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Does Education Signal Ability in Ghana? An Analysis Comparing Wage Earners with the Self-Employed

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Abstract

When education signals underlying abilities, income returns to education may not reflect true increases in productivity. This may be a particular concern in developing countries, where education is often prescribed as a major path to escaping poverty. Unfortunately, because education signaling occurs when underlying worker characteristics are difficult to observe, obtaining estimates of education signaling is extremely difficult. This paper uses Spence's 2002 model of signaling to develop a testable hypothesis: in the presence of education signaling, wage earners will see a higher return to education than the self-employed doing similar work. Using the 2005-2006 round of the Ghana Living Standards Survey, the study finds that returns to education are consistently higher for those in the wage-earning sector, which supports an education signaling hypothesis. Signaling appears to be more prevalent at higher levels of education and in large, unionized, and professional firms.

Keywords: Education Signaling; Returns to Education; Developing Nations; Ghana; Self-employment

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1. Introduction

While it has been widely documented that educated individuals earn higher incomes, the issue of education signaling continues to puzzle researchers. If education is actually signaling underlying attributes to employers, such as intelligence, income returns to education will not be true reflections of increases in productivity. Though widespread disagreement exists regarding the presence and magnitude of signaling, researchers agree that if signaling exists, it likely biases returns to education upwards.

Although education signaling is always a source of potential bias in education estimates, econometric papers testing for it are relatively rare. This may be because it is virtually impossible to obtain a dataset rich enough to directly measure signaling, or it might stem from the fact that basic signaling models lead to an unrealistic testable hypothesis: education has no productivity-improving effect. This study uses an extension of the basic theoretical signaling model (Spence 2002) to derive a testable hypothesis: in the presence of signaling, wage earners will see a higher income return to education than the self-employed doing similar work. Because self-employed individuals never went through a hiring process, their wages should not reflect any signaling and should better reflect productivity (Wolpin 1977, Psacharoupoulos et al. 1992, Spence 2002).

While some studies have tested for signaling, researchers continue to disagree about its true impact on the labor market. And, as Temple (2001) states, the lack of reliable evidence seems to “encourage, rather than discourage, strong views” (page 88). It is obvious, then, that there is more work to be done. This study makes two contributions to the literature. First, by drawing on Spence’s 2002 model and using a dataset with a large number of self-employed individuals, I am able to test for education signaling by using occupational groups similar in

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incomes and firm characteristics. By creating these groups, I am not only able to get cleaner estimates, but I can explore which types of firms are signaling. These results will help researchers understand the contexts in which signaling occurs. Second, this study provides one of the only estimates of education signaling in a developing country. This is both interesting, in that the relative scarcity of education may make signaling more prevalent, and important, given the focus on education as a means to escape poverty and generate growth. In the presence of signaling, simple income returns cannot be interpreted as clean measures of human capital improvements.

I examine various groups of occupations; including those with similar incomes between the wage earning and self-employed sectors, non-professional and professional occupations, firms with and without unions present, and firms of different sizes. I find that wage earners consistently see higher returns to education, which supports a signaling hypothesis in the Ghanaian labor market. The results appear to be driven by education levels above primary, and by larger firms, professional occupations, and the presence of unions. In order to control for selection bias, I also instrument for wage sector employment by parental occupations. Results are robust to this control, and even suggest that selection bias could be biasing estimates downward.

This paper proceeds as follows: Section two provides the econometric and theoretical context. Section three outlines the data and econometric methodology. Results are described in section four, and section five concludes.

2. Background

2.1 Education Signaling

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Upon hiring, employers are faced with a set of observable characteristics and must make inferences about an employee's future productivity. When an observable characteristic is correlated with an underlying attribute, employers may place extra weight on the observable characteristic in the hiring process. For example, an employer may believe that taller individuals are healthier and will show up for work more often than others. In the case of education signaling, employers believe education is correlated with a high level of productivity.

This belief is quite rational. Education requires effort and high ability individuals will have an easier time at school. Finishing school also requires that an individual be able to follow through and complete complex tasks, something that is prized by employers. As Spence (1973) shows, signaling can be Pareto efficient and quite useful to both employers and employees. It can lead to better matches and more appropriate salaries for high quality workers.

If signaling is present, however, it is virtually impossible to obtain accurate measures of human capital improvements from skills learned in school. Educated individuals will be rewarded for both learned skills and for underlying abilities which would have been there all along. Therefore, while income returns may be high, education may not be truly increasing productivity.

Income returns for education have, in fact, been relatively high throughout the world (Psacharapolous 1994, Psacharapolous and Patrinos 2004, Montenegro and Patrinos 2013). This finding has been robust to virtually all econometric methods, including twin studies and various instruments (Ashenfelter and Krueger 1994, Card 2001). However, as Weiss (1995) notes, even these studies may be biased by education signaling.

Though it is clearly important to have accurate information on the true human capital improvements caused by education, it is particularly important in developing countries. One

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reason is that an expansion of education is frequently prescribed as a main route to escaping poverty (United Nations 2015). Because educated individuals are found to make more money (Psacharopoulos 1994, Psacharopoulos and Patrinos 2004, Montenegro and Patrinos 2013), such a prescription is extremely intuitive. However, if these microeconomic returns are biased upwards by signaling, the true effects of education on human capital would be overstated, leading to lower social returns. It is also important to study education signaling in a developing country to test for potential differences in education as a signal. In particular, signaling may be stronger when education is relatively scarce, as it is in developing countries. For example, in my sample, the average observation only has 4.74 years of schooling. If only a proportion of the population completes school, those who do might seem particularly capable.

2.2 Measuring Education Signaling

Education signaling is notoriously difficult to measure. In order to accurately separate the signaling portion of an education premium it would be necessary to have data on all underlying worker qualities, such as motivation and problem solving skills. Given that no econometrician has the perfect set of data, it is impossible to directly measure the effect of education signaling. Instead, most econometric studies of education signaling measure the effect indirectly in one of three ways: examining sheepskin effects, evaluating returns over time using an employer-learning model, and comparing sectors assumed to have different levels of signaling.

Sheepskin effects occur when individuals with formal qualifications obtain higher wages than those with similar years of schooling but without qualifications. Sheepskin effects are consistent with a signaling story if diplomas are a mere formality and do not represent a higher skill level. In an influential study, Hungerford and Solon (1987) use data from the 1987 Current

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Population Survey in the US and find strong evidence of sheepskin effects. Tyler, Murnane, and Willett (2001) examine the effects of obtaining the GED on United States high school dropouts and find evidence of sheepskin effects for white, but not for minority students. Mora (2003) uses a similar approach in Colombia and again finds strong evidence of sheepskin effects. While sheepskin effects are consistent with a signaling hypothesis, they do not necessarily indicate that signaling is present. This is because if an individual obtains the same years of education but does not obtain a diploma (he drops out), he could be fundamentally different from graduates. If diplomas are designed to indicate that an individual possesses a certain skill set, it is reasonable to assume that individuals unable or unwilling to graduate lack certain skills. If this is true, then sheepskin effects might simply represent true productivity differences in graduates.

A second method that has been used to examine signaling uses an employer-learning model. Altonji and Pierret (2001) extend Farber and Gibbons (1996) to show that if education is acting as a signal for unobservable characteristics, then the returns to education should fall with experience. If employers develop a more accurate view of workers' productivity over time, then the premium paid for simply finishing school should decrease. Similarly, if ability is more accurately observed over time, returns to ability should increase with experience. Altonji and Pierret test the model using data from the US and find evidence of signaling. More recently, Lange (2007) adds to the model to provide estimates of the speed of employer learning and to also allow for estimates on an upper-bound on the role of signaling. While the model allows for an upper-bound as high as 45% of the gains from schooling, most estimates are less than 25% and Lange's preferred estimate is less than 15%.

Strobl (2003) uses an employer learning model to examine signaling in Ghana and finds evidence of signaling in individuals hired through formal channels, but not for individuals hired

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through direct contacts in the firm. Because his dataset does not contain an explicit measure of ability, he uses parent education as a proxy. Although Altonji and Pierret (2001) obtain broadly similar results using parental schooling as they do using test scores, parental education may be correlated with education rather than ability in Strobl's study, making it an inaccurate measure of ability in an employer-learning model (Lange 2007). For example, an individual may be induced to obtain an education because it is expected of him and not necessarily because he possesses a higher ability. In fact, parental education variables have traditionally been used as instruments for education, with researchers arguing they are not correlated with ability at all (Kahyarara and Teal 2008, Soderbom et al. 2006).

Even when adequate measures of ability are available, employer-learning models may not capture signaling entirely. Again, the models rest on the assumption that the non-productivity effects of schooling will diminish with time. This may not always be the case. First, there may be some instances where employers are never able to observe an employee's true abilities. The size or structure of the firm may prevent an accurate assessment, even over long periods of time. Second, raises in compensation are not always awarded for improvements in true productivity. For example, a rigid wage structure may exist that continues to reward education even with firm tenure. In this case, raises might be a set percentage of the base salary, resulting in educated individuals always receiving more than uneducated individuals. Finally, education may be misinterpreted as ability long after first impressions are made. For example, suppose an educated individual gains eloquence in speaking but no other skills. An employer may continue to view that individual as capable even if s/he is not necessarily productive, resulting in higher raises.

The third method for examining signaling compares returns to education between sectors where signaling is presumed to be different. Specifically, studies have compared returns to

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education between wage earners and self-employed individuals and between workers in government and private sectors.[1,2] If one sector is presumed to have no signaling, then returns to education in that sector should reflect true productivity effects of education. For example, since the self-employed are never hired, there is no need for them to use education as a signal for ability; underlying abilities are already known and wages will likely reflect true productivity and not signaling associated with hiring (Wolpin 1977, Psacharoupoulos et al. 1992).

Heywood and Wei (2004) provide a summary of 22 studies examining education returns between signaled and non-signaled sectors and find no obvious patterns in either developed or developing countries. For example, in the United States, Cohn et al. (1987) examine differences between the wage earners and the self-employed and find no evidence of signaling, while Grubb (1983) and Hamilton (2000) and do find some evidence of it. In any case, there is a lack of such analyses in Sub-Saharan Africa.[3] This study starts to fill in that gap.

2.3 Theoretical Background

In this study, I draw the testable hypothesis from Spence's (2002) model of signaling. The model is an extension of his earlier model (1973),[4] where high ability workers only obtain education to signal productivity to employers. By including human capital improving effects of education in his extended model, Spence is able to obtain a more realistic prediction than he did in the simple model.

2.3.1 Spence's Simple Signaling Model

In Spence's simple model, education does not improve productivity and is only used as a signal for ability. In the model, high ability workers face lower costs to education than low ability workers, and therefore find it worthwhile to invest in education in order to distinguish

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themselves. In a separating equilibrium, firms are able to identify high ability workers by their positive amount of education and pay them an efficient premium.

Because education is assumed to have no productivity-improving effects, any return to education will only be rewarding underlying ability. This implies that non-signaling workers will not receive income returns to education. This is an unintuitive prediction, especially when non-signaling workers (for example, the self-employed) choose to obtain positive amounts of education. In fact, Brown and Sessions (2004, pg. 94) argue that this strong hypothesis has prevented many researchers from conducting empirical analyses.[5]

In 2002, Spence extended his model to allow for both a signaling and a productivity-enhancing role of education. This extension provides a more reasonable hypothesis: in a separating equilibrium, income returns to education for high quality workers contain both a signaling and a human capital portion. Increased wages for educated workers will be partly due to underlying abilities (signaling) and partly due to improvements in productivity from skills learned in school (human capital).

2.3.2. Spence 2002 model of signaling

Like his simpler model, Spence's modified model assumes that there are underlying characteristics that influence a worker's effects on firm productivity and that firms cannot see them. The model assumes two types of workers: workers with naturally high ability and workers with naturally low ability, called types 1 and 2, respectively. Workers with low ability face higher costs of education, $c_1(E)>c_2(E)$ and higher marginal costs of education, $c'_1(E)>c'_2(E)$.

High ability workers have an $s_2(E)$ effect on firm productivity and low ability workers have an $s_1(E)$ effect on firm productivity, where $s_2(E)>s_1(E)$ and E is the amount of education.[6] While a worker's impact on firm productivity depends upon education, it is important to stress

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that firms still cannot see some worker characteristics. That is, even though education improves a worker's contribution to the firm, underlying abilities will still affect productivity separately. A worker's net income function is $n_i(E) = s_i(E) – c_i(E)$, which assumes workers are paid what they contribute to firm productivity, $s_i(E)$. An individual's type is unobservable, $s_i(E)$ is concave, $c_i(E)$ is convex, and the net income function, $n_i(E) = s_i(E) – c_i(E)$ is concave. Workers seek to maximize $n_i(E) = s_i(E) – s_i(E)$. Firms will pay $w_2=s_2(E)$ and $w_1=s_1(E)$ if the two groups are distinguishable. If the two groups are indistinguishable, however, firms will pay wages equal to average productivity, $w = \alpha*s_1(E) + (1-\alpha)*s_2(E)$. I refer the reader to Figure 2 in Spence (2002) to further demonstrate the model. In the figure, n2 is the high quality worker's income function, $n_2(E) = s_2(E) – c_2(E)$ and n_1 is the low quality worker's income function, $n_1(E) = s_1(E) – c_1(E)$. V_1 is the income function for a low quality worker who successfully mimics a high quality worker, $v_1(E) = s_2(E) – c_1(E)$. A separating equilibrium will occur when low-quality workers have no incentive to adopt the high quality worker signal, or when $v_1(E)<=n_1(E)$. Education levels E_1* and E_2* maximize n_1 and n_2 and $\bar{E}$ is the maximum value of education for which $v_1(E) > n_1(E)$. In other words, $\bar{E}$ is the highest level of education a low quality worker would be willing to get in order to pose as a high quality worker. If E_2* lies to the right of $\bar{E}$, then high quality workers will choose the income maximizing value of education without the risk of low quality workers posing as them, creating a separating equilibrium. Firms will therefore be able to correctly identify high quality workers by E_2*, and have an incentive to pay high quality workers wages w_2, to the right of $\bar{E}$.

In this case, signaling leads to a fully efficient outcome. Both types of workers choose the most efficient amount of education and the education signal contains accurate information about ability. Still, wages do not reflect only the increases in human capital. Recall that wages will be

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$w_2=s_2(E_2^*)$ and $w_1=s_1(E_1^*)$ and are based on a worker's value to the firm. Education both enhances productivity AND signals underlying characteristics. Here, any income return to education will have both a human capital and a signaling component.

Another separating equilibrium may occur where high quality workers must overinvest in education to differentiate themselves. I refer the reader to Figure 3 in Spence (2002), where he graphically shows this situation. Here, $\bar{E}$ is to the right of E_2^*. The difference here is that when high quality workers pursue the optimal amount of education, low quality workers now have an incentive to pose as high quality workers. In this environment, high quality workers will only be able to distinguish themselves by obtaining a level of education that is above $\bar{E}$, or the maximum level of education low-quality workers would be willing to obtain. Therefore, a separating equilibrium only exists when the wage schedule jumps to S_2 (E) at $\bar{E} + \delta$, where δ is a small number.

Note that, in this case, the equilibrium is socially inefficient and that high quality workers must overinvest in education in order to distinguish themselves from low quality workers. Wages will be $w_2=s_2(\bar{E} + \delta)$ and $w_1=s_1(E_1^*)$. Though the equilibrium level of education changes for high quality workers, this does not change the expected result regarding returns to education. Returns to education for high quality workers will still contain a human capital and a signaling element.

2.3.4 Connection to the Testable Hypothesis

Spence's model predicts two types of separating equilibria: one where workers overinvest and one that is efficient.[7] In both equilibria, signaling workers will make more money partly due to underlying ability and partly due to human capital improvements learned in school.

If a researcher is able to successfully identify a group that has signaled and a similar group that has not signaled, it is possible to disentangle the effects. A non-signaling group will only see

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returns to education for true human capital improvements learned in school, while a signaling group will see returns to education for both. A simple comparison of the two will therefore yield a measure of signaling.

The analysis hinges on the fact that groups are truly comparable. In particular, groups must be doing similar work and must contain similar individuals. The analysis also rests on the assumption that returns to education are homogeneous in ability for those workers being compared. If there are increasing returns to education in ability, high quality workers will obtain higher returns to education regardless of education signaling. If there are diminishing returns to education in ability, the opposite will be true. The empirical analysis, described below, attempts to control for each of these issues.

3. Empirical Analysis

3.1. Data

Data used is from the fifth round of the Ghana Living Standard Survey, which was undertaken in 2005-2006 (Ghana Statistical Service). Summary statistics are reported in Table 1. After dropping the observations under age 15 or with incomplete information, there are 9.227 observations. Of these, 18% are employed in the wage sector and 20% are non-agriculture self-employed. This analysis focuses on those individuals who are not working in agriculture for several reasons. First, income estimates for non-agriculture employees do not need to be imputed from crops, eliminating a potentially large source of measurement error. Second, the agricultural sector has been found to have complicated household dynamics (see Jolliffe 2002). Finally, the ISCO classifications used in the survey do not contain information on types of crops grown, making it difficult to create adequate comparison groups.

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<Table 1 about here>

Table 1 breaks down summary statistics by the wage earning and self-employed sectors. Income and sector figures are from the observation's main job, as reported in the last year.[8] . Income figures are around 34% higher for the wage-earning sector even though annual hours worked are roughly equal. Though 52% of the sample is female, the self-employed are much more likely to be female (71% versus 27% of wage earners). The mean years of schooling is only 4.74, but this is higher for the self-employed (6.53) and much higher for wage earners (11.3). Wage earners are slightly younger and are slightly less likely to be married or cohabit. Observations in both sectors are more likely to be located in an urban area than a rural area.

3.2. Empirical Methodology

This study tests whether or not signaling exists in the Ghanaian labor market. If signaling exists, returns to education will be greater for the signaling group than for the non-signaling group. To examine this, I compare returns to education for workers in the wage sector with those who are self-employed. The self-employed serve as the non-signaling group because they are never hired and because they have perfect information about their abilities. Also, the large number of self-employed workers in the Ghanaian labor market allows for various ways of disaggregating the labor markets, ensuring workers with similar jobs are being compared across sectors. Specifically, 20% of the sample in this study is self-employed while 18% work in the wage earning sector.

Because various employment groups, such as those in the professional fields, are not determined randomly, I must control for selection into the subsamples. This is done with Heckman's (1979) two step procedure, which first uses a probit model to estimate the probability

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of being in the sample, then includes a correction factor in the second stage. The final estimated equation, which will then be free of selection bias, is,

$$ln(INCOME_i) = \beta_0 + \sum_{m=1}^{k-1} \beta_{1m} WAGE_i + \sum_{m=1}^{k-1} \beta_{1m} EDUCATION_i + \sum_{m=1}^{k-1} \beta_{1m} WAGE * EDUCATION_i + \sum_{j=1}^{l-6} \beta_{2j} X_{ij} + \gamma(IMR_i) + \varepsilon_i \qquad (1)$$

where $INCOME_i$ is the annual income from the main occupation, $WAGE_i$ is a dummy variable which equals one if the observation works in the wage earning sector (versus being self-employed), $EDUCATION_i$ is estimated years of education, $WAGE*EDUCATION_i$ is a wage sector-education interaction term, X_i is a matrix of other independent variables, IMR_i is the inverse mills ratio, or correction factor from the first stage, and ε_i is the error term. If signaling exists, I expect the returns to education to be higher for the wage earners, so the $WAGE*EDUCATION_i$ interaction term will be positive and significant.

Years of education are estimated based on reported educational qualifications. Other independent variables include: experience,[9] experience squared, reported annual hours worked, and dummy variables for female, being married/cohabiting, being the head of the household, urban residency, ethnicity, and region.

In order for the Heckman procedure to work correctly, the first stage must contain all second stage variables along with at least one additional variable that would impact selection into the occupational group. The first stage variables used here are individual dummy variables representing parent occupations, being Ghanaian-born (to capture migration effects), and for spending time on child care. The first stage variables also include household variables representing land and dwelling status, the number of children, whether there is a child under five in the household, and the number of people over the age of sixteen earning income.

4. Results

4.1 Main Results

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The main results are shown in Table 2. Column one reports OLS results and columns two through ten report Heckman estimates. Column two examines returns to education for all self-employed and wage earning workers using the Heckman procedure. Both years of education and the education-wage interaction term are significant, indicating that the self-employed earn a 3.36% return to each year of education, while wage earners earn a 7.52% return. This rejects the null hypothesis that education returns are the same between sectors, and fits with a story of education signaling.

<Table 2 about here>

It is interesting to note that, after controlling for other variables, wage earners make 34.2% lower wages than the self-employed. While this may be unexpected in a developing country, it does not hold throughout the other specifications. Incomes rise with experience at a diminishing rate, and are also higher for those in urban areas, married individuals, and household heads. Females make 24.2% lower incomes than males.

Though these results fit with a signaling story, this analysis hinges on the fact that the wage sector and self-employed sector are composed of similar work and are distinguished only by the process of hiring. This is important for two reasons. First, because signaling has been argued to differ between occupations (Riley 1979), an aggregate comparison may contain industries with different levels of signaling. Second, the wage earning and self-employed sectors may contain fundamentally different jobs. If the occupations compared are dissimilar, differences in returns may only be due to differences in work. Care must be taken, therefore, to create groups of similar occupations.

The first group is found by comparing mean earnings within occupations. Using the International Standard Classification of Occupations codes (ISCO), mean incomes are compared

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between the self-employed and for wage earners for each occupational group. An occupation is included if the incomes are not statistically different at the five percent level and if there are more than five observations in each sector. Appendix A lists the included occupations. Column three reports the results using only this subgroup. Results are virtually identical. A year of education raises incomes by 2.96% for the self-employed and by 7.24% for wage earners.

Next, larger-scale entrepreneurs are dropped. If an individual describes himself as being “self-employed with more than one employee”, it is unlikely his work is the same as someone in the wage earning sector. The individual may spend more time managing or may be motivated in different ways. Column four drops these entrepreneurs and results are largely unchanged, with education returns at 2.28% and 6.8%, respectively.

Next, the sample is split into non-professional and professional workers. Wolpin (1977) argues that it is easier to assess the true productivity of non-professional self-employed workers than for professional self-employed workers, making it easier to obtain careful measures of wages. For instance, it is not easier to assess the productivity of a self-employed doctor than of a wage sector doctor. Furthermore, customers of self-employed professionals may pay attention to educational qualifications, resulting in returns to education with a signaling component. In order to capture these differences, professional and non-professional workers are considered separately. The included subsets of non-professional and professional workers are outlined in Appendix B.

Columns five and six contain the results for the non-professional and professional subgroups. Surprisingly, the wage-education interaction term is not significant for the non-professional sample, indicating that the returns to education are the sample for the self-employed and wage earners, at 2.53% per year. For the professional sample, only wage earners see returns, at 7%. In other words, signaling appears to be concentrated among professionals, but not non-

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professional occupations. While this does not fit with Wolpin's (1977) predictions, it may be driven by the fact that incomes are over ninety percent higher for the professional sample,[10] so that employers may be more careful in hiring this subgroup, paying more attention to education as a signal for ability.

Columns seven and eight show results comparing the self-employed workers in the similar income group with wage earners in both union and non-union workplaces. For the non-union sample, the wage-education interaction term is not significant, indicating signaling is not present in those firms. The result switches dramatically for the union sample, with union wage employees earning an 11.13% return for each year of education versus the self-employed in the same group earning a 2.64% return. It appears, therefore, that unionized workplaces are helping to drive the results, rewarding education dramatically. This is not surprising. First, firms with unions present are much larger, with an average of 61.18 employees versus 26.78. In larger firms, information may be more costly and signaling may be more necessary. Second, if the presence of a union provides obstacles for termination, these firms may be more cautious about hiring new workers and may pay more attention to education as a measure of ability.

In order to capture potential impacts of firm size, columns nine and ten split the wage earning sample by those working in firms above and below the median in the sample of six. As expected, the wage-education interaction term is only significant for firms with over six employees, again suggesting that signaling is stronger in larger firms.

4.2 Education Splines

Previous studies (Appleton 2000, Shultz 2004, Soderbom, Teal, Wambugu, and Kahyarara 2006, Kahyarara and Teal 2008) have found convex returns to education in Sub-Saharan Africa, where primary education generates lower returns than later education. In order to

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account for this, splines are included for years of schooling before and after six years. Results are reported in table three. In the entire sample of self-employed and wage earners, a convex wage structure exists where later education is rewarded dramatically. Income returns to years one through six are 2.59% for the self-employed and only .41% for wage earners, while returns to higher years are 5.01% and 15.81%, respectively. The extremely high wage-education interaction term suggests signaling is concentrated at higher levels. This result carries through to other groups, with most of the signaling estimates being driven by the higher education levels. In fact, the only early education-wage interaction term that is significant is for the largest sample, and that term is negative. Again, there does not appear to be signaling for the non-union or non-professional groups, and significance dropped in the professional group. Finally, it appears that signaling does exist at higher levels for the group containing wage earners in small firms.

<Table 3 about here>

4.3 Robustness Checks

While the results above fit with education signaling, it should be noted that if returns to education are heterogeneous in ability, differences in results may simply reflect differences in abilities between groups. Unfortunately, the GLSS5 dataset does not contain any direct measures of ability. I therefore use the following methods to indirectly test for this issue. First, observations with high levels of education are considered. If returns to education do vary with ability, individuals with similar abilities will optimize at similar levels of education. By including only those individuals who choose education levels ten and over, the median for wage earners, samples will likely be similar in ability. Column one in Table 4 shows the results. Again,

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the wage-education interaction term is significant, with wage earners earning 13.39% more for each year of schooling versus 4.48% for the self-employed.

<Table 4 about here>

Second, parent education variables are included and are interacted with education. Although the practice is controversial, some researchers consider parent education variables to be an adequate proxy for ability (Altonji and Pierret 2001, Strobl 2003). If this is true, then parent education/education interaction terms will contain heterogeneity in education returns. Column 2 in Table 4 contains these results.[11] Both the parent education variables and the interaction terms are significant, which would indicate heterogeneity in returns. However, the significance drops when the similar income group is considered in Column three. Furthermore, when the father and mother education terms are included in the base regressions to potentially control for ability in columns four and five, the wage sector-education interaction term continues to be significant, and point estimates are similar to the results in Table 2. Therefore, while there may be heterogeneity in education returns, it does not appear to be driving the most of the results.

Next, household fixed effects are included. This method assumes that members of the same household possess similar abilities (see Card 1994 for a helpful discussion),[12] minimizing the problem of different abilities between groups. Again, if returns to education are heterogeneous in ability, restricting the sample to those with similar abilities will minimize the issue. Although the years of education variable drops in significance, the wage-education interaction term is 4.65% and significant, suggesting signaling even within households. Both education terms are insignificant, however, when the similar income group is considered, but this

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may be due to low variation within households, with the average observation per household only at 1.1.

Finally, as Chevalier et al. (2004) discuss, selection bias could be driving the results. If self-employed individuals are fundamentally different from those in the wage sector, estimates may not capture true education signaling. In order to control for this, I instrument employment sector by using mother and father occupation dummy variables. Results are reported in Table 5. The instrumented wage sector-years of schooling variable is not only significant, but much higher for the most groups. Although significance drops for the professional sample, both the non-union and under six employee groups become significant. The results suggest that if selection bias is driving the results, it is actually making signaling estimates too low.

5. Conclusion

Education signaling occurs when firms use education as a proxy for underlying ability. If signaling is present, income returns to education will be upwardly biased, as the measurement will partially reward characteristics that would be present even without schooling, such as intelligence. While education signaling can be valuable and may lead to an efficient outcome, its presence makes it extremely difficult to examine true human capital improvements caused by education. This is a particular concern in developing countries, where education is believed to be an important investment and a route to escaping poverty. In the presence of signaling, simple income returns cannot be interpreted as clean measures of human capital improvements.

Unfortunately, because education signaling occurs when underlying worker characteristics are difficult to observe, it is extremely difficult to obtain estimates of education signaling. Therefore, studies of signaling are rare and the existing studies do not find robust results. Furthermore, of the existing studies, very few examine signaling in developing countries.

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This study begins to fill the gap in the literature by testing for education signaling in Ghana. Using the fifth round of the Ghana Living Standards Survey, I compare returns to education between the self-employed and wage earners doing similar work to test for educational signaling. Self-employed individuals do not need to be hired, and are therefore unlikely to signal abilities. Returns to education for these individuals should be a cleaner measure of productivity, while signaling would exist for wage earners. This analysis is based on Spence's 2002 model, which allows for education to have both a signaling and human capital component.

My results do, in fact, support a signaling hypothesis. Wage earners in my sample consistently see higher returns to education. This appears to be driven by professional occupations, firms with unions, and larger firms. Signaling also appears to be concentrated at education years above six. Results are robust to instrumenting wage sector employment by parental occupations.

Though the results are consistent with education signaling, this conclusion is subject to two major caveats. First, the results may be driven by differences in ability. If high ability individuals simply earn higher returns to education, and if these individuals work in the wage earning sector, this could potentially be causing the results. Though these results are robust when constraining to higher levels of education and controlling for parental education as a measure of ability, it would be interesting to conduct a similar analysis in the future using a study with better ability measures. Second, while occupational groups were made as homogeneous as possible, the differences may simply be due to differences in work. Unfortunately, this problem may always be difficult to overcome.

It is important to note that Ghana is a country with relatively low levels of education. This is significant for two reasons. First, because education is rare in this context, one could

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expect that it might be more likely to act as a signal for ability. In this context, with low mean levels of education, educated individuals may look particularly able. As might be expected, my results do indicate that signaling exists and is concentrated at the higher levels. Second, even though signaling is found, it is important to stress that self-employed individuals do enjoy returns to education, particularly at lower levels, which shows there is a human capital component. It would be a mistake, then, to conclude that education is only acting as a signal. There is clearly value in obtaining an education, even for the self-employed. This is a promising finding.

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Appendix A: Occupations included in Similar Income Group
These groups contain more than five individuals in each sector, and average incomes that are not statistically different between self-employed and wage earning sectors

Codes are from the International Standard Classification of Occupations (ISCO-88)
Major group 1: Legislators, senior officials and managers
121 Directors and chief executives
131 General managers
Major group 2: Professionals
214 Architects, engineers and related professionals
Major group 3: Technicians and associate professionals
314 Ship and aircraft controllers and technicians
323 Nursing and midwifery associate professionals
331 Primary education teaching associate professionals
342 Business services agents and trade brokers
347 Artistic, entertainment and sports associate professionals
Major group 4: Clerks
421 Cashiers, tellers and related clerks
Major group 5: Service workers and shop and market sales workers
513 Personal care and related workers
523 Stall and market salespersons
Major group 6: Skilled agricultural and fishery workers
None included
Major group 7: Craft and related trades workers
712 Building frame and related trades workers
713 Building finishers and related trades workers
714 Painters, building structure cleaners and related trade workers
721 Metal moulders, welders, sheet-metalworkers, structural-metal preparers and related trades workers
722 Blacksmiths, toolmakers and related trades workers
723 Machinery mechanics and fitters
724 Electrical and electronic equipment mechanics and fitters
733 Handicraft workers in wood, textile, leather and related materials
741 Food processing and related trades workers
742 Wood treaters, cabinet-makers and related trades workers
743 Textile, garment and related trades workers
Major group 8: Plant and machine operators and assemblers
814 Wood processing and papermaking plant operators
823 Rubber and plastic products machine operators
825 Printing, binding and paper products machine operators
827 Food and related products machine operators
Major group 9: Elementary occupations
911 Street vendors and related workers
913 Domestic and related helpers, cleaners and launderers
915 Messengers, porters, doorkeepers and related workers
932 Manufacturing labourers
Major group 0: Armed forces and other security personnel
None included

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Appendix B: Non-Professional and Professional Occupations

Non-Professional Occupations with average incomes not statistically different between self-employed and wage earning sectors

Codes are from the International Standard Classification of Occupations (ISCO-88)

Major group 5: Service workers and shop and market sales workers

513 Personal care and related workers

523 Stall and market salespersons

Major group 7: Craft and related trades workers

712 Building frame and related trades workers

713 Building finishers and related trades workers

714 Painters, building structure cleaners and related trade workers

721 Metal moulders, welders, sheet-metalworkers, structural-metal preparers and related trades workers

722 Blacksmiths, toolmakers and related trades workers

723 Machinery mechanics and fitters

724 Electrical and electronic equipment mechanics and fitters

733 Handicraft workers in wood, textile, leather and related materials

741 Food processing and related trades workers

742 Wood treaters, cabinet-makers and related trades workers

743 Textile, garment and related trades workers

Major group 8: Plant and machine operators and assemblers

814 Wood processing and papermaking plant operators

823 Rubber and plastic products machine operators

825 Printing, binding and paper products machine operators

827 Food and related products machine operators

Major group 9: Elementary occupations

911 Street vendors and related workers

913 Domestic and related helpers, cleaners and launderers

915 Messengers, porters, doorkeepers and related workers

932 Manufacturing labourers

Professional occupations with average incomes not statistically different between self-employed and wage earning sectors

Codes are from the International Standard Classification of Occupations (ISCO-88)

Major group 1: Legislators, senior officials and managers

121 Directors and chief executives

131 General managers

Major group 2: Professionals

214 Architects, engineers and related professionals

Major group 3: Technicians and associate professionals

314 Ship and aircraft controllers and technicians

323 Nursing and midwifery associate professionals

331 Primary education teaching associate professionals

342 Business services agents and trade brokers

347 Artistic, entertainment and sports associate professionals

Major group 4: Clerks

421 Cashiers, tellers and related clerks

Major group 6: Skilled agricultural and fishery workers

None included

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Endnotes

[1] One reason researchers have used government sectors in these studies is that such sectors have been found to lack evidence of signaling. For example, Heywood (1994) finds that in the United States, sheepskin effects exist only for the private, non-unionized workforce, and not for those working in the government or in private, unionized workplaces. While this may be true in developed countries, it is not as intuitive in developing countries, where government jobs tend to be highly coveted. In fact, education has been described as the ticket to better paying, public sector jobs (Pritchett 2001).

[2] It should be noted that the first paper to use this type of analysis, Wolpin 1977, uses a slightly different method than the papers mentioned above. Wolpin's analysis rests on the assumption that non-signaling individuals will simply pursue less education and tests for differences in years of education between sectors. While this is certainly plausible, the analysis excludes other reasons for obtaining education, such as family or societal norms, and has been criticized (Brown and Sessions 2004). Individuals may also be uncertain about future occupations at the time of education.

[3] In fact, to the author's knowledge, there has only been one study that explicitly compares returns between sectors to explicitly look at signaling in the region (Koch and Ntege 2008). Though the authors do find evidence of signaling, they treat the findings as preliminary due to the lack of ability, parent education, and distance to schooling variables.

[4] Arrow (1973) and Stiglitz (1975) also wrote influential papers about education signaling. Spence's (1973) paper is the focus here due to its (2002) extension.

[5] Brown and Sessions (1999) themselves test for a weak versus strong signaling hypotheses to overcome this difficulty.

[6] Specifically, Spence defines $s_i(E)$ as, "the value of worker of type i with education e to an employer".

[7] Spence explains that pooling may break the overinvestment separating equilibrium, but not when the low quality group is large enough.

[8] Observations were dropped if their reported occupation for the last seven days did not match the reported occupation for the last 12 months.

[9] Experience represents potential experience computed by the formula,

$$EX = AGE - 6 - ED, \qquad (2)$$

where 6 is the year the average student starts school and ED is an estimate of the years of school completed with a minimum work start age of 15.

[10] Specifically, mean earnings are 14,974,530 2005 Ghanain Cedi for the professional sample and 7,858,965 2005 Ghanaian Cedi for the non-professional sample.

[11] Parental education variables are years of education estimated from educational qualifications

[12] It should be noted that Card (1994) believes that ability will actually bias these estimates upwards

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Appendix A: Tables

Table 1: Summary Statistics

Sample	All	Wage Sector	Self Employed
Income (in 2005 Ghanaian Cedis)	11,100,000.00	12,900,000.00	9,602,910.00
	(14,700,000.00)	(14,900,000.00)	(14,300,000.00)
Wage Sector	0.18	0.00	0.00
	(0.38)	0.00	0.00
Self-Employed Sector	0.20	0.00	0.00
	(0.40)	0.00	0.00
Female	0.52	0.27	0.71
	(0.50)	(0.45)	(0.45)
Household Head	0.53	0.77	0.50
	(0.50)	(0.42)	(0.50)
Hours of Work (Annual)	2,063.07	2,495.74	2,420.21
	(1,181.48)	(1,130.29)	(1,659.91)
Years of School	4.74	11.30	6.53
	(5.91)	(4.64)	(5.79)
Experience	25.63	21.71	25.70
	(14.93)	(11.92)	(12.45)
Experience Squared	879.68	613.44	815.56
	(931.52)	(606.99)	(797.80)
Urban	0.34	0.78	0.66
	(0.47)	(0.42)	(0.47)
Married/Cohabit	0.73	0.70	0.74
	(0.45)	(0.46)	(0.44)
Age	41.72	40.04	42.03
	(14.72)	(11.65)	(12.15)
Observations	9,227.00	1,627.00	1,886.00

Standard deviations in parentheses

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Table 2: Heckman Estimates

Dependent Variable: Log of annual income from the main occupation

	OLS	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN
Estimate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GROUP	OLS All Wage Earners and Self-Employed	All Wage Earners and Self-Employed	Occupations with Similar Wages	Non-Entrepreneurs with Similar Wages	Non Professional Occupations with Similar Wages	Professional Occupations with Similar Wages	Non-Union Firms with Similar Wages	Union Firms with Similar Wages	Firms with Six or Fewer Employees with Similar Wages	Firms with Over Six Employees with Similar Wages
			Yes	Yes						
Wage Sector	-0.226***	-0.342***	-0.208	-0.154	-0.133	-0.969**	-0.102	-0.368	-0.141	0.0319
	(0.0844)	(0.103)	(0.156)	(0.157)	(0.155)	(0.432)	(0.168)	(0.424)	(0.192)	(0.261)
Years of School	0.0371***	0.0336***	0.0296***	0.0280***	0.0253***	0.00354	0.0270***	0.0263***	0.0268***	0.0287***
	(0.00496)	(0.00527)	(0.00659)	(0.00660)	(0.00676)	(0.0286)	(0.00674)	(0.00679)	(0.00686)	(0.00667)
Wage*Years of School	0.0369***	0.0416***	0.0428***	0.0452***	0.0192	0.0700**	0.0171	0.0850***	0.0270	0.0410**
	(0.00730)	(0.00764)	(0.0144)	(0.0143)	(0.0192)	(0.0329)	(0.0174)	(0.0319)	(0.0196)	(0.0202)
Female	-0.216***	-0.242***	-0.298***	-0.253**	-0.354***	0.355	-0.335***	-0.366***	-0.366***	-0.307***
	(0.0510)	(0.0525)	(0.0909)	(0.0986)	(0.112)	(0.222)	(0.0966)	(0.103)	(0.104)	(0.0973)
Household Head	0.278***	0.271***	0.243***	0.203***	0.204***	0.281	0.228***	0.197**	0.191**	0.211***
	(0.0512)	(0.0512)	(0.0713)	(0.0733)	(0.0745)	(0.214)	(0.0747)	(0.0784)	(0.0779)	(0.0765)
Hours of Work	6.87e-05***	6.29e-05***	8.82e-05***	8.66e-05***	8.11e-05***	0.000238***	8.78e-05***	8.53e-05***	7.45e-05***	9.24e-05***
	(1.28e-05)	(1.31e-05)	(2.34e-05)	(2.42e-05)	(2.47e-05)	(6.34e-05)	(2.43e-05)	(2.52e-05)	(2.53e-05)	(2.47e-05)
Experience	0.0386***	0.0374***	0.0354***	0.0398***	0.0352***	0.0287	0.0361***	0.0336***	0.0407***	0.0331***
	(0.00512)	(0.00514)	(0.00754)	(0.00784)	(0.00812)	(0.0193)	(0.00791)	(0.00828)	(0.00826)	(0.00802)
Experience Squared	-0.000675***	-0.000653***	-0.000632***	-0.000707***	-0.000642***	-0.000431	-0.000651***	-0.000609***	-0.000711***	-0.000607***
	(8.60e-05)	(8.63e-05)	(0.000126)	(0.000131)	(0.000135)	(0.000350)	(0.000131)	(0.000136)	(0.000135)	(0.000132)
Urban	0.167***	0.118**	0.0359	0.0348	0.0464	-0.222	0.0478	0.0347	0.0270	0.0359
	(0.0455)	(0.0520)	(0.0989)	(0.102)	(0.0991)	(0.217)	(0.107)	(0.103)	(0.106)	(0.103)
Married/Cohabit	0.279***	0.276***	0.273***	0.255***	0.213***	0.371**	0.269***	0.204***	0.258***	0.213***
	(0.0454)	(0.0452)	(0.0650)	(0.0675)	(0.0693)	(0.176)	(0.0687)	(0.0726)	(0.0719)	(0.0705)
Constant	14.21***	14.39***	14.61***	14.52***	14.74***	16.51***	14.63***	14.79***	14.62***	14.71***
	(0.117)	(0.149)	(0.295)	(0.324)	(0.330)	(1.018)	(0.309)	(0.327)	(0.330)	(0.313)
Lambda		-0.113*	-0.154	-0.164	-0.173	-0.834***	-0.148	-0.172	-0.186	-0.143
	3,513	(0.0579)	(0.117)	(0.127)	(0.130)	(0.310)	(0.123)	(0.119)	(0.126)	(0.118)
N	3,513	3,513	1,943	1,779	1,711	292	1,783	1,703	1,642	1,764
Adjusted R-Squared	0.2422									

Region and ethnicity control variables are included and are not reported

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 3: Heckman Estimations with Education Splines

Dependent Variable: Log of annual income from the main occupation

	OLS	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN	HECKMAN
Estimate		(1)	(2)	(3)	(5)	(6)	(7)	(8)	(9)	(10)
GROUP	OLS All Wage Earners and Self-Employed	All Wage Earners and Self-Employed	Occupations with Similar Wages	Non-Entrepreneurs with Similar Wages	Non Professional Occupations with Similar Wages	Professional Occupations with Similar Wages	Non-Union Firms with Similar Wages	Union Firms with Similar Wages	Firms with Six or Fewer Employees with Similar Wages	Firms with Over Six Employees with Similar Wages
Wage Sector	0.0444	-0.0586	4.21e-05	0.0534	-0.0716	-0.647	-0.0120	0.785	0.323	-7.40e-05
	(0.0910)	(0.109)	(0.170)	(0.171)	(0.154)	(0.543)	(0.178)	(0.684)	(0.306)	(0.205)
Education Splines Years 1-6	0.0291***	0.0259***	0.0269***	0.0263***	0.0255***	-0.0181	0.0242**	0.0242**	0.0264***	0.0251**
	(0.00757)	(0.00775)	(0.00947)	(0.00991)	(0.00989)	(0.0410)	(0.00972)	(0.00964)	(0.00959)	(0.0100)
Education Spline Years 7+	0.0531***	0.0501***	0.0353*	0.0311	0.0248	0.0238	0.0348*	0.0301	0.0340*	0.0313
	(0.0163)	(0.0164)	(0.0198)	(0.0221)	(0.0213)	(0.0533)	(0.0202)	(0.0202)	(0.0201)	(0.0213)
Wage*Education Spline 1-6	-0.0264**	-0.0218*	-0.00811	-0.00641	-0.00590	0.0210	-0.0109	-0.0669	-0.0141	-0.0176
	(0.0125)	(0.0128)	(0.0231)	(0.0232)	(0.0241)	(0.0653)	(0.0265)	(0.0767)	(0.0370)	(0.0296)
Wage*Education Spline 7+	0.104***	0.108***	0.107***	0.112***	0.0732	0.0884	0.0609	0.138***	0.0885**	0.105**
	(0.0200)	(0.0200)	(0.0335)	(0.0346)	(0.0507)	(0.0612)	(0.0425)	(0.0444)	(0.0395)	(0.0504)
Female	-0.231***	-0.254***	-0.307***	-0.267***	-0.356***	0.357*	-0.337***	-0.369***	-0.314***	-0.370***
	(0.0506)	(0.0521)	(0.0909)	(0.0987)	(0.113)	(0.216)	(0.0967)	(0.103)	(0.0974)	(0.104)
Household Head	0.269***	0.262***	0.238***	0.198***	0.205***	0.227	0.225***	0.191**	0.204***	0.189**
	(0.0508)	(0.0507)	(0.0713)	(0.0733)	(0.0745)	(0.215)	(0.0748)	(0.0784)	(0.0765)	(0.0779)
Hours of Work	7.38e-05***	6.87e-05***	8.85e-05***	8.64e-05***	8.19e-05***	0.000244***	8.85e-05***	8.46e-05***	9.36e-05***	7.41e-05***
	(1.27e-05)	(1.30e-05)	(2.33e-05)	(2.42e-05)	(2.46e-05)	(6.35e-05)	(2.43e-05)	(2.52e-05)	(2.47e-05)	(2.52e-05)
Experience	0.0441***	0.0431***	0.0380***	0.0422***	0.0367***	0.0340*	0.0377***	0.0347***	0.0343***	0.0427***
	(0.00516)	(0.00517)	(0.00766)	(0.00794)	(0.00826)	(0.0195)	(0.00806)	(0.00840)	(0.00816)	(0.00841)
Experience Squared	-0.000752***	-0.000732***	-0.000667***	-0.000739***	-0.000664***	-0.000488	-0.000674***	-0.000626***	-0.000624***	-0.000736***
	(8.63e-05)	(8.66e-05)	(0.000127)	(0.000132)	(0.000136)	(0.000354)	(0.000132)	(0.000137)	(0.000134)	(0.000137)
Urban	0.169***	0.126**	0.0343	0.0302	0.0513	-0.233	0.0484	0.0356	0.0369	0.0245
	(0.0451)	(0.0515)	(0.0986)	(0.102)	(0.0989)	(0.211)	(0.107)	(0.103)	(0.103)	(0.106)
Married/Cohabit	0.262***	0.259***	0.265***	0.247***	0.213***	0.352**	0.267***	0.195***	0.207***	0.257***
	(0.0450)	(0.0449)	(0.0649)	(0.0674)	(0.0693)	(0.176)	(0.0686)	(0.0727)	(0.0706)	(0.0718)
Constant	14.19***	14.35***	14.60***	14.52***	14.71***	16.71***	14.61***	14.80***	14.71***	14.60***
	(0.116)	(0.147)	(0.294)	(0.323)	(0.329)	(0.945)	(0.308)	(0.327)	(0.313)	(0.329)
Lambda		-0.0989*	-0.155	-0.169	-0.163	-0.888***	-0.145	-0.174	-0.141	-0.188
		(0.0574)	(0.116)	(0.127)	(0.130)	(0.281)	(0.123)	(0.119)	(0.117)	(0.126)
N	3,513	3.513	1,943	1,779	1,711	292	1,783	1,703	1,642	1,764
Adjusted R-Squared	0.2554									

Region and ethnicity control variables are included and are not reported

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 4:Ability Controls

Dependent Variable: Log of annual income from the main occupation

	Heckman	Heckman	Heckman	Heckman	Heckman	Fixed Effects	Fixed Effects
Estimate	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GROUP	Education 10+ with Similar Wages	All Wage Earners and Self-Employed	Occupations with Similar Wages	All Wage Earners and Self-Employed	Occupations with Similar Wages	All Wage Earners and Self-Employed	Occupations with Similar Wages
Wage Sector	-0.945**	0.117**	0.272***	-0.333***	-0.120	-0.349**	-0.0158
	(0.377)	(0.0554)	(0.0856)	(0.104)	(0.159)	(0.168)	(0.281)
Years of School	0.0448*	0.0385***	0.0301***	0.0323***	0.0316***	-0.000294	0.0214
	(0.0246)	(0.00483)	(0.00688)	(0.00545)	(0.00677)	(0.0122)	(0.0168)
Wage*Years of School	0.0891***			0.0433***	0.0383***	0.0465***	0.0194
	(0.0328)			(0.00779)	(0.0144)	(0.0142)	(0.0239)
Mother's Education		-0.0472***	-0.0334*	0.00551	-0.000975		
		(0.0152)	(0.0199)	(0.00528)	(0.00775)		
Years of School*Mother's Educatoin		0.00430***	0.00284				
		(0.00124)	(0.00175)				
Father's Education		-0.0368***	-0.0306**	-0.00326	-0.0101		
		(0.0113)	(0.0148)	(0.00466)	(0.00672)		
Years of School*Father's Education		0.00303***	0.00203				
		(0.000962)	(0.00135)				
Female	-0.217**	-0.138**	-0.231**	-0.189***	-0.259***	-0.186	-0.132
	(0.0989)	(0.0566)	(0.0913)	(0.0575)	(0.0929)	(0.118)	(0.182)
Household Head	0.250***	0.323***	0.255***	0.297***	0.236***	0.392***	0.500***
	(0.0845)	(0.0587)	(0.0781)	(0.0588)	(0.0782)	(0.126)	(0.183)
Hours of Work	0.000128***	9.21e-05***	9.90e-05***	9.21e-05***	9.99e-05***	4.75e-05	-1.25e-05
	(2.72e-05)	(1.66e-05)	(2.47e-05)	(1.67e-05)	(2.46e-05)	(3.46e-05)	(5.36e-05)
Experience	0.0342***	0.0358***	0.0330***	0.0333***	0.0316***	0.0665***	0.0794***
	(0.0122)	(0.00540)	(0.00774)	(0.00539)	(0.00772)	(0.0136)	(0.0207)
Experience Squared	-0.000602***	-0.000628***	-0.000616***	-0.000583***	-0.000591***	-0.00120***	-0.00144***
	(0.000233)	(8.86e-05)	(0.000126)	(8.84e-05)	(0.000126)	(0.000233)	(0.000337)
Urban	0.120	0.154***	0.0950	0.134**	0.0951		
	(0.112)	(0.0533)	(0.0986)	(0.0536)	(0.0981)		
Married/Cohabit	0.170**	0.323***	0.282***	0.312***	0.276***	0.205	0.0518
	(0.0766)	(0.0503)	(0.0720)	(0.0504)	(0.0720)	(0.152)	(0.204)
Constant	14.11***	14.17***	14.54***	14.31***	14.57***	14.30***	14.25***
	(0.559)	(0.157)	(0.288)	(0.164)	(0.293)	(0.231)	(0.343)
Lambda	0.0784	-0.0537	-0.0938	-0.113*	-0.0995		
	(0.161)	(0.0574)	(0.114)	(0.0598)	(0.116)		
Observations	9,243	8,044	7,979	8,044	7,979	3,513	1,943
R-squared						0.282	0.374
Number of Households						2,784	1,708
Average Observations Per Household						1.3	1.1

Region and ethnicity control variables are included and are not reported

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 5: Instrumenal Variables Estimates

Dependent Variable: Log of annual income from the main occupation

Wage Sector is instrumented by parental occupation dummy variables

Estimate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Group	All Wage Earners and Self-Employed	Occupations with Similar Wages	Non-Entrepreneurs with Similar Wages	Non Professional Occupations with Similar Wages	Professional Occupations with Similar Wages	Non-Union Firms with Similar Wages	Union Firms with Similar Wages	Firms with Six or Fewer Employees with Similar Wages	Firms with Over Six Employees with Similar Wages
Instrumented Wage Sector Dummy Variable	-1.974***	-1.396*	-1.538**	-0.541	-0.693	-1.202*	-1.261	-0.842	-1.245*
	(0.450)	(0.720)	(0.636)	(0.779)	(1.663)	(0.650)	(0.807)	(0.695)	(0.736)
Years of School	0.0380***	0.0357***	0.0363***	0.0308***	0.0403	0.0305***	0.0326***	0.0286***	0.0343***
	(0.00749)	(0.00971)	(0.00950)	(0.00955)	(0.0612)	(0.00996)	(0.0120)	(0.00892)	(0.0103)
Instrumented Wage Sector*Years of School	0.142***	0.0943**	0.103***	0.0275	0.0857	0.0712**	0.0940***	0.0595	0.0856**
	(0.0215)	(0.0395)	(0.0338)	(0.0418)	(0.0735)	(0.0358)	(0.0364)	(0.0379)	(0.0375)
Female	-0.306***	-0.314***	-0.302***	-0.276***	0.208	-0.321***	-0.352***	-0.293**	-0.350***
	(0.0661)	(0.0903)	(0.0863)	(0.103)	(0.272)	(0.0912)	(0.107)	(0.114)	(0.119)
Household Head	0.308***	0.293***	0.260***	0.237***	0.355	0.272***	0.247**	0.225**	0.258***
	(0.0598)	(0.0817)	(0.0879)	(0.0885)	(0.256)	(0.0915)	(0.0982)	(0.0998)	(0.0892)
Hours of Work	7.96e-05***	9.81e-05***	9.56e-05***	9.34e-05***	0.000223***	0.000102***	9.34e-05***	8.76e-05***	0.000101***
	(1.66e-05)	(2.47e-05)	(2.63e-05)	(2.49e-05)	(7.18e-05)	(2.61e-05)	(2.91e-05)	(2.79e-05)	(2.62e-05)
Experience	0.0391***	0.0370***	0.0404***	0.0375***	0.0292	0.0379***	0.0366***	0.0439***	0.0341***
	(0.00577)	(0.00713)	(0.00873)	(0.00923)	(0.0261)	(0.00768)	(0.00859)	(0.00960)	(0.00846)
Experience Squared	-0.000702***	-0.000684***	-0.000749***	-0.000700***	-0.000422	-0.000707***	-0.000676***	-0.000782***	-0.000646***
	(9.53e-05)	(0.000119)	(0.000137)	(0.000139)	(0.000399)	(0.000126)	(0.000143)	(0.000146)	(0.000131)
Urban	0.252***	0.206**	0.217**	0.183**	0.0177	0.219**	0.202**	0.185*	0.199**
	(0.0767)	(0.0850)	(0.0929)	(0.0850)	(0.410)	(0.0976)	(0.0991)	(0.0982)	(0.0948)
Married/Cohabit	0.252***	0.260***	0.242***	0.207***	0.444**	0.259***	0.211***	0.256***	0.209**
	(0.0473)	(0.0699)	(0.0803)	(0.0734)	(0.177)	(0.0740)	(0.0743)	(0.0769)	(0.0826)
Constant	14.33***	14.39***	14.32***	14.39***	14.13***	14.38***	14.49***	14.24***	14.54***
	(0.117)	(0.173)	(0.194)	(0.227)	(0.584)	(0.181)	(0.219)	(0.261)	(0.230)
Observations	3,513	1,943	1,779	1,711	292	1,783	1,703	1,642	1,764
Adjusted R-squared	0.246	0.203	0.197	0.164	0.257	0.181	0.200	0.172	0.199

Region and ethnicity control variables are included and are not reported

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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