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The impact of education in rural Ghana: examining household labor allocation and returns on and off the farm

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Abstract

Most of the human capital literature pertaining to developing countries focuses on the returns to education in either farm work or wage work; few studies examine how education affects the allocation of time between these activities. This paper estimates the returns to education in farm and off-farm work, and consequently the role of education in determining the allocation of labor. The results from this study show that off-farm work has a much higher return to education than does farm work and suggest that this divergence in returns affects the allocation of labor in farm households between farm and off-farm work.
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1. Introduction and literature review

1.1. Introduction

Most of the human capital literature pertaining to developing countries focuses on the returns to education in either farm work or wage work; yet many households in developing countries are engaged in several income-generating activities.[1] Measures of the farmers'

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[1] See Reardon (1997) and references therein for more information on household income diversification in developing countries.

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returns to education that only incorporate changes in farm profitability are likely to miscalculate the value of education to farmers who also engage in off-farm work. Estimating a farm household's returns to education on and off the farm will provide a more complete description of the value of education and may also help explain a connection between education and the development process.

Much research on growth and development from the 1970s stressed the importance of farmers moving into other types of work in response to a divergence in returns to farm and off-farm work. Chenery (1988) refers to these early studies of economic structure which document the "universal reallocation of the labor force from agriculture to manufacturing and services" (p. 197) and argues that:

> In the early stages of development, agriculture constitutes a very large, but declining, share of production, exports, and employment, while manufacturing is small but usually expanding more rapidly. There is a corresponding movement of labor and capital from agriculture to manufacturing in response to higher returns. There is also a tendency towards accelerated growth in the economy as a whole through this reallocation. [p. 199].

Timmer (1988, p. 276) states that, "The declining importance of agriculture is uniform and pervasive, a tendency obviously driven by powerful forces inherent in the development process. . .."

In pioneering work, Nelson and Phelps (1966) propose that education may enhance an individual's ability to adapt to change and to engage in different types of work.[2] Welch (1970) furthers this idea by explicitly modeling education as contributing to the production of two products. His model shows that education can both directly increase production of each item and education can improve the allocation of resources thereby indirectly increasing production. The purpose of this paper is to empirically consider a modified version of Welch's model where the two goods are farm and off-farm profit, and then to ask whether there is any evidence that education improves the profitability of both types of work and whether it affects the allocation of household labor into these activities.

The plan of this paper is as follows. The remaining part of this section discusses the empirical literature on measuring the returns to education for farmers. Section 2 provides a description of the data used in this paper and some descriptive statistics on the education levels and labor supplies of a sample of Ghanaian farmers. Section 3 provides a simple model of the farm household's maximization problem which is used to motivate the estimation strategy. An important feature of the model is that the returns to education in farm work can differ from the returns to off-farm work. Section 4 first presents reduced-form estimates of farm profit, farm labor supply, off-farm profit, and off-farm labor supply functions. Then, two-stage estimates of farm and off-farm profit are presented in which household labor supply is instrumented. This section finishes by showing that the more highly educated members of households are more likely to engage in off-farm work than the less educated members. Section 5 presents some concluding comments.

[2] Similarly, Schultz (1975) suggests that education improves an individual's ability to allocate resources in response to changing economic conditions or economic disequilibria.

1.2. Literature review

Jamison and Lau (1982) summarize the results of over 35 studies from Asia, Africa, and Latin America that measure returns to the education of farmers. All of these studies estimate whether education has a positive effect on farm output or profit, and most of them support the claim of Jamison and Lau that there are positive returns to educating farmers.[3] Fane (1975) and Huffman (1974) use data from the U.S. to test whether education improves allocative efficiency. Fane finds that better educated farmers come closer to a constructed measure of minimum cost, which he takes as evidence that education improves allocative efficiency. Huffman decomposes change in farm profits into an allocative and technical effect and finds that the return to education from increasing the allocative efficiency is three times larger than the return from the change in technical efficiency. Wu (1977) uses a sample of small family farms from Taiwan and finds, contrary to Huffman and Fane's results, that education increases technical efficiency by more than allocative efficiency. Wu suggests this reversal of Huffman's results is due to the smaller farm size and lower level of education of his sample, both of which are characteristic of many developing countries.[4]

Several studies look beyond whether education improves technical and allocative efficiency on the farm. For example, some studies test whether better educated farmers adopt newer technology (Lin, 1991; Feder et al., 1985); others test whether farmers with higher levels of education pay and receive better prices for inputs and outputs (Jamison and Lau, 1982, pp. 183–194). Foster and Rosenzweig (1996) present evidence that there is an important interaction between technological change and schooling for rural households.

In spite of the large and varied nature of the literature, the primary focus of the human capital literature for rural households is on whether education affects the household's behavior on the farm. An important exception to this focus has been the limited research on how education affects the off-farm behavior of farm households. Huffman (1980) shows that improved education levels increase the off-farm labor supply of US farmers. Schultz (1988) notes that increased educational attainment may induce rural residents to migrate to urban areas for higher returns. Reardon et al. (1994) discuss the important relationship between farm productivity and non-farm income of rural households. Using Chinese household data, Yang (1997) argues that better educated individuals improve efficiency on the farm regardless of whether they work on the farm,[5] and Yang and An (2002) show that education improves the allocation of household resources between agricultural and non-agricultural activities.

[3] Phillips (1987) notes though that the results from Jamison and Lau vary systematically by region, with studies from Asia most strongly supporting the hypothesis that education increases farm productivity. The estimated return to education is positive and significant at the 0.05 level in 17 of the 22 studies from Asia. Ten of the thirteen studies from Latin America estimate that education has no (or a negative) effect on productivity, and in the case of Africa, Jamison and Lau only discuss two studies both of which provide little evidence of any positive returns to education.

[4] The average farmer in Wu's sample has 6.7 years of schooling and cultivates 1.2 ha of land.

[5] Yang suggests that the best-educated members of households act as farm managers and many of the farm-management decisions do not require directly working on the farm. Yang also shows that conditional on working off of the farm, there are significant increases in wages associated with higher levels of schooling. (About 27% of the sample used by Yang work in the formal wage market.)

This paper is in the spirit of the literature that examines how education affects the off-farm behavior of farm households. I argue that measuring the returns to educating farmers by examining how education affects behavior only on the farm misses much of the value in rural education. The results presented in this paper suggest that the biggest gain to Ghanaian farmers from education is found off the farm, and consequently, better-educated farmers allocate more labor to off-farm work.[6]

2. Data

The data used in this paper are from the Ghana Living Standards Survey (GLSS), a nationwide household survey carried out by the Ghana Statistical Service with technical assistance from the World Bank. The sample design was implicitly stratified by geographic region and drawn in two-stages. In the first stage, 200 clusters were selected with probability proportional to estimated population; and then in the second stage, 16 households were randomly selected from each cluster. (For more details on the sample design, see Scott and Amenuvegbe, 1989.) The realized sample size was 3192 households (14,924 individuals). The survey instrument was administered from October 1988 to September 1989, and contains detailed information on the health, employment, fertility, income, expenditure, and nutritional status of household members (see Glewwe and Twum-Baah, 1991, for more information).

2.1. Labor hours and education levels

From the full sample, I select all farming households with at least one member who describes his/her primary or secondary occupation as farming and which have positive farm profit.[7] This selection criterion results in a sample of 2393 households. An interesting characteristic of some of the self-described secondary farmers is that they produce more agricultural output than some primary farming households. In 74% of the farm households, at least one member engages in some form of non-farm work. Table 1 divides total household working hours into time engaged in farming, in off-farm self-employment, and in wage work over a 1-year period.[8]

[6] In Jolliffe (1998), I use a similar methodology to show that performance on cognitive-skills tests helps control for variation in school quality across Ghana using a sample all households. The results illustrate that variations in school quality are significant, test scores are useful proxies to control for this variation, and they also suggest that there is a divergence in the returns to skills in farm and non-farm work. This last result prompts the analysis presented in this current paper.

[7] The inclusion of both primary and secondary farmers ensures variation in the intensity of farming. Forty households are dropped because they have negative farm profits. Twenty-one households are dropped due to incomplete land data, and 14 households are excluded from the sample because they do not have an adult member 20 years of age or greater (and therefore no measure of schooling).

[8] Labor hours per year is constructed from responses to several questions about primary and secondary work during the past 12 months. For each type of work, the respondent estimates how many weeks during the past 12 months they were engaged in the activity, the typical number of days per week during those weeks, and then the average number of hours per day. In some cases the questions differed slightly, and the respondent estimates how many hours per week and how many weeks per year worked.

Table 1
Allocation of labor hours by household

Household labor, hours per year	Observations	Mean	Standard error	No. of observations >0
Self-employed, off-farm hours	2393	1133.4	49.2	1397
Off-farm, wage hours	2393	436.7	27.3	776
Farm hours	2393	1919.9	75.1	2393

The sample consists of all households with positive farm profit. Standard errors are corrected for the sample design.

These 2393 farming households have 8727 individuals engaged in income-earning activities. Of these individuals, 5652 are occupied in self-employed, non-farm work, and 2956 spend some time working off their farms for wages. In Jolliffe (1996), I show that these self-employed and wage-earning individuals are engaged in a wide variety of income-generating activities.

Table 2 examines the average level of school attainment by sex, age, and whether the individual works off the farm. (To mitigate the potential for endogeneity bias, schooling information is used only for adults 20 years of age and older.) The oldest individuals, who were educated prior to the 1950s, have the lowest levels of schooling. The individuals in their 20s and early 30s, who received their education in the mid 1960s and early 1970s, have the highest levels of completed school years. The data also reveal that farmers who only work on their own farm have lower levels of education than those who find some employment off of the farm.

2.2. Farm and non-farm profit

To construct a measure of farm profit, I begin with the value (in Cedis) of all crops and animal products marketed in the last year. To this I add the value of crops kept for seed and given as presents. Also, since most farmers cover their subsistence needs from their own production, it is necessary to include home consumption of food and animal products. In this sample, the value of home-consumed crops is equal to 63% of the total value of farm

Table 2
Years of completed schooling by sex, age, and off-farm participation

Age	Full sample	Farm work only		Off-farm work	
		Male	Female	Male	Female
All adults (20+)	4.23 (0.18)	4.0	1.5	6.3	3.3
20–24	6.13 (0.27)	6.3	3.1	7.9	5.2
25–29	5.89 (0.27)	5.8	3.0	8.0	4.7
30–34	5.93 (0.27)	6.6	3.1	7.9	5.0
35–39	5.16 (0.31)	4.6	2.3	7.5	3.9
40–44	4.48 (0.32)	4.1	1.0	7.3	2.9
45–49	3.24 (0.26)	3.9	0.6	5.5	1.8
50 and older	1.19 (0.10)	1.5	0.2	2.5	0.5

The sample consists of the members of the 2393 farming households who are 20 years of age and older. ‘Off-farm Work’ includes all individuals who work off of the farm, regardless of whether they also work on the farm. Design-corrected standard errors are in parentheses.

output. Crops sold on the market comprise 34% of the total value of the farm product, and the remaining 3% comes from the sale and home consumption of animal products and processed food. From the total value of farm product, I then subtract expenditures on seed, fertilizer, insecticide, livestock, storage, transportation, and hired-in farm labor.

Off-farm profit is an aggregate measure of wage income and self-employment profit. Income from wage work includes payment in kind and income from self-employment is net of business expenses.[9] In defining profit from self-employment, I follow Vijverberg (1993) who asserts that for the GLSS data this measure is more reliable than proposed alternates. The decision to aggregate these sources of income clearly comes at the cost of confounding two distinct types of economic activity. In particular, self-employment income includes returns to entrepreneurship and capital whereas wage income does not. Nonetheless, in terms of estimation, the gains from aggregating these two income sources are important.

In particular, by aggregating the two types of income, the censoring problem becomes less severe. While 26% of the sample farm households have no off-farm profit, the proportion of observations that is censored at zero increases to 68% and 42% if wage and self-employed off-farm profit are considered separately. As the censored proportion increases, maximum likelihood estimators, such as the Tobit, rely relatively more on distributional assumptions and less on the actual data. This is particularly problematic if the distributional assumptions are not credible. In Section 4 it is shown that the assumption of normality is strongly rejected and for this reason, this paper uses Powell's (1984) censored least absolute deviations (CLAD) which relies significantly less on distributional assumption. In terms of the proportion of the sample censored, though, the CLAD estimator requires that the median is not censored.

Both measures of profit are at the household level, while the measures of labor hours and education are at the individual level. To make these comparable, I take the simple sum of the labor hours for each individual within a household. To measure education attainment at the household level, I use the average level of schooling of household members who are 20 years of age and greater.[10] Finally, over the year the data set was collected, the level of prices in Ghana increased 24% (Ghana Statistical Service, 1991a). To correct for this, all Cedi values are deflated to October 1988.[11]

3. Model

To find out how the returns to education differ between farm and off-farm work and whether the farm household's labor allocation changes as a result of this difference in

[9] For both farm and off-farm profit, I do not impute a value to household labor and treat this as a cost. The resulting measure is sometimes referred to as restricted profit, or profit conditional on the cost of certain inputs. (See Lau and Yotopoulos, 1971, for more details on the restricted profit function.) Throughout the paper, I will use the term profit to mean restricted profit.

[10] In Jolliffe (1996), using a subset of the data used in this paper, I compare various measures of household schooling, including the minimum, maximum, and average, and argue that the average level of schooling is a good proxy for household schooling when predicting farm and off-farm profit. I also show that the education level of the head of the household is not a good proxy for the household's schooling.

[11] The average exchange rate in 1988 was 200 Cedis to the U.S. dollar. (Ghana Statistical Service, 1991b).

returns, it is necessary to examine how education affects farm profits, farm labor, off-farm profits, and off-farm labor supply. To focus on these effects, household utility is modeled as a function of leisure and the sum of farm and off-farm profit. Household leisure is the difference between the total stock of household time and the sum of hours worked on and off the farm.

3.1. The farm household's problem

I assume that the farmer's problem can be stated as:

$$\begin{aligned}&\max_{L_f, L_o, Z_o, Z_f} U\{Y_f(E, L_f, X_f, p_f, \theta_f) + Y_o(E, L_o, X_o, p_o, \theta_o), L(X_h) - L_f - L_o\} \\ &\text{subject to: } L(X_h) \geq L_f + L_o, \quad L_f \geq 0, \quad L_o \geq 0\end{aligned} \tag{1}$$

where Y measures restricted profit (income less expenditures on variable inputs), E is education, L is household labor supply, X measures experience and the stock of quasi-fixed inputs (farmland and non-farm business assets), p is a vector of prices of variable inputs, Z is the corresponding vector of the quantity of variable inputs, and θ represents unforseen shocks in farm and off-farm profit. The subscript, f, denotes a farm variable and o denotes off-farm. The total stock of potential household labor supply, L, is a function of a vector of household characteristics including the gender and age composition of the household and is given by X_h.[12] The restricted profit functions are assumed to have the usual properties of positive and non-increasing marginal returns to labor. Both farm and off-farm profits are functions of education, labor, prices, quantities of fixed inputs (farmland and non-farm business assets), and measures of experience. In other words, they are restricted profit functions conditional on the quantities of fixed inputs and household labor.[13]

There are two important assumptions made in how education is modeled. The first is that education is treated as a within-household, non-rival factor of production (in other words, within any particular household, the use of education in the farm sector does not diminish its value for use in the off-farm sector). This assumption is consistent with the work of Basu and Foster (1998) who argue that measures of literacy should account for the distribution of literate persons across households. Their argument relies on the notion that the effective literacy rate differs if an additional literate person is added to a household where every other member is already literate as compared to another household where no one else is literate.

The second assumption is that education cannot be purchased on the labor market. This means that the household cannot hire a manager to make the farming decisions. Implicit in

[12] To the extent that household size and composition are chosen by the household through fertility, fostering, and marriage, the decision to model these characteristics as exogenous may result in biased estimates. As examples of theoretical models of fertility choice, see Schultz (1969) and Willis (1973). For an empirical example see Rosenzweig and Schultz (1985), who show that variation in fertility in the US is in part endogenously determined by household preferences and in part exogenously determined by reproductive potential.

[13] I assume that hired labor and household labor are not perfect substitutes. Hired labor is modeled like the other variable inputs, and expenditures on hired labor are subtracted from farm income when estimating restricted profit.

this assumption is that labor markets for hiring managers are incomplete. While this is not directly tested in this paper, there is little evidence that suggests that hiring managers plays even a modest role in Ghanaian agriculture. The GLSS data indicate that the average Ghanaian farm household spends 5% of the farm income on hiring outside labor, the large majority (78%) of which is spent on clearing land.

If it is assumed that markets are complete, then production and consumption decisions of the household are separable. For those households that supply labor to the wage market, solving Eq. (1) results in an allocation of household labor such that the values of the marginal product of farm and off-farm labor are equated to an exogenously determined market wage.[14] While the assumption of complete markets and separability simplifies the empirical specification, it does not appear to be tenable in the case of Ghanaian farm households.

Benjamin (1992) shows that a testable implication of complete labor markets is that the total supply of labor (household plus hired-in labor) to farming will not depend on household characteristics such as age and gender composition. The GLSS data strongly reject the hypothesis of well functioning labor markets and thereby suggest that production and consumption decisions can not be modeled recursively.[15] This result is also consistent with Udry (1996) who found evidence against farm profit maximization of farmers from Kenya and Burkino Faso.[16]

When labor markets are not complete, de Janvry et al. (1991) show that the solution to Eq. (1) results in Eq. (2), an allocation of household labor such that the marginal product of labor is equated to an endogenously determined shadow wage, w^{s}:

$$\partial Y_{\mathrm{f}}(E, L_{\mathrm{f}}, X_{\mathrm{f}}, p_{\mathrm{f}}, \theta_{\mathrm{f}})/\partial L_{\mathrm{f}} = \partial Y_{\mathrm{o}}(E, L_{\mathrm{o}}, X_{\mathrm{o}}, p_{\mathrm{o}}, \theta_{\mathrm{o}})/\partial L_{\mathrm{o}} = w^{\mathrm{s}} \tag{2}$$

They also show that w^{s} is function of household characteristics and all factors that affect profit, and the household supply of labor into farm and off-farm activities is given by:

$$L_i{*} = L_i(X_{\mathrm{h}}, Y_{\mathrm{f}}(E, L_{\mathrm{f}}, X_{\mathrm{f}}, p_{\mathrm{f}}, \theta_{\mathrm{f}}), Y_{\mathrm{o}}(E, L_{\mathrm{o}}, X_{\mathrm{o}}, p_{\mathrm{o}}, \theta_{\mathrm{o}})) = L_i(E, X_i, p_i, \theta_i) \qquad i = \mathrm{o}, \mathrm{f} \tag{3}$$

The important distinction is that L_{f} and L_{o} depend on X_{h} when separability does not hold.[17]

[14] See Singh et al. (1986) for further discussion of this result.

[15] The null hypothesis is that labor markets are complete and hired-in labor is a perfect substitute for household labor. The test is carried out by estimating the number of hours of hired in (and bartered) labor from the reports of expenditure on hired in labor, farm wages, and the number of days of bartered labor obtained. Hours of hired-in labor are added to hours of household farm-labor and this sum is regressed (using OLS with cluster fixed effects) on the same model as that reported in Table A1. The F-statistic for the joint significance of the household characteristics has a p-value less than 0.001.

[16] For a theoretical justification of when separation may not hold, see for example, Lopez (1986).

[17] Note that this result rests on the assumption that nonseparability is due to incomplete labor markets. Evidence supporting the assumption of incomplete labor markets is provided in the test results above. Also, results from overidentification tests reported later in the discussion of the two-stage estimates support the validity of the restriction that household characteristics are excluded from the conditional profit functions.

de Janvry et al. (1991) note that in some cases markets may exist, but selectively fail for some households. In this outcome, Eq. (2) would be equated to the market wage for those households for whom markets are well functioning and the shadow wage for households facing incomplete markets. The assumption implicit in Eq. (2), that labor markets are incomplete for all households, helps to simplify estimation and sidesteps the difficult issue of trying to determine which households face labor market imperfections.[18]

Substituting Eq. (3) into the farm and off-farm profit functions yields:

$$Y_i = Y_i(E, L_i{}^*(E, X, p, \theta), X_i, p_i, \theta_i) \qquad i = \mathrm{o}, \mathrm{f} \tag{4}$$

$$Y_i = Y_i(E, X_i, p_i, \theta_i) \qquad i = \mathrm{o}, \mathrm{f} \tag{4$'$}$$

Estimation of Eq. (3) provides a measure of the extent to which education affects the allocation of labor into farm and off-farm activities. Estimation of Eq. (4′) provides an estimate of the total effect that education has on farm and off-farm profit. This total effect includes a direct effect of profit changing due to increased efficiency, and it also includes the indirect effect of education changing the supply of household labor to farm and off-farm work and thereby changing profit. Estimation of Eq. (4) provides the measure of the direct effect of education on farm and off-farm profit by conditioning on the level of household labor supply.

4. Estimation

The aim of this paper is to show that farm households accrue large returns to education in their off-farm activities, and to also show that households respond to these large returns by allocating more household labor into off-farm work. An implication of this result is that measuring only the returns to education on the farm both underestimates the value of education to the farmer and ignores the importance of education to the allocation of labor into higher return activities. The estimation strategy is to first estimate the two reduced-form, farm and off-farm labor supply Eq. (3), and the two reduced-form, farm and off-farm profit Eq. (4′). All four dependent variables are regressed on the same set of regressors which include: education, household composition variables, farmland area, business assets, experience and prices. The parameter estimates on education from estimating Eq. (4′) will combine the direct effect that education has on farm and off-farm profitability with the indirect effect on profit through the re-allocation of household labor.

In order to separate out these two effects, the next stage of the estimation strategy is to estimate Eq. (4), farm and off-farm profit conditional on the level of household labor supply to each activity. To address the concern that the allocation of household labor to farm and off-farm work is endogenous, a two-stage approach is followed. In the fist-stage,

[18] It is not necessarily the case that participation in the labor market implies perfectly functioning markets. Households will supply labor, even in imperfect markets, if their shadow wage is less than the market wage. An important shortcoming of this model is that it assumes all households supply some off-farm labor, which is clearly not supported by the data.

the reduced-form farm and off-farm labor supply Eq. (3), are again estimated. Then these first-stage estimates are used to estimate the two farm and off-farm profit functions (Eq. (4)). The parameters on education from these regressions provide estimates of the direct effect that education has on increasing farm and off-farm profitability.

4.1. Reduced-form estimation

To estimate Eqs. (3) and (4′), I regress the logs of farm profit, farm labor, off-farm profit, and off-farm labor on E, X_h, X_f, X_o, p_f, and p_o.[19] The household average level of schooling of members 20 years of age and older serves as a measure of E. The X_h vector contains the log of the number of household members, a measure of gender composition, and a set of eight variables that give the number of household members by cohort and gender.[20] The X_f vector contains the log of the area of land cultivated and the log of the maximum level of farm experience in the household. To measure output and input prices, the p_f vector contains regional average prices of maize, okra, cassava, pepper, and the log of insecticide prices. The X_o vector contains the log of the experience in non-farm self-employed work and in wage work, and the log of the value of the business assets. The p_o vector contains a regional average wage for the types of non-farm work engaged in by the farmers.

A concern with the X_f vector is that it treats the quantity of cultivated land as fixed in the short run. If land markets function well, the farmer may be renting the profit-maximizing level of land each year, in which case land should be treated as a variable input. In this case, the rental value of the land should be subtracted from the farm's profits and the rental price of land should be included in the set of regressors. Only 17% of the farmers rent any land at all which means that land rental prices are not well defined in the data. The fact that land markets are not very active also suggests that treating land as fixed is not too egregious an assumption.

In Jolliffe (1996), I estimate all reduced-form regressions, Eqs. (3) and (4′), with and without land.[21] In none of the numerous specifications does omitting the quantity of cultivated land significantly change the estimated effect of education on farm profit, farm labor supply, off-farm profit, or off-farm labor supply. These estimates are very robust to the exclusion of cultivated land which suggests either that land is correctly modeled as exogenous or, if land is endogenous, it is orthogonal to education. In either case, land does not appear to bias the education estimate.

For ease of interpretation, schooling is modeled as affecting profit and labor supply linearly and with no interaction effects. This restrictive assumption is clearly a concern and should temper interpretation of the results. Nonetheless, specification testing suggests that treating education linearly and without interaction effects does not significantly bias the results. In Jolliffe (1996) I estimate all four reduced-form models

[19] To allow the log transformation I have added the constant one to both off-farm profit and labor.

[20] The gender composition variable is the household average of the dummy variable assigning a zero to women and a one to men. The eight variables give the number of men and women in the household who fall into the following four age categories: 10–19, 20–39, 40–59, and 60 years and older.

[21] In Jolliffe (1996), I use a randomly selected subset of the data used in this paper.

with schooling in levels, squared and cubed. In all of the models, the squared and cubed schooling terms are jointly insignificant.[22] I also interact schooling with all of the variables in the X_f, X_o, and X_h and in none of the models are the interaction terms jointly significant.[23]

In light of the differences in education levels by gender and the diversification of farm tasks by gender, it is also important to consider specifications of education that allow for different effects by gender. Again in Jolliffe (1996), I explore whether there are significant differences in the reduced-form estimates when using the years of schooling of the male with the highest school attainment within the households and years of schooling of the female with the highest school attainment in the household. In the case of all four models, there are very little differences between the estimates on whether the years of schooling of the most educated female or male are used. This result suggests that increasing the education levels of men and women alike increases off-farm profit by more than farm profit and results in a re-allocation of labor from farm work to off-farm work.

Table 3 below presents a summary of the reduced-form results by listing the impact of education on farm profit, farm labor supply, off-farm profit, and off-farm labor supply. The estimates for the farm profit and farm labor supply are estimated by both ordinary least squares (OLS) and least absolute deviations (LAD). The variance-covariance matrix of the OLS estimates is adjusted for the complex survey design, and the LAD standard errors are bootstrap estimates. The least-squares estimates for off-farm profit and off-farm labor supply are Powell's (1986) symmetrically trimmed least squares (STLS) and the absolute-deviations estimates are Powell's (1984) censored least absolute deviations (CLAD) estimates.[24] The STLS and CLAD standard errors are bootstrap estimates of the design matrix, where the design matrix is resampled in a manner that replicates the sample design.[25]

The two-stage nature of the sample design introduces some costs and benefits in terms of estimation. An advantage of having several observations clustered close together geographically is that one can treat the clusters as fixed effects and reduce the potential for omitted-

[22] The adjusted R-squared statistics (and pseudo R-squared statistics for the quantile regressions) for all four models drop slightly when the squared and cubed terms of average schooling are added. The results are the same for the models in which the level of schooling of the highest educated person in the household is used. Adding squared and cubed terms of the highest school level does not increase the explanatory power of the model, nor are the parameter estimates of the added variables jointly significant.

[23] When examining the schooling interaction terms separately, the only significant interactions are with the farm and off-farm experience variables. The interaction terms between experience and farm and off-farm profit are both negative, suggesting that as experience increases, the positive effect that education has on both farm and off-farm profit decreases. In the case of labor supply, as farm experience increases, the negative effect that education has on farm labor supply is reduced; and as off-farm experience increases, the positive effect that education has on off-farm labor supply is also reduced. These results both suggest that experience diminishes somewhat the allocative effect that education has on labor supply.

[24] The fixed-effects estimates for the censored models are Honoré's (1992) fixed-effects model for trimmed least squares (TLS_FE) and trimmed least absolute deviations (TLAD_FE).

[25] Tables A1 and A2 provide the full regression results for the LAD estimates. The least squares estimates are available from the author upon request. See Jolliffe (1996) for a comparison of the CLAD with the Tobit.

Table 3
The effect of schooling on profit and labor supply reduced-form estimates

Dependent variable	Least squares, ordinary and trimmed		Least absolute deviations	
	Parameter estimate	Standard error	Parameter estimate	Standard error
Farm profit	0.007	(0.0074)	− 0.005	(0.0097)
with cluster effects	0.014**	(0.0064)	0.007	(0.0071)
Farm labor	− 0.028***	(0.0079)	− 0.028***	(0.0090)
with cluster effects	− 0.006	(0.0078)	− 0.017**	(0.0069)
Off-farm profit[a]	0.129***	(0.0171)	0.204***	(0.0428)
with cluster effects[b]	0.105***	(0.0201)	0.122***	(0.0265)
Off-farm labor[a]	0.054***	(0.0162)	0.079***	(0.0256)
with cluster effects[b]	0.049***	(0.0132)	0.065***	(0.0170)

The full set of LAD parameter estimates are presented in Tables A1 and A2. Least-squares results are available from the author. The OLS standard errors are Huber-corrected for sample design effects. The LAD, STLS and CLAD standard errors are boot-strapped estimates with 1000 replications. The parameter estimates are superscripted with *, **, or *** if the p-value is less than 0.1, 0.05 or 0.01, respectively. (For the bootstrap estimates, the superscripts indicate whether the 90th, 95th, and 99th percentiles of the bias-corrected empirical density function of the parameters exclude zero.)

[a] Powell's (1986) symmetrically trimmed least squares (STLS) and Powell's (1984) censored least absolute deviations (CLAD) estimates.

[b] Honoré's (1992) trimmed least squares (TLS_FE) and least absolute deviations (TLAD_FE) estimates with fixed effects.

variable bias.[26] For example, in the case of farm production in Ghana, a large amount of the variation in land quality (typically considered to be an important missing variable) is likely to occur at the cluster level. Since it may occur that higher quality land is used by those with higher levels of schooling, without controlling for cluster-level fixed effects some of the estimated return to schooling may be picking up the return to higher quality land.

A disadvantage of a cluster-based sample is that observations drawn from within a cluster are likely to have characteristics that are more similar than observations drawn from different clusters. If these similarities are not specified in the model (as is done with the fixed-effects models), the intra-cluster correlations will result in heteroscedasticity, which will bias the estimated standard errors for the on-farm functions. Scott and Holt (1982) show that the OLS estimator for the covariance matrix may be severely biased.

The Breusch–Pagan test for heteroscedasticity strongly rejects the assumption of homoscedasticity for both the farm profit and farm labor supply functions.[27] To correct

[26] While the choice to include cluster fixed-effects estimates is to reduce the potential for omitted variable bias, the decision to include estimates which do not control for the cluster fixed effects is based on the concern that the cluster fixed-effect will absorb some of the variation in school attainment. It is possible that the determinants of school attainment include important cluster-level variables such as simply whether a school (or more importantly to the context of Ghana, a secondary school) exists near the cluster, and this variation should be included in the model (and not swept away with a cluster fixed effect). An analysis of variance shows that in the case of average household schooling of adults, 22% of the variation in attainment is attributable to differences across clusters, with the remaining variation due to differences across households.

[27] The test statistic for farm profit is 1953 with 288 degrees of freedom, which is distributed as a χ^2 under the null hypothesis of homoscedasticity. The probability of observing a value this large when the null is true is much less than 0.001. Similarly the test statistic for farm labor is 9958 with 288 degrees of freedom, and again the null hypothesis of homoscedasticity is rejected with a p-value less than 0.001.

for the impact of heteroscedasticity on the estimated standard errors, all OLS regression models of farm profit and farm labor reported in Table 3 have been corrected for the sample-design effect.[28]

OLS estimation of the off-farm functions, Eqs. (3) and (4′), results in biased estimates because both off-farm profit and off-farm labor supply are censored at zero (26% of the farm households in this sample do not have any members who work off the farm). A standard way to correct for censoring is to use either the Tobit estimator or Heckman's two-step estimator. Hurd (1979) and Nelson (1981) show that these estimators are biased when the assumption of homoscedastic errors is violated, as is likely to be the case with both the off-farm profit and labor regression models. Arabmazar and Schmidt (1981) investigate the potential magnitude of the bias and show that it can be large.

For the same reasons that heteroscedasticity is present in the farm labor and profit functions, it is to be expected that heteroscedasticity is a characteristic of both the off-farm profit and off-farm labor functions. Determining whether the error terms are heteroscedastic is more important for the censored (off-farm) functions, because the standard estimators of both the parameter and covariance matrix are biased. Pagan and Vella (1989) propose a test for heteroscedasticity when the dependent variable is censored by using generalized residuals to carry out the Breusch–Pagan test. In spite of the fact that the power of this test declines with the number of trimmed observations, the modified Breusch–Pagan test strongly rejects the null hypothesis of homoscedasticity.[29]

In the presence of heteroscedasticity and censored dependent variables, Powell's STLS and CLAD estimators both result in consistent estimates.[30] The advantage of the CLAD, or any quantile estimator, is that it is more robust to outliers than least-squares estimators because the median regression is affected by whether observations fall above or below the median and not by the distance from the median. Due to a concern about outliers, and a desire not to arbitrarily drop (or alter) seemingly unreasonable values, I present both least-squares and least-absolute-deviations estimators for all of the primary models considered.

Powell's symmetrically trimmed least squares (STLS) estimator is the $\hat{\beta}$, which minimizes:

$$R(\beta) = \Sigma I(x_i'\beta > 0)[\min(y_i, 2x_i\beta) - x_i'\beta]^2 \tag{5}$$

where the indicator function, I, takes the value of one if the argument is true or zero otherwise. This estimator is obtained by trimming the dependent variable by dropping negative predicted values and imposing an upper bound censoring point at twice the predicted value. This trimming results in residuals that are distributed over $(-x_i\beta, x_i\beta)$.

[28] The estimation is done in Stata with the svyreg command.

[29] Powell's STLS estimator is used to construct generalized residuals and the Breusch–Pagan statistic for the off-farm profit function is 1033 with 288 degrees of freedom and a p-value of less than 0.001. Similarly for off-farm labor supply the statistic is 907 with 288 degrees of freedom and a p-value of less than 0.001.

[30] Both estimators are consistent and asymptotically normal for a wide class of error distributions, but the CLAD is consistent to a wider class of error distributions.

Powell's censored least absolute deviations (CLAD) estimator is found by minimizing

$$\Sigma\,|\,y_i - \max(0, x_i'\,\beta)\,| \tag{6}$$

This estimator builds on the least absolute deviations (LAD) estimator, for which Koenker and Bassett (1978) provide a proof of consistency and a derivation of its distribution. The consistency of the CLAD estimates rests on the fact that medians are preserved by monotone transformations of the data, and Eq. (7) is a monotone transformation of the LAD.

The algorithm used in this paper for the CLAD estimator is Buchinsky's (1994) iterative linear programming algorithm (ILPA). The ILPA first produces LAD estimates on the full sample, then deletes observations associated with negative predicted values, re-estimates the LAD on the trimmed sample. The ILPA converges if there are no negative predicted values on two successive iterations, and Buchinsky (1991) shows that if the process converges, then a local minimum is obtained.[31]

Standard errors for the STLS, CLAD and LAD estimates are obtained through a bootstrap procedure. The complex sample design of the GLSS complicates the bootstrap in two ways: first it is likely to introduce within cluster dependence (or residuals which are not independently distributed), and more broadly it introduces heteroscedasticity of a general form. To address the first issue, Deaton (1997) asserts that in the case of complex survey data the bootstrap needs to be modified such that primary sampling units are resampled, and that one should not just randomly redraw the ultimate sampling units (as is done in the naive, simple random sample bootstrap). He further asserts that failure to correct the bootstrap for the within-cluster dependence will result in an underestimate of the true sampling variance. To address the second issue of heteroskedasticity in general, Buchinsky (1995) shows in a Monte Carlo study that the design-matrix bootstrap performs the best for approximating the sampling variance of the CLAD.

Following the suggestions of Deaton and Buchinsky, the standard errors in this paper are found through a design matrix bootstrap which re-samples the data following a two-stage design similar to the actual design used in the original data collection. In the first stage of resampling, clusters are randomly selected, and then in the second stage, households are drawn in each of the selected clusters.[32] By following this method the empirical density function estimated from the redrawn samples more closely exhibits the properties of the initial sample, and the estimated standard errors are robust to violations both of the assumptions that the residuals are identically and independently distributed.

The final estimation issue to discuss is the cluster fixed-effects estimator for the censored off-farm dependent variables. In the linear model, controlling for fixed effects can be easily implemented by maximizing a likelihood function over all the parameters

[31] See Fitzenberger (1997) for a discussion of some shortcomings of the ILPA as well as an alternative algorithm. As verification that the ILPA performs fine in this context, I also found CLAD estimates for Eq. (5) using *simplex* (Barr, 1996)), a simplex-based search method designed for minimizing non-differentiable likelihood functions. The ILPA and *simplex* resulted in similar point estimates, though the ILPA located the minimum much more quickly (about 0.01 of the *simplex* time).

[32] For a general discussion of the bootstrap, see Efron and Tibshirani (1993).

(the parameters for the cluster effects and the primary parameters of interest). In the nonlinear model, though, Chamberlain (1984) notes that this approach will generally not result in consistent estimates. Due to the small sample size of each cluster, Neyman and Scott (1948) show that the estimated cluster effects are inconsistent; and in the nonlinear model the cluster effects are not independent of the parameters of interest and will therefore contaminate the estimates.

Honoré (1992) proposes two semiparametric estimators which are generalizations of Powell's STLS estimators: the trimmed least squares with fixed effects (TLS_FE) and the trimmed least absolute deviations with fixed effects (TLAD_FE). The estimators are a generalization of the STLS in the sense that Powell imposes symmetry through trimming of y around $X\beta$. Honoré extends this idea into many dimensions, and shows that the symmetry produces orthogonality conditions that hold at the true parameter values. The solution to these conditions results in estimators that are consistent fixed effects estimators for the censored model, and they do not require that any parametric assumptions be placed on the error structure. Also, a simplifying aspect of these estimators for this model is that because the estimator controls for the cluster fixed effect, the variance–covariance matrix need not be adjusted for the sample design.

To summarize the results of the reduced-form estimation, Table 3 is strongly supportive of the hypothesis that most of the returns to education for farm household members is found in off-farm activities and not on the farm. The total impact of the average level of education is significantly greater for off-farm profit than for farm profit. The least-squares, fixed-effects estimates indicate that the total impact of education on off-farm profit is 4.1 times greater than it's effect on farm profit. The difference is even more stark when considering the least-absolute-deviations, fixed-effects estimates which indicate that the impact of education on off-farm profit is more than 8.6 times greater than on farm profit.[33] In addition, the results indicate that part of the divergence between the farm and off-farm profit estimates is due to better-educated households allocating more household labor to off-farm activities. The average level of household education has a negative effect on the supply of household labor to farming activities, and a strongly positive effect on the supply to off-farm work. These results support the hypothesis that households allocate labor according to the relative returns in the two activities.

The estimates of the reduced-form profit functions, Eq. (4′), give the total impact of education on profit and thereby aggregate the effect that education may have on: improving farm and off-farm productivity, improving the allocation of inputs and choice of outputs, as well as the change in profit resulting from the change in labor to each activity. While Table 3 supports the hypothesis that the off-farm profitability effect is larger than the farm profitability effect, it is still necessary to examine some slightly more structural estimates of the profit functions to compare the relative returns to education.

[33] Because the dependent variables in both the farm and off-farm profit functions are in log form, comparing parameter estimates across equations requires adjusting the estimates by the levels of profit. The average value of off-farm profit is equal to 55% of the average value of farm profit. It has also been pointed out by an anonymous referee that these estimates may be downward biased since some workers with higher education will completely leave farming (and thereby the sample) for higher returns.

4.2. Two-stage estimation

In this section of the paper, the farm and off-farm profit functions conditional on household labor supply, Eq. (4), are estimated using instrumental-variable methods to control for the endogeneity of household labor supply decisions. The reduced-form farm and off-farm labor functions, Eq. (3), are used for the first stage estimates. By estimating the somewhat more structural model of profit that includes labor supply, it is possible to obtain a measure of the direct effect that education has on farm and off-farm profitability.[34] These measures are useful to examine whether the opposite signs on the impact of education on farm and off-farm labor supply are associated with a difference in the (education-induced) profitability effects.

The necessity to control for the endogeneity of household labor supply is confirmed by a Hausman test. A comparison of the farm-profit model with farm labor supply instrumented and the model with farm labor supply treated as exogenous reveals that the labor supply point estimate is significantly different across the two models (p-value < 0.001). Further, there is also evidence that the endogeneity bias resulting from erroneously treating farm labor supply as exogenous also contaminates the point estimate on schooling. For the farm profit function, instrumenting farm labor supply has the effect of increasing the education parameter by 25%, though this difference is statistically quite weak (p-value $= 0.11$).[35]

In order to instrument the level of household farm and off-farm labor, it is necessary to find variables that are correlated with labor supply while not directly determining farm and off-farm profit. The identifying instruments implied by Eq. (4) that are used to estimate household labor supply and excluded from the profit functions, are the set of household characteristics, X_{h}. While this choice of exclusion restrictions is not based on an economic theory of household behavior, specification testing indicates that the variables are both well correlated with labor supply and properly excluded from the profit functions (thereby identifying the labor supply parameters).[36]

Farm profit is estimated by both two-stage least squares (2SLS) and Amemiya's (1982) two-stage least absolute deviations estimators (2SLAD).[37] Off-farm profit is similarly

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[34] Increased profit, as measured in this two-stage model, can result from improved productivity as well as from a more efficient allocation of all variable inputs except for household labor.

[35] For both models used in the Hausman test, the variance-covariance matrix is corrected for sample-design effects. The OLS point estimate on the farm labor variable is 0.23 while the IV estimate is 0.63, and the OLS estimate for schooling is 0.024 while the IV estimate is 0.030.

[36] The Breusch–Godfrey statistic which tests the null hypothesis that a subset of the excluded variables are jointly equal to zero in the second-stage regression has a p-value of 0.25, suggesting that the exclusion restrictions are valid. The variables tested for exclusion are: the number of male household members between the ages of 10 and 20 and the number of male household members between the ages of 40 and 60. The F-statistic of the predictive power of these variables is 75.7 with (2, 2393) degrees of freedom and a p-value of $1.3\mathrm{e}-32$. Following the critique of Bound et al. (1995), these instruments also appear to have sufficient predictive power to mitigate the IV-bias associated with weak instruments.

[37] The estimator used in this paper is actually what Amemiya calls the double two-stage least absolute deviations estimator (D2SLAD). Constructing this estimator is easier than the 2SLAD estimator, because it simply entails predicting farm labor supply with the LAD estimator and then using this predicted value in the second stage estimation.

Table 4
The effect of schooling on farm and off-farm profit two-stage estimates (household labor instrumented)

Dependent variable	Least squares, ordinary and trimmed		Least absolute deviations	
	Parameter estimate	Standard error	Parameter estimate	Standard error
Farm profit	0.030***	(0.0084)	0.028***	(0.0107)
with cluster effects	0.020***	(0.0073)	0.021***	(0.0067)
Off-farm profit[a]	0.063*	(0.0279)	0.111*	(0.0591)
with cluster effects[b]	0.082***	(0.0166)	0.085***	(0.0209)

The full set of LAD parameter estimates are presented in Table A3. Least-squares results are available from the author. The OLS standard errors are corrected for sample design effects. The LAD, STLS, CLAD, TLS_FE, TLAD_FE standard errors are bootstrapped estimates with 1000 replications. The parameter estimates are superscripted with *, ** or *** if the p-value is less than 0.1, 0.05 or 0.01, respectively. (For the bootstrap estimates, the superscripts indicate whether the 90th, 95th and 99th percentiles of the bias-corrected empirical density function of the bootstrap parameters excludes zero.)

[a] Powell's (1986) symmetrically trimmed least squares (STLS) and Powell's (1984) censored least absolute deviations (CLAD) estimates.

[b] Honoré's (1992) trimmed least squares (TLS_FE) and least absolute deviations (TLAD_FE) estimates with fixed effects.

estimated using two-step versions of STLS, CLAD, TLS_FE, and TLAD_FE. Except for the 2SLS, all estimates and standard errors are constructed in the same manner. In the first stage, consistent point estimates for farm and off-farm labor supply are obtained. In the second stage, farm and off-farm profit are estimated using the predicted levels labor supply to obtain consistent point estimates. Standard errors are estimated by bootstrapping the design matrix and re-estimating both stages after each bootstrap replication. Table 4 provides a summary of the regression estimates and Table A3 provides the complete LAD results for farm and off-farm profit.[38]

The reduced-form results show that higher levels of schooling are associated with a higher level of household labor supply in off-farm work, and they also show that increased levels of schooling increase off-farm profit by a much greater amount than farm profit. From the reduced-form results, though, it is not clear whether the large increases in off-farm profit are due completely to the increased level of labor supply to those activities, or whether education improves the profitability of these activities.

The two-stage estimates are supportive of the hypotheses that education increases both farm and off-farm profitability (conditional on labor supply), that it increases off-farm profit by a greater amount, and that the association between increased levels of education and increased levels of off-farm work results partly from the divergence in returns to education. In the case of the fixed-effects, LAD estimates, improved levels of schooling increases off-farm profitability by 123% more than the increase in farm profit (118% when not controlling for cluster effects). In the case of the fixed-effects, LS estimates, education increases off-farm profitability by 126% more than the increase in farm profit. Only in the case of the least squares estimates without controlling for fixed effects, is there no statistically significant divergence in returns.

[38] The full set of least-squares results is suppressed for the sake of brevity and are available from the author.

Comparative statics help to illustrate the connection between Tables 3 and 4. The total change in farm and off-farm profit from a change in education can be found by differentiation of Eq. (4) with respect to education:

$$\mathrm{d}Y_i/\mathrm{d}E = [\partial Y_i/\partial E + (\partial Y_i/\partial L_i)(\mathrm{d}L_i/\mathrm{d}E)] \qquad i = \mathrm{o}, \mathrm{f} \tag{7}$$

The term on the left-hand side gives the total effect on profit from a change in education, and these estimates are found in Table 3 from the reduced-form equations. The first term in the square brackets gives the direct effect that education has on profit, and this estimate is found in Table 4 from the regression estimates conditional on labor supply. The second term in the square brackets reflects the indirect change in profit from the household reallocating labor. This labor reallocation term is the product of the marginal value of labor, estimated in the conditional regressions, and the change in household labor supply from education, estimated in the reduced-form equations.

Table 4 indicates that conditional on labor supply, education increases off-farm profits by more than farm profit. The reduced-form estimates from Table 3 indicate that higher levels of education are associated with reduced (increased) levels of household labor supply to farm (off-farm) work. The implication of Eq. (7) and the reduced-form labor supply estimates is that the education-induced change in farm profit unconditional on labor supply is less than the estimate conditional on labor supply. Similarly, because households with higher education levels allocate more labor to off-farm activities, the unconditional change in off-farm profit from education is greater than the change conditional on household labor supply.

4.3. Intra-household labor supply decisions

The results of this paper have shown that households with higher education levels allocate more labor to off-farm work than to farm work. Throughout this paper, these results have been presented at the household and not the individual level. A natural question to pose is whether there is any evidence that, within households, those individuals with more education are more likely to work off of the farm and whether more of their labor hours are spent in off-farm work.

Table 5 examines if schooling affects the three binary outcomes of whether individuals work only on the farm, or engage in some off-farm work, or work solely off of the farm. All three of these dummy variables are separately regressed on schooling, age, and sex of the individuals. While the probit model is most typically used to estimate binary outcomes, the need to control for household fixed effects complicates the choice of estimators. In the case of the probit model, the household fixed effects can not be conditioned out of the likelihood and the unconditional model, treating each fixed effect as a dummy, results in biased estimates. Consistent estimates for the random-effects probit exist, but this model imposes distributional assumptions on the household effect. In the case of the logit model, it is possible to derive a likelihood conditional on the household effects which is the analog of taking all observations as differences from the household means. Table 5 presents both estimates

Table 5
Labor participation in farm and off-farm work (binary outcomes, household-specific effects)

	Only farm work		Some off-farm work		Only off-farm work	
Logit, household fixed effects						
Years of schooling	– 0.083***	(0.0156)	0.083***	(0.0156)	0.066***	(0.0255)
Age (in years)	0.002	(0.0038)	– 0.002	(0.0038)	– 0.012*	(0.0068)
Male (1 = male, 0 = female)	0.865***	(0.0990)	– 0.865***	(0.0990)	– 1.421***	(0.1778)
Probit, household random effects						
Years of schooling	– 0.078***	(0.0054)	0.078***	(0.0054)	0.106***	(0.0093)
Age (in years)	0.007	(0.0016)	– 0.007***	(0.0016)	0.001	(0.0028)
Male (1 = male, 0 = female)	0.460	(0.0457)	– 0.460***	(0.0457)	– 0.900	(0.0813)

The three binary dependent variables take the value of one if the individual worked only on the farm, if the individual did some work off of the farm, and if the person worked strictly off of the farm. Standard errors in parentheses. The sample consists of the 5595 workers who are at least 20 years of age. The intercept estimates are suppressed from the table.

to examine the robustness of the results to the assumptions of both models. (See Chamberlain, 1984, for further discussion and comparison of the random-effects probit and the fixed-effects logit.)

In the model predicting the probability of only working on the farm, the negative schooling parameter suggests that those individuals who have more schooling than the other members of their household, are less likely to work on the farm.[39] Similarly, for the outcomes of engaging in some off-farm work and working strictly off of the farm, the positive value on schooling indicates that having more schooling than the other members of the household increases the probability of off-farm work. The qualitative nature of these results holds whether considering the fixed-effects logit or the random-effects probit estimates, indicating robustness to the differences in the model assumptions.

The dependent variable considered in Table 6 is the ratio of hours worked off of the farm to total labor hours. Two samples are considered in this table: all workers and all workers at least 20 years of age. The proportion of time spent in off-farm work is regressed on schooling, age, sex, and experience in farm and off-farm work.[40] Again the results are contrasted across two estimators: Honoré's trimmed LAD and trimmed least squares with household fixed effects. Across both estimators and both samples, the coefficient on schooling is positive and statistically significant. The positive coefficient indicates that individuals, who have more schooling than the other members in their household, spend a greater proportion of their working hours in off-farm work. Also, within each sample, the school point estimates are the same whether estimated

[39] The sample size is 5595 which includes all working individuals at least 20 years of age. For the fixed-effects logit model, households are excluded from the estimation if the dependent variable is the same for all members. They are valid observations, but add nothing to the likelihood. This left 743 households for the only-off-farm model and 1881 households for the only-farm and some-farm models.

[40] As opposed to the binary outcome dependent variables, the continuous nature of this dependent variable allows a slightly fuller model.

Table 6
Ratio of off-farm labor hours to total labor hours Honoré's trimmed estimates with household-fixed effects

	Honoré's trimmed LAD		Honoré's trimmed least squares	
	Estimate	(Standard error)	Estimate	(Standard error)
Sample: workers 20+years of age				
Years of Schooling	0.011*	(0.0059)	0.012***	(0.0023)
Age (in years)	− 0.001	(0.0073)	− 0.001	(0.0010)
Male (1 = male, 0 = female)	− 0.110***	(0.0148)	− 0.110***	(0.0149)
Farm work experience	− 0.011	(0.0075)	− 0.011***	(0.0011)
Off-farm work experience	0.020***	(0.0057)	0.019***	(0.0012)
Sample: all workers				
Years of schooling	0.020***	(0.0049)	0.020***	(0.0020)
Age (in years)	0.002	(0.0066)	0.002***	(0.0008)
Male (1 = male, 0 = female)	− 0.198***	(0.0149)	− 0.188***	(0.0134)
Farm work experience	− 0.008	(0.0070)	− 0.009***	(0.0010)
Off-farm work experience	0.023***	(0.0055)	0.019***	(0.0012)

The dependent variable is the ratio of hours spent in off-farm work to total labor hours. For the sample of workers at least 20 years of age, there are 1726 households with more than one person per household. For the sample of all workers, there are 2062 household with more than one person per household.

by the trimmed least-squares or LAD method which suggests a robustness to extreme values.

5. Conclusion

A large proportion of the existing empirical studies of how education affects farmers in developing countries is limited to a discussion of how education affects behavior on the farm or how it affects farm productivity. This paper argues that much of the value from increasing the educational attainment of farm households is found in its impact on off-farm activities, including the reallocation of time away from farm work. The reduced-form result that education increases off-farm profit by a greater amount than it increases farm profit is robust and statistically significant. Also robust and statistically significant is the result that increases in education levels are associated with decreases in the household's labor supply on the farm and increases in household's off-farm labor supply.

The two-stage results show that when conditioning on the level of labor supply, an increase in school attainment at the household level results in a greater gain in off-farm than farm profit. These results suggest that the household's labor supply responds to this gap in profitability by allocating more labor into off-farm activities as school attainment increases. In the last section, the household-fixed-effects models are used to show that those individuals who have more education than the other members in their household are less likely to work strictly on the farm, more likely to work off of the farm, and expend a larger proportion of their working hours in off-farm activities.

The argument put forth in this paper, that the farmer's returns from education are significantly larger in off-farm activities than in farm activities, counters the argument put forth by some researchers (for example, Robertson, 1984) that formal education is of little value to the rural poor in developing countries. These researchers conclude that farmers benefit more from learning farming skills than from learning reading, writing, and arithmetic skills. This paper concludes that this argument fails to note that the returns to formal schooling in off-farm work are significant. Focusing only on the returns to education on the farm could lead to the erroneous conclusion that farmers do not significantly benefit from investments in formal education.

In addition to providing a more complete measure of the value of schooling to the farmer, estimating the returns to education both on and off the farm sheds light on the importance of education to the development process. Much of the earlier development literature stressed the importance to economic growth of a labor force shifting away from agricultural work to non-agricultural employment in response to higher returns. The results presented in this paper suggest that education may be one of the powerful forces to which Timmer refers, that leads labor out of agriculture and into other activities with higher returns.

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Appendix A

Tables A1–3.

Table A1
Farm profit and labor supply reduced form, least absolute deviations estimates

	Farm profit				Farm labor	
	LAD		Fixed effects		LAD	
	Estimate	(Standard error)	Estimate	(Standard error)	Estimate	(Standard error)
Avg Hh level of schooling, 20+	− 0.005	(0.0097)	0.007	(0.0071)	− 0.028***	(0.0090)
Farm						
Log: acres of land cultivated	0.470***	(0.0402)	0.352***	(0.0257)	0.183***	(0.0314)
Log: max experience farming	0.190***	(0.0493)	0.158***	(0.0309)	0.235***	(0.0520)

(continued on next page)

Table A1 (*continued*)

	Farm profit				Farm labor	
	LAD		Fixed effects		LAD	
	Estimate	(Standard error)	Estimate	(Standard error)	Estimate	(Standard error)
Farm						
Log: region avg. insect. price	– 0.249	(0.1631)			– 0.223**	(0.1170)
Log: region avg. maize price	1.114	(14.962)			1.010	(11.082)
Log: region avg. okra price	– 0.720	(24.310)			– 0.118	(17.969)
Log: region avg. cassava price	0.799	(32.716)			0.344	(24.180)
Log: region avg. pepper price	0.923	(16.119)			0.111	(11.921)
Off-farm						
Log: max experience wage sector	0.010	(0.0567)	0.027	(0.0317)	– 0.164***	(0.0638)
Log: max exp. self-employment	– 0.117***	(0.0330)	– 0.070***	(0.0208)	– 0.038	(0.0297)
Dummy: wage earner in household	– 0.102	(0.1099)	– 0.127**	(0.0619)	0.004	(0.1322)
Log: asset value own business	0.026***	(0.0100)	0.021***	(0.0070)	– 0.017**	(0.0087)
Log: cluster wage, dropout avg	0.088	(0.0945)			– 0.128**	(0.0579)
Household composition						
Log: household size	0.333***	(0.0792)	0.223***	(0.0461)	0.284***	(0.0771)
Hh gender composition, 1 = Male	0.084	(0.1742)	0.054	(0.0989)	0.013	(0.1498)
No. of males in Hh: 10–19 years old	0.004	(0.0414)	0.033	(0.0239)	0.057	(0.0388)
No. of males in Hh: 20–39 years old	0.129***	(0.0589)	0.131***	(0.0284)	0.302***	(0.0605)
No. of males in Hh: 40–59 years old	– 0.007	(0.0875)	0.142***	(0.0505)	0.276***	(0.0830)
No. of males in Hh: 60+ years old	– 0.003	(0.1026)	0.075	(0.0546)	0.104	(0.0907)
No. of females in Hh: 10–19 years old	– 0.010	(0.0457)	0.031	(0.0213)	0.023	(0.0414)

Table A1 (*continued*)

	Farm profit				Farm labor	
	LAD		Fixed effects		LAD	
	Estimate	(Standard error)	Estimate	(Standard error)	Estimate	(Standard error)
Household composition						
No. of females in Hh: 20–39 years old	0.023	(0.0586)	0.075**	(0.0322)	0.138**	(0.0562)
No. of females in Hh: 40–59 years old	– 0.043	(0.0765)	– 0.013	(0.0411)	0.096	(0.0661)
No. of females in Hh: 60+ years old	– 0.170**	(0.0952)	– 0.068	(0.0434)	– 0.162**	(0.0867)
Intercept	– 5.548	(282.29)			– 1.800	(208.94)
	Pseudo R^2: 0.270		χ^2 stat: 880 ($p<0.001$)		Pseudo R^2: 0.257	
	obs: 2393		obs: 2393		obs: 2393	

The log of farm profit and household labor supply are least absolute deviation (LAD) estimates with and without controls for the clusters. Standard errors are in parentheses. The variance for the LAD estimates is estimated by a bootstrap procedure with 1000 replications, following the methodology in Jolliffe et al. (2000). The reported standard errors are the standard deviations of the bootstrap density functions. Estimates are superscripted with *, ** or *** if the (two-sided) 90th, 95th, or 99th percentile of the bias-corrected empirical density function excludes zero.

Table A2
Off-farm profit and labor supply reduced form, least absolute deviations estimates

	Off-farm profit				Off-farm labor	
	Powell's CLAD		Honoré's fixed effects		Powell's CLAD	
	Estimate	(stnd error)	Estimate	(stnd error)	Estimate	(stnd error)
Avg Hh level of schooling, 20+	0.204***	(0.0428)	0.122***	(0.0265)	0.079***	(0.0256)
Farm						
Log: acres of land cultivated	– 0.006	(0.1225)	– 0.057	(0.1040)	– 0.127**	(0.0720)
Log: max experience farming	– 0.598***	(0.1839)	– 0.573***	(0.1219)	– 0.334***	(0.1096)
Log: region avg. insect. price	0.010	(0.3492)			0.138	(0.2109)
Log: region avg. maize price	– 2.750	(16.769)			– 1.341	(6.9922)
Log: region avg. okra price	1.104	(27.039)			0.678	(11.217)
Log: region avg. cassava price	– 4.649	(36.371)			– 3.801**	(15.066)
Log: region avg. pepper price	– 0.911	(17.921)			– 0.154	(7.4683)

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Table A2 (*continued*)

	Off-farm profit				Off-farm labor	
	Powell's CLAD		Honoré's fixed effects		Powell's CLAD	
	Estimate	(stnd error)	Estimate	(stnd error)	Estimate	(stnd error)
Off-farm						
Log: max experience wage sector	0.683***	(0.2404)	0.523***	(0.1297)	0.512***	(0.1429)
Log: max exp. self-employment	2.072***	(0.1810)	2.242***	(0.1325)	1.555***	(0.0977)
Dummy: wage earner in household	4.390***	(0.6236)	3.671***	(0.4007)	3.065***	(0.3765)
Log: asset value own business	0.280***	(0.0500)	0.364***	(0.0346)	0.198***	(0.0294)
Log: cluster wage, dropout avg.	0.348	(0.2613)			0.264*	(0.1655)
Household composition						
Log: household size	0.325	(0.3203)	0.834***	(0.2794)	0.223	(0.1988)
Hh gender composition, 1 = male	0.750	(0.6300)	0.914**	(0.3653)	0.581	(0.4209)
No. of males in Hh: 10–19 years old	−0.287	(0.1721)	−0.392***	(0.1206)	−0.189*	(0.1083)
No. of males in Hh: 20–39 years old	−0.162	(0.2496)	−0.363**	(0.1663)	−0.097	(0.1407)
No. of males in Hh: 40–59 years old	−0.692	(0.4177)	−0.932***	(0.2296)	−0.487***	(0.2081)
No. of males in Hh: 60+ years old	−0.738*	(0.3991)	−0.678**	(0.2975)	−0.240	(0.2297)
No. of females in Hh: 10–19 years old	0.098	(0.1679)	0.082	(0.1263)	0.129	(0.1182)
No. of females in Hh: 20–39 years old	0.222	(0.2579)	0.092	(0.1945)	0.257**	(0.1711)
No. of females in Hh: 40–59 years old	−0.054	(0.2792)	−0.093	(0.2227)	0.061	(0.1826)
No. of females in Hh: 60+ years old	−0.341	(0.3971)	−0.607**	(0.3031)	−0.154	(0.2312)
Intercept	47.229	(314.60)			27.130*	(130.72)
	Pseudo R^2: 0.271 obs: 2393		χ^2 stat: 982 ($p < 0.001$) obs: 2393		Pseudo R^2: 0.307 obs: 2393	

Table A3
Farm and off-farm profit (with labor supply instrumented) two-stage, least absolute deviations estimates

	LAD		FE	
	Estimate	(stnd error)	Estimate	(stnd error)
Panel A: farm profit				
Avg. Hh level of schooling, 20+	0.028***	(0.0107)	0.021***	(0.0067)
Log: household farm labor, instrumented	0.573***	(0.2577)	0.656***	(0.0593)
Log: acres of land cultivated	0.384***	(0.0811)	0.268***	(0.0277)
Log: max experience farming	0.034	(0.0913)	−0.010	(0.0369)
Log: region avg. insect. price	−0.068	(0.2050)		
Log: region avg. maize price	0.276	(14.368)		
Log: region avg. okra price	−0.451	(23.377)		
Log: region avg. cassava price	0.614	(31.412)		
Log: region avg. pepper price	0.679	(15.498)		
Intercept	−1.941	(271.18)		
	Pseudo R^2: 0.254	obs: 2393	χ^2 stat: 764 ($p<0.001$)	obs: 2393
Panel B: off-farm profit				
Avg. Hh level of schooling, 20+	0.111*	(0.0591)	0.085***	(0.0209)
Log: household off-farm labor, instrumented	1.168***	(0.3790)	1.388***	(0.1002)
Log: max experience wage sector	0.128	(0.2620)	0.017	(0.1088)
Log: max exp. self-employment	−0.078	(0.5849)	−0.176	(0.1633)
Dummy: wage earner in household	0.075	(1.3584)	0.018	(0.3953)
Log: asset value own business	0.039	(0.0875)	0.022	(0.0287)
Log: cluster wage, dropout avg.	0.022	(0.1742)		
Intercept	1.774	(1.6558)		
	Pseudo R^2: 0.260 obs: 2393		χ^2 stat: 361 ($p<0.001$) obs: 2393	

In Panel A, the dependent variable is the log of farm profit which is estimated with a two-stage, least absolute deviations (D2SLAD) estimator with and without cluster fixed effects. In Panel B, the dependent variable is the log of off-farm profit which is again estimated with a two-stage, censored least absolute deviations estimator with and without fixed effects. For all models the standard errors are estimated by bootstrapping the design matrix with 1000 replications. (For each replication, both stages of the model are re-estimated.) Estimates are superscripted with *, ** or *** if the (two-sided) 90th, 95th or 99th percentile of the bias-corrected empirical density function of the parameter estimates excludes zero.

Note to Table A2:
The log of off-farm profit is estimated by both Powell's censored least absolute deviations (CLAD) estimator and Honoré's trimmed least absolute deviations with fixed effects (TLAD_FE) estimator. The log of off-farm, household labor supply is estimated with the CLAD estimator. Standard errors are in parentheses. The variance for the LAD estimates is estimated by a bootstrap procedure with 1000 replications, following the methodology in Jolliffe et al. (2000). The reported standard errors are the standard deviations of the bootstrap density functions. Estimates are superscripted with *, ** or *** if the (two-sided) 90th, 95th or 99th percentile of the bias-corrected empirical density function excludes zero.

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