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Are educated workers really more productive?

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Abstract

This paper presents a new method for examining the productive nature of education. It outlines an econometric model which simultaneously estimates an earnings function and a production function for workers and the firms where they are employed. This approach permits a direct comparison to be made between the relative wage and relative productivity of workers with different levels of education. Using a unique data set from Ghana, two primary questions are addressed: (1) Are educated workers more productive than workers with no formal education? and (2) Do earnings differentials between workers with different levels of education reflect genuine productivity differentials? The results suggest that education is positively correlated with productivity in Ghanaian manufacturing, and that firms pay workers according to their productivity. © 2001 Elsevier Science B.V. All rights reserved.

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1. Introduction

Education is widely believed to play an important role in economic development. At the aggregate level, there are strong theoretical reasons for linking the expansion of education to higher rates of economic growth. Solow (1956), for example, argues that changes in national income are determined by changes in a country's stock of physical and human capital. More recently, the "new" growth

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theories, such as those formulated by Romer (1986, 1993) and Lucas (1988), focus on the importance of "idea gaps" and learning externalities in explaining why some countries are richer than others. Many predictions of growth theory have been tested empirically but, surprisingly, the macroeconomic evidence linking education to growth remains far from conclusive. Indeed, much of the empirical evidence is so weak that some economists have questioned the whole role of education in the growth process (e.g., Bils and Klenow, 1998).

By contrast, there is overwhelming evidence at the microeconomic level that education and productivity—measured by workers' earnings—are positively correlated. So why are the macroresults so different from the microresults? One possibility is that workers' education and earnings are strongly correlated but workers' education and productivity are not. In other words, earnings differentials between workers with different levels of education do not reflect genuine productivity differentials. This would explain why workers earn such large returns from investing in education, yet, at the same time, positive changes in a nation's stock of human capital have only a small impact on aggregate productivity. In this paper, we examine the relationship between education and productivity by using a new method that allows us to test whether the earnings differentials of workers with different levels of education correspond to their productivity differentials.

Specifically, we present new evidence on the complex relationship between wages, productivity, and schooling by focusing on two related questions: (1) Are educated workers more productive than workers with no formal schooling? and (2) Do earnings differentials between workers with different levels of education reflect genuine productivity differentials? While we feel these are interesting and important questions concerning the operation of the labor market, it is important to recognize that they shed no light whatever on the issue of whether education actually *causes* productivity (i.e., whether or not there is signalling. See, for example, Card, 1998; Hellerstein et al., 1999). Instead, the major contribution of this paper is to offer an alternative framework for examining the relationship between education and worker productivity.

To investigate how education, wages, and productivity interact, we analyse a rich data set from Ghana which matches information on workers' schooling characteristics with information on the firms where they are employed. These data are from a panel survey of 200 manufacturing firms organized under the World Bank's 'Regional Programme for Enterprise Development (RPED) and collected during the summers of 1992, 1993, and 1994. The main advantage of these data is that they provide all the relevant information needed to simultaneously estimate an earnings function and a production function for workers and the firms where they are employed. By estimating these two functions simultaneously, we can test whether the estimated private return to schooling is statistically different from the productivity differential associated with one additional year of schooling. Our results suggest that earnings differentials by education reflect genuine productivity differentials.

Although many studies have examined the impact of education on agricultural productivity, none to the author's knowledge has examined how education is related to productivity in the manufacturing sector of a developing country. The RPED data provide strong evidence that education is highly correlated with productivity in Ghanaian manufacturing. Specifically, we find evidence that workers with tertiary education are more productive than those with secondary school education; workers with secondary school education are more productive than those with primary school education; and workers with primary school education are more productive than those with no formal education. Furthermore, we find evidence that these productivity differentials correspond directly to workers' earnings differentials.

The remainder of this paper is organized in the following manner. Section 2 reviews the micro literature on education, which makes use of Mincer's (1974) log-linear earnings function. Section 3 summarizes the empirical evidence available on productivity and education. Section 4 describes the methodology developed in this study for (1) incorporating education into a production framework and (2) simultaneously estimating this production function with an earnings function using a matched set of data on workers. Section 5 discusses the definitions of the variables used for analysis and their descriptive statistics. Section 6 describes the empirical results. And finally, Section 7 concludes the paper.

2. Education and earnings

Mincer (1974) demonstrates that the relationship between a worker's years of schooling and earnings is log-linear. Typically, this relationship, the earnings function, is written as

$$\ln w = \alpha + \beta S + \varepsilon \tag{1}$$

where $\ln w$ is the logarithm of earnings, S is years of schooling, and ε represents random forces that affect wages. This relationship holds provided that: (1) the only cost of an additional year of schooling is foregone earnings and (2) the marginal increase in earnings due to the additional year of schooling is constant during the worker's lifetime. Under these conditions, β is interpreted as the "rate of return" on schooling which, by definition, equals the proportional change in a worker's wages associated with one additional year of schooling.

Alternatively, suppose we allocate workers into $(n+1)$ educational levels denoted by $i = 0,\dots,n$, where the levels are ranked so that 0 is the lowest, corresponding to no schooling, and n is the highest, corresponding to university or professional training. Then we may write an alternative form of the earnings function as

$$\ln w = \beta_0 + \sum_{i=0}^{n} \beta_i D_i + \varepsilon \tag{1a}$$

where D_i is the dummy variable for educational level i. The constant term β_0 represents the log earnings at educational level zero.

Variations of Eqs. (1) or (1a) have been estimated for most countries in the world (see Psacharopoulos, 1994). One result that emerges from these studies is that poor countries have much higher rates of return to schooling than rich countries. Psacharopoulos, for example, estimates the average returns to one additional year of schooling in sub-Saharan Africa at 13%, Latin America and the Caribbean at 12%, Asia (non-OECD) at 10%, and the OECD countries at 7%. But what do these high returns mean? There are two issues here. First, do these high returns reflect true productivity differentials? And second, are these productivity differentials actually caused by the differences in education or are the differentials merely correlated with education as in the signalling model? In this paper, we are concerned only with the first of these issues.

The question as to whether cross-sectional earnings differentials reflect "true" productivity differentials has been tackled in a number of different ways. First, measures of natural ability, like raven test scores, have been added to the earnings equations (Boissiere et al., 1985; Glewwe, 1996). Second, data on siblings or twins have been used to difference-out unobserved family characteristics when estimating the effect of education on earnings (Ashenfelter and Krueger 1994; Butcher and Case, 1994). Third, natural experiments in which the variability of workers' schooling is generated by some exogenous shock or random force have been used to calculate β (Angrist and Krueger, 1991; Kane and Rouse, 1995; Harmen and Walker, 1995). And finally, test scores have been used as measures of human capital rather than years of schooling (Boissiere et al., 1985; Alderman et al., 1996; Glewwe, 1996; Jolliffe, 1998).

While the question of how to interpret β is by no means resolved, there is a growing consensus among economists working on OECD data that the Mincer model provides a relatively unbiased measure of the private returns to schooling. Two sets of results have led economists to this conclusion. First, most studies examining the issue of ability bias tend to find the same result reached by Griliches (1977) over 20 years ago; that is, any bias introduced by the omission of ability controls is very small and largely offset by other biases. Second, most studies which use instrumental variable (IV) analysis to estimate β find that the IV estimates are larger than the OLS estimates but not statistically different.[1]

[1] Recently, two explanations have been proposed as to why the IV estimates are larger than the OLS estimates. Card (1988) suggests that there is heterogeneity among the general population. This heterogeneity leads to larger IV estimates when the sub-population chosen by the natural experiment has characteristics (e.g., higher discount rates) which are correlated with higher returns to schooling. Krueger and Lindahl (1998) propose that the IV estimates are larger than the OLS estimates because researchers report only those results that are statistically significant. Since IV variables have weaker explanatory power than non-instrumented variables, the coefficients on IV variables must be larger to be statistically significant.

Similar support for the Mincer model does not exist among economists working on educational issues in developing countries. Skeptics have criticized the use of wage models in labor markets where a majority of the labor force is employed outside the wage sector (Vivjerberg, 1993; Bennell, 1996; Glewwe, 1996; Jolliffe, 1998). Estimates of the returns to schooling based on wage data have been shown to suffer from sample selection bias (Glewwe, 1996) and loss of efficiency due to measurement error (Jolliffe, 1998). Sample selection bias arises because of the non-random sorting of workers into the formal wage sector, whereas measurement error can result when wage income comprises only a small proportion of workers' total income. Other sources of bias include the omission of school quality controls in earnings equations (Berhman and Birdsall, 1983). For Ghana, there is some evidence that more motivated students go to better quality schools (Glewwe and Jacoby, 1994) and that school quality improvements generate a higher rate of return to workers than additional schooling (Glewwe, 1996).

One method of controlling for the variation of school quality is to use cognitive test scores as a measure of human capital rather than years of schooling. While such data were extremely scarce 10 years ago, an increasing number of household surveys being conducted in developing countries now include basic literacy and numeracy tests. Indeed, data on cognitive skills were collected in Ghana during 1988–1989 as part of the Ghana Living Standards Survey (GLSS). These data have been used to measure the importance of school quality in determining student test performance (Glewwe and Jacoby, 1994) and to measure the impact of cognitive skills on worker wages (Glewwe, 1996) and household income (Jolliffe, 1998). The evidence from these studies indicates that school quality is an important determinant of student test scores and that student test scores are strongly correlated with workers' non-farm income.

3. Education and productivity

Microeconomic theory suggests at least three different ways in which education can affect productivity. First, Becker's (1975) theory of human capital argues that education teaches workers valuable skills that make them more productive. Given their higher productivity, more-educated workers earn higher wages. To choose the optimal level of education, workers compare the present value of lifetime earnings associated with different levels of schooling. They remain in school as long as the marginal benefits of schooling outweigh the marginal costs. If human capital theory is "correct," the coefficient on schooling estimated by Mincer's (1974) human capital earnings function provides an unbiased estimate of the impact of education on productivity, provided two conditions hold: (1) workers' wages equal their marginal product, and (2) no variables correlated with schooling which affect wages are excluded from the earnings analysis.

Second, the "signalling" or "sorting" model of education argues that more educated workers receive higher wages, not necessarily because school has taught them any valuable skills, but because firms use education as an informational signal to differentiate high-quality workers from low-quality workers. Underlying this theory is the idea that a worker's educational attainment is correlated with other unobserved characteristics that existed before he made his schooling decision. As explained by Weiss (1995),

> "an accurate measure of the change in wages for a person who goes to school for 12 years instead of 11 would not measure the effect of that year of education on his productivity, but rather the combined effect of one additional year of learning and the effect of being identified as the type of person who has 12 rather than 11 years of schooling"

(p. 134). If the "signalling" theory holds, the coefficient on schooling estimated by the Mincerian earnings function may overstate the impact of education on productivity. In a signalling world, however, education still *reflects* productivity, even if it does not cause all of it.

Third, it is possible that all workers with the same level of schooling do not have the same productivity due to differences in their environment which affect the productivity-enhancing effects of education. According to this school of thought, the returns to schooling are higher in dynamic environments because education improves workers' access to information (Thomas et al., 1991) and their ability to decode and understand new information (Nelson and Phelps, 1966; Schultz, 1975). In addition, the demand for skills is assumed to rise during periods of technological change because of the comparative advantage that educated workers have in implementing new technology (Bartel and Lichtenberg, 1987; Rosenzweig, 1995). In this paper, we test only the "human capital" view of education; data constraints prevent empirical tests of the other two views.

While micro theory suggests several avenues through which education can affect productivity, little consensus exists among economists on how education is related to productivity. To date, empirical research has been limited because few data sets contain information on both workers' output and their education. Recently, such data have become available which enable researchers to compare the earnings and productivity of different groups of workers (Hellerstein and Neumark, 1995; Hellerstein et al., 1999).

Despite the paucity of micro data, several studies have used macro data to examine the impact of education on aggregate productivity measures. Within a growth accounting framework, changes in a country's average level of schooling should be correlated to changes in national income. Surprisingly, little evidence exists to support this relationship. Instead, much of the macro evidence based on cross-country regressions reveals a positive relationship between a country's *initial* level of schooling and its GDP growth rate. Theoretically, this result implies that a country's initial level of schooling will affect its growth rate forever, which seems highly implausible. Krueger and Lindahl (1998) and Topel (1998) demonstrate that this result is spurious, arising from either measurement error or model mis-specification. Once these problems are eliminated, they find that changes in a country's average level of schooling are positively correlated to its rate of economic growth.

Other studies have examined the impact of education on particular sectors within an economy. Griliches (1970), for example, uses industry-level manufacturing data from the United States to determine whether labor "quality" is correlated with greater output. Welch (1970) conducts a similar study using US farm data and finds, like Griliches, that education has a positive impact on output. Within the development literature, a number of studies carried out during the 1970s examined the impact of education on agricultural output. This research has produced largely mixed results. Nearly half of the studies surveyed by Lockheed et al. (1980) and Appleton and Balihutu (1996), for example, find that educated farm workers are not necessarily more productive than uneducated farm workers in developing economies.

The insignificance of education in agricultural production functions is often attributed to the low level of technology existing in most rural labor markets. If the benefits of education arise mainly in dynamic environments, it is unlikely that farmers who use traditional technologies would have very high returns to education. This is the view taken by Nelson and Phelps (1966) who argue that the marginal productivity of education is an increasing function of the rate of technological innovation. Jovanovic and Nyarko (1995) and Rosenzweig (1995) present a more sophisticated version of this idea by developing a Bayesian learning model in which education improves a worker's ability to make optimal choices under uncertainty.

Rosenzweig suggests two channels through which education can affect productivity: first, education may widen a worker's access to different sources of information; and second, education may increase a worker's ability to learn from past experience. According to Rosenzweig, these characteristics are productivity-enhancing in environments which place a premium on learning. For example, it is expected that educated workers have a comparative advantage over uneducated workers when it comes to activities like technology adoption. Why? Because educated workers have a better idea of how to use the technology before it arrives and they learn more from each use of the technology.

A number of microstudies provide empirical evidence in support of this viewpoint. Thomas et al. (1991) find a positive relationship between the amount of education completed by women and the number of information sources they use each week. Rosenzweig and Schultz (1989) demonstrate that educated women are more efficient at controlling their own fertility when using the rhythm method, a traditional style of contraception requiring the ability to evaluate individual-specific fertility information. More recently, Foster and Rosenzweig (1996) examine the profitability of education across different states in India using panel data, which cover the period both before and after the introduction of green revolution technology. They find increasing returns to schooling during the years when the new hybrid seeds were being introduced.

In a related literature, there is evidence that educated workers have faster rates of learning by doing than uneducated workers. Jones and Barr (1996) test the hypothesis that learning by doing is slower in developing countries and in industries that use simpler technologies. Using the same data set from Ghana, their study reveals three main findings. First, the learning curve in Ghana is flatter than the learning curve in developed countries. Second, any industry-wide spillovers are small and insignificant. And third, learning-by-doing effects are stronger at low levels of technology than at intermediate levels. In another study, Foster and Rosenzweig (1995) find that a farmer's own experience (and the experience of his neighbors) influenced the net profitability of adopting green revolution technology in India.

4. Methodology

The relationship between productivity and education can be investigated using an approach similar to that developed by Brown and Medoff (1978) for examining the impact of unionization on labor productivity. Suppose that firm output is produced according to a modified constant returns Cobb–Douglas relationship

$$Y = AK^{1-\alpha}\left[L_0 + \sum_{i=1}^{n}(\gamma_i + 1)L_i\right]^{\alpha} \tag{2}$$

where Y is firm output, K is firm capital, L_0 represents the number of workers employed with no formal schooling, L_i represents the number of workers employed at educational level i, $(1-\alpha)$ is the elasticity of output with respect to capital, and A reflects the state of firm technology. An implicit assumption of this model is that all workers are perfect substitutes. That is, firms choose workers from $n+1$ educational categories by making hiring decisions based solely on the productivity differences between workers. In our study, i represents the highest level of schooling completed by a worker which is measured by six educational categories: no schooling (L_0), junior secondary school (L_1), vocational training (L_2), senior secondary school (L_3), polytechnic school (L_4), and university or professional training (L_5). In addition, we construct three more aggregate measures of education: primary education, which combines L_1 and L_2, secondary education, which is L_3, and tertiary education, which combines L_4 and L_5.

The parameter $(\gamma_i + 1)$ represents the ratio of marginal products between educated workers and uneducated workers. That is, $(\gamma_i + 1) = \dfrac{\delta Y/\delta L_i}{\delta Y/\delta L_0} = \dfrac{\mathrm{MPL}_i}{\mathrm{MPL}_0}$.

If $\gamma_i > 0$, educated workers are more productive than uneducated workers. Likewise, if $\gamma_i < 0$, uneducated workers are more productive than educated workers. Note that while evidence that $\gamma_i > 0$ provides strong evidence that educated workers are more productive than uneducated workers, it does not rule out the "signalling" hypothesis as a possible explanation for the positive correlation between productivity and schooling.

In addition, this paper examines whether education has the same relative effects on wages as on productivity. Economic theory predicts that education up to a given level will be associated with increases in workers' relative wages and relative productivities in the same proportion, if firms pay workers their marginal product. To see the intuition behind this result, let us compare the relative wages and relative productivities of workers with educational levels 0 and i. The wages of these two groups of workers can be written as

$$w_0 = \frac{\delta Y}{\delta L_0} = \alpha K^{1-\alpha}\left[L_0 + \sum_{i=1}^{n}(\gamma_i + 1)L_i\right]^{\alpha-1} = \mathrm{MPL}_0 \tag{3}$$

and

$$w_i = \frac{\delta Y}{\delta L_i} = \alpha K^{1-\alpha}\left[L_0 + \sum_{i=1}^{n}(\gamma_i + 1)L_i\right]^{\alpha-1}(\gamma_i + 1) = \mathrm{MPL}_i. \tag{4}$$

By dividing Eq. (4) by Eq. (3), we find that $\frac{w_i}{w_0} = (1+\gamma_i)$, i.e., the wage differential equals the productivity differential. So, in logs we have

$$\ln w_i = \ln w_0 + \ln(\gamma_i + 1) \tag{5}$$

where $\ln(\gamma_i + 1)$ represents the average wage premium which workers at educational level i receive relative to uneducated workers.

It should be obvious that $\ln(\gamma_i + 1)$, in Eq. (5), is the same as the estimated coefficient on schooling, β_i, in Eq. (1a).[2] Stated differently, the proportional rise in wages associated with a move from educational level 0 to educational level i should be equivalent to the proportional rise in worker productivity when firms pay workers their marginal product. We examine the accuracy of this prediction by testing the null hypothesis that $\mathrm{H}:\beta_i = \ln(\gamma_i + 1)$ against the alternative that $\mathrm{H}:\beta_i \neq \ln(\gamma_i + 1)$. Tests of the null hypothesis that $\mathrm{H}:\beta_i = \ln(\gamma_i + 1)$ tell us whether the average marginal return to education, β_i, is equivalent to the average marginal productivity differential between different education groups, $\ln(\gamma_i + 1)$.

[2] If γ_i is small, $\beta_i = \ln(\gamma_i + 1)$ is equivalent to $\beta_i = \gamma_i$ using Taylor's expansion. We do not use the Taylor expansion to approximate this relationship because we want to maintain the highest degree of accuracy.

A few more steps are needed to transform Eq. (2) into the production function which we estimate. First, we define $\lambda_i = L_i / L_0$, where λ_i represents the proportion of a firm's labor force with i years of education. Second, we rewrite Eq. (2) as

$$Y = AK^{1-\alpha}L^{\alpha}\left[1 + \sum_{i=1}^{n}\gamma_i\lambda_i\right]^{\alpha}, \tag{6}$$

where $L = \sum_{i=0}^{n} L_i$ and $\sum_{i=0}^{n}\lambda_i = 1$. Next, we divide Eq. (6) through by L in order to express the different groups of workers in terms of their productivity. After dividing both sides by L and taking logarithms, we get

$$\ln\left(\frac{Y}{L}\right) = \ln A + (1-\alpha)\ln\left(\frac{K}{L}\right) + \alpha\ln\left[1 + \sum_{i=1}^{n}\lambda_i\gamma_i\right] \tag{7}$$

which we shall estimate by non-linear least squares.[3]

We make two final modifications to our model. First, we relax the assumption of constant returns to scale by adding $\Theta\ln L$ to the production function. Second, we add a vector of firm control variables, $\boldsymbol{\psi X}$, to control for productivity variations associated with different firm characteristics (e.g., unionization, state ownership, industry, etc.). We estimate the following two production functions

$$\ln\left(\frac{Y}{L}\right)_j = \ln A + (1-\alpha)\ln\left(\frac{K}{L}\right)_j + \Theta\ln L_j + \alpha\ln\left[1 + \sum_{i=1}^{n}\lambda_i\gamma_i\right] + \boldsymbol{\psi X}_j + \epsilon_j, \tag{8}$$

and

$$\ln\left(\frac{Y}{L}\right)_j = \ln A + (1-\alpha)\ln\left(\frac{K}{L}\right)_j + \Theta\ln L_j + \alpha\gamma\bar{S}_j + \boldsymbol{\psi X}_j + \epsilon_j, \tag{9}$$

where $\ln(Y/L)_j$ is the logarithm of the jth firm's value-added, $\ln(K/L)_j$ is the logarithm of the jth firm's capital–labor ratio, $\bar{S}_j$ is the average years of schooling of workers in firm j, $\boldsymbol{X}_j$ is a vector of firm variables that can affect productivity (e.g., industrial sector, union status, market share, etc.), and ε_j represents random disturbances.

The γ coefficients have different interpretations in Eqs. (8) and (9). In Eq. (8), they represent the productivity differential between workers in the ith educational category and those in the base category. For example, if λ_1 represents the proportion of workers with primary education, γ_1 represents the productivity differential between workers with primary education and those with no education (see Eqs. (3)–(5)). In this case, we test the null hypothesis whether H:$\ln(\gamma_1 + 1)$

[3] We could, of course, estimate Eq. (7) directly, but we chose to use the logarithmic form of the Cobb–Douglas with an additive error, as is commonplace in the production function literature.

$= \beta_1$ where β_1 represents the estimated coefficient on a school dummy variable which takes the value 1 if the highest level of worker education is primary school.

In Eq. (9), the estimated coefficient $\alpha\gamma$ represents the proportional rise in productivity associated with increasing the average level of firm education by 1 year. This is based on an alternative "years of schooling" based production function of the form

$$Y = AK^{1-\alpha}\left[e^{\gamma\bar{S}}L\right]^{\alpha} \tag{10}$$

where S is the average years of schooling of workers in the firm. By setting $\bar{S} = S$ and $\bar{S} = S + 1$, profit maximization implies

$$\frac{\delta Y/\delta L_{(S+1)}}{\delta Y/\delta L_S} = \frac{W_{S+1}}{W_S} \tag{10a}$$

or, alternatively,

$$e^{\alpha\gamma} = \frac{w_{S+1}}{w_S} \tag{10b}$$

or, alternatively

$$\alpha\gamma = \ln w_{S+1} - \ln w_S. \tag{10c}$$

Consequently, the null hypothesis we test is H: $\alpha\gamma = \beta$ where β represents the private returns to schooling (see Eq. (1)).

To test the null hypothesis that $\beta_i = \ln(\gamma_i + 1)$, we estimate, along with Eq. (8), the following augmented earnings function

$$\ln w_k = \beta_0 + \sum_{i=1}^{n} \beta_i D_{ik} + \kappa_1 E_k + \kappa_2 E_k^2 + \kappa_3 \boldsymbol{Z}_k + \varepsilon_k \tag{11}$$

where $\ln w_k$ is the logarithm of weekly earnings (i.e., wages plus all allowances) of the kth worker, D_{ik} is a dummy variable for educational level i, E_k is the total number of years of work experience completed by the kth worker, $\boldsymbol{Z}_k$ is a vector of firm characteristics[4] that can affect earnings (e.g., industrial sector, union status, firm size, etc.), and ε_k represent random disturbances. Alternatively, to test the schooling based hypothesis, $\alpha\gamma = \beta$, we estimate, along with Eq. (9), the standard earnings function

$$\ln w_k = \beta_0 + \beta S_k + \kappa_1 E_k + \kappa_2 E_k^2 + \kappa_3 \boldsymbol{Z}_k + \varepsilon_k \tag{11a}$$

where S_k is the years of schooling of the kth worker. All the definitions and descriptive statistics for the variables used in the analysis are listed in Appendix A.

[4] Note that these can affect wages because of their impact on productivity or for other reasons, such as they reflect compensating differentials.

5. Data

The data used in this analysis are from a panel survey of Ghanian manufacturing firms. This survey is part of a nine-country (Burundi, Cameroon, Cote d'Ivoire, Ghana, Kenya, Rwanda, Tanzania, Zambia, and Zimbabwe) study of the manufacturing sector in Africa which was organized by the World Bank and funded by several European governments and the Canadian government. The Ghana case study was funded by the British Overseas Administration (ODA) and conducted by a team combining staff from the Centre for the Study of African Economies at Oxford University and the University of Ghana at Legon.

The data collected are extremely rich for an industrial survey and provide numerous indicators of how firms in Ghana have performed in the structural adjustment period (i.e., 1983–1993). Most importantly, these data also include information on a sub-sample of workers employed by the firms interviewed. During the RPED surveys, up to 20 workers were interviewed from each firm in the sample. Workers were asked questions about their own educational background, work experience, on-the-job training, wages, benefits, and numerous other personal characteristics. In total, 1211 workers were used for the earnings analysis.

The RPED survey covers firms which operate in nine three-digit manufacturing sectors (food processing (311–312), beverages (313), textiles (321), garments (322), wood processing (331), furniture (332), metal products (381), and machinery (382). Approximately 200 firms were interviewed during each of the three waves, which included firms in both the formal and informal sectors of the economy. Twelve of these firms were misclassified as manufacturers and had to be dropped. In total, we have information on 151 firms from wave 3 and 127 firms from wave 2 which makes 278 firm observations. We do not use the first wave data, except for lagged variables. We lag both the value of capital stock and firm size in order to reduce any possible bias caused by endogeneity. All production variables are deflated by the GDP deflator and expressed in 1985 prices.

Most of the variables used in the analysis are quite standard and their definitions are included in Appendix A. We define the dependent variable as the log of value-added per worker, where value-added is calculated as profits (i.e., sales revenue minus variable costs) plus the wage bill. Firm size is defined as the sum of full-time workers (employees who work 40+ h/week) plus apprentices. The inclusion of apprentices is slightly unusual, although necessary, given the fact that apprentices make up a large proportion of the workforce in informal sector firms.

For the earnings analysis, the dependent variable is the logarithm of weekly earnings. We use weekly earnings rather than hourly earnings because the reporting hours variable is extremely noisy. To control for hours, we included the logarithm of weekly hours as an explanatory variable. We do not control for occupation in the earnings function because we want to capture the full effect of education on earnings. Controls are included, however, for firm characteristics so that the results of the earnings function are directly comparable to the results of the production function.

In Table 1, we present the descriptive statistics of our sample of Ghanaian workers and the firms where they are employed. The average education of workers in the manufacturing sector appears to be quite high, approximately 10 years according to the data reported at the individual level. Less than 10% of the workers have no formal education, which is much lower than the national rate of illiteracy. According to the World Bank (1995, Table 1), 40% of all Ghanaian adults are functionally illiterate. This suggests that manufacturing workers are, on average, better educated that the typical Ghanaian worker, which is not surprising given the higher wage paid to manufacturing workers. In 1990, the earnings of workers in the manufacturing sector were twice that of workers in the agricultural sector and a third more than the national average (Ghana Statistical Service, 1994, Table 48).

Table 1
Descriptive statistics of all workers and the firms where they are employed

	Workers ($N = 1211$)	Firms ($N = 278$)
Human capital variables		
Experience	12.1	10.32
Female	0.18	0.22
Years of education	9.74	10.22
Primary schooling	0.48	0.57
Secondary schooling	0.26	0.23
Tertiary schooling	0.18	0.13
Junior secondary school	0.48	0.57
Vocational training	0.14	0.08
Senior secondary school	0.13	0.14
Polytechnic training	0.13	0.10
University	0.05	0.03
Production variables		
$\ln(K/L)$	–	7.27
$\ln(L)$	–	2.89
Metal	0.25	0.22
Furniture	0.23	0.20
Wood	0.08	0.06
Garments	0.09	0.22
Textiles	0.03	
Food	0.27	0.22
Beverages	0.03	0.01
Machinery	0.03	0.04
ln(average hours worked per week)	3.79	6.58
State-owned	0.08	0.05
Unionized	0.57	0.28
1993 Dummy	–	0.46

The RPED data cover firms in nine three-digit industries which represent approximately 80% of all firms in the manufacturing sector. Approximately 60% of all Ghanaian manufacturing workers work in these nine three-digit industries.[5] We split our sample into six broad industry groups: foods (311, 312), beverages (313), textiles (321), garments (322), wood (331), furniture (332), metal (381), and machinery (382). Although state ownership of firms in Ghana is prevalent, only 5% of the firms covered by the RPED data are public enterprises.[6] We also control for union coverage in the production analysis and union membership in the earnings analysis. Collective bargaining plays an important role in determining the levels of wages in many firms. Minimum wages, for example, are set by a negotiating process between members of the Trade Union Congress, the government, and the Ghana Employer's Association. These minimum wages are binding for most manufacturing workers outside the informal sector (see Jones, 1997). In the RPED sample, union coverage is just over half of all firms while union membership is much lower at just over a quarter of all workers.

6. Empirical results

6.1. All firms and workers

Table 2 presents the results from estimating both the earnings function and the production function for our sample of workers and the firms where they are employed. First, we investigate the years of schooling model based on Eqs. (9) and (11a). In columns (1) and (4), we report the average returns to one additional year of schooling at the firm-level, $\alpha\gamma$, and individual-level, β, respectively. As revealed by column (1), a 1-year increase in the average level of education within a firm is associated with a 7.0% rise in labor productivity. Remarkably, this rise in labor productivity is almost identical to the private returns to schooling estimated for manufacturing workers in the RPED sample. Column (4) reports that workers' earnings rise by 7.1% with each additional year of schooling.

To test whether these two coefficients are statistically different, we calculate a Wald statistic and test whether our results fall within the 90% confidence interval formed by the χ^2 distribution. The productivity and earnings coefficients are not statistically different from one another at the 90% and the 95% level when the Wald statistic is less than 2.71 and 3.84, respectively. Since the Wald statistic in

[5] These percentages are based on the number of firms in the latest industrial census for which data are available. See Ghana Statistical Service (1989).

[6] According to the latest industrial census, 25% of all firms were state-owned.

Table 2
The relative productivity and returns to schooling of workers in all firms

Dependent variable	Productivity equation ($N = 278$)			Earnings equation ($N = 1211$)			
	Non-linear least squares			Ordinary least squares			
	Log(value-added per worker)			Log(weekly earnings)			
	(−1)	(−2)	(−3)	(−4)	(−5)	(−6)	(−7)
Constant	1.505 (0.95)	0.490 (1.60)	−1.467 (2.31)	−0.305 (0.43)	0.190 (0.43)	0.30 (0.42)	
$\ln(K/L)$	0.152 * (0.04)	0.157 * (0.04)	0.152 * (0.04)				
$\ln(L)$	−0.155 (0.21)	−0.139 (0.21)	−0.124 (0.21)	0.142 * (0.02)	0.138 * (0.02)	0.13 * (0.02)	
Experience	0.082 * * * (0.05)	0.061 (0.05)	0.053 (0.05)	0.042 * (0.01)	0.039 * (0.01)	0.04 * (0.01)	
Experience squared 10^{-2}	−0.150 (0.23)	−0.111 (0.22)	−0.09 (0.22)	−0.06 * (0.00)	−0.054 * (0.00)	−0.01 * (0.00)	
Female	−0.427 * * * (0.25)	−0.551 * * (0.25)	−0.618 * (0.20)	−0.150 * (0.04)	−0.139 * (0.04)	−0.12 * (0.04)	
Average / years of education	0.070 * (0.03)			0.071 * (0.00)			0.001
Primary schooling		0.079 (0.28)			0.297 * (0.06)		0.5806
Secondary schooling		0.538 * * (0.30)			0.555 * (0.07)		0.003
Tertiary schooling		0.789 * (0.33)			0.907 * (0.07)		0.1249
Junior secondary school			0.080 (0.28)			0.298 * (0.06)	0.5824
Vocational training			0.721 * * (0.35)			0.501 * (0.07)	0.3837
Senior secondary school			0.432 (0.31)			0.610 * (0.07)	0.3059
Polytechnic training			0.783 * * (0.34)			0.727 * (0.07)	0.0263
University			0.923 * * * (0.54)		1.328 * (0.09)	0.5836	
Adjusted R^2	0.392	0.41	0.41	0.35	0.37	0.41	

Standard errors are reported in parentheses. All regressions control for seven industry dummies (metal, furniture, wood, garments, foods, beverages, and machinery), the log of hours worked, state ownership, unionization, and the year of interview. Statistical significance at the 1%, 5%, and 10% statistical levels is indicated by *, * *, and * * *, respectively. The Wald statistics in column (7) refers to the hypothesis that the productivity and earnings coefficients are the same. The coefficients on schooling levels in columns (2) and (3) are of the form $\ln(\gamma_i + 1)$.

this case is 0.001, the coefficients are obviously, to all intents and purposes, identical. This result indicates that, in the years of schooling model, there is no statistical difference between the relative wages paid to workers and their relative productivities which is strong evidence in support of the view that education reflects productivity.

The remainder of the table compares the relative wages and relative productivities of workers with different levels of education. This is based on Eqs. (8) and (11). In columns (2) and (5), we split workers into three broad educational categories: primary, secondary, and tertiary schooling. Once again, there is very little difference between the returns to schooling estimated by the production and earnings analysis. The coefficient on secondary schooling, for example, is 0.54 in column (2) and 0.56 in column (5). Somewhat larger differences emerge from the estimates on primary and tertiary schooling, although none of these differences are statistically significant according to the Wald statistics in column (7).[7]

One surprising result which emerges is that primary schooling is insignificant in the production analysis. This result contradicts the usual finding for developing countries that primary schooling has large returns. Foster and Rosenzweig (1996), for example, reveal that only households with primary schooling, not higher levels of schooling, earned greater agricultural profits after the introduction of green revolution technology. Appleton and Balihutu (1996), whose study is one of the few which uses African data, also find evidence that primary schooling in Uganda is associated with greater agricultural productivity. By contrast, our results indicate that secondary schooling and tertiary schooling have a significant impact on productivity.

The results of the regressions, which include all educational variables are reported in columns (3) and (6) and note again that they are not significantly different according to the Wald statistics in column (7). From column (3), we see that only vocational training, polytechnic training, and university are significant in the production analysis. In Ghana vocational, training is run almost entirely outside the formal education system. In 1991 there were approximately 1100 vocational schools, of which, 160 were public, 250 were private, and about 700 were unregistered private institutions (Adu-Sakordie, 1994). More than 95% of the 634,233 students who attended these training centers choose those operating within the private sector.[8]

[7] The reported coefficients in columns (2) and (3) have been adjusted by adding 1 and then taking the logarithm in order to test the null hypothesis that $\beta_i = \ln(\gamma_i + 1)$. Because we adjusted the coefficients, we needed to adjust the standard errors also. The standard errors have been adjusted by multiplying them by $1/(1+\gamma_i)$, the derivative of $1/(\gamma_i + 1)$ using the Taylor expansion.

[8] These numbers do not include apprentices. According to the Ministry of Employment and Social Welfare, it is estimated that “traditional apprenticeships” account for 80% of all skill training in Ghana (Adu-Sakordie, 1994, p.15).

One additional result which is not related to education, but worth mentioning, is that the gender coefficient is negative in both the earnings equation and the production function. The result that women receive lower earnings than men (controlling for other human capital variables) is a very common finding in earnings analysis. Many have interpreted this result as evidence that women are being discriminated against in the labor market. What is interesting is that women in Ghana are not only paid less than men, they are also less productive.[9] Calculation of the Wald statistic indicates that the lower relative wages of women are not statistically different from their lower relative productivity. Similar evidence has been found for Israeli women in a study by Hellerstein and Neumark (1999) who use firm-level data from Israel to estimate marginal productivity and wage differentials by sex. By contrast, a related study for the US found that American women were paid about 25–35% less than American men, but their productivity differential was generally no more than 15% less (Hellerstein et al., 1999).

6.2. Wage-setting in different types of firms

Up to this point, the results provide fairly strong evidence that education differentials reflect genuine productivity differentials. One possibility that we have not investigated is whether the impact of education on productivity varies across different types of firms. To examine this issue, we split our sample of firms into two broad classes: (1) formal sector versus informal sector firms and (2) unionized versus non-unionized firms. We define the formal sector as all firms with more than 10 employees and the informal sector as all firms with less than 10 employees.[10] According to the 1987 industrial census, approximately 25% of firms were in the formal sector and the remaining 75% were in the informal sector. We define a firm as unionized if the firm manager has reported that his firm has recognized union membership. According to the RPED data, more than half of all manufacturing firms are unionized.

Table 3 reports the relative wages and relative productivity of workers in different types of firms based on the years of schooling model (Eqs. (9) and (11a)). While the productivity differentials are approximately 2–3% points larger than the earnings differentials in all four specifications, it can be seen from the

[9] It is possible, of course, that women are being discriminated against in the Ghanaian labor market if they face barriers to certain occupations which result in them being sorted into low productivity occupations.

[10] According to the International Labour Organization, one of the defining characteristics of informal sector enterprises is their small size. Typically, informal sector enterprises employ "fewer than 10 people, mostly immediate family" (see www.ilo.org).

Table 3
Wage-setting in different types of firms OLS estimation

	Relative productivity	Returns to schooling	Wald statistic
(i) Formal sector: ≥ 10 employees	0.051*** (0.029) [258]	0.073* (0.005) [1150]	0.073
(ii) Informal sector: ≥ 10 employees	0.070** (0.031) [120]	0.039*** (0.022) [61]	0.039
(iii) Unionized	0.115*** (0.064) [110]	0.090* (0.082) [685]	0.09
(iv) Non-unionized	0.071* (0.022) [268]	0.055* (0.006) [526]	0.055

The number of observations are reported in the brackets. All the explanatory variables included in the regressions are the same as those reported in Table 2.

Wald statistics that none of these differences are statistically significant. Once again, the results provide evidence that is consistent with the view that education is strongly correlated with productivity in manufacturing. Perhaps most surprising is the result that there is no statistical difference between the earnings differentials and productivity differentials of workers with different levels of education in the informal sector. One might expect a wedge between earnings and productivity in informal sector firms, where competition among firms is typically assumed to be imperfect. However, the RPED data indicate that education is positively associated with productivity in the informal sector and that earning differentials between informal sector workers reflect genuine productivity differentials.

One last remark about the results in Table 3. Notice that the education premium for workers in unionized firms is bigger than the education premium for workers in non-union firms. The average return to schooling for unionized workers is estimated at 9.0%, while the returns to non-union workers are a full 3% less. According to the (unreported) Wald statistic, this education premium is statistically bigger for workers in unionized firms. By contrast, the productivity differential between unionized workers and non-unionized workers is not significant. These results suggest that the education premium is bigger for workers in unionized firms, even though the productivity of unionized workers is not significantly higher than their non-union counterparts.

7. Conclusion

This paper examines the productive nature of education using an unusually rich data set from Ghana which matches information on workers' characteristics with information on the firms where they are employed. These data enable us to compare the productivity differentials and earnings differentials between different groups of workers. Two primary questions are addressed: (1) are educated workers more productive than workers with no formal schooling? and (2) do earnings differentials between workers with different levels of education reflect genuine productivity differentials? We find strong evidence that education and productivity are positively correlated, and that firms pay workers according to their productivity.

To examine the relationship between education and productivity, we incorporate several education variables into an augmented Cobb–Douglas production function. The RPED data indicate a strong, positive monotonic relationship between education and productivity. Specifically, we find evidence that workers with tertiary education are more productive than those with secondary schooling; workers with secondary schooling are more productive than those with primary schooling; and workers with primary schooling are more productive than those with no formal education. Only when the education variables are defined by very narrow classes (including non-formal education like vocational training and polytechnic training) does this monotonic relationship breakdown. When we estimate the augmented Cobb–Douglas production function with all five educational classes, there is evidence that workers with vocational training are more productive than workers with secondary schooling, despite the fact that workers with secondary schooling typically have more years of education than workers with vocational training. One possible explanation for this contradictory result is that the education variables at this level of aggregation may be measured with error.

To investigate whether workers' earnings differentials reflect genuine productivity differentials, we present a model which simultaneously estimates an earnings function and production function for workers and the firms where they are employed. Almost without exception, the RPED data indicate that there is no statistical difference between the earnings differentials and productivity differentials of workers with different levels of education. Indeed, the data indicate that the private returns to education (7.1%) are the same as the rise in productivity (7.0%) associated with one additional year of average education. This result suggests that educated workers in Ghana earn higher wages than uneducated workers because they contribute more to firm output.

So what are the policy implications of these results? One positive result to emerge from the RPED data is the important role of education in manufacturing. Not only is there evidence that educated workers are more productive than uneducated workers, but there is also evidence that firms reward workers according to their productivity. The data indicate that the Ghanaian labor market works remarkably well, even by developed country standards. On average, the relative earnings differentials and productivity differentials between different groups of workers are equivalent. This result implies that the estimated returns to schooling based on Mincer's model provide a good estimate of real productivity differentials (at least for workers in the manufacturing sector). Whether or not this result holds in other developing countries is an empirical question that can be answered only by further analysis.

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Appendix A. Definition of variables used in the production and earnings functions

Name	Definition
Production variables	
ln(Vaddl)	The log of value-added divided by total labor input. Value-added is calculated as the sum of profits (i.e., the value of sales minus all variable costs) plus labor costs.
Ln(K/L)	The log of the capital–labor ratio. Capital is defined as the replacement value of the total capital stock. This endogenous variable is lagged by 1 year.
ln(L)	The log of total labor input. The labor input is defined as the sum of all full-time workers (i.e., those working 40 + h/week). Workers include apprentices. This variable is lagged by 1 year.
Food	Equals one if the firm has a SIC classification of 311 and 312; zero otherwise.
Beverages	Equals one if the firm has a SIC classification of 313; zero otherwise.
Garments	Equals one if the firm has a SIC classification of 322; zero otherwise.
Wood	Equals one if the firm has a SIC classification of 331; zero otherwise.
Furniture	Equals one if the firm has a SIC classification of 332; zero otherwise.
Metal	Equals one if the firm has a SIC classification of 381; zero otherwise.
Machinery	Equals one if the firm has a SIC classification of 382; zero otherwise.
ln(hours)	The log of the average number of hours worked per week.
Union	Equals one if the firm is unionized; zero otherwise.
State	Equals one if the firm is a state enterprise; zero otherwise.
Year92	Equals one if the observation comes from Wave 2 of the RPED survey; zero otherwise.

Human capital variables	
Educ; Avged	A worker's years of completed schooling; the average years of education completed by a firm's workforce
Primary	Worker's who have completed either primary school (6 years) or junior secondary school (9 years)
Secondary	Worker's who have completed either vocational training (JSS + 3 years) or Senior secondary school (9 years)
Tertiary	Worker's who have completed either professional training (university + 1 year), university (SSS + 4 years), polytechnic training (SSS + 3 years) years)
JSS	Workers who have completed junior secondary school
Voc	Workers who have completed vocational training. These courses are designed so that classroom study is alternated each 6 months with on-the-job training. Options include courses in the building trade (e.g., metal fabrication, electrical installation, etc), as well as clerical and domestic studies (e.g., secretarial work, dressmaking, cookery, etc.).
SSS	Workers who have completed senior secondary school
Poly	Workers who have completed polytechnic courses. Polytechnic institutes offer advanced craft and technician course in fields such as engineering, building and business.
Univ	Workers who have completed either university or professional training.
Female	Equals one if the worker is female; zero otherwise.
Experience	Total years of work experience.

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