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Multidimensional Human Capital, Wages and Endogenous Employment Status in Ghana

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ABSTRACT

Multidimensional Human Capital, Wages and Endogenous Employment Status in Ghana[*]

Previous studies of labor market outcomes such as employment and wages have mostly been limited to investigating the impact of formal schooling only and, as a consequence, have seldom considered skills or alternative routes to acquiring skills, such as adult literacy programs, or other types of education. This paper examines these issues for Ghana, by estimating the joint effects of formal schooling, literacy and numeracy skills, and adult literacy programs on employment and wage outcomes. Wage and employment status equations are estimated jointly, allowing employment status to be endogenous. Substantial returns to basic cognitive skills are established, while the education system – especially the lower levels of formal education – is found to be relatively successful in creating these skills. At the same time the results hint at there being substantial returns to skills other than basic literacy and numeracy. These skills appear to be produced mostly from technical and vocational education and training and at higher levels of formal education. Adult literacy participants are less likely to be economically inactive and more likely to be self-employed, hinting at the income-generating activities component of these programs having indirect effects on wages through its effect on labor market participation, especially for females, individuals with no formal education, and in urban areas.

JEL Classification: I31, J24, O15

Keywords: wage equations, employment status, human capital, literacy and numeracy, cognitive and non-cognitive skills, formal education, adult literacy programs, Ghana

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1. Introduction

One of the most important ways to improve one's livelihood comes through the acquisition of education and its subsequent return in the labor market. As a consequence, the issue of education – and especially how to improve it and bring more access to more people – has been at the center of the policy debate in most countries for quite some time. The effect of education on labor market outcomes, especially earnings, also has received considerable interest in the academic literature, which has confirmed the positive association between education and economic success.[1]

Yet, there are still issues related to education and labor market outcomes that would seem to require more attention, both related to the transition into the labor market and among different employment categories and to enumeration. Which types of education are successful in generating employment or self-employment? How are different types and levels of schooling enumerated? How much of the enumeration is accounted for by basic literacy and numeracy ability and how much by other human capital? These questions are particularly relevant for developing countries. The evidence here is more scarce due to data limitations but at the same time, addressing these questions is even more pertinent due to having less resources available for education.

Hence, while much of the human capital literature for developed countries has focused on formal education and within this further focused on higher levels of education, other types and other levels of education may be more relevant. In Ghana, for example, while few people attend tertiary education, technical-vocational education is popular. Also, due to the low levels of formal educational attainment in Ghana, adult literacy programs have been offered for a number

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[1] See, for example, Card (1999), Psacharopoulos (1973, 1981, 1985, 1994), Psacharopoulos and Patrinos (2004), and Willis (1986).

of years. The labor market in developing countries also differs from developed countries by having more individuals working either as self-employees or as unpaid family workers. Whereas previous studies have often focused on regular wage employees, a more appropriate approach may be to include all categories of work simultaneously.

Estimating wage and employment status equations simultaneously, this paper examines the three questions posed earlier for the case of Ghana, taking the issues discussed previously into account. First, the set of human capital variables included in the wage and employment equations contain formal education, technical-vocational education, adult literacy programs and basic literacy and numeracy, thus broadening the more common approach of focusing at formal education, only. This will allow for contrasting and comparing the relative impact of different types and levels of education, as well as literacy and numeracy, on wages and employment status. Second, the categories in the employment status equation include regular wage employees, the self-employed, unpaid family workers and individuals not working. In addition to enabling me to examine the returns to human capital among regular wage employees and the self-employed, this also lets me examine how different human capital components affect the transition among different labor market categories, say, between unemployment and self-employment or between being an unpaid family worker and being self-employed. In doing so, the empirical analyses account for the endogeneity of employment status using a two-stage procedure, where the employment status is estimated in the first stage, and conditional on employment status, the wage structure is then estimated in the second stage.

2. Conceptual Framework

This section presents a theoretical analysis of wages and employment status and how they are

affected by skills and schooling. Conditional on employment status (the *j* subscript), wages are assumed to be a function of skills (*S*); other observed individual background characteristics including age, gender and geographical location (*B*); and unobserved individual characteristics including ability (*δ*), giving rise to the following wage function:

$$W_j = W_j(S, B, \delta) \tag{1}$$

In (1), an increase in skills leads to an increase in wages, as well, holding the other factors constant.

I extend this discussion by considering, first, the different routes though which skills may be acquired, and, second, different types of skills. Following Blunch (2006), there are several routes for achieving skills, namely formal schooling obtained during childhood and adult literacy program participation later in life. Similarly, there are different skills that may affect wages through separate channels. Most importantly, an individual's wages may increase from participation in childhood schooling. This could be due to a direct productivity effect from cognitive skills such as literacy and numeracy in line with a standard human capital explanation or from non-cognitive skills such as socialization or discipline skills (Heckman, Stixrud and Urzua, 2006). Alternatively, earnings capacity may increase either from credentialism or signaling (Spence, 1973) obtained from schooling, especially at higher levels.

Wages may also increase from learning about income generating activities, which is an integral component of adult literacy programs in Ghana (Blunch and Pörtner, 2005). In addition to merely learning about different income generating activities, participants also frequently directly engage in income generating activities. Under the guidance of the teacher participants may, for example, engage in pottery, weaving or groundnut oil extraction. Both the learning and the more practical of these program components may affect wages (failing that, they still may

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affect the labor supply of participants, especially in terms of moving from being economically inactive to becoming self-employed).

Now, from (1), the wage structure is conditional on employment status, so that employment status clearly affects wages – for example, regular employees might earn higher wages than the self-employed, all else equal.[2] While this may be accounted for by merely including employment status as a variable in the vector of other observed background characteristics (B), employment status might more appropriately be treated as endogenous. For example, regular employees may be systematically different from individuals who are either self-employed or working as unpaid family workers. Similarly, individuals who are inactive may be systematically different from either of these groups. Additionally, however, the returns to skills and schooling may differ systematically depending on employment. For example, one might expect that the returns to certain skills may be greater for regular wage employees than for self-employed workers.

These considerations lead me to consider employment status as being governed by a separate process; this depends on five factors: skills (S), other observed individual background characteristics described previously (B), unobserved individual characteristics, including employment status preferences (δ), expected wages if working as a regular wage employee (W_1) and as a self-employed worker (W_2), and other job characteristics (η), giving rise to the following employment status[3] function:

$$E = E(S, P, B, \delta, W_1, W_2, \eta) \tag{2}$$

[2] Or vice versa: self-employment may not necessarily be inferior to regular wage employment (Maloney, 2004).

[3] Due to rationing and barriers to entry into regular wage employment there might not be much of a choice between this and self-employment. There still is a choice between economic inactivity and self-employment, however. Again, at the other end of the spectrum, there is also still the possibility that self-employment is a sector of choice rather than a marginal sector (Maloney, 2004); in turn, this would induce selection for the full range of employment status possibilities.

The pathways through which skills and the other factors affect employment status in (2) include the following. Education may have a non-productivity effect, for example through signaling, connections or networks. For example, an educated individual would seem to be more likely to be working than not working and also more likely to be a regular wage employee than to be either self-employed or working as an unpaid family workers. Parental occupation is likely to affect search cost, so that individuals whose parents were white-collar workers would also seem to be more likely to work and, conditional on working, also more likely to be regular wage employees than to be either self-employed or unpaid family workers. The individual may also have strong preferences for one employment status over another, for example preferring the relative autonomy of self-employment or the job-security of being a regular wage employee. The employment choice is, thus, a trade-off between opportunity and return: the individual simply chooses the employment status, which yields the highest indirect utility in terms of monetary and non-monetary returns, conditional on having access to the employment category in question.[4]

From this discussion, there are several implications for the empirical analyses. First, due to possibility of employment status being endogenous, this framework highlights the importance of modeling the determinants of wages and employment status simultaneously. Second, the model points to the variables that should be included in the empirical analyses as explanatory variables. These include skills, parental employment status, and other observed individual background characteristics such as age, gender, and geographical location. Third, the model indicates that skills have both direct and indirect effects on wages, the latter coming through the impact on employment status.

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[4] Regular wage employment may require personal connections and networks or self-employment may require credit for start-up costs, for example.

Based on the previous discussion I will examine whether basic literacy and numeracy (basic cognitive skills) affect wages, in particular whether they have effects beyond those of schooling itself. Additionally, I will examine what the effect is on the schooling estimates from introducing literacy and numeracy. This effectively amounts to examining, on one hand, the relative importance of basic cognitive skills vis-à-vis schooling for individual earnings capacity, and, on the other, the efficiency of schooling in cognitive skills production.

I will also examine the impact of basic literacy and numeracy and schooling on employment status. As with the wage analyses, the focus is on whether skills have effects beyond those of schooling itself. This effectively amounts to examining the possibility of indirect wage effects – that is, effects coming through the effect on employment status.

For both sets of analyses two additional issues will be examined. First, one may ask whether economic conditions affect the returns to education and literacy and numeracy and/or their effect on employment status. Here, it is possible that both the returns to education and literacy and numeracy and their effect on employment status vary with characteristics such as geographical location. That is, rather than merely including geographical location in equations (1) and (2), these equations could be made conditional on geographical location. For example, I expect the returns to schooling and literacy and numeracy to be higher in areas where the returns to skilled labor are higher and in areas where incomes and/or the cost of living are higher.[5] The insight here is that urban areas are generally better off in terms of economic conditions than rural areas.[6] Second, attitudinal and social factors may affect schooling and skills returns and

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[5] While migration for education and/or work purposes may be a potential issue here, incorporating migration would greatly complicate the analyses.
[6] Some regions are better off than others, as well; most notably the Greater Accra region is better off than the other nine regions in terms of economic conditions. However, since for the analyses here I am mainly interested in the gross returns to education and literacy and numeracy, I want to avoid including variables beyond an absolute minimum.

employment status, especially gender. To be sure, in many developing countries social norms and traditions prescribe "traditional" gender roles, which could, in turn, affect education and labor market outcomes and lead to substantial gender wage and employment status gaps. For example, it might be expected that males both earn more and are more likely to be regular wage employees than females, controlling for other factors.

3. Previous Research

Starting with the literature on schooling and wages, this literature generally finds large private returns to education. [7] For example, reviewing 133 studies for 98 different countries, Psacharopoulos and Patrinos (2004) calculate the average private returns to a year of education to be 10 percent. Developing regions generally experience much higher returns to education than OECD countries. The regional average Mincerian return for Sub-Saharan Africa, for example, is 11.7 percent, as compared to 7.5 percent for OECD countries.

These general findings for the (formal) schooling-wage (earnings) relationship also have been established for Ghana. For example, Glewwe (1996, 1999) found that an additional year of schooling increased wages by about 8.5 percentage-points for government and private sector workers as a whole. Similarly, positive effects of schooling are found on manufacturing sector wages (Teal, 2000), non-farm self-employment income (Vijverberg, 1995) and on farm and non-farm (i.e. wage income and self-employment) profit (Joliffe, 2004).

Studies that have considered cognitive skills in the human capital-wage (earnings) relationship have generally found evidence of a separate effect from these skills, controlling for schooling. Adding controls for cognitive skills to a wage or earnings regression typically leads

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[7] Extensive reviews of this literature are provided in Card (1999), Psacharopoulos (1973, 1981, 1985, 1994), Psacharopoulos and Patrinos (2004), and Willis (1986).

to a decrease in the estimated effect of formal schooling. In a seminal study of Kenya and Tanzania, Boissiere, Knight, and Sabot (1985) simultaneously considered formal educational attainment and cognitive skills. Introduction of the cognitive skills measures decreased the estimated association between formal educational attainment and log earnings by nearly two-thirds. Similar results are found in Moll's (1998) study of South Africa.[8]

The literature examining the impact of cognitive skills on earnings (wages) in Ghana is much in line with that from other countries. Including English reading and mathematics test scores in a study of public and private sector wages, Glewwe (1996)[9] found a positive and statistically significant effect from numeracy on government sector wages of about 2.5-3.5 percentage-points depending on the specification – but not on private sector wages – even when formal educational attainment is included. English reading skills, on the other hand, were found to affect wages in the private sector positively, by about 3-3.5 percentage-points but were not found to affect wages in the government sector. Years of schooling and teacher training were positive and statistically significant in the government sector, which was taken to indicate the existence of diploma effects.

The impact of cognitive skills on non-farm self-employment income in Ghana was examined by Vijverberg (1999), using the same dataset as Glewwe (1996, 1999). Linear specifications with either schooling or cognitive skills did not yield significant effects of human capital on non-farm self-employment income while interacted models (with years of schooling and cognitive skills) led to "sporadic evidence of positive links between elements of human capital (schooling or skills) and enterprise income" (p. 241).

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[8] One should be careful in interpreting these results as "only – or even mainly – cognitive skills matter", since these skills are produced from schooling. Rather, they both indicate that schooling is successful in producing these skills and that there are additional components of schooling that affect wages in addition to cognitive skills.
[9] The results in Glewwe (1999) are similar as far as cognitive skills are concerned (schooling were not included in the specifications where cognitive skills were included).

Summing up, numerous studies find evidence of a positive association between formal schooling and wages. This is true for the general literature and also to some extent for the smaller literature, which examines wage determinants in Ghana. Only a subset of studies, for Ghana and elsewhere, incorporates literacy and numeracy in addition to formal educational attainment. The individual studies generally consider regular wage employment or self-employment separately, or alternatively aggregate employment categories, for example aggregating formal and non-formal (non-farm) employment into non-farm employment, rather than simultaneously examining regular wage employment and self-employment. Lastly, very few studies directly examine the effect of other types of schooling than formal schooling on wages (earnings). Participation in adult literacy programs or technical and vocational education may provide participants with literacy and numeracy and/or other skills, which may positively affect wages via their influence on productivity and therefore also would seem to belong in the human capital-wage relationship.

4. Estimation Strategy and Issues

From the conceptual framework in Section 2, I have suggested that skills can affect wages either directly or indirectly through their impact on employment status. Empirically, the direct effects can be estimated by a Mincer-equation (Mincer, 1974), augmented with skills, whereas the indirect effects can be estimated by a multinomial logit model of employment status, including skills as explanatory variables. Again, the endogeneity of wages and employment status warrants an estimation strategy that takes this into account.

These considerations lead me to pursue a two-stage estimation procedure. In the first stage, the employment status is estimated by a multinomial logit model. Let the indirect utility

of individual i associated with employment status j be given as:

$$v_{ij} = \alpha_{0j} + \alpha_{1j}S_i + \alpha_{2j}B_i + \alpha_{3j}P_i + \varepsilon_{ij} \tag{3}$$

where S_i includes variables for formal educational attainment, adult literacy program

participation, and literacy and numeracy, P_i includes variables for parental employment status,

and B_i include other (control) variables, including age, gender and geographical location. ε_{ij} is an

error-term capturing unobservables, and j = regular wage employee, self-employed, unpaid

family worker, or not working. Individual i chooses employment status j if the indirect utility of

status j exceeds that of all the other possible employment categories. Assuming that the errors

across choices are independently and identically distributed such that $F(\varepsilon_{ii}) = \exp(e^{-\varepsilon_{ij}})$, this

yields the multinomial logit model.

In the second stage, the conditional wage equation is estimated, including the Durbin-

McFadden (1984) correction for selectivity (based on the multinomial logit model from the first

stage):

$$W_{ij} = \beta_{0j} + \beta_{1j}S_i + \beta_{2j}B_i + \beta_{3j}\hat{\lambda}_{ij} + \psi_{ij}, \tag{4}$$

Where W_{ij} denotes (log) wages for individual i in employment status j, $\hat{\lambda}_{ij}$ is a vector of

selection-terms (inverse Mills ratios) estimated from the first-stage employment equation, ξ_{ij} is

an error-term capturing unobservables, and the other variables are defined similar to equation

(3). While the parameter estimates are consistent, the standard errors must be corrected to take

the two-stage nature of the estimation procedure into account. This is done by bootstrapping the

standard errors. Also, the survey design (see the next section) is explicitly accounted for by

incorporating sampling weights and clustering in the estimations throughout. In order to identify

the model one or more exclusion restrictions must be imposed that is, one or more variables

should be included in the employment status equation (4) but excluded from the wage equation (3). The parental occupation measures play that role, although this requires the somewhat unrealistic assumption that parental occupation has no independent effect on productivity. Marital status and marital status interacted with gender are included as additional exclusion restrictions. As motivated earlier, wage and employment status equations are estimated for the full sample, for females and males separately, for rural and urban areas separately, and for individuals with no formal education.

5. Data

The empirical analyses of this paper examine household survey data from the fourth round of the Ghana Living Standards Survey. The survey gathered information on income, labor supply, literacy and numeracy, formal educational attainment, and participation in adult literacy courses as well as other information such as age, gender, and geographical location.

One primary dependent variable in this paper is the natural logarithm of the hourly wage rate for the person's main occupation (if any); it is calculated as the average hourly earnings, including all monetary and (monetized) non-monetary payments. The other primary dependent variable in this paper is employment status: working for pay for other enterprise (employee), working for pay for own enterprise (self employed), working but not for pay (unpaid family worker), and not working (economically inactive).

Moving to the explanatory variables, I construct a binary "functional literacy" measure. This measure is one if the individual can either write in a Ghanaian language *or* English *and* do written calculations, and zero otherwise (in sensitivity analyses I examine other specifications of cognitive skills). Educational attainment is measured as the highest level completed, ranging

from "none" through "university" and also includes technical/vocational training. I consider a set of four binary variables, corresponding to the completion of primary school, middle and junior secondary school, secondary school and above, and technical/vocational training.[10] I also construct a binary measure, indicating whether an individual has ever attended an adult literacy course program.[11] Other explanatory variables include controls for rural-urban location and female gender, as well as age and age squared, marital status, and parental employment status, including white-collar and agriculture.[12]

Turning next to sample restrictions, individuals should have had a chance to complete primary schooling, while at the same time being eligible for participation in adult literacy programs (the lower age limit). Also, individuals should not be "too old," since measurement issues then start to become more important (the upper age limit). This leads me to restrict the initial sample to adults between 15 and 54 years of age (both included), which yields an initial 10,139 observations for the selection equation for the full sample. Some of these observations are missing on one or more variables, however. This leads to a drop in the estimation sample to 10,003 individuals. Further, 13 individuals report having completed "other" education; since it is not clear exactly what this means and since there are so few of these – leading to extremely thinly populated cells for some of the sub-group analyses – these are dropped, as well. The final, effective estimation sample for the selection equation therefore contains 9,990 individuals – corresponding to a drop of less than 1.5 percent relative to the initial sample. Descriptive statistics of the main variables (log hourly wages, employment status, literacy and numeracy,

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[10] Thirteen individuals in the full sample report having completed "other education." These are dropped since it is not clear what "other education" is.

[11] There are of course some issues here, related to timing and intensity of participation, and so on. See Blunch (2006) for more discussion of this.

[12] A more detailed discussion of both dependent and explanatory variables and their definitions is provided in Blunch (2006).

schooling) for the analyses samples are reported in Tables A1 and A2 in the Appendix.

6. Results

In this section reduced form estimates of the employment status and wage models are presented and discussed. The models are estimated for the full sample, and for five different sub-samples: females, males, rural areas, urban areas, and for individuals with no formal education completed. Since the focus of the paper is on the effect of literacy and numeracy and schooling, the results for the other explanatory variables – including variables for gender, age, age squared, rural-urban location, and, for the employment status regressions, only (i.e., the exclusion restrictions): marital status, marital status interacted with gender, and variables for parental employment status – are not reviewed here (they are available upon request).

Employment Status

Since the multinomial logit model is non-linear, estimated parameters depend on the values of all the other variables in the model. To ease the interpretation of the estimated effects, therefore, the results are presented in Table 1 in terms of marginal effects, evaluated at the mean of the other explanatory variables. Starting from the top of the table, the first set of results is for regular employees, followed by the self-employed, unpaid family workers and inactive individuals. For each of these categories, the table gives the results for the full sample in the first column and the sub-groups – the female, male, rural and urban samples, and the sample for individuals with no completed formal education – in columns two through six. From Table 1 a few overall results stand out in particular.

[Table 1 about here]

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First, not surprisingly, formal education – especially at the higher levels – predominantly leads to regular wage employment, while adult literacy program participation leads to self-employment. Noticeably, this last result is both substantively large, ranging from about 2 percentage-points for individuals from urban areas to about 16 percentage-points for males, and mostly also statistically significant. Note that while it may appear that adult literacy course participation is "bad" for regular wage employment, the preferred estimation sample for judging the effect on adult literacy course participation is the sample of individuals with no formal education. And for this estimation sample, the estimated association between adult literacy program participation and formal wage employment is nil, both in substantive and statistical terms.

Second, adult literacy course participation decreases economic inactivity, especially for females and in urban areas. So, while – as we will see later – participation in adult literacy programs does not have a direct effect on wages, conditional on employment status, it does have a substantial indirect effect on wages through its impact on employment status – namely by enabling individuals to move from economic inactivity into self-employment.

Third, employment status is strongly affected by parental employment status (results not shown in the Table). Individuals whose parents were white collar workers are more likely to be regular employees and less likely to be self-employed, unpaid family workers or not working.

Wages

Turning to the results for the wage equation, the marginal effects of the schooling and literacy and numeracy variables – using Kennedy's (1981) bias correction[13] – are shown in Table 2. The

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[13] The marginal effects for dummy variables in semi-logarithmic models are not merely given as the estimated coefficients (although some studies treat them as such); therefore, the estimated coefficients are not interpretable "as

Table is organized similar to the employment status regression results in Table 1, except that now there are only results from the employment categories, which obtain wages – namely regular employees and the self-employed; also, the models are estimated in two flavors: one, where everything but literacy and numeracy is included and one, which adds literacy and numeracy.[14] Again, the reason for this is that I want to examine the extent to which literacy and numeracy skills affects the schooling premium and the extent to which literacy and numeracy adds additional explanatory power to the wage equations.

[Table 2 about here]

From Table 2 the first specification, which is estimated for the full sample and includes formal schooling and adult literacy participation, reveals a large positive and statistically significant association between formal education and wages. This is true across all estimation samples. The finding of a large return to formal education accords with the findings in the previous literature reviewed in Section 3 in this paper. Again, while it may appear that adult literacy course participation is "bad" for wages, the preferred estimation sample for judging the effect on adult literacy course participation is the sample of individuals with no formal education. And for this estimation sample, the estimated association between adult literacy program participation and wages, while negative, is not statistically significant for regular wage employment. For self-employment, it is positive (but not statistically significant).

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is." While direct exponentiation (via the formula: marginal effect = exp(coefficient) – 1) is a common way of converting the estimated coefficients of dummy variables from semi-logarithmic models into marginal effects, Kennedy (1981) suggests that this is a biased estimator for the "true" marginal effect. He offers a bias correction – involving the variance of the estimate – which is used here, as well.

[14] Estimating the employment status equation in both flavors revealed that the results generally were quite robust to whether or not literacy and numeracy was included.

Adding literacy and numeracy in the second specification causes a substantial drop in the premium to formal education for wage employees, often also losing statistical significance, while the skills premium at the same time is large and positive. The returns to middle and junior secondary school, for example, drops from about 51 percentage-points to about 3 percentage-points in the full sample. This is consistent with earlier findings for Kenya and Tanzania (Boissiere, Knight, and Sabot; 1985) and South Africa (Moll; 1998). The literacy and numeracy premium ranges from about 13 to 95 percentage-points for regular wage employment and from 2.6 to about 13 percentage-points for self-employment; it is mostly statistically significant for the regular wage employees, while it is somewhat imprecisely measured for the self-employed and therefore not statistically significant. R^2 remains constant, indicating very little independent explanatory power in literacy and numeracy, once schooling has been controlled for.

What do these results mean? The finding of an individual skills effect, separate from that of education, confirms that it is not only schooling per se that is important for wages: the cognitive skills obtained from schooling are important, too, possibly through their impact on productivity and therefore on wages. It also confirms that the Ghanaian education system is successful in creating skills; this has been examined more extensively elsewhere, however (Blunch, 2006). This is all consistent with a standard human capital explanation.

While literacy and numeracy are important determinants of wages, however, the results also indicate that education is important, even after controlling for cognitive skills – in accord with the findings in Boissiere, Knight, and Sabot (1985), Moll (1998), and Glewwe (1996). In other words, skills achieved through schooling other than basic cognitive skills are important, as well. Such skills may include more advanced cognitive skills and non-cognitive skills such as socialization or discipline skills (Heckman, Stixrud and Urzua, 2006); conceptually, these skills

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would seem to be produced mainly at higher levels of formal education, and through technical-vocational education or adult literacy course participation. Formal education may also generate diploma or signaling effects (Spence, 1973), which would also affect wages; conceptually, the signaling effect would only seem to be relevant for higher levels of formal education and that only for regular wage employees. Hence, for secondary education, it is not possible empirically to distinguish between production of more advanced cognitive skills or non-cognitive skills and the "production" of signaling.

Empirically, the results are consistent with the advanced cognitive skills, non-cognitive skills, or signaling explanation for secondary education and the advanced cognitive skills explanation for technical-vocational education. The former is particularly strong for females and individuals from urban areas, while the latter is particularly strong in urban areas. Again, this is also consistent with the returns to these more advanced skills partly coming about through the existence of better economic opportunities in urban areas.

Turning to the differences between regular employees and self-employed, the drop in the education premium when including cognitive skills is not nearly as dramatic for the self-employed; the statistical significance of estimates is also retained to a greater degree than what was the case for regular wage employees. The education premium in self-employment is much lower to begin with, however – for secondary and above for the full sample, for example, less than a third of that of regular wage employees. These results indicate that the returns to human capital generally are lower for the self-employed – which is consistent with this segment of the labor market possibly employing relatively less skilled labor, as is also revealed by the descriptive statistics in Table A2.

In sum, the human capital effects have been decomposed into two individual groups of

effects: basic cognitive skills and advanced cognitive, non-cognitive skills, or signaling effects, both of which are important in the human capital-wage relationship.

Lastly, the selection terms are frequently statistically significant, supporting the importance of employing the Durbin-McFadden (1984) procedure used here. To further assess the validity of this procedure, tests for the joint significance of the over-identifying variables[15] in the employment status equation were undertaken. The results (not shown) indicate that the set of identifying instruments as a whole are strong predictors of employment status, being statistically significant at 0.01 percent or better in all cases. Since conceptually the instruments should not affect wages, conditional on employment status, the selectivity correction procedure employed here appears both justified and valid.

Besides these main patterns in the wage regression results, there are also some additional interesting results pertaining to some of the subgroup analyses. For example, the cognitive skills and education premia are substantially higher in urban regular wage employment than in rural regular wage employment. The reason for this is probably that the labor market conditions and economic opportunities more generally are greater in urban than in rural areas, especially as they pertain to skilled workers, and here especially regular wage employees. Expanding educational opportunities, therefore, have the highest effect if carried out in an environment with economic opportunities. Alternatively, educational expansion might benefit from associated policies aiming at enabling such economic opportunities. Also, in rural areas the results for formal education are strongest and most consistent for technical and vocational education and training. This is consistent with practical skills being more valued in rural areas, which again is in line with signaling and non-cognitive skills mainly mattering for regular wage employment.

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[15] Marital status, marital status interacted with gender, and dummy variables for parental employment status.

Sensitivity Analyses

I also performed sensitivity analyses to assess the robustness of the previous results. Specifically, I experimented with several different alternative functional literacy (cognitive skills) measures. Specifically, in addition to the preferred measure (Ghanaian *or* English writing *and* written calculations), I re-estimated the model for the full sample using Ghanaian *or* English reading *and* written calculations, Ghanaian *and* English reading *and* written calculations, and Ghanaian *and* English writing *and* written calculations. The wage premium to the three alternative functional literacy measures was found to be substantial, though of differing magnitude depending on the measure in question; it was also not always statistically significant. These discrepancies notwithstanding, the results from the sensitivity analyses do not appear to detract from the overall conclusions of the main analyses of there existing large returns to literacy and numeracy, controlling for schooling.

7. Conclusion

This paper examines the determinants of wages in Ghana, focusing on the effect from a set of human capital variables that captures formal and non-formal education and cognitive and non-cognitive skills, treating employment status as endogenous. Previous research has mostly treated human capital as a "black box," typically incorporating measures for formal education but not for nonformal education or literacy and numeracy when examining the association of human capital and wages.

Among the main findings, the introduction of basic literacy and numeracy in the human capital-wage relationship decreases the estimated effects of formal schooling, especially at the lower levels, often rendering the effect statistically insignificant. In turn, this indicates that

"cognitive skills matter," not only schooling in and by itself is what matters. At the same time, these results also confirm that the Ghanaian education system is successful in creating basic cognitive skills. This is all consistent with a standard human capital explanation.

Additionally, the continued importance of technical-vocational education and secondary and higher indicate that skills achieved through schooling other than basic cognitive skills are important, as well. Such skills may include more advanced cognitive skills and non-cognitive skills such as socialization or discipline skills (Heckman, Stixrud and Urzua, 2006). Formal education may also generate diploma or signaling effects (Spence, 1973), which would also affect wages, however. The results are consistent with both explanations for secondary education.

In addition to the direct effects from skills and schooling on wages, however, several indirect effects – coming through the impact on employment status – are established. First, not surprisingly, formal education predominantly leads to more regular wage employment. Second, the opposite is true for self-employment, where workers are less likely to have completed formal education but more likely to have attended an adult literacy program. Third, adult literacy course participation decreases economic inactivity, especially for females, individuals with no formal education, and in urban areas. So, while participation in adult literacy programs does not have a direct effect on wages, conditional on employment status, it does have a substantial indirect effect on wages through its impact on employment status.

What are the policy implications of these results? First, policy makers should care more about educational outputs rather than education and educational enrollment per se. If educational programs – in the broadest sense, including formal and non-formal education alike – do not produce useful skills, such as literacy and numeracy, for example, they should either be adjusted

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and improved or abandoned in favor of programs that do.

Cost-effectiveness is crucially important in this connection, especially for developing countries. If adult literacy programs indeed have positive indirect effects on wages, through the effect on employment status – as the evidence here suggests they do, especially for females and in urban areas – they may well be cost-effective relative to formal education; at least they may be a useful complement to formal education, especially for individuals with low stocks of formal human capital. Since participants meet a couple of hours a few times a week, typically of a duration of about two years, and participation is mostly free, except for a small reward to the facilitator (typically in the form of a bike or a sewing machine), the main cost are foregone earnings. At such modest costs even moderate returns in terms of wages (through the decrease in economic inactivity) would seem to make these programs and their further strengthening worthwhile. Indeed, there are other potential effects from these programs which will positively affect peoples' livelihoods in addition to wages, such as increased child health arising from the health component of these programs (Blunch, 2006).

A few comments are in order, however, regarding the frequently quite high returns to skills and schooling estimated here. As Glewwe (1991: 318) also notes, since such estimates are conditional on past choices in asset accumulation, estimated returns tend to overestimate the returns to education for the general population. Policy makers, therefore, should not expect quite as massive results if human capital levels were to increase for the economy at large. Even if these estimates are upper bound estimates of the "true" effects, however, continued investment in human capital in Ghana should remain a priority for Ghanaian policy makers and international development organizations in the future.

Also, while suggestive, the results and analyses here represent only a first attempt at

opening the black box in the human capital-wage relationship, however – more research is needed. Above all, the analysis of more and better data is required: do the results here pertain to other (West) African countries – and other developing countries more generally? Also, the measures of literacy and numeracy examined here were arguably crude. Rather than self-reported (binary) measures of literacy and numeracy ability, one would prefer more objective (continuous) test score based measures.

Similarly, there are obvious timing issues related to the adult literacy course participation measure: it is known if a person participated but not when, in which program or whether the program was completed. With that information, much richer analyses could be performed. Future research, using more precise measures of participation, could validate the findings here while also more precisely estimating impacts and possible asymmetries in effects from different providers of adult literacy programs.

As researchers, we mostly have to simply accept the data, we are given – only rarely do we have the resources available to collect exactly the data, we need for a particular analysis. One can only urge national statistical agencies, the World Bank, UNICEF, ILO and others carrying out large-scale household surveys in developing countries to continuously refine their survey instruments, keeping in mind the issues raised here.

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Table 1. Marginal Effects for Education and Literacy and Numeracy from Employment Status Equation

	Full sample:	Female:	Male:	Rural:	Urban:	No formal educ.:
Regular wage emp.:						
Primary	0.042*	0.013	0.095*	0.040	0.030	
Middle/JSS	0.109***	0.070***	0.183***	0.088***	0.137***	
Secondary and above	0.467***	0.442***	0.548***	0.461***	0.462***	
Technical/Vocational	0.316***	0.241***	0.404***	0.361***	0.332***	
Literacy course	-0.034**	0.010	-0.130***	-0.040***	0.048	-0.009
Literate and numerate	-0.015	0.010	-0.087	-0.013	-0.017	-0.005
Self-employed:						
Primary	0.004	0.060*	-0.083	0.034	-0.022	
Middle/JSS	-0.053	0.024	-0.180***	0.010	-0.111**	
Secondary and above	-0.422***	-0.356***	-0.537***	-0.382***	-0.418***	
Technical/Vocational	-0.206***	-0.067	-0.352***	-0.263***	-0.197***	
Literacy course	0.106***	0.092**	0.164***	0.111***	0.023	0.097**
Literate and numerate	0.026	0.001	0.105**	0.031	0.008	-0.018
Unpaid fam. worker:						
Primary	-0.052***	-0.088***	-0.018**	-0.077***	-0.023***	
Middle/JSS	-0.068***	-0.123***	-0.012	-0.108***	-0.018	
Secondary and above	-0.041***	-0.096***	-0.004	-0.068**	-0.015*	
Technical/Vocational	-0.092***	-0.165***	-0.036***	-0.125***	-0.042***	
Literacy course	-0.020	-0.032	-0.017*	-0.046**	0.016	-0.055
Literate and numerate	-0.029*	-0.029	-0.030	-0.031	-0.020	-0.070*
Not working:						
Primary	0.005	0.016	0.006	0.002	0.014	
Middle/JSS	0.013	0.029	0.008	0.010	-0.009	
Secondary and above	-0.004	0.010	-0.006	-0.011	-0.030	
Technical/Vocational	-0.019	-0.008	-0.017	0.027	-0.094**	
Literacy course	-0.052***	-0.070***	-0.017	-0.025***	-0.086**	-0.033***
Literate and numerate	0.018	0.018	0.013	0.013*	0.029	0.093**
Pseudo-R^2	0.27	0.21	0.32	0.26	0.23	0.23
N	9881	5560	4321	6382	3499	3937

Notes: Estimations employ Robust Huber-White (Huber, 1967; White, 1980) standard errors and incorporate sampling weights and adjust for within-community correlation/clustering (Froot, 1989; Williams, 2000). *: statistically significant at 10 percent; **: statistically significant at 5 percent; ***: statistically significant at 1 percent.
Source: Ghana Living Standards Survey (Round 4, 1998/99).

Table 2. Marginal Effects for Schooling and Literacy and Numeracy from Wage Equation

	Full sample:		Female:		Male:		Rural:		Urban:		No formal education:	
	Only schooling	Sch. + lit/num	Only schooling	Sch. + lit/num	Only schooling	Sch. + lit/num	Only schooling	Sch. + lit/num	Only schooling	Sch. + lit/num	Only schooling	Sch. + lit/num
Regular wage employee:												
Primary	0.074	-0.019	0.311	0.256	-0.189	-0.218	-0.175	-0.292	0.374	0.345		
Middle/JSS	0.513***	0.028	1.178***	0.124	0.092	-0.035	0.247	-0.302	0.681**	0.431		
Secondary and above	3.071***	1.649***	5.663***	2.072***	1.968***	1.596***	2.634***	0.895**	3.023***	2.428***		
Technical/Vocational	1.124***	0.425	0.959	-0.178	-0.943	-0.021	1.368**	0.025	-0.990	-0.716		
Literacy course	-0.324	-0.312	0.047	0.140	-0.634	-0.633	-0.206	-0.186	-0.346	-0.342	-0.518	-0.545
Literate and numerate		0.519***		0.950***		0.129		0.860		0.165		0.264
Selection term, self-employment	0.759***	0.741***	1.154**	1.025*	0.654**	0.657***	0.827**	0.774***	0.665*	0.650**	1.071	1.130
Selection term, unpaid family worker	-0.078	-0.075	0.120	0.134	-0.330*	-0.322*	-0.188*	-0.189*	-0.018	-0.020	-0.379*	-0.373*
Selection term, not working/inactive	-0.105	-0.103	-0.051	0.038	0.013	0.013	-0.022	-0.007	-0.124	-0.121	0.131	0.138
R^2	0.26	0.27	0.40	0.41	0.23	0.23	0.33	0.35	0.21	0.21	0.21	0.23
N	1162		297		865		488		674		149	
Self-employed:												
Primary	0.185**	0.140*	0.085	0.082	0.137	0.142	0.225**	0.188**	-0.055	-0.103		
Middle/ JSS	0.313***	0.190*	0.053	0.033	0.139	0.273	0.397***	0.268**	0.121	0.009		
Secondary and above	0.867***	0.675***	0.759**	0.708*	0.661***	0.850**	0.398**	0.248	1.275***	1.014**		
Technical/Vocational	0.614***	0.421	0.051	0.072	-0.936	-0.977	1.091***	0.889**	-0.983	-0.955		
Literacy course	-0.154*	-0.160*	-0.089	-0.105	-0.322	-0.324	-0.012	-0.019	-0.172	-0.169	0.079	0.071
Literate and numerate		0.121		0.026		-0.134		0.115		0.121		0.134
Selection term, self-employment	0.109*	0.107*	0.246**	0.239*	-0.049	-0.047	0.189***	0.187**	-0.070	-0.079	0.050	0.055
Selection term, unpaid family worker	-0.041	-0.041	0.088	0.083	-0.324*	-0.323*	0.035	0.034	-0.156*	-0.156*	-0.091	-0.085
Selection term, not working/inactive	-0.168***	-0.171**	-0.034	-0.049	0.002	0.002	-0.137***	-0.137**	-0.010	-0.015	0.046	0.040
R^2	0.12	0.12	0.10	0.10	0.14	0.14	0.07	0.07	0.06	0.07	0.07	0.07
N	5263		2983		2280		3590		1673		2171	

Notes: Models are estimated using the multinomial selection model developed in Durbin-McFadden (1984). Marginal effects are calculated using Kennedy's (1981) bias correction for binary variables in semi-logarithmic equations. Estimations employ Robust Huber-White (Huber, 1967; White, 1980) standard errors; incorporate sampling weights and adjust for within-community correlation/clustering (Froot, 1989; Williams, 2000). *: statistically significant at 10 percent;; and bootstrap standard errors using 100 replications. *: statistically significant at 10 percent; **: statistically significant at 5 percent; ***: statistically significant at 1 percent.
Source: Ghana Living Standards Survey (Round 4, 1998/99).

APPENDIX: Descriptive Statistics

Table A1. Descriptive Statistics for Employment Status from Estimation Samples (Employment Status Equations)

	Full sample:		*Females:*		*Males:*		*Rural:*		*Urban:*		*No education:*	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Regular employee	0.131	0.337	0.062	0.241	0.219	0.413	0.088	0.284	0.209	0.407	0.043	0.204
Self-employed	0.560	0.496	0.565	0.496	0.554	0.497	0.595	0.491	0.495	0.500	0.594	0.491
Unpaid family worker	0.167	0.373	0.222	0.415	0.098	0.297	0.225	0.418	0.060	0.238	0.269	0.443
Not working (reference)	0.142	0.349	0.152	0.359	0.129	0.336	0.091	0.288	0.236	0.424	0.094	0.292
N	9881		5560		4321		6382		3499		3937	

Notes: Calculations incorporate sampling weights and adjust for within-community correlation/clustering (Froot, 1989; Williams, 2000).
Source: Ghana Living Standards Survey (Round 4, 1998/99).

Table A2. Descriptive Statistics for Wages, Schooling, and Literacy and Numeracy (Wage Equations)

	Full sample:		Females:		Males:		Rural:		Urban:		No education:	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Regular employee:												
Hourly wages (Cedis)	1375.1	8197.5	876.8	1285.6	1550.5	9496.0	1008.0	1234.0	1656.4	10835.0	542.4	567.7
No education	0.133	0.339	0.154	0.362	0.125	0.331	0.167	0.373	0.106	0.308	1.000	0.000
Primary	0.070	0.254	0.067	0.250	0.070	0.256	0.091	0.288	0.053	0.224	0.000	0.000
Middle/JSS	0.372	0.484	0.368	0.483	0.373	0.484	0.384	0.487	0.363	0.481	0.000	0.000
Secondary and above	0.348	0.477	0.333	0.472	0.353	0.478	0.319	0.467	0.370	0.483	0.000	0.000
Technical/Vocational	0.078	0.268	0.078	0.268	0.078	0.269	0.039	0.194	0.108	0.311	0.000	0.000
Literacy course	0.028	0.166	0.060	0.238	0.017	0.130	0.024	0.152	0.032	0.177	0.104	0.306
Literate and numerate	0.791	0.406	0.753	0.432	0.805	0.397	0.736	0.441	0.834	0.373	0.042	0.201
N	1162		297		865		488		674		149	
Self-employed:												
Hourly wages (Cedis)	764.0	4714.4	693.4	2719.3	855.4	6435.3	498.1	1085.5	1331.4	8166.3	463.3	842.2
No education	0.414	0.493	0.485	0.500	0.323	0.468	0.469	0.499	0.298	0.458	1.000	0.000
Primary	0.152	0.359	0.168	0.374	0.130	0.337	0.155	0.362	0.143	0.351	0.000	0.000
Middle/JSS	0.360	0.480	0.297	0.457	0.441	0.497	0.331	0.471	0.421	0.494	0.000	0.000
Secondary and above	0.049	0.215	0.029	0.167	0.074	0.262	0.036	0.187	0.075	0.263	0.000	0.000
Technical/Vocational	0.026	0.159	0.022	0.145	0.032	0.176	0.009	0.093	0.063	0.244	0.000	0.000
Literacy course	0.094	0.292	0.098	0.298	0.088	0.283	0.119	0.324	0.039	0.194	0.160	0.367
Literate and numerate	0.459	0.498	0.345	0.476	0.606	0.489	0.404	0.491	0.577	0.494	0.026	0.159
N	5263		2983		2280		3590		1673		2171	

Table A2.   cont…

	Full sample:		Females:		Males:		Rural:		Urban:		No education:	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Unpaid family worker:												
No education	0.645	0.479	0.707	0.455	0.466	0.499	0.669	0.471	0.479	0.501	1.000	0.000
Primary	0.114	0.318	0.111	0.315	0.121	0.327	0.116	0.320	0.100	0.301	0.000	0.000
Middle/JSS	0.192	0.394	0.158	0.365	0.288	0.454	0.174	0.380	0.313	0.465	0.000	0.000
Secondary and above	0.047	0.211	0.021	0.143	0.120	0.326	0.038	0.191	0.104	0.306	0.000	0.000
Technical/Vocational	0.003	0.050	0.002	0.046	0.004	0.062	0.002	0.048	0.004	0.064	0.000	0.000
Literacy course	0.070	0.255	0.085	0.279	0.026	0.160	0.072	0.259	0.051	0.221	0.090	0.286
Literate and numerate	0.231	0.422	0.173	0.379	0.397	0.490	0.208	0.406	0.391	0.489	0.009	0.096
N	1728		1283		445		1504		224		1093	
Not working:												
No education	0.266	0.442	0.322	0.467	0.183	0.387	0.327	0.470	0.223	0.416	1.000	0.000
Primary	0.144	0.351	0.157	0.364	0.125	0.331	0.142	0.350	0.145	0.353	0.000	0.000
Middle/JSS	0.452	0.498	0.434	0.496	0.480	0.500	0.464	0.499	0.444	0.497	0.000	0.000
Secondary and above	0.115	0.319	0.073	0.260	0.179	0.383	0.055	0.228	0.158	0.365	0.000	0.000
Technical/Vocational	0.022	0.148	0.015	0.121	0.033	0.180	0.012	0.109	0.030	0.169	0.000	0.000
Literacy course	0.016	0.127	0.018	0.133	0.014	0.118	0.018	0.133	0.015	0.123	0.038	0.191
Literate and numerate	0.590	0.492	0.499	0.500	0.726	0.446	0.508	0.500	0.649	0.478	0.065	0.246
N	1430		824		606		567		863		351	

Notes: Calculations incorporate sampling weights and adjust for within-community correlation/clustering (Froot, 1989; Williams, 2000).
Source: Ghana Living Standards Survey (Round 4, 1998/99).