Does Human Capital Raise Farm or Non-farm Earning More? New Insight from Rural Pakistan Panel Survey

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Abstract

This study explores how human capital affects farm household earnings using two tools to refine measurement of human capital effects. First, it employs a two-sector model to allow the allocation of family labor between farm and non-farm activities. Second, it accounts for village fixed effects to evaluate whether results from panel data differ meaningfully from a cross-sectional data analysis with local binary variables. The results show that education has a negligible effect on farm earnings; instead, experience appears to be the principal channel by which human capital affects agricultural performance in a traditional rural setting. Our results also suggest that prior models that fail to separate non-farm activities spuriously exaggerated the effect of education to the farm sector. In addition, typical cross-sectional analyses that ignore fixed effects may cause the effects of education on rural household earnings to be significantly overstated. The fact that panel data regressions accounting for village-level fixed effects found only one instance of education raising earnings – the effect of literacy on non-farm income – suggests that considerable heterogeneity may have been ignored in cross-sectional data analyses, especially ones that omitted village binary variables.

1. Introduction

Although human capital augments labor productivity in theory, empirical studies of productivity in rural developing areas have shown contradictory results. Many studies have shown that more educated individuals work more productively and efficiently, thus generating more income. Others have found education to help determine many other outcomes such as child nutritional status, occupational choice, and labor supply (see Schultz, 1988, and Strauss and Thomas, 1995, for comprehensive literature surveys). In the agricultural sector, many studies have shown education to be critical determinant of farm productivity and profitability. Education has been linked to significant increases in farm productivity, particularly through improved efficiency (see for example Lockheed et al., 1980, and Jamison and Lau, 1982).

But other studies have found less clear evidence of a relation between agricultural production and human capital. Phillips (1987) found that while the Asian cases support a strong positive relationship between the two, experiences from Latin America and Africa are mixed. Using two-stage estimation to control for the endogeneity of sectoral labor allocation, Taylor and Yunez-Naude (2000) find strong evidence of the schooling effect on aggregate income. They also show that while average schooling causes the farm household to allocate labor more toward wage activities, a more highly educated household head diverts household labor away from production of staple crops. In studying the relative efficiency of large and small rice farms in Cote d'Ivoire, Adesina and Djato (1996) find education to be insignificant in shaping farm profits.

The inconsistent benefit of education to the farm sector may be partly due to the growing importance of the non-farm sector for many rural households. Huffman (1980) and Rosenzweig (1980) show that in the United States and in low-income developing countries, a growing share of the income comes from the non-farm sector. Schultz (1988) observes that while better educated rural laborers are the first to leave agriculture when the returns to education are larger elsewhere, they will return to it if there is an agricultural boom.

Two more recent studies that use a two-sector framework find little effect of education on agricultural production and earnings in the presence of a non-farm sector. Using twelve rounds of panel data in rural Pakistan, Fafchamps and Quisumbing (1999) have shown that education has no significant effect on crop and livestock income, despite finding that households with better educated males earn higher off-farm income. Yang and An (2002), using cross-sectional data from rural China, find that schooling increases farm household earnings only when they use instrumental variables for the endogenous quasi-fixed input variables. Yet even that effect is small relative to the one for non-farm earnings –which is robust and consistent across all model specifications.

Another explanation for the inconsistency in the literature may be that misspecified models failed to control unobserved heterogeneity that eventually drive the relation between human capital and agricultural productivity or income. Studies like Foster and Rosenzweig (1996), Fafchamps and Quisumbing (1999), and Yang (2004) that have utilized panel data and explicitly controlled for the presence of unobserved heterogeneity using fixed-effects are the exceptions rather than the rule. Focusing on the Green Revolution period, Foster and Rosenzweig (1996) find that primary schooling increased farm profits, particularly in the areas with highest economic growth rates. Yang (2004), using panel data from one province in China, find that allocation of capital and labor to the non-farm sector are positively related to educational attainment in the household. But, he also showed that, while experience is important, education plays no role in shaping aggregate household income.

We revisit the question of how human capital affects farm household earnings using two tools to refine the measurement of human capital effects. First, we develop a two-sector econometric specfications to allow the allocation of family labor between farm and nonfarm activities. A two-sector framework more realistically captures farmers' involvement in both farm and non-farm activities. Modeling both options may be especially relevant in a modern rural setting where more off-farm employment is available as rural development grows.

Second, we use panel data to explicitly model village fixed effects, so as to account for unobserved heterogeneity. Most previous studies have used cross-sectional data. Yet cross-sectional studies can be susceptible to bias in parameter estimates due to endogeneity of explanatory variables as well as omitted variables. To address this problem, we use panel data analysis accounting for village fixed effects and evaluate whether results differ meaningfully from a cross-sectional data analysis.

We adopt the conceptual framework of Yang and An (2002) to estimate the effect of human capital on farm profit functions in rural Pakistan. Their two-sector framework permits allocation of household resources, including human capital, between farm and non-farm activities. We extend the standard profit maximization paradigm by allowing human capital to affect the level of `inefficient´ management leading to lower earnings.

In order to explore the effect of cross-sectional versus panel data on econometric inferences, we also extend their empirical strategy to estimate models using both cross-sectional and panel data. In both analyses, we examine the effect of human capital factors in total earnings, farm earnings, and nonfarm earnings.

2. Conceptual Framework

Yang and An (2002) suggest that the key decisions of the household are to allocate quasi-fixed inputs to the two sectors, farm and off-farm, to choose variable inputs for the individual activities, and to execute specific production plans. Following their lead, we build the static, short-run maximization problem which consists of two-sector (gross) profit maximization problem as follows:

$$\Pi = \sum_{j=1}^{2} \Pi_j = \sum_{j=1}^{2} (p_j y_j - w_j x_j) \qquad (1)$$

Let sector-specific production functions take the form,

$$y_j = \delta_{ij} f_j(z_j), \quad j = 1,2 \qquad (2)$$

where (y_j, x_j, p_j, w_j) are respectively output, input, and price of output and input for sector j (j$\in${1,2}), while z_j represents a quasi-fixed factor input (such as human capital), and f_j (.) reflects the sector-specific, neo-classical production function. Here we assume that the every household uses identical technology, but they may differ in technical efficiency, which is captured by different δ_{ij}. We also assume that while the selection of x_j is sector-specific , the choice of z_j must satisfy following household constraint:

$$z = \sum_{j=1}^{2} z_j \tag{3}$$

Yang and An (2002) characterize the choice of z_j as reflecting the household's entrepreneurship in deciding how much resource must be supplied to each sector. Including entrepreneurship as a measure of managerial ability requires a model that allows the household to behave inefficiently in allocating the productive inputs (Jamison and Lau, 1982 and Yang and An, 2002). This "managerial inefficiency" is, represented below in equation 4, as deviation from standard profit maximization conditions for input allocation both within and between sectors.

$$\begin{aligned} & p_j \delta_j \frac{\partial f_j(x_j, z_j)}{\partial x_j} = \gamma_j w_j \\ & j = 1,2 \\ & p_1 \delta_1 \frac{\partial f_1(x_1, z_1)}{\partial z_1} = \theta p_2 \delta_2 \frac{\partial f_2(x_2, z_2)}{\partial z_2} \end{aligned} \tag{4}$$

where $\gamma_j \in (0,1]$ and $\theta \in (0,1]$ reflect the efficiency parameters for using the sector-specific purchased-inputs and the quasi-fixed input. It is easy to see that when γ_j=1 and θ=1 the case will return to the standard profit maximization problem, which implies that the more efficient case, the smaller the deviation of γ_j and θ from 1 (Yang and An, 2002).

Solving equation (4) for x_j and z_j we obtain the input demand functions:

$$
\begin{aligned}
x_j &= x_j(z_j, p_j, w_j, \delta_j, \gamma_j) \\
z_j &= z_j(z, p, w, \delta, \gamma, \theta)
\end{aligned} \tag{5}
$$

for $j=1, 2$

Yang and An (2002), as well as Welch (1970) and Schultz (1988), argue that human capital works through technical and allocative efficiency parameters, γ, θ, and δ, each of which is a function of human capital, H, and some unobserved heterogeneity, μ. It is not hard to see that z_j is reduced-form, while x_j is structural function that contains endogenous z_j. By substituting $\gamma(H, \mu)$, $\theta(H, \mu)$, and $\delta(H, \mu)$ into equation (5), we include the human capital factors and unobserved heterogeneity leading to the following:

$$
\begin{aligned}
x_j &= x_j(z_j, p_j, w_j) \\
z_j &= z_j(z, p, w, \delta, H, \mu)
\end{aligned} \tag{6}
$$

Substituting the factor demand x_j and the corresponding output supply function in equations (6) back to the equation (1) produces an aggregate function and two sector-specific profit functions that contain human capital variables:

$$\Pi = \Pi(z, p, w, H, \mu) \tag{7}$$

and

$$\Pi_j = \Pi_j(z_j(z, p, w, H), p_j, w_j, H_j, \mu) \tag{8}$$

for $j=1, 2$

3. Empirical Strategy

Our empirical strategy is twofold. First, we follow Yang and An's (2002) empirical strategy to see how human capital affects household earnings in a cross-sectional model. We estimate aggregate and sectoral profit functions in which quasi-fixed input and human capital factors enter the function linearly:

$$\pi_i = \alpha + z_i\beta + H_i\lambda + u_i \tag{9}$$

$$\pi_{ij} = \alpha_j + z_{ij}\beta_j + H_{ij}\lambda_j + u_{ij} \tag{10}$$

where *i* in index of the household, j is for sector (farm and off-farm), π_i (π_{ij}) is the aggregate profit (sectoral), z_i (z_{ij}) is aggregate (sectoral) quasi-fixed factor, H_i (H_{ij}) is a vector of aggregate (sectoral) human capital variables, α is scalar parameter, and β and λ are column vectors of parameters. The disturbances u_i and u_{ij} are assumed to have zero mean. Thus, equation (9), which is in reduced form, estimates the effect of human capital on aggregate profit. In equation (10), Cov(z_{ij}, u_{ij})≠0 because z_{ij} is potentially endogenous. Estimating equation (10) with OLS thus generally produces inconsistent estimators of all β and λ. The most common method to deal with this problem is to adopt instrumental variable (IV) estimation using two-stage least squares (2SLS) (for details on 2SLS, see Wooldridge, 2002).

To address the omitted variable/unobserved heterogeneity problem, we propose to use fixed-effect estimation, given the access to panel data. Let μ_c denote a time-constant unobserved variable that enters the model additively. Then equations (9) and (10) become:

$$\pi_{it} = \alpha_0 + z_{it}\beta + H_{it}\lambda + \mu_c + u_{it} \tag{11}$$

$$\pi_{ijt} = \alpha_{j0} + z_{ijt}\beta_j + H_{ijt}\lambda_j + \mu_c + u_{ijt} \tag{12}$$

Ignoring μ_c and leaving it in the error term will not be a problem if μ_c is uncorrelated with the other explanatory variables. But if it correlates with one or more explanatory variables, then putting it in the error term may lead to inconsistent parameter estimates (Wooldridge, 2002). The fixed effect method enables us to capture an indicator of unobserved heterogeneity in such omitted variables as soil quality, weather, and input/output market conditions. By applying these two strategies to the same data set and model, we will evaluate whether there exists significant unobserved heterogeneity in the simple cross-sectional model that, if ignored may lead to biased results.

4. Data

This study uses the rural Pakistan panel data set from the International Food Policy Research Institute (IFPRI). This 12-round panel data set covers close to 1000 randomly selected households in 44 randomly selected villages. The 12-round interviews –with three- to four-month intervals between rounds—were conducted between July 1986 and September 1989 (Nag-Chowdhury, 1991). We use only the first four rounds, which contain the human capital variables of interest. The cross-sectional model used the first round of the data set.

In both models, profitability is the outcome of interest. Profitability deals with monetary outcomes and it reflects not only productivity, but also technical and allocative[1] efficiency. Thus, a change in human capital may not affect physical productivity, but it may still influence profitability through allocation and/or choice of inputs, given prices in the markets. We proxy profitability with gross household earnings that include earnings from crop sales, farm labor, and payment received from non-farm activities. Unlike some

[1] Jamison and Lau (1982) explain that allocative efficiency is the extent to which farmers optimally choose their input and output mix in light of their production functions and prevailing prices. A farm household is said to be allocative-efficient if the marginal product of every variable input is equal to the price of the variable input normalized by the price of output.

previous studies, we exclude remittances from earnings as we focus on the returns of education to household members only.

In this study, human capital is measured by the number of adults in the household with particular levels of education and experience of adult household members. These educational levels allow associating change in earnings with change in the number of adults per household having a particular level of education. Post-schooling work experience, a measure of accumulated learning, has been found to contribute to agricultural performance (e.g. Foster and Rosenzweig, 1995). Following Yang and An (2002), we approximate experience in a household by the worker's age minus years of schooling minus 7, summed over all adults in the household. Also we, as Yang and An (2002), divide human capital variables between farm and non-farm activities by weighting those human capital variables according to the proportion of each individual's total labor time that is devoted to a given sector (farm or no-farm).

In order to address the potential endogeneity problem of sectoral labor allocation, we will test the effect of applying 2SLS to the cross-sectional data models. The variables chosen to instrument sectoral labor allocation are average age for adults in the household and education of the head of household. Both are believed to shape household preferences about where to allocate family labor. The IVs are assumed to be uncorrelated with the error term.

Table 1 below provides descriptive statistics for the included variables. The summary statistics in Table 1 indicate that non-farm activities generate earnings more than twice as high as farm activities. Consistent with this finding, households tend to allocate more labor toward non-farm than farm activities. As for human capital, adults with primary education are equally divided between farm and non-farm activities. However adults who can read or attended middle school are more often found in non-farm than farm activities.

5. Econometric Results

5.1. Cross-sectional model

We begin by estimating household earnings using the cross-sectional model. Yang and An's (2002) model is applied to the July 1986 baseline survey data from rural Pakistan. The first model includes education but not experience. As displayed in table 2, when experience is omitted (specification 2.1), two of the education variables, number of adults in the household with primary and middle school, contribute significantly to household earnings (along with labor and land). Including experience in the model (specification 2.2) causes the number of adults with primary education to drop from significance, while experience becomes significant. That change also lowers the effect of adults with middle schooling on farm household aggregate earnings. These results are parallel with Yang and An (2002) and some previous studies using cross-sectional data. Interestingly, when we include a regional district dummy (specification 2.3), all significant effects of education found in the previous model specifications disappear, leaving the land, labor and work experience as the only factors significantly affecting the household earnings in rural Pakistan. These findings suggest that there may be unobserved heterogeneity driving the relationship between education and household total earnings.

The determinants of farm earnings are similar to those of aggregate household earnings. As shown in table 3, when farm work experience is omitted from the OLS model (specification 3.1), the number of adults with primary and middle education are found to contribute significantly to farm household earnings. Upon including experience (specification 3.2), number of literate adults and those with middle schooling still matters for farm earnings. Unexpectedly, the number of literate adults appears to reduce farm earnings. Finally, upon including a district dummy variable (specification 3.3), all education variables become insignificant. Consistent with the results from aggregate earnings, this also implies the existence of an unobserved effect that could mislead by causing the educational factors to appear significant in shaping farm earnings.

Instrumenting the quasi-fixed input (labor) using the average age of adults in the household and highest education level attained by the head of household and estimating equation (10) for farm earnings using 2SLS (specification 3.4 in Table 3) does not change the result except in their magnitude: While the effect of land becomes greater those of labor and experience become less influential for farm earnings.

In contrast to the farm earnings results, those for non-farm earnings are very different from the aggregate household results. Table 4 shows that, using simple OLS (specifications 4.1, 4.2 and 4.3), non-farm labor is the only significant factor contributing to household non-farm earnings. Education and experience appear to be insignificant for non-farm earning. Furthermore, instrumenting non-farm labor with average age of adults in the household changes the results only slightly. IV estimation causes the effect of non-farm labor to non-farm earnings even stronger. More importantly, adults with reading ability (but no formal education) become significant for household non-farm earnings. This result may be linked to the results on farm earnings (specification 3.2), which indicate that adult literacy is negatively associated with farm earnings. This implies that adult literacy diverts family labor away from farm to non-farm sector. It also suggests that these fixed effects drive aggregate earnings more than education does.

These results are consistent with previous studies (like Adesina and Djato 1996) that find that low importance of schooling in shaping household earnings. Consistent with Yang and An (2002), our results also suggest that experience is a form of human capital that strongly affects farm earnings but not non-farm. In term of schooling, Yang and An (2002) find that it has a significant and positive effect on farm earning using 2SLS, but more robust positive effect across specification for non-farm. In our results, only when we do not control for district dummy we find that minimal education (adult literacy) matters for farm earnings (specification 3.2). In contrast, for non-farm earnings, after we control for district dummy and endogeneity, we find the effect of adult literacy is significant and positive (specification 4.4).

The results from the cross-sectional models thus imply at least two things: First, simple OLS clearly does not take into account the problems generated by the potential endogeneity of labor allocation across farm vs non-farm sectors. The application of IV estimation in 2SLS changes the coefficient magnitude and the significance of the variables of interest. Second, while the application of IV estimation has been useful to deal with endogeneity of labor allocation, it does not address the unobserved heterogeneity. Including a district dummy in the model seems to enable us to capture some such unobserved effects. In the next section we explore the use of panel data and fixed effect estimation to deal with unobserved effects.

5.2. Panel Data Model

In the panel data model (Tables 5-7), we apply pooled OLS and evaluate the results of including village fixed effects. Without experience and village fixed effect (Table 5, specification 5.1), the main contributors to aggregate earnings are labor, literate adults and those with middle schooling. Interestingly, household labor affects total earnings strongly: the elasticity of earning with respect to labor is greater than one, implying that an increase in a labor-day by 1% increases the earning by 1.078%. Including experience (specification 5.2) only results in experience becoming an additional contributor to total earnings. But including village fixed effects has a major impact. Both education variables become insignificant, leaving only labor and experience to affect aggregate earnings. The education variables are only significant when unobserved effects are not controlled.

This result implies that the village fixed effects drive aggregate earnings more than education does. Using data from the same rural Pakistan households but slightly different variables, with a different panel period, Fafchamps and Quisumbing (1999), who also control for village fixed effects apply nonlinear least squares estimation and find that men's education contributes to non-farm and aggregate earnings. But they also find that women's education does not affect earnings, farm productivity or labor allocation.

In the pooled OLS model of farm earnings (Table 6), education, particularly adult literacy, is significant (specification 6.1), when experience and village fixed-effect are excluded (Table 6). However when experience and village fixed-effects are included (specification 6.2 and 6.3), literacy again loses significance, leaving only land and labor as determinants of farm earnings. Experience is the only human capital factor affecting farm earnings. Its positive role is consistent across specifications. These results, as with aggregate earnings, suggest that there is unobserved heterogeneity driving the results.

Our finding is consistent with Fafchamps and Quisumbing (1999). Controlling for village fixed effects, they find that (whether of women or men) education has no effect on farm productivity. Like theirs, our results differ from Foster and Rosenzweig (1996). Using fixed-effect and controlling for farm capital/assets, the latter authors show that primary schooling matters for conditional household farm profits in a period of rapid technological change. They also find that the number of adult men and women with primary school is significant for farm productivity when using only a fixed effects model. Using IV estimation with fixed effects changes their results slightly: only male adult with primary schooling is significant.

Results of the non-farm earnings pooled OLS model appear in Table 7. Non-farm labor strongly affects non-farm earnings in all specifications. Among human capital factors, we find that all education variables seem to contribute to non-farm earning when experience is omitted (specification 7.1). Including experience makes the effect of adult primary education insignificant. Controlling for village fixed effects removes all human capital effects except for adult literacy and experience. As found in all model specifications here, experience remains highly significant, though with a relatively small marginal effect. This is consistent with findings from other recent previous panel data studies looking at the impact of education on non-farm earnings (e.g., Taylor and Yunez-Naude, 2000, and Fafchamps and Quisumbing, 1999).

The results from the pooled OLS model above are comparable with results from previous panel data studies. Our results support those from most previous studies, concluding that human capital –through literacy and work experience-- contributes significantly to non-farm earnings. Consistent with Fafchamps and Quisumbing (1999) and Yang (2004), we find that controlling for unobserved heterogeneity renders most education variables insignificant, particularly, in the farm sector.

That unobserved heterogeneity matter is not surprising. Many variables that are likely to affect farm productivity and profitability are frequently omitted from household data. When those unobserved effects such as soil fertility and weather are ignored, correlated included variables like education may appear to be significant (Griliches, 1957). However once these unobserved effects are proxied by village fixed effects, we find that the significance of education vanishes, implying the important role of those unobserved effects on farm income.

Even with village fixed effects included, the omitted variable problems may persist. Controlling for local weather and interacting it with education, Gurgand (2003) shows that education improves farmers' technical and allocative efficiency in Taiwan in the presence of adverse weather implying that education increases farmers' ability to adjust to an unstable environment. Likewise, Foster and Rosenzweig (1996) observe that the return to primary schooling increased in rural India during the rapid technological change of the Green Revolution, particularly in areas with the highest growth.

6. Summary and Conclusions

In this paper, we apply a two-sector framework to examine the effect of human capital factors on rural household earnings. We model the determinants of farm, non-farm and aggregate earnings using cross-sectional and panel data from rural Pakistan. Our results show that education has a very small effect on farm earnings. On the other hand, adult literacy does contribute meaningfully to non-farm earnings. Work experience appears to be the principal channel by which human capital affects agricultural performance. Our results support other recent findings that education has a negligible effect on farm earnings in developing countries when we include non-farm activities as occupational choice available to rural households and control for unobserved heterogeneity.

These results imply that typical cross-sectional data analysis without village fixed effect may cause the effects of education on rural household earnings to be significantly overstated. Both the panel data models accounting for village-level fixed effects and cross-sectional model with district dummy variables find only one instance of education raising earnings – the effect of literacy on nonfarm income in the fixed effect pooled OLS model. These findings also highlight the importance of properly specifying primary sampling units in the analysis of survey data (Deaton, 1997).

Table 1. Descriptive Statistics of Aggregate and Sectoral Farm Production

Variable	Aggregate	Farm	Non-Farm
Gross Earning (rupees)	4,950(8200)	1,600(4,800)	3.350(7,000)
Labor (days)	123(117)	49(68)	75(105)
Land owned (acre)	8.5(19.2)	8.5(19.2)	0.0(0.0)
# of literate adults	0.5(1.9)	0.2(1.3)	0.3(1.3)
# of adults with primary school	1.4(2.7)	0.7(1.9)	0.7(1.9)
# of adults with middle school	0.7(2.0)	0.3(1.3)	0.4(1.4)
Work experience (sum of years)	141.1(72.3)	74.7(78.1)	66.3(77.0)

Note: Standard errors are in parentheses.

Table 2. OLS estimates of household aggregate earning,

Cross-sectional survey of rural Pakistan, 1986.

Explanatory Variables	**2.1**	**2.2**	**2.3**
Constant	3.71 (7.72)**	3.51 (7.21)**	3.28 (6.02)**
Land owned (log)	0.195 (2.62)**	0.154 (2.03)**	0.211(2.80)**
Total labor (log)	0.695 (7.27)**	0.657 (6.80)**	0.801 (8.12)**
# of literate adults	-0.002 (-0.05)	-0.018 (-0.35)	0.004 (0.09)
# of adults with primary school	0.074 (2.04)**	0.051 (1.35)	0.011 (0.29)
# of adults with middle school	0.145 (3.0)**	0.120 (2.42)**	0.065 (1.32)
Work experience	-	0.003 (2.34)**	0.003 (1.94)*
District dummies	No	No	Yes
Adj. R^2/F-stat	0.07/15.17**	0.08/13.62**	0.12/15.02**
Sample size	889	889	889

Note: Dependent variable is natural log of total earning; t-stats are in parentheses.
* Significant at the 10% level
** Significant at the 5 % level

Table 3. OLS and 2SLS estimates of farm earnings,

Cross-sectional data from rural Pakistan, 1986

Explanatory Variables	**OLS**			**2SLS**
	3.1	**3.2**	**3.3**	**3.4**
Constant	2.516 (14.54)**	2.335 (13.24)**	1.352 (4.93)**	1.187 (2.43)**
Land owned (log)	0.499 (5.70)**	0.391 (4.34)**	0.282 (3.22)**	0.720 (4.04)**
Farm labor (log)	0.612 (15.89)**	0.538 (12.87)**	0.652 (15.60)**	0.276 (3.05)**
# of literate adults	-0.106 (-1.19)	-0.156 (-1.77)*	-0.111 (-1.31)	-0.113 (-1.32)
# of adults with primary school	0.146 (2.46)**	0.064 (1.03)	0.030 (0.50)	0.029 (0.48)
# of adults with middle school	0.253 (3.38)**	0.154 (1.98)**	0.090 (1.20)	0.096 (1.24)
Work experience	-	0.008 (4.31)**	0.008 (4.62)**	0.007 (2.14)**
District dummies	No	No	Yes	Yes
Adj. R^2/F-stat	0.31/81.03**	0.33/71.96**	0.38/62.29**	0.38/36085**
Sample size	889	889	889	889

Note:

- Dependent variable is natural log of total earning; t-stats are in parentheses.
- The instruments used for farm labor are set of average age of adults within the household and highest education of head household.

* Significant at the 10% level, ** Significant at the 5 % level.

Table 4. OLS and 2SLS estimates of non-farm earnings,

Cross-sectional data from rural Pakistan, 1986

Explanatory Variables	**OLS**			**2SLS**
	4.1	**4.2**	**4.3**	**4.4**
Constant	3.899 (34.42)**	3.810 (22.89)**	4.068 (15.51)**	4.427 (9.64)**
Non-farm labor (log)	0.591 (24.63)**	0.572 (15.82)**	0.573 (15.87)**	0.720 (4.55)**
# of literate adults	0.128 (1.60)	0.115 (1.40)	0.129 (1.56)	0.145 (1.70)*
# of adults with primary school	0.036 (0.56)	0.021 (0.30)	0.010 (0.14)	0.021 (0.30)
# of adults with middle school	0.124 (1.40)	0.110 (1.20)	0.089 (0.98)	0.098 (1.06)
Work experience	-	0.002 (0.73)	0.001 (0.35)	-0.007 (-0.80)
District dummies	No	No	Yes	Yes
Adj. R^2/F-stat	0.47/198.32**	0.47/158.68**	0.48/100.89**	0.46/70.71**
Sample size	889	889	889	889

Note:

- Dependent variable is natural log of total earning; t-stats are in parentheses.
- The instrumental variable is average age of adults in the household.

* Significant at the 10% level, ** Significant at the 5 % level.

Table 5. Pooled OLS Estimates of Household Aggregate Earnings, Panel Data from Rural Pakistan, 1986-1987.

Explanatory Variables	5.1	5.2	5.3
Constant	1.244 (4.35)**	0.965 (3.30)**	0.517 (1.63)
Land owned (log)	-0.008 (-0.48)	-0.024 (-1.33)	-0.012 (-0.61)
Total labor (log)	1.078 (17.4)**	1.030 (16.39)**	1.174 (17.44)**
# of literate adults	0.049 (2.42)**	0.039 (1.95)*	0.028 (1.28)
# of adults with primary school	0.028 (1.46)	0.008 (0.42)	-0.006 (-0.29)
# of adults with middle school	0.083 (3.08)**	0.067 (2.46)**	0.005 (0.19)
Work experience	-	0.004 (4.23)**	0.003 (3.61)**
Village fixed-effect	No	No	Yes
Adj. R^2/F-stat	0.10/68.83**	0.10/60.63**	0.17/64.70**
Sample size	3209	3209	3209

Note: Dependent variable is natural log of total earning; t-stats are in parentheses; standard errors are robust.
* Significant at the 10% level;
** Significant at the 5 % level

Table 6. Pooled OLS Estimates of Farm Household Earnings,

Panel data from Rural Pakistan, 1986-1987.

Explanatory Variables	**6.1**	**6.2**	**6.3**
Constant	2.031 (26.41)**	1.807 (20.17)**	1.780 (21.15)**
Land owned (log)	0.060 (3.46)**	0.042 (2.38)**	0.041 (2.06)**
Farm labor (log)	0.420 (22.89)**	0.373 (18.40)**	0.402 (21.69)**
# of literate adults	0.051 (1.72)*	0.031 (1.05)	0.010 (0.25)
# of adults with primary school	0.019 (072)	-0.029 (-1.05)	0.005 (0.14)
# of adults with middle school	0.032 (0.81)	-0.014 (-0.35)	0.031 (0.64)
Work experience	-	0.005 (4.83)**	0.004 (3.43)**
Village fixed-effect	No	No	Yes
Adj. R^2/F-stat	0.17/134.83**	0.18/117.03**	0.21/177.4**
Sample size	3209	3209	3209

Note: Dependent variable is natural log of total earning; t-stats are in parentheses; in the regression with fixed effects, standard errors are robust.
* Significant at the 10% level
** Significant at the 5 % level

Table 7. Pooled OLS Estimates of Non-farm Household Earnings, Panel data from Rural Pakistan, 1986-1987.

Explanatory Variables	7.1	7.2	7.3
Constant	3.874 (62.89)**	3.668 (44.26)**	3.743 (42.72)**
Non-farm labor (log)	0.611 (46.30)**	0.565 (31.37)**	0.545 (29.21)**
# of literate adults	0.091 (3.52)**	0.070 (2.66)**	0.066 (3.09)**
# of adults with primary school	0.046 (1.81)*	0.018 (0.69)	-0.007 (-0.27)
# of adults with middle school	0.100 (3.02)**	0.074 (2.20)**	0.011 (0.31)
Work experience	-	0.004 (3.71)**	0.004 (3.64)**
Village fixed-effect	No	No	Yes
Adj. R^2/F-stat	0.50/801.96**	0.5/646.87**	0.54/477.44**
Sample size	3209	3209	3209

Note: Dependent variable is natural log of total earning; t-stats are in parentheses; in the regression with fixed effects, standard errors are robust.
* Significant at the 10% level
** Significant at the 5 % level.

References

Adesina, Akinwumi A., and Kouakou K. Djato, 1996, Farm Size, Relative Efficiency and Agrarian Policy in Cote d'Ivoire: Profit Function Analysis of Rice Farms, *Agricultural Economics*, Vol. 14, p. 93-102.

Deaton, A., 1997. *The Analysis of Household Surveys: Microeconometric Analysis for Development Policy,* Johns Hopkins Press.

Fafchamps, Marcel, and Agnes Quisumbing, 1999, Human Capital Productivity and Labor Allocation in Rural Pakistan, *Journal of Human Resources*, Vol. 34/2, p.369-406.

Foster, Andrew and Mark Rosenzweig, 1995, Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture, *Journal of Political Economy,* Vol 103/6, p. 759-90.

______________________________, 1996, Technical Change and Human Capital Returns and Investment: Evidence from Green Revolution, *American Economic Review*, Vol 86/4, p. 931-953.

Griliches, Zvi, 1957, Specification Bias in Estimates of Production Functions, *Journal of Farm Economics*, Vol. 39, p. 8-20.

Gurgand, Marc, 2003, Farmer Education and the Weather: Evidence from Taiwan (1976-1992), *Journal of Development Economics*, Vol. 71, p. 51-70.

Huffman, Wallace E**,** 1980, Farm and Off-farm Work Decisions: The Role of Human Capital, Review Economics and Statistics, Vol. 62, p. 14-23.

Jamison, Dean T., and Lawrence I. Lau, 1982, *Farmer Education and Farm Efficiency*, The John Hopkins University Press (for World Bank), Baltimore.

Lockheed, M., D. Jamison, and L. Lau, 1980, Farmer Education and Farm Efficiency: A Survey, *Economic Development and Cultural Change*, Vol 29/1.

Nag-Chowdhury, Dipa, 1991, *Pakistan Rural Household Survey 1986-198: Documentation of Primary Files*, IFPRI, Washington DC.

Phillips, Joseph M., 1987, A Comment on Farmer Education and Farm Efficiency: A Survey. *Economic Development and Cultural Change*, Vol 35/3. p. 637-44.

Rosenzweig, Mark R., 1980, Neo-classical Theory and the Optimizing Peasant, *Quarterly Journal of Economics*, Vol. 94, p. 31-56.

Schultz, T. Paul, 1988, Education Investment and Returns, in H. Chenery and T.N. Srinivasan, *Handbook of Development Economics Vol. 1*, Elseveir, Amsterdam.

Strauss, J and D. Thomas, 1995, "Human Resources: Empirical Modeling of Household and Family Decisions", in Behrman, J. and T.N. Srinivasan (eds), 1995, Handbook of Development Economics, Volume IIIA, Amsterdam, Elsevier, pp 1883-2023.

Taylor, J. Edward and Antonio Yunez-Naude, 2000, The Returns from Schooling in Diversified Rural Economy, *American Journal of Agricultural Economics*, Vol. 82, p. 287-297.

Yang, Dennis T., 2004, Education and Allocative Efficiency: Household Income and Growth during Rural Reforms in China, *Journal of Development Economics*, Vol. 74, p. 137-162.

Yang, Dennis T., and Mark Yuying An, 2002, Human Capital, Entrepreneurship, and Farm Household Earning, *Journal of Development Economics*, Vol. 68, p. 65-88

Wooldridge, Jeffrey, 2002, *Econometric Analysis of Cross Section and Panel Data*, The MIT Press, Cambridge-MA.

Welch, F., 1970, Education in Production, *Journal of Political Economy*, Vol. 38, p. 35-59.