793	0.2531	0.4348
	(-3.85)	(-5.88)		
[illegible]	-1.1241	-2.4687	0.4711	0.4992
	(-4.80)	(-9.06)		
[illegible]annah	-1.2141	-2.2440	0.1917	0.3937
	(-4.50)	(-7.15)		
[illegible]en	-0.3265	-0.1924	19.4176	6.6958
	(-5.41)	(-2.74)		
[illegible]^2	0.0092	0.0061	421.8644	296.2742
	(5.61)	(3.20)		
[illegible]rs Schooling	0.0059	0.0100	131.6295	153.6734
	(4.98)	(7.22)		
[illegible]Years Schooling	0.0260	0.0328	119.9919	132.7214
	(7.52)	(8.14)		
[illegible]	0.6675	0.7142	-	-
[illegible]ple Size	3568	3568	3568	-

[illegible] in English probably has a much higher contribution to productivity in [illegible]place than reading ability in the African languages. Regarding the [illegible] post-secondary scores, two points should be made: 1. Instruction at [illegible] [illegible]-secondary level is not intended to improve an individual's reading ability, and in fact is often intended to develop specialized skills which are not picked up by either the mathematics or reading tests; and 2. This result is based on only 23 persons out of a sample of 3568, 17 of whom were working for the government. For this reason it is probably best to assume that the impact of post-secondary education on reading skills is zero.

Table 13 presents private rates of return by level of schooling analogous to those in Table 7. For the private sector the rates of return are very low for primary school, about 1-3%, and highest for middle school, about 9-11%. At higher levels of education they drop somewhat (5-7% for secondary and 1-2% for post-secondary) but some of this decline reflects the fact that skills are being obtained which are not reflected in the mathematics and the reading scores. As in Table 7, one sees that rates of return are lower for people who have attended school more recently, which again suggests that schooling quality has declined in recent years. The results also imply that investments in primary schooling yield very poor returns, and as such improvement in the quality of primary schooling (as opposed to building new schools at the same level of quality) is a critical need in Ghana. Finally,

TABLE 12: Marginal Impact on Math and Reading Skills from One Year of School

Mathematics

	Age:	10	15	25	40	55
Level:	Primary	0.2411	0.2708	0.3302	0.4192	0.5083
	Middle	-	1.0612	1.1206	1.2096	1.2987
	Secondary	-	-	0.7730	0.8620	0.9511
	Post-Sec.	-	-	0.5500	0.6390	0.7281

Reading

Age:		10	15	25	40	55
Level:	Primary	-0.0253	0.0247	0.1248	0.2748	0.4249
	Middle	-	1.9308	2.0309	2.1809	2.3310
	Secondary	-	-	0.9524	1.1024	1.2525
	Post. Sec.	-	-	-1.7996	-1.6496	-1.4995

TABLE 13: Private Rates of Return to Schooling by Level of Education

Private Sector

Level \ Age:	10	15	25	40	55
Primary	0.5% (0.0%)	0.7% (0.1%)	1.1% (0.4%)	1.9% (1.0%)	2.6% (1.5%)
Middle	-	9.1% (6.9%)	9.5% (7.2%)	10.3% (7.8%)	11.0% (8.3%)
Secondary	-	-	5.0% (3.4%)	5.7% (3.9%)	6.5% (4.5%)
Post-Sec.	-	-	1.1% (0.0%)	1.3% (0.0%)	1.5% (0.0%)

Public Sector

Level \ Age:	10	15	25	40	55
Primary	0.6% (0.8%)	0.7% (0.9%)	0.9% (1.1%)	1.1% (1.4%)	1.3% (1.7%)
Middle	-	2.8% (3.6%)	2.9% (3.8%)	3.1% (4.1%)	3.4% (4.4%)
Secondary	-	-	2.0% (2.6%)	2.2% (2.9%)	2.5% (3.3%)
Post-Sec.	-	-	1.4% (1.9%)	1.7% (2.2%)	1.9% (2.5%)

Note: Figures in parentheses assume that the impact of mathematics skills on wages in private sector equals zero, since it is not significantly different from zero. For the public sector, figures in parentheses are based on the 2-step estimator in Table 4. Finally, negative terms in Table 12 are set to zero for Table 13.

---

note that the returns to schooling at all levels are rather weak in the public sector, unless credentialism is taking place or formal schooling aids one in obtaining a government job.

VI: RATES OF RETURN TO SCHOOLING INVESTMENTS RECONSIDERED

This section critically assesses whether the private rates of return to schooling presented in Sections IV and V provide useful information for governments' schooling investment decisions.[24] Those estimates assume that the derivative of the log of wages with respect to years of schooling, albeit calculated indirectly via test scores, can be interpreted as the private rate of return to investments in additional years of schooling. It is worthwhile to critically examine this assumption, which amounts to assuming two things: that benefits from additional years of schooling can be measured by the percentage increase in the wage rate due to cognitive skills acquired from an additional year of schooling, and that the costs can be measured by forgone wages. The first two subsections will examine whether these assumptions are reasonable. The third will examine whether estimates of private rates of return to additional years of schooling are relevant to government schooling investment decisions.

Benefits of Schooling. There are several reasons to suspect that the demand for schooling is not simply a matter of an investment which is undertaken solely to increase the present discounted value of earnings. First, education can be viewed as a consumption good as well as an investment good, so that overall demand will reflect the "sum" of these two aspects. Thus, the rate of return as measured by increments in wages will underestimate the true private value of investments in education and may lead to the false conclusion that too much investment in education is taking place.

---

[24] Social rates of return are often calculated which adjust private rates of return by incorporating government costs of providing schools which are not borne by the individual. Social returns will be discussed below; for now it is important to keep in mind that virtually all problems with estimating private rates of return will also be present when social rates are calculated.

Second, any individual's return to investments in education will depend on the stream of future earnings over his or her lifetime. In almost all estimates of rates of return to schooling it is assumed that cross-sectional data are a reasonable predictor of these future earnings. What little data that exist suggest that this assumption is simply not true (cf. Mincer, 1974, p.77). In fact, to accurately predict the returns to education, one needs to know how real wage rates will grow or decline at each level of education over the life cycle of an individual. Estimates of rates of return to education from cross-sectional data are thus conditional on no systematic change in relative wage rates across different levels of education, which is likely to be unrealistic.

Third, schooling has other benefits in addition to its contribution to wages and the direct consumption benefits (Haveman and Wolfe, 1984). Schooling may make individuals more productive in home work, more efficient in maintaining their health and more effective in imparting human capital to their own children, just to cite a few examples. Neglect of these factors leads to underestimation of the returns to education. In addition, in countries such as Ghana where the majority of the population is self-employed, one would have to assume that the returns to education equalize across the wage and self-employment sectors. There are several reasons for thinking that this may not be true (cf. Singh, Squire and Strauss, 1986), which implies that one should estimate the returns to education in self-employment activities directly instead of assuming they are the same as those in the wage sector.

Fourth, schooling may provide private returns by enabling one to get a government job. About 9% of the population in the sample from Ghana worked for the government, and this figure is even higher for those with higher levels of education (32% with upper secondary education and 74% with post-secondary education). In fact, most wage workers in Ghana (61%) work for the government. If human capital and or years of schooling enable one to get a government job (cf. Section V), the private benefit of education to those who do obtain government jobs is not reflected in the rate of return for the private sector, and thus is completely ignored when that rate is used as a measure of the private benefit of education. Further, the social benefit of education depends on the productivity (in the most general sense) of well-educated government workers, which can be very difficult to ascertain.

Fifth, although general depreciation of human capital stock is easily accomodated in human capital models (cf. Mincer, 1974), and amounts to interpreting the rate of return as a net return rather than a gross one, human capital which becomes obsolete due to its "vintage" characteristics cannot be so easily handled. The real issue is the extent of future obsolescence of human capital being acquired today relative to the obsolescence of human capital emodied in today's older population cohorts, since cross-sectional data are being used to predict future earnings. *A priori*, this could lead to either under- or overestimation of rates of return to education.

Costs of Schooling. The assumption that the cost of attending school be measured by forgone wages is also open to question. First, there are tuition and other costs (cf. footnote 4), which in some countries can be substantial. In Ghana school fees are not very large (cf. Keith, 1985), so this problem is not a serious one for the estimates given here. Even if they were, there are mechanisms to incorporate school fees and other costs to determine the rate of return to schooling, which involve solving for a rate of return that equalizes the present discounted value of total costs and total benefits from education. Yet even these calculations suffer from some problems, as one must implicitly assume that either no post-schooling investment exists or that the present discounted value of all possible schooling investments are equalized (cf. Becker, 1975, Chapter 3).

A second difficulty stems from the fact that parents usually pay the costs of children's schooling, especially at the primary or secondary level, while children reap the benefits later in life. Strong assumptions must be made about intergenerational relations to treat the the parents and child together as a single unit. Some parents may calculate benefits only in terms of what they expect to receive from their children. Others may be altruistic and provide their children with education even at a high cost. A related issue is that parents may have limited education themselves and thus may not have a very realistic understanding of the benefits of education.

A third problem arises in many developing countries since a large proportion, even the majority, of the working population are self-employed. If household labor on the household farm is not perfectly substitutable for non-family labor on the family farm, the marginal product of labor on the family farm in equilibrium may differ from the wage rate prevailing in the rural labor market (cf. Singh, Squire and Strauss, 1986). Thus the opportunity costs of education may be incorrect, as would estimated rates of return.

A fourth problem with assuming that the cost of education is the opportunity cost of market labor is that one assumes away differences in ability among students. Students with high ability may be able to skip grades while those with low ability may repeat grades or even be unable to proceed past a certain level. Estimates of the return to education for the population as a whole are, at best, averages across different ability groups. But if investments in education are advocated as a means of raising the educational levels of disadvantaged groups, and these disadvantaged groups have lower levels of ability, the rate of return among these groups will be lower than that among the general population. Data on innate ability could be used to overcome this problem, but to do so would require a much more elaborate procedure than simply estimating equation (1).

A fifth and final problem is that in many cases developing countries even the "average" student repeats many grades. For example, in Côte d'Ivoire the typical child who has finished the 6th year of schooling (i.e. finished the primary cycle) has actually attended school for 9 years (World Bank, 1987). This underestimate of the true costs of education will result in overestimates of the true private rate of return to schooling.[25]

Social Investment Decisions. The two previous subsections point out several problems that cast doubt on estimates of private rates of returns to additional years of schooling. Even if these problems could be handled, transforming these private rates to social rates by incorporating government costs of providing education are unlikely to lead to useful guides for government policy makers for 2 reasons: 1. Social rates of return do not incorporate externalities in the benefits of education; 2. Rates of return to additional years of schooling are unlikely to be relevant for most government investment decisions in education.

Turning to the first point, if education were like any other private investment good there may not be any economic rational for its being financed by the government. Yet, most education is provided or heavily subsidized by the governments in both developing and developed countries. One economic argument for government provision or subsidization of education is that the

---

25/ In Ghana such repetition is relatively low, but this mostly reflects the fact that children progress through the system regardless of their progress in cognitive achievement.

benefits of one individual's education may accrue to other persons, i.e. there may be externalities. One probable externality is that the cost of conveying information to an educated (literate) person is likely to be lower than that for an uneducated person, and part of this cost may well be born by other members or institutions in society. To the extent that these externaltities exist (which will not be debated here), social rates of returns to government projects should include them when calculating benefits. At present, despite the somewhat misleading name, virtually all estimates of the social rate of return to education exclude positive and, to the extent that they may exist, negative externalities. If positive externalities dominate any negative ones, existing social rates of return are only lower bounds to the actual rate.

(Another reason for government subsidization and promotion of education is that persons with little or no education do not realize the benefits of education. Thus the government must subsidize education and use other methods to persuade parents to send their children to school. This is clearly a paternalistic argument, but it cannot be dismissed simply for that reason.)

Turning to the second point, many discussions on social investment [illegible]sions implicitly assume that decisions by governments to invest in different levels and types of schooling is a matter of modifying the "investment portfolio" among the different types of education <u>given their social rates of return</u>. For example, Psachoropoulos (1985, p. 591) argues that "primary schooling remains the number-one priority for investment. This is evidenced by the fact that the social rate of return to primary education exceeds by several percentage points the returns to secondary and higher education." Indeed, the World Bank (1986, p. 9) officially advocates this position, reasoning that "The social rates of return...suggest that in most developing countries primary education should receive the highest investment priority..."

The implicit scenario behind this view is that there are capacity constraints at all levels of education, i.e. children do not obtain access to schools because all schools are "full", and the decision faced by the government is which types of new schools (primary, secondary or higher) should be built to accomodate this unmet demand. This scenario also assumes that rates of return at each level of schooling are given, so that the only choice is which types of schools to build, not which types of investments in schools may raise rates of return. However, in countries where school quality is low the problem is often not lack of capacity but enrollment stagnation due to low school quality. In fact, government investments in schooling, especially in developing countries, are often designed to raise the social rates of return at existing schools, not to build new schools to satisfy excess demand.

Thus rates of return to schooling need to be interpreted in a new way. Relatively low rates of return to certain types of education do not necessarily imply that future investments should be directed away from those types, in fact they may indicate that relatively small investments there can have very high returns by raising the routes of return to education. Taking Ghana as an example, the apparent low rates of return to primary education do not mean that investments should be away from primary and toward other forms of education. In fact, they may mean the opposite, more investments are needed to raise the rate of return to education in primary schools.

From the previous paragraph it should be clear that the statements to the effect that educational investments should be given to those schools which have the highest rates of return may well be erroneous; more detailed analysis is needed of the reasons for low returns. This should be done along the lines of the model embodied in equations (3) and (4) in Section II. Equation (3) should be estimated for all activities for which human capital raises household incomes, not only wage employment but self-employment activities as well.[26] Then equation (4) should be estimated using detailed data on school characteristics which are (or can be) altered by government investments in schooling (school quality variables). With such estimates one can estimate $\partial w/\partial Q = \partial w/\partial H \times \partial H/\partial Q$ to get rates of return to particular investments that raise school quality. To the extent that increased school quality also leads to increases in time spent in school ($\partial S/\partial Q > 0$), this should also be included in the analysis. Obviously, the data requirements for such an exercise are much larger than those embodied in equation (1). However, this is what is needed to provide estimates of rates of return to government investments in schooling; there is little reason to think that rates of return to years of schooling in estimated earnin functions could serve as substitutes.

[26] In fact, this should be extended to non-financial benefits of education (e.g. better educated adults are more able to maintain their health as well as that of their children) and could be done if one could measure the money value of these benefits.

VII. SUMMARY AND CONCLUSION

Estimates of rates of return to education are often calculated to judge the wisdom of investments in education, both relative to non-education investments and across different types or levels of education. Presumably, these judgements are then used to inform policy decisions in education. This paper has critically examined the validity of estimating private rates of return to additional years of schooling from wage data, illustrating the pitfalls using data from Ghana, and moreover questioned the usefulness of those estimates for government investment decisions. Several conclusions stand out.

First, when school quality varies widely across time and space, years of schooling may be a very imperfect indicator of human capital attained, and simple estimates of the private rate of return to schooling may be substantially biased. In the case of Ghana the data can either overestimate (if sample selectivity of wage earners is ignored) or underestimate (if one controls for selectivity but ignores school quality) the rate of return to schooling. Obviously, this could bring about misleading policy conclusions.

Second, when data on cognitive skills and a measure of innate ability are used to assess the impact of education on wages, it appears that it is cognitive skills acquired, rather than accumulation of schooling credentials or innate ability, that determine wages in the private sector In Ghana. This is consistent with the findings of Boissiere, Knight and Sabot for East Africa. However, in the public sector credentialism appears to be present.

Third, private returns to primary schooling do <u>not</u> always exceed those of higher levels of schooling. In Ghana they have the <u>lowest</u> returns, which reflects the poor quality of primary schools in Ghana. However, this does not imply that government investments in primary school are inappropriate, because government investments in many cases are intended to raise these rates of return. This leads to the last, and most important, conclusion.

Fourth, estimates of private rates of return to additional years of schooling are of little relevance to education investment decisions in developing countries, even if they are adjusted to become social rates of return. First, there are so many qualifications and difficulties to estimates of rates of return to schooling based on cross-sectional wage data that they are unlikely to give accurate rates of return (private or social) to additional years of schooling. Second, rates of return to additional years of schooling are useless in countries where the problem is low school quality and stagnating enrollments. What is needed are rates of return to improvements in school quality, and these cannot be obtained from standard estimates of rates of return to additional years of schooling. This requires investigation of the determinants of the acquisitions of human capital in schools, and the contribution of this capital, measured in terms of cognitive skills, to household incomes.

REFERENCES

Arrow, Kenneth. 1973. "Higher Education as a Filter." Journal of Public Economics, vol. 2, pp. 193-216.

Beaudry, P., and N. K. Sowa. 1989. "Labour Markets in an Era of Adjustment: A Case Study of Ghana." SDA Unit. The World Bank. Washington, D.C.

Becker, Gary. 1975. Human Capital. Second Edition. University of Chicago Press. Chicago.

Behrman, Jere, and Nancy Birdsall. 1983. :The Quality of Schooling: Quantity Alone is Misleading." American Economic Review, vol. 73, no. 5, pp. 926-46.

Boissiere, Maurice, John Knight and Richard Sabot. 1985. "Earnings, Schooling, Ability, and Cognitive Skills." American Economic Review, vol. 75, no. 5, pp. 1016-1030.

Fisher, Raymond, R.P. Trost and Philip Lurie. 1981. "Labor Force Earnings and College Choice of Young Women: An Analysis of Selectivity Bias and Comparative Advantages." Economics of Education Review, vol 1, no. 2, pp. 169-191.

Glewwe, Paul, and Kwaku A. Twum-Baah. 1990. "The Distribution of Welfare in Ghana in 1987-88." Mimeo. World Bank. Washington, D.C.

Griliches, Zvi. 1977. "Estimating the Returns to Schooling: Some Econometric Problems." Econometrica, vol. 45, no. 1, pp. 1-22.

Haveman, Robert, and Barbara Wolfe. 1984. "Schooling and Economic Well-Being: The Role of Non-Market Effects." Journal of Human Resources, vol. 19, pp. 377-407.

Hausman, Jerry. 1978. "Specification Tests in Econometrics." Econometrica, vol. 46, no. 6, pp. 1251-71.

Heckman, James. 1979. "Sample Selection as a Specification Error." Econometrica, vol. 47, no. 1, pp. 153-61.

Keith, Sherry. 1985. "Ghana: Education Sector Review and Proposed Investment Strategy." Western Africa Regional Office. The World Bank, Washington, D.C.

Lau, Lawrence, Dean Jamison and Frederic Louat, 1990. "Education and Productivity in Developing Countries: An Aggregate Production Function Approach." Mimeo. The World Bank. Washington, D.C.

Lee, Lei-Fung. 1979. "Identification and Estimation in Binary Choice Models with Limited (Censored) Dependent Variables." Econometrica, vol. 47, no. 4, pp. 977-996.

Mincer, Jacob. 1974. Schooling, Experience and Earnings. National Bureau of Economic Research. New York.

Poirier, Dale. 1980. "Partial Observability in Bivariate Probit Models." Journal of Econometrics, vol. 12, pp. 209-17.

Psacharopoulos, George. 1985. "Returns to Education: A Further International Update and Implications." Journal of Human Resources, vol. 20, no. 4.

Psacharopoulos, George. 1986. "Welfare Effects of Government Interventions in Education." in Contemporary Policy Issues, Economic Analysis for the Decision Maker, vol. 4, pp. 51-62.

Raven, J.C., J.H. Court and J. Raven. 1984. "Manual for Raven's Progressive Matrices and Vocabulary Scales." H.K. Lewis & Co., London.

Singh, Inderjit, Lyn Squire and John Strauss. 1986. Agricultural Household Models: Estimations, Applications and Policy.

Spence, Michael. 1976. "Competition in Salaries, Credentials and Signaling Prerequisites for Jobs." Quarterly Journal of Economics vol. 90, pp. 51-74.

van der Gaag, Jacques, and Vim Vijverberg. 1988. "A Switching Regression Model of Wage Determinants in the Public and Private Sectors of a Developing Country." Review of Economics and Statistics, vol. 70, pp. 244-52.

Willis, Robert. 1986. "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions," in Ashenfeather and Layard, eds., Handbook of Labor Economics. North Holland, Amsterdam.

World Bank. 1986. Financing Education in Developing Countries: An Exploration of Policy Options. The World Bank, Washington, D.C.

World Bank. 1987. "The Côte d'Ivoire in Transition: From Structural Adjustment to Self-Sustained Growth". West African Region. The World Bank, Washington, D.C.

World Bank. 1988. Education in Sub-Saharan Africa: Policies for Adjustment, Revitalization and Expansion, Washington, D.C.

World Bank. 1989. "Basis Education for Self-Employment and Rural Development." Western Africa Region. The World Bank. Washington, D.C.

APPENDIX I: Derivation of Functional Forms of Earnings Equations

This appendix demonstrates how the loglinear functional form of equation (1) in Section II can be derived from economic theory. Ignoring differences in post-schooling investment as approximated by years of experience,[1/] assume that the difference between the wage of an individual i with S years of schooling, w_{is}, and the wage he or she would receive with S-1 years of schooling, w_{is-1}, is the return to the capital accumulated during that year of schooling, H_{is}:

$$w_{is} - w_{is-1} = r_{is}H_{is} \qquad \text{(A.1)}$$

where r_{is} is the private rate of return, which varies by individual and year of schooling. The human capital variable H_{is} refers to the physical amount possessed today, but is expressed in terms of its cost at the time of accumulation in order to interpret r_{is} as a return on a past investment.

Omitting any direct costs of schooling, the cost is simply forgone wage income for the period of time spent in school:

$$H_{is} = w_{is-1} \qquad \text{(A.2)}$$

where the wage is expressed in the same units as the period of schooling (e.g.

1/ Mincer (1974) accounts for post-schooling investment in human capital in a way which does not alter the interpretation of α_1. See Willis (1986) for a detailed exposition of human capital and earnings functions.

yearly wage income).[2] Substituting (A.2) into (A.1) repeatedly results in:

$$w_{is} = w_{io}(1+r_{i1})(1+r_{i2})\ldots(1+r_{is}), \qquad (A.3)$$

which, after taking the logarithm of both sides, becomes:[3]

$$\ln(w_{is}) = \ln(w_{io}) + \ln(1+r_{i1}) + \ln(1+r_{i2}) +\ldots+ \ln(1+r_{is})$$
$$\cong \ln(w_{io}) + r_{i1} + r_{i2} +\ldots+ r_{is}. \qquad (A.4)$$

Assuming further that the private rates of return for all years of school are the same, i.e. that $r_{i1} = r_{i2} =\ldots= r_{in} = r_i$, yields:

$$\ln(w_i) = \log(w_{io}) + r_i S_i, \qquad (A.5)$$

where S_i is the years of schooling completed by person i. The expression of variation across i in w_{io} and r_i as an additive error term, u_i, and the addition of a quadratic experience specification to control for differences in post-schooling investments (cf. Mincer, 1974) yields equation (1) in the text. A more general variant allows different schooling levels (e.g. primary,

---

[2] A general inflation in prices and wages over time (i.e. relative prices unchanged) does not invalidate the cost expression in (A.2); the cost at the time of investment is simply being expressed in today's prices. However, ignoring direct costs of schooling (tuition, books, uniforms, etc.) will lead to overestimates of the private rate of return due to underestimates of costs.

[3] The simplification that $\ln(1 + r_{ij}) \cong r_{ij}$ will lead to an underestimate of r_{ij} since $\ln(+r_{ij}) < r_{ij}$ for $r_{ij} > 0$. The bias rises exponentially as r_{ij} increases.

secondary and higher) to have different private returns:

$$\ln(w_i) = \ln(w_{io}) + r_{ip}S_p + r_{is}S_s + r_{it}S_t \qquad \text{(A.6)}$$

where S_p, S_s and S_t are the number of years in primary, secondary and tertiary education, respectively, and r_{ip}, r_{is}, and r_{it} the corresponding rates of return.

Interpretation of α_1 as the private rate of return to additional schooling can also be justified in other ways. For example, if one assumes that years of schooling across the population represents an equilibrium whereby the present discounted value of earnings is equalized across all levels of schooling, one has

$$w_S\int_S^{S+N} e^{-rt}dt = w_S e^{-rS}(1 - e^{-rn})/r = w_0(1 - e^{-rn})/r = w_0\int_0^N e^{-rt}dt \qquad \text{(A.7)}$$

where the i subscripts have been suppressed and N is a fixed span of time (independent of S) spent working. Clearly, (A.7) gives $\ln(w_s) = \ln(w_o) + rS.)$[4/]

4/ The formulation in (A.7) omits the assumption in (A.1) that differences in wage rates across schooling levels are due to differences in stocks of human capital, but it still implicitly assumes that the cost of schooling is forgone earnings. The formulation in (A.1)-(A.5) did not require any assumption about equalizing the present discounted value of life-cycle earnings.

APPENDIX II: Likelihood Functions of Equations (7) - (10) in Section III

The likelihood function of equations (7) - (10) in Section III is:

$$L = \prod_{t=1}^{T} [\Phi(-Z_2\alpha_2)]^{(1-I_2)} \times \left[\int_{-Z_2\alpha_2}^{\infty}\int_{-\infty}^{-Z_1\alpha_1} f_p(e,v|w_p - X_p\beta_p)dv\, de\, \frac{1}{\sigma_p}\phi\left(\frac{w_p - X_p\beta_p}{\sigma_p}\right)\right]^{I_2(1-I_1)}$$

$$\times \left[\int_{-Z_2\alpha_2}^{\infty}\int_{-Z_1\alpha_1}^{\infty} f_g(e,v|w_g - X_g\beta_g)dv\, de\, \frac{1}{\sigma_g}\phi\left(\frac{w_g - X_g\beta_g}{\sigma_g}\right)\right]^{I_2 I_1} \quad \text{(A2.1)}$$

where f_p and f_g are conditional bivariate normal distributions. The logarithm of the likelihood function can be expressed as:

$$\ln(L) = \sum_{t=1}^{T} (1-I_2)\ln[\Phi(-Z_2\alpha_2)] + I_2(1-I_1)\{\ln[B(\infty,\psi_{1p},\rho_p) - B(\psi_{2p},\psi_{1p},\rho_p)]$$

$$+ \ln[\frac{1}{\sigma_p}\phi(\frac{w_p - X_p\beta_p}{\sigma_p})]\}$$

$$+ I_2 I_1\{\ln[B(-\psi_{2g},-\psi_{1g},\rho_g)] + \ln[\frac{1}{\sigma_g}\phi(\frac{w_g - X_g\beta_g}{\sigma_g})]\} \quad \text{(A2.2)}$$

where $\psi_{1k} = (-Z_1\alpha_1 - \frac{\rho_{kv}}{\sigma_k}(w_k - X_k\beta_k))/(1-\rho_{kv}^2)^{1/2}$

$$\psi_{2k} = (-Z_2\alpha_2 - \frac{\rho_{ke}}{\sigma_k}(w_k - X_k\beta_k))/(1-\rho_{ke}^2)^{1/2}$$

$$\rho_k = \frac{\rho_{ev} - \rho_{ek}\rho_{vk}}{((1-\rho_{ek}^2)(1-\rho_{vk}^2))^{1/2}} \quad \text{and } \rho_{kj} = \frac{\sigma_{kj}}{\sigma_k\sigma_j} \quad k = g,p \quad j = e,v.$$

and $B(\cdot,\cdot,\cdot)$ is the bivariate standard normal distribution. In this paper full maximum likelihood estimation is used to test whether $\sigma_{ge} = \sigma_{pe} = \sigma_{ve} = 0$. If this hypothesis cannot be rejected one can limit estimation to (7)-(9) in the text, a model studied by Lee (1979), which simplifies the estimation.

APPENDIX III: Maximum Likelihood Results for Full Model

	Estimate for Equation (1)				Estimates for Equation (3)			
Probit Equations:	Equation (9)		Equation (10)		Equation (9)		Equation (10)	
Constant	-0.9434	(-0.57)	-1.8530	(-7.45)	0.2925	(0.45)	-1.8207	(-7.30)
Family Size	0.0373	(1.12)	-0.0548	(-6.73)	0.0616	(2.41)	-0.0567	(-6.98)
Sex	0.5885	(1.86)	-0.6282	(-7.41)	0.6476	(3.85)	-0.6388	(-7.49)
Raven's Test	-0.0460	(-3.12)	0.0093	(1.31)	-0.0435	(-3.40)	0.0101	(1.40)
Reading	0.0272	(1.53)	0.0163	(2.03)	0.0078	(0.58)	0.0166	(2.02)
Mathematics	0.0491	(2.53)	0.0109	(1.20)	0.0190	(1.22)	0.0113	(1.22)
Years Schooling	0.0364	(0.70)	0.0809	(5.40)	0.0389	(1.37)	0.0773	(5.28)
Coast	0.0390	(1.59)	-0.0328	(-2.40)	0.0433	(2.23)	-0.0342	(-2.51)
Forest	0.0785	(3.29)	-0.0546	(-4.23)	0.0770	(4.36)	-0.0555	(-4.35)
Savannah	0.1421	(4.37)	-0.0492	(-3.05)	0.1226	(4.33)	-0.0509	(-3.16)
Married	0.2817	(1.63)	-0.2611	(-0.28)	0.1313	(0.95)	0.2829	(0.30)
Parent Govt.	0.1276	(0.51)	-0.2442	(-0.18)	0.2395	(1.09)	-0.4475	(-0.33)
Experience	0.0092	(0.19)	0.0804	(6.58)	-0.0135	(-0.52)	0.0772	(6.23)
Experience^2	0.0007	(0.97)	-0.0011	(-4.69)	0.0009	(1.82)	-0.0011	(-4.46)
Wage Equations:	Equation (7)		Equation (8)		Equation (7)		Equation (8)	
Constant	4.1178	(6.06)	4.2080	(2.79)	3.6690	(7.38)	4.4673	(4.01)
Year's Schooling	0.0427	(1.57)	-0.0094	(-0.14)	-		-	
Reading	-		-		0.0023	(0.20)	0.0368	(1.94)
Mathematics	-		-		0.0301	(2.87)	0.0253	(0.95)
Raven's Test	-		-		0.009[illegible]	(0.90)	-0.0306	(-1.20)
Experience	0.0068	(0.30)	-0.0035	(-0.73)	0.0211	(1.11)	-0.0211	(-0.59)
Experience^2	-0.0002	(-0.43)	0.0004	(0.42)	-0.0005	(-1.26)	0.0008	(0.91)
Female	0.0483	(0.28)	-0.1664	(-0.38)	-0.0474	(-0.28)	0.1602	(0.44)
Coast	0.0986	(0.58)	0.0803	(0.26)	0.0093	(0.05)	0.3125	(1.08)
Forest	0.1732	(0.97)	-0.1411	(-0.36)	0.1137	(0.62)	0.3349	(0.85)
Savannah	-0.1581	(-0.80)	-0.5866	(-0.85)	-0.2418	(-1.21)	0.2606	(0.33)
Cov. Matrix:								
σ_g, σ_p	0.6703	(18.28)	1.1727	(8.31)	0.6837	(7.34)	0.9803	(8.17)
ρ_{gv}, ρ_{pv}	-0.7547	(-5.53)	-0.6835	(-2.78)	-0.7448	(-4.26)	0.2465	(0.43)
ρ_{ge}, ρ_{pe}	0.0936	(0.22)	-0.1320	(0.22)	0.4171	(1.33)	-0.2885	(-0.65)
ρ_{ve}		-0.3509	(-0.57)			-0.8263	(-6.47)	
Log likelihood		-3172.23				-3162.61		

Note: t-statistics are in parentheses.

APPENDIX IV: Results of Specification Tests

TABLE 1. Endogeneity of Years of Schooling in Equation (4)

	Dependent Variables				
Independent Variables	Math Score		Reading Score		School Years
Intercept	6.4155	6.4016	4.7665	4.6967	0.7112
	(8.63)	(8.48)	(5.25)	(5.10)	(1.10)
Age	-0.0758)	-0.0815	-0.0324	-0.0579	0.2692
	(-2.54)	(-2.13)	(-0.89)	(-1.24)	(10.53)
Age^2	0.0006)	0.0007	0.0001	0.0007	-0.0065
	(1.27)	(0.92)	(0.21)	(0.78)	(17.37)
Sex	-0.7901	-0.7710	-0.4627	-0.3751	-0.9181
	(-5.99)	(-4.94)	(-2.87)	(-1.97)	(-8.06)
Raven	-0.7190	-0.7179	-0.6794	-0.6735	-0.0603
	(-12.14)	(-12.05)	(-9.40)	(-9.26)	(-1.17)
$Raven^2$	0.0203	0.0202	0.0204	0.0200	0.0049
	(15.54)	(14.38)	(12.79)	(11.64)	(4.30)
Coast	-1.1502	-1.1272	-1.8555	-1.7501	-1.1053
	(-4.52)	(-3.97)	(-5.97)	(-5.05)	(-5.00)
Forest	-1.4335	-1.4248	-2.7421	-2.7041	-0.4045
	(-5.93)	(-5.74)	(-9.30)	(-8.93)	(-1.92)
Savannah	-0.9716)	-0.9040	-1.6654)	-1.3624	-3.2046
	(-3.48)	(-1.98)	(-4.88)	(-2.45)	(-13.50)
Raven*Age	0.0046	0.0044	0.0057	0.0051	0.0064
	(5.38)	(4.14)	(5.46)	(3.86)	(8.73)
Years Schooling	0.6866	0.6866	0.8806	0.8806	-
	(35.67)	(35.68)	(37.48)	(37.49)	
Predicted Years Schooling	-	0.0211	-	0.0945	-
		(0.21)		(0.76)	
Mother's Years Schooling	-0.0020	-	0.0150	-	0.0689
	(-0.09)		(0.52)		(3.32)
Father's Years Schooling	0.0036	-	0.0076	-	0.1122
	(0.26)		(0.45)		(9.37)
Number of Obs.	3568	3568	3568	3568	3568
	0.6393	0.6393	0.6588	0.6588	0.5011

Note: The 1st and 3rd columns demonstrate that mother's and father's years of schooling do not have significant effects on math and reading skills, and thus can serve as the identifying variables in the school years equation in the 5th column. Columns 2 and 4 demonstrate that the coefficients on predicted years of schooling are statistically insignificant (Hausman test). T-statistics are given in parentheses.

TABLE 2. Endogeneity of Test Scores in Equation (3): Mathematics Score Dependent Variables

Independent Variables	Private Sector Wage		Government Sector Wage			
Intercept	3.9047	(7.69)	3.4161	(9.29)	3.5521	(6.88)
Experience	-0.0100	(-0.32)	0.0255	(1.83)	0.0154	(1.13)
Experience^2	0.0006	(0.86)	-0.0003	(-1.19)	-0.0002	(-0.55)
Sex	0.0169	(0.07)	0.2527	(2.40)	0.1315	(1.23)
Raven	-0.0300	(-1.08)	-0.0157	(-1.38)	-0.0042	(-0.30)
Reading	0.0348	(1.65)	0.0045	(0.53)	-0.0010	(-0.12)
Mathematics	0.0198	(0.96)	0.0314	(3.55)	0.0291	(3.22)
Predicted Mathematics	0.0204	(0.48)	0.0290	(2.15)	0.0055	(0.20)
Coast	0.2854	(1.04)	0.2016	(1.64)	0.1126	(0.89)
Forest	0.2398	(0.81)	0.4109	(3.16)	0.2455	(1.81)
Savannah	0.0771	(0.15)	0.2853	(1.43)	0.1218	(0.58)
Years Schooling	-		-		0.0165	(0.50)
Middle School Certificate	-		-		0.0456	(0.45)
O-Level Diploma	-		-		0.0267	(0.16)
Teacher Training Degree	-		-		0.5009	(3.21)
Higher Diploma	-		-		-0.2441	(-1.03)
Lambda	0.0079	(0.02)	0.1218	(0.52)	0.0356	(0.15)
R^2	0.1517		0.2961		0.3564	
Sample Size	152		237		237	

Note: The instrumented mathematics score is that given in column 1 of Table 1. Thus the instruments are age and its square, the square of the Raven's test, an interaction term between the Raven's test and age, mother's and father's years of schooling, and, for the first 2 regressions, years of schooling.

Table 3. Endogeneity of Test Scores in Equation (3): Reading Score Dependent Variables

Independent Variables	Private Sector Wage	Government Sector Wage	
Intercept	3.8926 (7.64)	3.4081 (9.23)	3.5600 (6.65)
Experience	-0.0135 (-0.44)	0.0236 (1.73)	0.0150 (1.09)
Experience^2	0.0006 (0.88)	-0.0003 (-1.05)	-0.0001 (-0.53)
Sex	-0.0085 (-0.04)	0.2421 (2.36)	0.1290 (1.25)
Raven	-0.0250 (-0.87)	-0.0160 (-1.40)	-0.0043 (-0.29)
Reading	0.0347 (2.11)	0.0041 (0.49)	-0.0010 (-0.12)
Predicted Reading	0.0084 (0.24)	0.0242 (2.17)	0.0048 (0.19)
Mathematics	0.0198 (0.96)	0.0317 (3.58)	0.0291 (3.23)
Coast	0.2558 (0.88)	0.2189 (1.75)	0.1154 (0.89)
Forest	0.2109 (0.66)	0.4385 (3.24)	0.2506 (1.70)
Savannah	0.2572 (0.05)	0.3060 (1.50)	0.0455 (0.58)
Years Schooling	- -		0.0158 (0.43)
Middle School Certificate	- -		0.0455 (0.45)
O-Level Diploma	- -		0.0269 (0.16)
Teacher Training Degree	- -		0.5014 (3.22)
Higher Diploma	- -		-0.2438 (-1.02)
Lambda	0.0761 (0.16)	0.1338 (0.56)	0.0352 (0.14)
R^2	0.1508	0.2964	0.3564
Sample Size	152	237	237

Note: The instrumented reading score is that given in column 3 of Table 1. Thus the instruments are age and its square, the square of the Raven's test, the interaction term between the Raven's test and age, mother's and father's years of schooling, and, for the first 2 regressions, years of schooling.

Distributors of World Bank Publications

ARGENTINA
Carlos Hirsch, SRL
Galeria Guemes
Florida 165, 4th Floor-Ofc. 453/465
1333 Buenos Aires

AUSTRALIA, PAPUA NEW GUINEA, FIJI, SOLOMON ISLANDS, VANUATU, AND WESTERN SAMOA
D.A. Books & Journals
648 Whitehorse Road
Mitcham 3132
Victoria

AUSTRIA
Gerold and Co.
Graben 31
A-1011 Wien

BAHRAIN
Bahrain Research and Consultancy Associates Ltd.
P.O. Box 22103
Manama Town 317

BANGLADESH
Micro Industries Development Assistance Society (MIDAS)
House 5, Road 16
Dhanmondi R/Area
Dhaka 1209

Branch offices:
156, Nur Ahmed Sarak
Chittagong 4000

76, K.D.A. Avenue
Kulna

BELGIUM
Jean De Lannoy
Av. du Roi 202
1060 Brussels

CANADA
Le Diffuseur
C.P. 85, 1501B rue Ampère
Boucherville, Québec
J4B 5E6

CHINA
China Financial & Economic Publishing House
8, Da Fo Si Dong Jie
Beijing

COLOMBIA
Infoenlace Ltda.
Apartado Aereo 34270
Bogota D.E.

COTE D'IVOIRE
Centre d'Edition et de Diffusion Africaines (CEDA)
04 B.P. 541
Abidjan 04 Plateau

CYPRUS
MEMRB Information Services
P.O. Box 2098
Nicosia

DENMARK
SamfundsLitteratur
Rosenoerns Allé 11
DK-1970 Frederiksberg C

DOMINICAN REPUBLIC
Editora Taller, C. por A.
Restauración e Isabel la Católica 309
Apartado Postal 2190
Santo Domingo

EL SALVADOR
Fusades
Avenida Manuel Enrique Araujo #3530
Edificio SISA, 1er. Piso
San Salvador

EGYPT, ARAB REPUBLIC OF
Al Ahram
Al Galaa Street
Cairo

The Middle East Observer
8 Chawarbi Street
Cairo

FINLAND
Akateeminen Kirjakauppa
P.O. Box 128
SF-00101
Helsinki 10

FRANCE
World Bank Publications
66, avenue d'Iéna
75116 Paris

GERMANY, FEDERAL REPUBLIC OF
UNO-Verlag
Poppelsdorfer Allee 55
D-5300 Bonn 1

GREECE
KEME
24, Ippodamou Street Platia Plastiras
Athens-11635

GUATEMALA
Librerias Piedra Santa
5a. Calle 7-55
Zona 1
Guatemala City

HONG KONG, MACAO
Asia 2000 Ltd.
6 Fl., 146 Prince Edward Road, W.
Kowloon
Hong Kong

INDIA
Allied Publishers Private Ltd.
751 Mount Road
Madras - 600 002

Branch offices:
15 J.N. Heredia Marg
Ballard Estate
Bombay - 400 038

13/14 Asaf Ali Road
New Delhi - 110 002

17 Chittaranjan Avenue
Calcutta - 700 072

Jayadeva Hostel Building
5th Main Road Gandhinagar
Bangalore - 560 009

3-5-1129 Kachiguda Cross Road
Hyderabad - 500 027

Prarthana Flats, 2nd Floor
Near Thakore Baug, Navrangpura
Ahmedabad - 380 009

Patiala House
16-A Ashok Marg
Lucknow - 226 001

INDONESIA
Pt. Indira Limited
Jl. Sam Ratulangi 37
P.O. Box 181
Jakarta Pusat

ITALY
Licosa Commissionaria Sansoni SPA
Via Benedetto Fortini, 120/10
Casella Postale 552
50125 Florence

JAPAN
Eastern Book Service
37-3, Hongo 3-Chome, Bunkyo-ku 113
Tokyo

KENYA
Africa Book Service (E.A.) Ltd.
P.O. Box 45245
Nairobi

KOREA, REPUBLIC OF
Pan Korea Book Corporation
P.O. Box 101, Kwangwhamun
Seoul

KUWAIT
MEMRB Information Services
P.O. Box 5465

MALAYSIA
University of Malaya Cooperative Bookshop, Limited
P.O. Box 1127, Jalan Pantai Baru
Kuala Lumpur

MEXICO
INFOTEC
Apartado Postal 22-860
14060 Tlalpan, Mexico D.F.

MOROCCO
Société d'Etudes Marketing Marocaine
12 rue Mozart, Bd. d'Anfa
Casablanca

NETHERLANDS
InOr-Publikaties b.v.
P.O. Box 14
7240 BA Lochem

NEW ZEALAND
Hills Library and Information Service
Private Bag
New Market
Auckland

NIGERIA
University Press Limited
Three Crowns Building Jericho
Private Mail Bag 5095
Ibadan

NORWAY
Narvesen Information Center
Book Department
P.O. Box 6125 Etterstad
N-0602 Oslo 6

OMAN
MEMRB Information Services
P.O. Box 1613, Seeb Airport
Muscat

PAKISTAN
Mirza Book Agency
65, Shahrah-e-Quaid-e-Azam
P.O. Box No. 729
Lahore 3

PERU
Editorial Desarrollo SA
Apartado 3824
Lima

PHILIPPINES
International Book Center
Fifth Floor, Filipinas Life Building
Ayala Avenue, Makati
Metro Manila

POLAND
ORPAN
Palac Kultury i Nauki
00-901 Warszawa

PORTUGAL
Livraria Portugal
Rua Do Carmo 70-74
1200 Lisbon

SAUDI ARABIA, QATAR
Jarir Book Store
P.O. Box 3196
Riyadh 11471

MEMRB Information Services
Branch offices:
Al Alsa Street
Al Dahna Center
First Floor
P.O. Box 7188
Riyadh

Haji Abdullah Alireza Building
King Khaled Street
P.O. Box 3969
Damman

33, Mohammed Hassan Awad Street
P.O. Box 5978
Jeddah

SINGAPORE, TAIWAN, MYANMAR, BRUNEI
Information Publications Private, Ltd.
02-06 1st Fl., Pei-Fu Industrial Bldg.
24 New Industrial Road
Singapore 1953

SOUTH AFRICA, BOTSWANA
For single titles:
Oxford University Press Southern Africa
P.O. Box 1141
Cape Town 8000

For subscription orders:
International Subscription Service
P.O. Box 41095
Craighall
Johannesburg 2024

SPAIN
Mundi-Prensa Libros, S.A.
Castello 37
28001 Madrid

Librería Internacional AEDOS
Consell de Cent, 391
08009 Barcelona

SRI LANKA AND THE MALDIVES
Lake House Bookshop
P.O. Box 244
100, Sir Chittampalam A. Gardiner Mawatha
Colombo 2

SWEDEN
For single titles:
Fritzes Fackboksforetaget
Regeringsgatan 12, Box 16356
S-103 27 Stockholm

For subscription orders:
Wennergren-Williams AB
Box 30004
S-104 25 Stockholm

SWITZERLAND
For single titles:
Librairie Payot
6, rue Grenus
Case postale 381
CH 1211 Geneva 11

For subscription orders:
Librairie Payot
Service des Abonnements
Case postale 3312
CH 1002 Lausanne

TANZANIA
Oxford University Press
P.O. Box 5299
Dar es Salaam

THAILAND
Central Department Store
306 Silom Road
Bangkok

TRINIDAD & TOBAGO, ANTIGUA BARBUDA, BARBADOS, DOMINICA, GRENADA, GUYANA, JAMAICA, MONTSERRAT, ST. KITTS & NEVIS, ST. LUCIA, ST. VINCENT & GRENADINES
Systematics Studies Unit
#9 Watts Street
Curepe
Trinidad, West Indies

UNITED ARAB EMIRATES
MEMRB Gulf Co.
P.O. Box 6097
Sharjah

UNITED KINGDOM
Microinfo Ltd.
P.O. Box 3
Alton, Hampshire GU34 2PG
England

VENEZUELA
Libreria del Este
Aptdo. 60.337
Caracas 1060-A

YUGOSLAVIA
Jugoslovenska Knjiga
P.O. Box 36
Trg Republike
YU-11000 Belgrade

LSMS Working Papers (continued)

No. 43 *Profits from Self-Employment: A Case Study of Côte d'Ivoire*

No. 44 *The Living Standards Survey and Price Policy Reform: A Study of Cocoa and Coffee Production in Côte d'Ivoire*

No. 45 *Measuring the Willingness to Pay for Social Services in Developing Countries*

No. 46 *Nonagricultural Family Enterprises in Côte d'Ivoire: A Descriptive Analysis*

No. 47 *The Poor during Adjustment: A Case Study of Côte d'Ivoire*

No. 48 *Confronting Poverty in Developing Countries: Definitions, Information, and Policies*

No. 49 *Sample Designs for the Living Standards Surveys in Ghana and Mauritania/Plans de sondage pour les enquêtes sur le niveau de vie au Ghana et en Mauritanie*

No. 50 *Food Subsidies: A Case Study of Price Reform in Morocco* (also in French, 50F)

No. 51 *Child Anthropometry in Côte d'Ivoire: Estimates from Two Surveys, 1985 and 1986*

No. 52 *Public-Private Sector Wage Comparisons and Moonlighting in Developing Countries: Evidence from Côte d'Ivoire and Peru*

No. 53 *Socioeconomic Determinants of Fertility in Côte d'Ivoire*

No. 54 *The Willingness to Pay for Education in Developing Countries: Evidence from Rural Peru*

No. 55 *Rigidité des salaires: Données microéconomiques et macroéconomiques sur l'ajustement du marché du travail dans le secteur moderne* (in French only)

No. 56 *The Poor in Latin America during Adjustment: A Case Study of Peru*

No. 57 *The Substitutability of Public and Private Health Care for the Treatment of Children in Pakistan*

No. 58 *Identifying the Poor: Is "Headship" a Useful Concept?*

No. 59 *Labor Market Performance as a Determinant of Migration*

No. 60 *The Relative Effectiveness of Private and Public Schools: Evidence from Two Developing Countries*

No. 61 *Large Sample Distribution of Several Inequality Measures: With Application to Côte d'Ivoire*

No. 62 *Testing for Significance of Poverty Differences: With Application to Côte d'Ivoire*

No. 63 *Poverty and Economic Growth: With Application to Côte d'Ivoire*

No. 64 *Education and Earnings in Peru's Informal Nonfarm Family Enterprises*

No. 65 *Formal and Informal Sector Wage Determination in Urban Low-Income Neighborhoods in Pakistan*

No. 66 *Testing for Labor Market Duality: The Private Wage Sector in Côte d'Ivoire*

No. 67 *Does Education Pay in the Labor Market? The Labor Force Participation, Occupation, and Earnings of Peruvian Women*

No. 68 *The Composition and Distribution of Income in Côte d'Ivoire*

No. 69 *Price Elasticities from Survey Data: Extensions and Indonesian Results*

No. 70 *Efficient Allocation of Transfers to the Poor: The Problem of Unobserved Household Income*

No. 71 *Investigating the Determinants of Household Welfare in Côte d'Ivoire*

No. 72 *The Selectivity of Fertility and the Determinants of Human Capital Investments: Parametric and Semiparametric Estimates*

No. 73 *Shadow Wages and Peasant Family Labor Supply: An Econometric Application to the Peruvian Sierra*

No. 74 *The Action of Human Resources and Poverty on One Another: What We Have Yet to Learn*

No. 75 *The Distribution of Welfare in Ghana, 1987–88*

The World Bank

Headquarters
1818 H Street, N.W.
Washington, D.C. 20433, U.S.A.

Telephone: (202) 477-1234
Facsimile: (202) 477-6391
Telex: WUI 64145 WORLDBANK
RCA 248423 WORLDBK
Cable Address: INTBAFRAD
WASHINGTONDC

European Office
66, avenue d'Iéna
75116 Paris, France

Telephone: (1) 40.69.30.00
Facsimile: (1) 47.20.19.66
Telex: 842-620628

Tokyo Office
Kokusai Building
1-1, Marunouchi 3-chome
Chiyoda-ku, Tokyo 100, Japan

Telephone: (3) 3214-5001
Facsimile: (3) 3214-3657
Telex: 781-26838

Glewwe

BEST COPY AVAILABLE