# The Impact of Human Capital on Farm Operator Household Income

**Hisham El-Osta**

Data from the 2006 Agricultural Resource Management Survey and multivariate regression procedures are used to examine the role of human capital in impacting the incomes of farm households. The paper uses an "adjusted" concept of income where government payments are subtracted from total household income thus allowing for the utilization of government payments as a potential control variable in the regression models. Findings indicate a significant and positive role for higher education except for farm households at the very lower and upper ends of the income distribution.

***Key Words:*** farm households, ARMS data, quantile regression, government payments, human capital, off-farm wages and salaries

Economists have long recognized that a major source of U.S. productivity growth and economic mobility in the first part of the past century was the growth in the quality of the workforce, which was ascribed in turn to the rise in educational attainment among workers (Becker 1995, Carneiro and Heckman 2003). The recent decline in the growth in the quality of the workforce attributed to a large extent to the deceleration in the growth in the educational attainment among cohorts of American workers born since 1950 has serious implications for growth in aggregate real wages (Heckman 2005). The slowing of real wage growth, in turn, could have an adverse impact on the economic well-being of households.

The objective of this paper is to use data from the 2006 Agricultural Resource Management Survey (ARMS) to assess the role of human capital, as proxied here by farmer's education, in impacting the incomes of farm operator households.[1] Providing practitioners involved in formulating rural development and farm policies with a better understanding of the potential favorable impact of education on the incomes of farm families is crucial considering the continued rise in the adult educational attainment in nonmetro areas. For example, a USDA published report (Kusmin 2007) shows about 17 percent of the rural population aged 25 and older in these areas with at least a 4-year college degree in 2005, up by a 1.5 percentage point from 2000. For farm households, and based on data from the 2000 and 2005 ARMS, the improvement in the educational attainment of farm operators in the same age group is more evident than for the rural population as indicated by an increase over the same time period by 5.8 percentage points (from 19.3 percent to 25.1 percent) in the number of operators with at least a 4-year college degree. The importance of higher educational attainment to income goes even well beyond the current generation of farmers, as recent work on social capital—a theory of social interaction first introduced by Coleman (1988 and 1990) and later examined and commented on by others (e.g., Astone et al. 1999, Manski 2000)—has alluded to the benefits of parents' education, which provides the potential for a cognitive environment for the child, on the prospect of having educated children.[2] Hill and Duncan (1987) and

Hisham El-Osta is an agricultural economist at the Economic Research Service, U.S. Department of Agriculture, in Washington, D.C.

The author gratefully acknowledges the helpful comments of two anonymous reviewers and the editors of the *Agricultural and Resource Economics Review*. The views expressed are the author's and do not necessarily represent the policies or views of the U.S. Department of Agriculture.

[1] The phrase "human capital" as it relates to a person's own educational attainment was coined by Theodore Schultz (see Schultz 1960). Some researchers extend the phrase to relate to a person's job experience in addition to a person's own education (e.g., Mincer and Polacheck 1974).

[2] An interesting line of research on the relationship between social capital and household income distributions in the United States was

*Agricultural and Resource Economics Review* 40/1 (April 2011) 95–115

Haveman, Wolfe, and Spaulding (1991) found a strong effect of parents' education on children's educational success, thus pointing to social capital in the household as being a major determinant of the development of human capital for the children of farmers.

## Literature Review

The most cohesive literature on the relationship between human capital development and the potential for higher earnings dates back to the early work of Friedman and Kuznets (1945) and a few decades later to, among others, Mincer (1962 and 1974), Ben-Porath (1967), Ritzen and Winkler (1977), and Becker (1962, 1966, 1975, and 1994). The central thesis of this body of research which underlies what is commonly known as the "human capital" model is that investment in skill through formal education and/or through experience acquired through on-the-job training is rewarded in the labor market, because of enhanced productivity of workers, through higher earnings. Freeman (1979) and Dooley and Gottschalk (1984), among others, document the importance of education to the earnings of households. A study by Lazear (1980), which has noted based on earlier studies that attained levels of schooling tend to be positively associated with parents' income, developed a model that allowed for the estimation of costs and returns to education across individuals in various income groups. Findings of this research showed that the poor face implicit borrowing costs to finance their education that are greater than those for the rich.

For the farming population, Schultz (1972 and 1975) and Huffman (1985) emphasized the importance of the ability to adapt to exogenous market forces and to structural changes as a relevant concept of human capital of farm operators. In the same vein, Schultz (1964 and 1975) and Nelson and Phelps (1966), among others, hypothesized that education may enhance farmers' innovative ability, thereby facilitating the diffusion of new technology, a premise that was later demonstrated by the pioneering work by Huffman (1972, 1974, 1977, 1980, and 1981).[3] Griliches (1964), Gisser (1965), Welch (1970), and Khaldi (1975) stressed the need to account for education as an important factor when modeling production agriculture.

Many researchers have documented the direct linkage between low educational levels and low earnings (e.g., Blank 1997, Deavers and Hoppe 1992, Parker 2005, Schiller 2004), which stems from a reduction in the incentive to enter the labor market and from the increased likelihood of limited opportunities for higher earnings and stable employment. A study by Goetz (1993) provided specific ideas on how agricultural economists can aid policymakers in figuring out where to invest marginal public dollars in order to most efficiently move rural people out of poverty. Despite the preponderance of studies that covered the direct relationship between education and innovation in U.S. agriculture and/or earnings in rural and non-rural areas, there seems to be paucity in the literature of the role that education plays in impacting the incomes of farm households [see Ahearn, Perry, and El-Osta (1993), Mishra et al. (2002), El-Osta, Mishra, and Morehart (2007), and Chang, Lambert, and Mishra (2008) for a peripheral exploration of the topic], a gap which this paper tries to mitigate. The main hypothesis that underlies this study is thus of the direct and positive relationship that exists between increases in the educational attainment of farm operators and the incomes of their households. A high formal educational level contributes to a farmer's ability to adapt to the changing agricultural marketplace and to adopt new farming techniques with their attending positive impact on farmer's income; this is in addition to the expectation that higher education is financially rewarding for the majority of farmers who work off the farm (Ahearn and Gibbs 2009).

## Human Capital Model

Following closely and adapting the human capital model presented by Wilson (2001), the economic decisions of the $i$th individual (referred to henceforth as the farm operator) are characterized by the following objective:

explored by Robison and Siles (1999). The study's findings, based on data from the 1980 and 1990 U.S. Census, indicated a strong association between changes in social capital and changes in income distribution.

[3] Innovative ability as described by Wozniak (1984) is the proficiency to search for, collect, interpret, and evaluate efficiently any needed information in making pioneering decisions.

(1) $$\text{Max } U_i = U(E_i, B_c \ln C_i, \varepsilon_{e_i}),$$

where $U$ is a separable utility function, $C$ is lifetime discounted stream of consumption, $E$ is utility received from schooling (referred to here as education consumption good), $B_c$ is the weight of consumption in utility, $e$ is amount of schooling, and $\varepsilon_e$ is an education-conditioned random utility term. The consumption good $E_i$, which is the net effect of the utility benefits (e.g., pleasure received by $i$th farm operator from social contacts and from learning) and costs (e.g., perceived negative externalities of schooling such as classroom restrictions and time spent on homework), is depicted in the following production function:

(2) $$E_i = g(e_i, x_i),$$

where $x_i$ is a vector of inputs (e.g., family background, neighborhood and school characteristics, etc.) that affect the net utility of being schooled, and $g(.)$ is the technology that transforms $x_i$ into $E_i$.

Maximization of equation (1) by the $i$th farm operator is subject to the following budgetary constraints:

(3) $$Y_i = \alpha(Q_i)\, e_i + \xi_i,$$

(4) $$C_i \le Y_i,$$

where $Y_i$ is lifetime discounted income stream—which, according to equation (4), will always equate with or exceed the lifetime discounted stream of consumption—$\alpha$ is the returns to schooling, $Q_i$ is a vector of variables that affect the returns to schooling (e.g., family characteristics such as parental education, family structure during childhood, family income, neighborhood and school factors, etc.), and $\xi_i$ is the random component of income. As defined in equation (3), $\alpha(Q_i)$ transforms the schooling of the $i$th farm operator into income. Accordingly, if the $i$th operator chooses to have the same amount of schooling as the $j$th operator when both of these operators are also similar in terms of the characteristics that affect income (i.e., $Q_i = Q_j$), then operator $i$ will expect his or her income to be the same as operator $j$ as described in the following (see Wilson 2001); otherwise, the incomes among these two operators are expected to vary:

(5) $$E[Y_i \mid Q_i, e_i = e_j] = \alpha(Q_j)\, e_j \qquad \text{for } Q_i = Q_j.$$

Substituting equations (2)–(5) into equation (1) yields the following Lagrangian, which describes the maximization of expected utility for the $i$th farm operator:

(6) $$g(e_i, x_i) + E[\ln Y_i]B_c - \lambda[\alpha(Q_i)\, e_i - Y_i].$$

The optimization problem described in equation (6), when solved, yields the following:

(7) $$\alpha(Q_j) = \frac{-U_b \dfrac{\partial g(e_i, x_i)}{\partial e_i}}{U_c}.$$

As described by Wilson (2001), the left-hand side of equation (7) is the marginal rate of transformation of educational attainment to income. For the $i$th farm operator, a change in the level of schooling will be associated with a $\alpha(Q_i)$ change in expected income. The right-hand side describes the relative utility of schooling and marginal utility of consumption for the $i$th operator, or when stated differently, is the marginal rate of substitution of consumption of good $E$ and the marginal rate of substitution of consumption. Based on equation (7), the $i$th operator will continue to seek higher levels of schooling until the marginal utility benefits equal the marginal utility costs.[4]

[4] The human capital model by Wilson (2001) allows for the examination of the role of "social capital"—as captured, for example, by the role of family members (e.g., spouses, parents, grandparents, etc.), neighborhood characteristics, and school variables—in impacting the level of schooling attained by the farm operator. This is captured by examining the following:

$$\frac{\partial e_i}{\partial \alpha(Q_i)} > 0 \Leftrightarrow \frac{\partial e_i}{\partial\left(-[U_E\, \partial g(e_i, x_i)/\partial e_i]\right)} > 0,$$

where

$$U_E = \frac{U_g}{U_c}.$$

The interpretation of this is that variables in $Q_i$ that increase the returns to education as represented by $\alpha(Q_i)$ will also increase educational attainment, a result known in the literature as the income effect of the variable. In the same vein, variables in $x_i$ that increase the non-pecuniary benefits of education will also increase the level of schooling.

## Data and Methods

### *Data Sources*

The primary data source is the 2006 ARMS. The ARMS, which has a complex stratified, multiframe design, is a national survey conducted annually by the National Agricultural Statistics Service (NASS) and the Economic Research Service.[5] Each observation in the ARMS represents a number of similar farms (e.g., based on land use, size of farm, etc.), the particular number of which is the survey weight (or the inverse of the probability of the surveyed farm being selected for surveying). The size of the sample after deleting observations with incomplete information on some of the variables used in the analysis was 6,155, which when properly expanded using survey weights yielded a population of farm operator households totaling 1,951,253.

### *Empirical Estimation*

Building upon the income-generation process described above in the human capital model for the farm operator, the econometric representation of such a process for the $i$th ($i$ = 1, …, $n$) farm household is depicted by the following linear regression model:

$$(8) \qquad Y_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + \varepsilon_i ,$$

where $Y$ denotes the total income earned by the operator and by all other members of the household from all farm (except for income from farm program payments) and off-farm sources, $X_j$ is the $j$th explanatory variable, and $\varepsilon_i$ is an error term. The income-generation process that underlies the analysis predicts a positive impact of education on the incomes of farm households. To the extent that government payments are excluded from $Y$, this variable is referred to henceforth as "adjusted" farm household income.[6]

Conventional methods of inference and prediction based on the linear regression model hinge on the requirement that the basic assumptions of the normality of distributions and the constancy of error variances are being met (see Box and Cox 1964, Kmenta 1986). In terms of the assumption of a normally distributed $\varepsilon_i$, this is violated since the distribution of $Y$ in the selected sample is positively skewed, as evidenced by the wide gap that exists between the unweighted mean and median estimates ($120,732 and $56,711, respectively) and by the excessively large measured skewness and kurtosis coefficients (20.61 and 815.25, respectively).[7] A consequence of this violation is that the resulting estimates of the model's parameters are inconsistent (Burbidge, Magee, and Robb 1988). A frequently used remedy for this violation is to utilize a logarithmic transformation on the dependent variable because of its ability to generate something closer to symmetry (see Deaton 1989, Altonji and Doraszelski 2001). This approach, however, is not practical here since 1,027 of the 6,155 observations (or 16.7 percent) in the selected sample have non-positive values of $Y$. Instead, the paper ameliorates the effects of nonnormal distribution of $Y$ in the presence of negative observations by implementing an inverse hyperbolic sine (IHS) transformation approach, as was delineated by Burbidge, Magee, and Robb (1988), and as was used by, among others, Carroll, Dynan, and Krane (2003). Specifically, the IHS transformation of observations containing negative, zero, and positive values is described by the following:

$$(9) \qquad \begin{aligned} g\,(Y_i,\theta) = g_i &= \frac{\log\left[\theta\ Y_i\ + (\theta^2 Y_i^2 + 1)^{1/2}\right]}{\theta} \qquad i=1,\dots,n, \\ &= \frac{\sinh^{-1}(\theta\ Y_i)}{\theta} \\ &= \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + \upsilon_i , \end{aligned}$$

[5] For more detail, see http://www.ers.usda.gov/Briefing/ARMS/.

[6] Gundersen and Offutt (2005) utilized a closely related concept of income. Specifically, three selected levels of government support payments (e.g., low, midway, and high) reflecting a 2-year range of average payments received by low-income households were subtracted out from total farm household income, thus allowing for the derivation of three varied vectors of adjusted incomes. This was done by the authors in their attempt to examine the eligibility rates for food stamps for farm households with and without the farm safety net payments.

[7] The normality assumption of the distribution of $Y$, if found valid, would have implied that the mean and median estimates are closer to each other and that the measured skewness and kurtosis coefficients are very close to zero. The null hypothesis that $Y$ is normally distributed was also rejected based on the Anderson-Darling (AD) test of normality (i.e., computed AD statistic = 1,156.77; $p$-value < 0.005).

where equation (9) is defined over all the possible positive values of the dampening parameter $\theta$, $\beta_j$ is a parameter to be estimated, and $\upsilon_i$ is an error term.[8] While $\beta_j$ from equation (9) does not have the same direct interpretation as in the case of least squares regression, it nevertheless can be interpreted as the marginal effect of a change in a particular $X_j$ on thousands of dollars in adjusted farm household income by applying the transformation $1/2(e^{\theta g_i} + e^{-\theta g_i})\hat{\beta}_j$, or $\phi\hat{\beta}_j$, and then averaging the resultants over all observations in the sample [for more detail, see Pence (2006)].

As for the requirement in the linear regression model of constancy of error variances [i.e.,

$$V(\upsilon_i \left| X_{ij} \right.) = \sigma_\upsilon^2 \text{ ],}$$

a violation of this assumption may be associated with the presence of outliers in the data. A potential drawback of linear regression models in the presence of non-constant error variance is that the estimated standard errors of parameters (and therefore *p*-values) could be incorrect, thereby leading to wrong inferences. Figure 1 provides a graphical illustration of these two concerns. For example, the upper chart shows a scatter plot of all the *leverage* (i.e., indicator of the amount of influence an observation has on the regression line) points, or $h_{ii}$'s, in the regression model described in equation (8) against their corresponding squared residuals. To the extent that a particular $h_{ii}$ measures the distance between the values of each of the explanatory variables (henceforth referred to as $X$ values) for the $i$th observation and the corresponding means of $X$ values for all $n$ observations, it provides an indication as to whether or not the $X$ values for the $i$th observations are outlying (Neter 1985).[9] Nearly 5 percent out of the 6,155 observations used in the regression model are shown to be influential based on leverage values that are greater than twice the average value for all $h_{ii}$'s as reflected in the dashed horizontal line in the upper chart of Figure 1. Despite this, nearly all of these outlying observations appear to fall on the plane corresponding to where the majority of the data is located. Based on Rousseeuw and van Zomeren (1990), these points are nevertheless considered "good" leverage points because of their ability to improve the precision of the regression coefficients. In contrast, observation 1 is a "bad" leverage point since in addition to having an above-average leverage value it also lies far from the plane corresponding to the majority of the data. Careful investigation of the reported characteristics (e.g., acres, value and type of production, etc.) of this outlying observation revealed, despite its potential influence on the regression line, that this observation was a valid data-point, and as such, it could not be excluded from the dataset.[10] The lower chart of Figure 1 demonstrates the presence of heteroscedasticity, where some of the values of $Y$ in equation (8) exhibit more variability at some levels of $X$ compared to others.[11] Specifically, while the residuals above and below the line in this chart depicting a zero-valued residual across all the fitted values of $Y$ were expected to be randomly distributed with no apparent pattern based on the homoscedasticity assumption in the classical linear regression model, the distribution of these residuals instead exhibits a "funnel"-shaped pattern,

---

[8] The paper estimates the dampening parameter $\theta$ based on an estimation strategy that involves the maximization of a concentrated likelihood function [for more detail, see Burbidge, Magee, and Robb (1988)]. The author is grateful to Charlie Hallahan at the Economic Research Service who provided the SAS/IML computer code to estimate $\theta$ and its corresponding standard error.

[9] When the regression model in equation (8) is presented in matrix notation, the vector of predicted values for $Y_i$ is $\hat{Y} = X(X'X)^{-1}X'Y = HY$. As noted in Neter (1985, pp. 402–403), $h_{ii}$, which is the $i$th diagonal element in the hat matrix $H$, has the following properties: $0 \le h_{ii} \le 1$ and

$$\sum_{i=1}^{n} h_{ii} = k,$$

where $k$ is the number of explanatory variables including the intercept term. As a rule of thumb, a leverage value $h_{ii}$ is considered large, thus indicating the presence of an outlying observation with regard to the $X$ values if $h_{ii} > 2\bar{h}$, where

$$\bar{h} = \frac{\sum_{i=1}^{n} h_{ii}}{n} = \frac{k}{n}$$

(see Neter 1985, p. 403).

[10] As Neter (1985, p. 115) notes, the presence of an outlier may be the result of an interaction with another explanatory variable, one which is omitted from the regression model. A Ramsey RESET test (see Ramsey 1969), using powers of fitted values of $Y$ to test the null hypothesis that the model has no omitted variables, was rejected at the 1 percent level of significance based on $F(3, 6{,}131) = 15.01$.

[11] The null hypothesis that the error variances are all equal versus the alternative that the error variances are a multiplicative function of one or more variables was tested using the Breusch-Pagan test (see Breusch and Pagan 1979). The resulting large $\chi^2_{df=1}$ value of 10,744.43 (*p*-value = 0.0000) indicates that heteroscedasticity is present in the regression model, just as was detected based on the graphical representation of the distribution of the error terms.

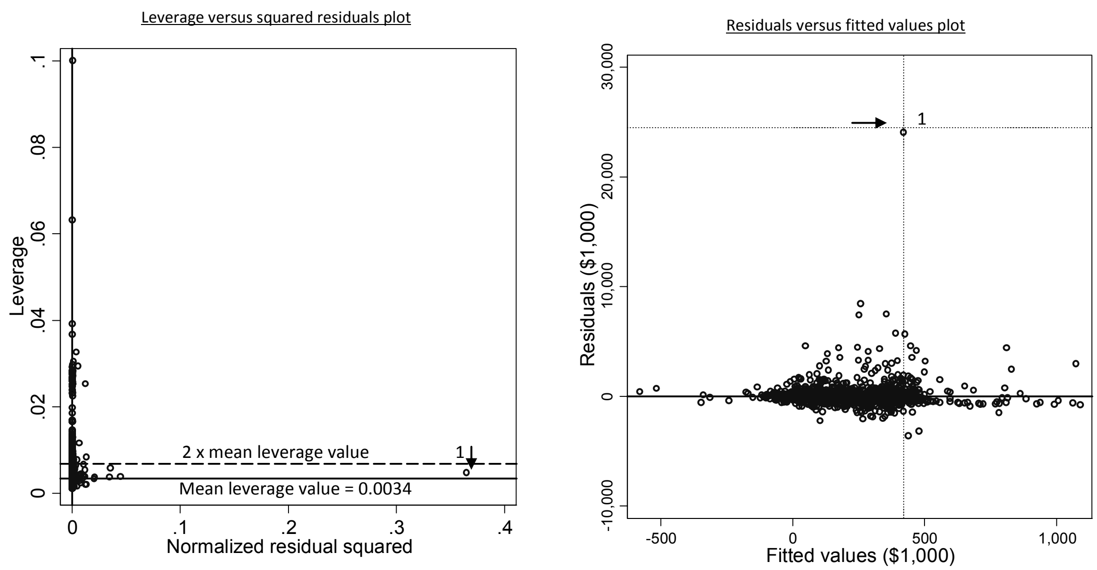


**Figure 1. Scatter Plot Evidence of Influential Observations and of Heteroscedasticity (2006)**

Source: USDA (2006).

which also indicates an increase in the error variance as the value of $Y$ increases. An example of the ill-effect of non-constant variance in the distribution of the error terms is observation 1 where the model in equation (8), if used in its current form, would have predicted an adjusted farm household income of $420,000 when the true income level is $24.5 million.

As evident from the above discussion, the use of the linear regression model in the presence of outliers and heteroscedastic error terms is problematic. While the use of IHS transformation is one way to mitigate the problems associated with the non-normality of the disturbance terms due to outliers, the linear quantile-regression model is yet another technique that allows for the mitigation of this problem (see Hao and Naiman 2007). This regression model, as originally proposed by Koenker and Bassett (1978), differs from least squares regression in that it minimizes the absolute residuals' sum by giving different weights to the quantiles being investigated, rather than just the sum of squared residuals. Specifically, as delineated in Buchinsky (1994 and 1995) and in Chen, Lin, and Chang (2009), the linear quantile regression procedure specifies the $\tau$th conditional quantile relationship, denoted by *Quant*(.), between $g$, the variable depicted by the IHS-transformed $Y$, and the set of explanatory variable $X$ as

$$(10) \qquad Quant_{\tau}(g_i \mid X_i) = X_i^{'}\beta_{\tau},$$

where

$$\tau = \int_{-\infty}^{X_i^{'}\beta_{\tau}} f_g(s \mid X)\, ds$$

and where $f_g$ (.) is the probability density function of $g$. The quantile regression model for the sample is thus

$$(11) \qquad g_i = X_i^{'}\beta_{\tau} + u_{i,\tau}, \quad i = 1, \ldots, n.$$

Letting $\rho_{\tau}$ denote a weighting function used to center the data subject to the $\tau$th quantile, the estimator $\hat{\beta}_{\tau}$ of the $\tau$th sample quantile ($0 < \tau < 1$) of $g$ is obtained by means of linear programming by solving the following:

$$(12) \qquad \min_{\beta} \frac{1}{n} \sum_{i=1}^{n} \rho_{\tau}\left(g_i - X_i^{'}\beta\right)$$

$$= \min_{\beta} \frac{1}{n} \left[ \begin{array}{l} \sum\limits_{i \in \{i: g_i \geq X_i^{'}\beta\}}^{n} \tau \left| g_i - X_i^{'}\beta \right| \\ + \sum\limits_{i \in \{i: g_i < X_i^{'}\beta\}}^{n} (1-\tau) \left| g_i - X_i^{'}\beta \right| \end{array} \right].$$

As τth increases from 0 to 1, equation (12) allows for the conditional distribution of $Y$ conditional on $X$ to be obtained in its entirety (Buchinsky 1998). In this paper, the estimates $\hat{\beta}_\tau$ were obtained for $\tau$ = 0.05, 0.25, 0.50 (i.e., the median), 0.75, and 0.95. The use of IHS transformation in a quantile regression framework has two specific advantages. First, it helps with the occasional lack of convergence, and second, it ameliorates the problems with heteroscedasticity (see Pence 2006). Another approach used in the paper to deal with heteroscedasticity was to implement bootstrapping (see Efron and Tibshirani 1994, Adkins and Hill 2004) as a means of obtaining an estimator for the covariance matrix of the vector $\beta$, which was done under both the linear least squares and the quantile regression models.[12]

## Results

Table 1 presents definitions and summary statistics of the variables used in the estimation of the adjusted farm household income model, with a graphical delineation of the variables used to control for farm location, shown in Figure 2. Operators of farm households are, on average, relatively old with modest levels of education, and are more likely to be white men. The households of these operators rely heavily on income from off-farm sources, as evidenced by the large income they earned from off-farm wages and salaries in 2005. The farms of these operators are fairly specialized, as indicated by the entropy measure.[13] These farms are also more likely to be located in either a medium- or a medium-large density county than in either a low- or a large-population density county, and in terms of regional location, they are more likely to be located in the regions of the South or the Midwest than in the regions of the West or the Northeast. In terms of government payments, this income source, which was subtracted out from the dependent variable, accounts for only 6.6 percent of these households' average total household income of $75,307.

Of the variables listed in Table 1, age of the operator, an operator's gender as being male and race as being white and family structure defined as being married with children, a potential for having higher off-farm earnings and a bigger size of farm, precipitation and soil productivity, and a farm location other than in the Northeast or in a large population density area are all factors that are expected to be positively associated with household income (see Hoppe and Bluestone 1987, Marchant 1997, Gardner 2000, Ahearn and Gibbs 2009, Ahearn and Gibbs 2010, Mishra et al. 2002, El-Osta, Mishra, and Morehart 2007, Whitener and Parker 2007, and De Frahan et al. 2008). Evidentiary evidence from published USDA reports suggests that farm household income increases with age of the operator, but at a decreasing rate (see Ahearn and Gibbs 2009). The impact of the remaining variables on the income of the farm household is harder to predict *a priori*. Among the potential impacts of these variables, one that is most relevant from a farm policy perspective is the direction of association between government payments and farm household income. While increases in government payments can increase total farm household income if there are no transfer efficiency losses or slippage, payments can also decrease overall income by inducing operators to consume more leisure and/or change the factor mix and/or the commodity composition to less profitable enterprises (see Dewbre and Mishra 2002). Yet another likely reason for the decrease in total income is that increases in payments may induce farmers—particularly those with decreasing marginal utility of income—to allocate

[12] When data with a complex survey design is used in full rather than as a subset, as in this paper, the jackknife (JK) variance estimation method provides a proper approach to measure the variances of estimated parameters of regression models [for further detail in the context of the ARMS, see Kott (1997) and Dubman (2000)]. In lieu of the JK method, and to remedy the computational limitation caused by the partial use of the ARMS data, this paper uses the bootstrapping technique. In fact, this method of variance estimation in the context of quantile regression is preferred over other direct nonparametric methods because, under this technique, assessing whether the distribution of the covariates is influenced by stochastic effects becomes feasible (see Baguio 2009) and the construction of confidence intervals based on quantile regression estimator is greatly simplified (see Hahn 1995).

[13] The extent of farm diversification among $N$ possible enterprises is measured using the following index (see Theil 1971):

$$\text{entropy} = \sum_{i=1}^{N} (\%\text{ value of production from enterprise } i) \times \frac{\log\left[\dfrac{1}{(\%\text{ value of production from enterprise } i)}\right]}{\log(N)},$$

where the index ranges from 0 percent (i.e., a completely specialized farm producing only one commodity) to 100 percent (i.e., a completely diversified farm with equal shares of each commodity).

**Table 1. Definitions and Weighted Means of Variables Used in the Income Model (2006)**

| Definitions | Mean | Standard Deviation |
|---|---|---|
| DEPENDENT VARIABLE | | |
| Adjusted farm household income: total farm household income excluding govt. payments ($1,000) [a] | 70.31* | 1.95 |
| IHS-transformed total farm household income excluding government payments ($1,000) [b] | 43.96* | 0.81 |
| EXPLANATORY VARIABLES | | |
| *Operator and household characteristics* | | |
| Age of farm operator (years) | 56.70* | 0.36 |
| Education of farm operator: [c] | | |
| High school (= 1, 0 otherwise) | 0.40 | -- |
| Some college (= 1, 0 otherwise) | 0.23 | -- |
| College and beyond (= 1, 0 otherwise) | 0.26 | -- |
| Gender of farm operator (= 1 if operator is male, 0 otherwise) | 0.90 | -- |
| Ethnicity of farm operator (= 1 if operator is white, 0 otherwise) | 0.96 | -- |
| Operator is married with children aged 13 or younger (=1, 0 otherwise) | 0.19 | -- |
| Operator working full-time (at least 2,000 hours per year) on farm (=1, 0 otherwise) | 0.25 | -- |
| Last year's income from off-farm wages and/or salaries and/or from an off-farm business ($1,000) | 48.48* | 1.99 |
| *Farm Characteristics* | | |
| Government payments to farm household ($1,000) | 5.0* | 0.23 |
| Last year's gross value of farm sales ($1,000) | 64.75* | 2.47 |
| Entropy (%) | 13.51* | 0.30 |
| Precipitation (millimeters) | 965.91* | 8.55 |
| Soil productivity index | 73.37* | 0.35 |
| Farm location: | | |
| County: [d] | | |
| Medium density county (= 1 if population equals 10–49 per square mile, 0 otherwise) | 0.39 | -- |
| Medium-large density county (= 1 if population equals 50–249 per square mile, 0 otherwise) | 0.39 | -- |
| Large density county (= 1 if population equals 250 or more per square mile, 0 otherwise) | 0.13 | -- |
| Region: [e] | | |
| Midwest (= 1, 0 otherwise) | 0.38 | -- |
| West (= 1, 0 otherwise) | 0.13 | -- |
| South (= 1, 0 otherwise) | 0.44 | -- |
| Sample size | 6,155 | |
| Farm operator households | | 1,951,253 |

* Means for continuous variables are statistically significant at 5 percent (standard deviations are computed using 1,000 bootstrap replicate samples).

[a] Median total household income excluding government payments ($1,000) = $53.50.
[b] Median IHS-transformed total household income excluding government payments ($1,000) = $45.44.
[c] Excluded category (11 percent): "less than high school."
[d] Excluded category (9 percent): "if population is less than 10 per square mile."
[e] Excluded category (5 percent): "Northeast."

Source: USDA (2006).

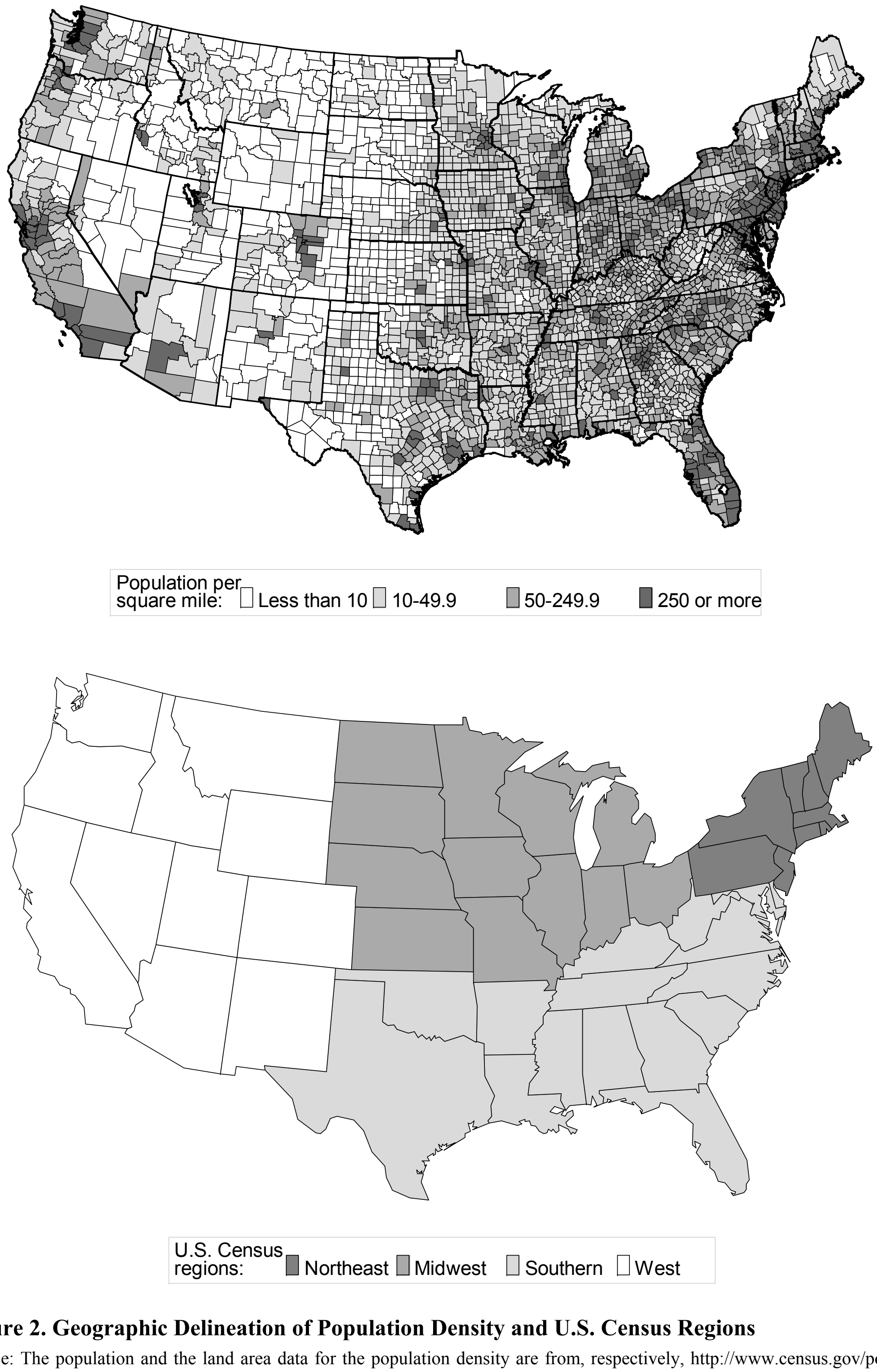


**Figure 2. Geographic Delineation of Population Density and U.S. Census Regions**

Source: The population and the land area data for the population density are from, respectively, http://www.census.gov/popest/estimates.html and the U.S. Census Bureau, Summary File 1, 2000 Census of Population.

more hours to on-farm work and less to off-farm work where the potential for higher earnings tends to be higher (El-Osta, Mishra, and Ahearn 2004, Ahearn, El-Osta, and Dewbre 2006, Key and Roberts 2009). In addition, receipt of payments as in the case of conservation payments often requires farms to incur costs to adopt conserving practices (Ahearn and Gibbs 2010). Another likely factor that may allow government payments to adversely impact farm household income is the fact that payments tend to increase land values and land rental rates (see Roe, Somwaru, and Diao 2002, Goodwin, Mishra, and Ortalo-Magne 2003), which is particularly relevant for farm households as evidence from the 2006 ARMS shows that nearly 50 percent of all farm households that participate in farm programs are either part owners or full tenants, compared to nearly 29 percent for their non-participating counterparts. Yet another variable with an indeterminate effect on household income is the "entropy" variable, which is an indicator of enterprise diversification that farm businesses often use as one method of reducing income variability (Harwood et al. 1999, Newbery and Stiglitz 1985, Robison and Barry 1987). While Purdy, Langemeier, and Featherstone (1997) and Mishra, El-Osta, and Johnson (1999) found evidence that risk is reduced with diversification, the results with regard to the impact of diversification on farm returns and farm income were mixed.

Table 1 shows that the weighted average adjusted farm household income is \$70,310, and when compared to a weighted median income of \$53,500, this points to a skewed income distribution with a long right tail. After the IHS transformation, both the weighted mean income and the weighted median income are almost identical, at \$43,960 and \$45,440, respectively. The upper panel of Figure 3 demonstrates the extent of the skewness in the residuals that would result if the weighted least squares regression model of adjusted farm household income is estimated without performing the IHS transformation on the dependent variable as described in equation (9). In contrast, the lower panel of the figure, which utilizes this transformation technique (with $\theta$ = 0.0221478; standard error = 0.0006597), shows a distribution of residuals that is much closer to normal, thus allowing for a more accurate estimation of the model's coefficients.

Before equation (9) is estimated using weighted least squares, the issue of the presence of a likely endogenous explanatory variable was investigated using a two-step procedure.[14] In the first step, a vector of residuals was obtained from a tobit regression model of government payments that was estimated using a maximum likelihood procedure.[15] The "exclusion restriction" variable used in the tobit equation is a dummy variable indicating whether or not the farmer had worked on the farm full-time (i.e., more than 2,000 hours) in 2006. This variable is considered an "appropriate" instrument [i.e., $\mathrm{Cov}(X_k, Y) \neq 0$] since, although it was not correlated with the IHS-transformed adjusted total income of the farm household based on a low value of the Pearson correlation coefficient (= -0.18), it was nevertheless correlated with government payments based on the statistical significance ($p$-value = 0.0001) of its estimated parameter [for more detail, see Angrist and Krueger (1991), Bound, Jaeger, and Baker (1995), Mallar (1977), Wooldridge (2002, p. 212)]. The second step involved re-estimating the regression model with the vector of residuals being included as an additional explanatory variable. The exogeneity of the government payments variable is asserted based on the finding of a statistically insignificant ($p$-value = 0.688) coefficient of the vector of residuals [see Smith and Blundell (1986), Rivers and Voung (1988), Wooldridge (2002, pp. 472–477)].

[14] One could argue that the education variable is potentially endogenous to the economic outcome models in equations (10) and (12) since a financially well-positioned household has the ability to invest in education, and a high level of education contributes to the ability of the household to earn higher levels of income. To account for the potential endogeneity of education on earnings, Angrist and Krueger (1991) used the season of birth as an instrument for education. A study later by Bound, Jaeger, and Baker (1995) found that the instrument used by Angrist and Krueger was not reliable. Card (1994), on the other hand, handled the potential simultaneity between the schooling variable and wages by using region and time variation in school construction as instruments for education. This paper can only presume, with a caveat, that education is exogenous, since finding a valid instrument in the ARMS dataset to deal with the potential simultaneity that might exist between this variable and economic outcome has proven unsuccessful.

[15] The expected value of the censored variable $y_j$ is

$$\mathrm{E}\,[y_j|x] = \Phi\left(\frac{x'_j\beta}{\sigma}\right)(x'_j\beta+\sigma\lambda_j), \quad \text{where } \lambda_j = \frac{\varphi(x'_j\beta/\lambda)}{\Phi(x'_j\beta/\lambda)} ,$$

and where $\sigma$ is the standard deviation of $\mu$, and $\phi(.)$ and $\Phi(.)$ are the standard normal probability density function and the standard normal cumulative density function, respectively (see Greene 2002, Long 1997). Consequently, the residuals are calculated as $y_j - \hat{y}_j$ .

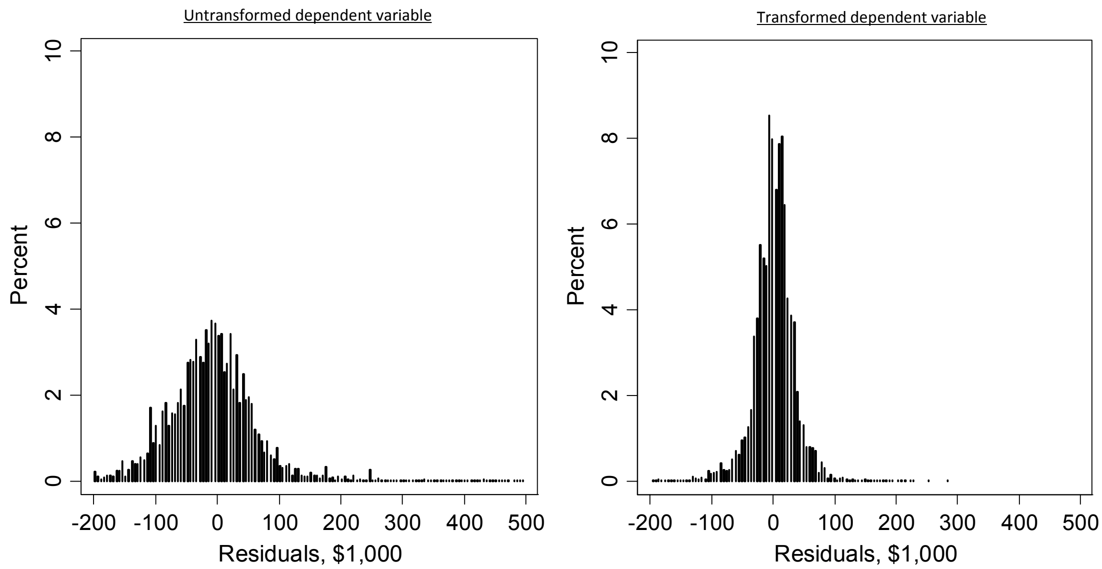


**Figure 3. Histograms of the Residuals of "Adjusted" Income Regression Models (2006)**

Source: USDA (2006).

The results of the least squares IHS-transformed income model are presented in the first column of Table 2. The estimated least squares regression model appears to provide, taking into account the cross-sectional nature of the data, an acceptable explanatory power based on an $R^2$ value of 0.1597. Of the variables denoting operator's characteristics, the age, the race, and the gender of the operator appear, *ceteris paribus*, with no significant impact on the adjusted income levels of farm households. In contrast, the positive and statistically significant coefficients of the dummy variables denoting educational attainment, and with the values of the coefficients increasing as the levels of education increase, asserts the importance of operators' human capital on the income-generation capacity of farm households.[16] In terms of household characteristics, a positive yet significant association is found between expected earnings from off-farm work and adjusted farm household income. In terms of farm characteristics, findings point to the importance of size of the farming operation and of a farm location in a large population density county or in a census region other than in the Northeast on the ability of the farm household to generate higher levels of

[16] For the sake of demonstration with regard to the inappropriateness of using the jackknife variance (JK) estimation method when the survey data that underlie the analysis are not used in full as in this study, two additional vectors of parameter variances of the OLS model of the adjusted farm household income (AFHI) in Table 2 were estimated: one based on the JK method and another based on the robust variance estimator method using the robust Huber/White/sandwich estimator (HW) (see Huber 1967, White 1980). The following is a partial listing of the results of the standard errors (in parentheses) under the three methods of variance estimation (significant coefficients are in bold; *p*-value = 0.05 or better):

bootstrapping: $AFHI = -7.46 + .. + \mathbf{6.51} \times HS + \mathbf{8.36} \times SOME\_COL$
$\qquad (14.12)\ (2.92)\qquad (3.11)$
$+ \mathbf{20.13} \times COL\_BEYOND + \ldots + \ldots$
$\qquad (3.08)$

jackknife: $AFHI = -7.46 + .. + \mathbf{6.51} \times HS + \mathbf{8.36} \times SOME\_COL$
$\qquad (12.15)\ (2.13)\qquad (2.45)$
$+ \mathbf{20.13} \times COL\_BEYOND + \ldots + \ldots$
$\qquad (2.53)$

Huber/White: $AFHI = -7.46 + .. + \mathbf{6.51} \times HS + \mathbf{8.36} \times SOME\_COL$
$\qquad (14.07)\ (2.95)\qquad (3.15)$
$+ \mathbf{20.13} \times COL\_BEYOND + \ldots + \ldots$
$\qquad (3.09)$

As can be seen from these results, the HW method, which produces consistent estimators for the coefficient variances even in the presence of heteroskedasticity (see Williams 2000), produces also standard errors that are very close to those obtained from using the bootstrap method. In contrast, the JK method here when a sub-sample of the ARMS is used seemed to have underestimated the sample-to-sample variability of the parameter estimates, which could lead potentially to wrong statistical inference, particularly for border-line cases.

**Table 2. Weighted Least Squares (WLS) and Weighted Quantile (WQ) Regression Estimates of Factors Affecting the IHS-Transformed "Adjusted" Income (*g*) Levels of Farm Households (2006)**

| | *WLS*-regression | *Q*-regression | | | | |
|---|---|---|---|---|---|---|
| Variables | $\hat{\beta}$ | $\hat{\beta}_{0.05}$ | $\hat{\beta}_{0.25}$ | $\hat{\beta}_{0.5}$ | $\hat{\beta}_{0.75}$ | $\hat{\beta}_{0.95}$ |
| *Intercept* | -7.46 | -64.21$^{**}$ | -19.54 | -21.87 | 25.89 | 84.10$^{***}$ |
| | (14.12) | (29.87) | (14.23) | (13.70) | (18.15) | (31.68) |
| *Age* | 0.50 | -0.64 | 0.41 | 1.02$^{***}$ | 0.08 | -0.66 |
| | (0.41) | (0.75) | (0.34) | (0.38) | (0.59) | (0.91) |
| *Age, squared* | -0.54 | 0.61 | -0.44 | -1.01$^{***}$ | -0.06 | 0.55 |
| | (0.35) | (0.62) | (0.31) | (0.32) | (0.51) | (0.79) |
| *High school* | 6.51$^{**}$ | 2.56 | 8.16$^{***}$ | 10.31$^{***}$ | 7.39$^{**}$ | -8.81 |
| | (2.92) | (6.34) | (2.54) | (2.70) | (3.16) | (8.03) |
| *Some college* | 8.36$^{***}$ | -4.29 | 10.05$^{***}$ | 11.70$^{***}$ | 11.37$^{***}$ | -7.01 |
| | (3.11) | (8.64) | (2.56) | (3.00) | (3.37) | (7.79) |
| *College and beyond* | 20.13$^{***}$ | 8.80 | 22.72$^{***}$ | 20.90$^{***}$ | 18.71$^{***}$ | -0.48 |
| | (3.08) | (7.32) | (2.90) | (2.92) | (3.41) | (8.02) |
| *Male* | 3.14 | 7.18 | 2.83 | 4.35$^{*}$ | 0.20 | 5.50 |
| | (2.48) | (8.01) | (2.80) | (2.58) | (3.57) | (5.30) |
| *White* | 4.46 | 4.91 | 1.76 | 6.61$^{*}$ | 4.48 | 2.85 |
| | (3.36) | (11.18) | (4.33) | (3.60) | (5.79) | (11.82) |
| *Married with children* | 2.84 | 8.36 | 4.63$^{*}$ | 1.69 | 4.59 | -3.18 |
| | (2.30) | (7.29) | (2.46) | (2.07) | (2.90) | (5.63) |
| *Last year's off-farm income* | 0.10$^{***}$ | 0.06$^{***}$ | 0.13$^{***}$ | 0.21$^{***}$ | 0.20$^{***}$ | 0.16$^{***}$ |
| | (0.01) | (0.01) | (0.03) | (0.02) | (0.02) | (0.03) |
| *Government payments* | -0.34$^{***}$ | -1.19$^{***}$ | -0.82$^{***}$ | -0.45$^{***}$ | -0.11 | 0.20 |
| | (0.06) | (0.28) | (0.11) | (0.09) | (0.07) | (0.14) |
| *Last year's gross value of farm sales* | 0.01$^{**}$ | -0.11$^{***}$ | -0.02 | 0.04$^{***}$ | 0.07$^{***}$ | 0.09$^{***}$ |
| | (0.00) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) |
| *Entropy* | -0.12$^{**}$ | 0.01 | -0.05 | -0.01$^{***}$ | -0.10 | -0.13 |
| | (0.06) | (0.19) | (0.08) | (0.06) | (0.07) | (0.17) |
| *Precipitation* | 0.00 | 0.01 | 0.00 | -0.00 | 0.00 | 0.00 |
| | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) |
| *Soil productivity index* | 0.06 | 0.27$^{*}$ | 0.10 | 0.01 | -0.02 | 0.03 |
| | (0.06) | (0.16) | (0.09) | (0.06) | (0.07) | (0.18) |
| *Medium population density county* | 0.78 | 17.30$^{*}$ | 2.46 | -0.17 | -3.00 | -10.47 |
| | (2.96) | (10.36) | (3.69) | (2.89) | (3.42) | (7.36) |
| *Medium-large population density county* | 3.15 | 16.97$^{*}$ | 3.50 | 2.58 | -1.55 | -8.22 |
| | (3.04) | (10.27) | (3.70) | (3.02) | (3.53) | (7.86) |
| *Large population density county* | 6.51$^{*}$ | 20.28$^{*}$ | 6.79$^{*}$ | 2.61 | 1.90 | 8.89 |
| | (3.62) | (12.09) | (4.03) | (3.52) | (4.69) | (9.00) |
| *Midwest region* | 11.17$^{***}$ | 23.78$^{**}$ | 11.70$^{**}$ | 10.26$^{***}$ | 4.10 | 5.85 |
| | (3.27) | (11.48) | (4.72) | (3.67) | (3.92) | (8.67) |
| *West region* | 10.18$^{***}$ | 19.66$^{*}$ | 9.30$^{*}$ | 9.51$^{***}$ | 5.21 | 10.72 |
| | (3.56) | (11.84) | (4.88) | (3.76) | (3.75) | (9.12) |
| *South region* | 13.71$^{***}$ | 24.36$^{**}$ | 13.81$^{***}$ | 12.34$^{***}$ | 7.78$^{**}$ | 13.40$^{***}$ |
| | (3.21) | (10.48) | (4.66) | (3.45) | (3.75) | (8.10) |
| $R^2$ | 0.1597 | | | | | |
| Pseudo $R^2$ | | 0.2392 | 0.1330 | 0.1431 | 0.1733 | 0.2309 |

Notes: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, and $^{***}$ $p < 0.01$. Standard errors computed based on 1,000 bootstrap replicate samples are in parentheses. Dependent variable is ($1,000): $g = \sinh^{-1}(\theta Y_i)/\theta$, where $\theta = 0.0221478$. Pseudo $R^2 = 1 - V_\tau^f / V_\tau^0$, where $V_\tau^f$ is the sum of the weighted distances for the full quantile regression model [see equation (12)], and $V_\tau^r$ is the sum of the weighted distances for the restricted model that includes only the intercept [for more detail, see Hao and Naiman (2007, pp. 51–52)].

income. In contrast, government payments, perhaps reflecting the consumption of more leisure and/or an increase in on-farm work hours, which results in a decrease in the commitment to off-farm work by participating farm operators and for the potential of higher off-farm earnings, are inversely related to adjusted total farm household income. El-Osta, Mishra, and Morehart (2007) found that an increase in the probability of receiving either a loan-deficiency or a production-flexibility-contract payment in 2001 had an adverse impact on the measure of economic well-being chosen for the study where the incomes of farm households were combined with annualized values of their marketable wealth. Data from the ARMS show that the 44 percent of farm households who participated in government programs in 2006 have reported, on average, much less income from off-farm wages and salaries than their non-participating counterparts (\$51,471 versus \$66,127, respectively). The fact that participating farm households had earned much less income from this income source is consistent with their lower participation rate in off-farm work (60.1 percent versus 67.8 percent) and with the higher percentage in terms of their operators having worked full-time on the farm (36.6 percent versus 15.3 percent). Similar adverse impact on farm household income is found to result as farm production becomes more diversified. Katchova (2005) found crop/livestock diversified farms and commodity diversified farms had, respectively, in comparison to specialized farms, diversification discount to farms' values of 5.8 percent and 9.4 percent.

While the results from the least squares regression provide insights with regard to the mean of the dependent variable for each fixed value of the covariates in the regression model, the estimated coefficients from quantile regression allow for a description of the entire conditional distribution of the dependent variable (Hao and Naiman 2007). The last five columns of Table 2 provide the results of estimating the quantile regression model as described in equation (11).[17] Based on the estimated coefficients, findings show that increases in operator's age and educational attainment (from a high school education to some college, or to college and beyond) are the most relevant contributors to the income-generation capacity of farm households at the 0.5th quantile of the income distribution. Similarly, the impact of off-farm income is found most notable at the 0.5th quantile of the income distribution. Figure 4, which provides a visual representation of the quantile regression results with a 95 percent confidence interval, demonstrates how the estimated parameters vary over the conditional quantiles, while identifying those that are significantly different than zero. Of all the covariates considered in the analysis, those that depict operator's education, earnings from off-farm wages and salaries, size of farm, and whether the farm is located in the South are found to positively impact adjusted farm household income at all or nearly all of the conditional income quantiles.

Without an IHS transformation to the dependent variable $Y$, the $j$th coefficient from a quantile regression can be interpreted as the partial derivative of the conditional quantile of $Y_i$ with respect to the $j$th regressor [i.e.,

$$\hat{\beta}_j = \partial Quant_\tau (Y_i \big| X_{ij}) / \partial X_j \text{ ].}$$

In other words, the estimated $j$th coefficient is interpreted as the marginal change in $Y$ at the $\tau$th conditional quantile due to marginal change in the $j$th regressor (Coad and Rao 2006). With an IHS transformation to the dependent variable $Y$, $\hat{\beta}_j$ will have the same interpretation as in the case without the transformation but only after its value is multiplied by $1/2(e^{\theta g_i} - e^{-\theta g_i})$, or by $\varphi$, as was discussed before. Table 3 presents the results of the quantile regression shown in Table 2 alongside the results from least squares regression, but with adjustments made to the estimated coefficients to allow for these coefficients to be interpreted as marginal effects. The marginal effects for the "education" dummy variables in the conditional-mean model highlight the importance of human capital to the incomes of farm households. Specifically, a farmer with a high school education earns \$14,140 more than a farmer with a lesser amount of education, with the extent of the income benefit increasing to \$18,160 if the farmer had some college education, and to \$43,700 if the educational attainment was at the college

[17] The pseudo $R^2$ results reported in Table 2 are not directly comparable across quantiles (see Barnes and Hughes 2002).

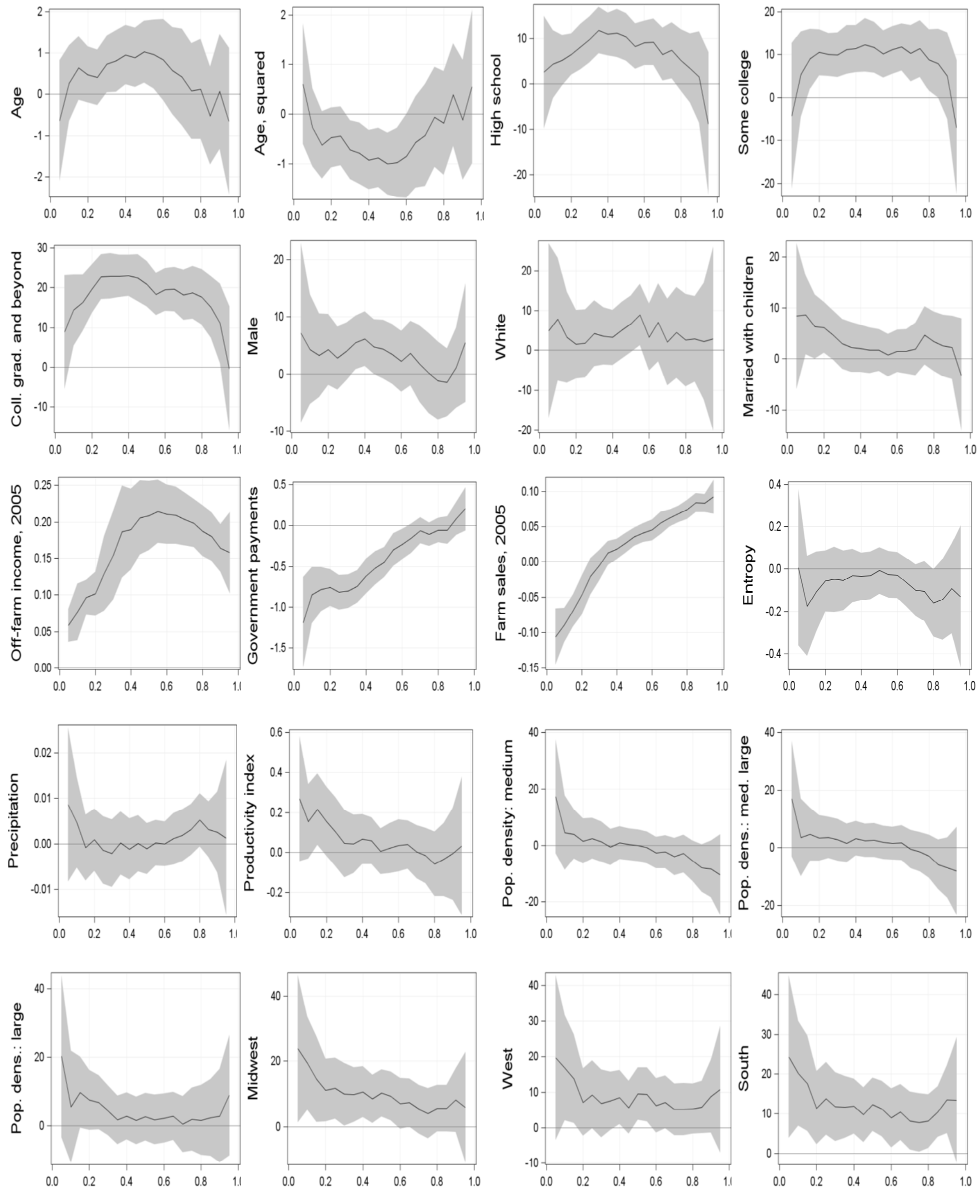


**Figure 4. Quantile Regression Coefficient Estimates and Bootstrap 95 Percent Confidence Envelopes for "Adjusted" Income Model (2006)**

**Table 3. Marginal Effects Based on Weighted Least Squares (WLS) and Weighted Quantile (WQ) Regressions of Factors Affecting the "Adjusted" Income Levels of Farm Households (2006)**

| | *LS*-Regression | $Q$–Regression[a] | | | | |
|---|---|---|---|---|---|---|
| Variables | $\hat{\beta}$ | $\phi\hat{\beta}_{0.05}$ | $\phi\hat{\beta}_{0.25}$ | $\phi\hat{\beta}_{0.5}$ | $\phi\hat{\beta}_{0.75}$ | $\phi\hat{\beta}_{0.95}$ |
| Intercept | -16.19 | -139.41** | -42.42 | -47.48 | 56.22 | 182.61*** |
| Age | 1.08 | -1.38 | 0.89 | 2.22*** | 0.17 | -1.43 |
| Age, squared | -1.17 | 1.32 | -0.96 | -2.18*** | -0.13 | 1.20 |
| High school | 14.14** | 5.57 | 17.73*** | 22.39*** | 16.04** | -19.12 |
| Some college | 18.16*** | -9.32 | 21.81*** | 25.40*** | 24.69*** | -15.22 |
| College and beyond | 43.70*** | 19.10 | 49.32*** | 45.38*** | 40.61*** | -1.03 |
| Male | 6.83 | 15.59 | 6.14 | 9.44* | 0.44 | 11.95 |
| White | 9.68 | 10.66 | 3.82 | 14.36* | 9.73 | 6.18 |
| Married with children | 6.17 | 18.15 | 10.05* | 3.66 | 9.96 | -6.90 |
| Last year's off-farm income | 0.22*** | 0.13*** | 0.28*** | 0.45*** | 0.43*** | 0.34*** |
| Government payments | -0.73*** | -2.58*** | -1.77*** | -0.97*** | -0.24 | 0.44 |
| Last year's gross value of farm sales | 0.03** | -0.23*** | -0.04 | 0.08*** | 0.14*** | 0.20*** |
| Entropy | -0.26** | 0.02 | -0.11 | -0.02*** | -0.23 | -0.28 |
| Precipitation | 0.01 | 0.02 | -0.00 | -0.00 | 0.01 | 0.00 |
| Soil productivity index | 0.14 | 0.58* | 0.23 | 0.01 | -0.03 | 0.07 |
| Medium population density county | 1.67 | 37.56* | 5.33 | -0.36 | -6.50 | -22.73 |
| Medium-large population density county | 6.830 | 36.85* | 7.61 | 5.59 | -3.36 | -17.84 |
| Large population density county | 14.14* | 44.04* | 14.73* | 5.67 | 4.12 | 19.29 |
| Midwest region | 24.24*** | 51.63** | 25.41** | 22.29*** | 8.92 | 12.71 |
| West region | 22.09*** | 42.68* | 20.19* | 20.64*** | 11.31 | 23.28 |
| South region | 29.76*** | 52.90** | 29.99*** | 26.79*** | 16.90*** | 29.10*** |

[a] $\phi = \frac{1}{2}\left[e^{\theta g} + e^{-\theta g}\right]$, where $g = \frac{\sinh^{-1}(\theta Y_i)}{\theta}$ and $\theta = 0.0221478$ [for more detail, see Pence (2006)].

Note: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Significance of coefficients is based on respective standard errors as reported in Table 2.

and beyond level.[18] Findings further indicate that the marginal effects for the educational dummy variables in the conditional-mean model are smaller than their corresponding magnitudes in the conditional-first- and conditional-second-quartiles of the income distribution. For operators at the 0.05th quantile of the income distribution, a higher educational attainment level appears to have no impact on their income levels [see Chang, Lambert, and Mishra (2008) for a similar finding]—just as was the case for those operators at the 0.95th quantile of the income distribution. While a higher level of education tends to increase the income level of an average operator, the potential of an increase in income due to higher education is not uniform across all farm households, as for some—particularly those in the lower and upper end of the income distribution—the impact is insignificant, while for others the impact of such an increase is significant and quite large. A marginal increase in expected earnings from off-farm work appears to increase adjusted farm household income across all the income quantiles, with the largest increase being captured by those farm households located above the 0.50th quantile. Similarly, in increasing the expected size of the farming operation, while it has the potential of increasing the adjusted income levels of the average farm household, the impact of such a marginal increase is the largest for those households in the upper-half portion of the income distribution. Findings indicate that married farm operators with children who are located at the 0.25th quantile of the income distribution earn $10,050 more than their counterparts who are either married but with no children or not married. This finding is consistent with the observation made by Lass, Findeis, and Hallberg (1991) that the presence of more children may exert higher pressure on the parents to obtain additional income, perhaps by working additional hours off the farm as was asserted by, among others, Huffman (1980) and Furtan, Van Kooten, and Thompson (1985), to meet the consumption needs of a larger family. Yet another explanation for the higher income by married farm operators, in general, is the increased opportunity for income pooling (see Marchant 1997). Differentials in the positive and statistically significant impact of some farm characteristics (e.g., farm size, precipitation, productivity, farm location) are also exhibited across the full spectrum of the income distribution, particularly at the 0.05th quantile. For those farms at the 0.05 quantile of the income distribution that are located in large- relative to low-population-density counties, findings indicate that their incomes, perhaps due to greater access to off-farm jobs (see De Frahan et al. 2008), are significantly higher (at $44,040) than their counterparts in low-population-density counties. That higher-population density areas are shown with higher incomes is consistent with Whitener and Parker's (2007) study, which notes that rural low-population-density areas, because of their remoteness from major urban markets and limited nonfarm sector development, have not been as prosperous as others.

---

[18] An interesting point was raised by a reviewer who noted that to the extent that most of the income of the farm household originates from working off the farm, the reported results are for the most part reflecting the impact of education on off-farm earnings. Based on the suggestion by the reviewer, a separate OLS regression model was run with an IHS-transformed adjusted net-farm income (i.e., net farm income without income from government payments) as the dependent variable (*IHS_ ANFI*). In these models, an IHS-transformation of the dependent variable was done due to the skewness of *ANFI* (e.g., mean = -$62, while median = $-4,189). Furthermore, the same covariates as listed in the specified model above were used except for the "government payment" variable, which was found endogenous based on a Smith and Blundel test and which was replaced in the models with predicted values (*PR_GOV*) from a first-stage estimation of a Tobit model of government payments with a dummy variable indicating whether the farmer uses the Internet as an instrument (*R*-squared: 0.276). The chosen instrument is deemed appropriate since it was found statistically significant (*p*-value = 0.00) and positively correlated with government payments while being poorly and negatively correlated with adjusted net-farm income (Pearson correlation = -0.01; *p*-value = 0.39). The finding of poor correlation between Internet use and farm income is in line with Smith et al. (2004), who found about half of farmers in the Great Plains who use the Internet for farm-related business reporting zero economic benefit from such use. The following are two equations depicting in each a selected partial listing of the retransformed marginal-effect results for adjusted farm household income (AFHI) extracted from Table 3 and *ANFI* (see equation in note under Table 3; full results can be provided by the author upon request), with significant coefficients listed in bold letters (*p*-value = 0.10 or better; based on 1,000 bootstrap replicate samples):

$$\text{AFHI} = -16.19+..+\mathbf{14.14} \times HS + \mathbf{18.16} \times SOME\_COL + \mathbf{43.70} \times COL\_BEYOND +\ldots+\ldots\ \mathbf{0.22} \times LAST\_YR\_OFF\ \mathbf{-0.73} \times GOV\ \mathbf{+0.03} \times LAST\_YR\_SALES\ \mathbf{-0.26} \times ENTROPY+..+ \mathbf{29.76} \times SOUTH.\ (R\text{-squared: } 0.16)$$

$$\text{ANFI} = 3.17+..+0.32 \times HS - 5.99 \times SOME\_COL - 1.45 \times COL\_BEYOND+\ldots\mathbf{-0.06} \times LAST\_YR\_OFF\ \mathbf{-0.97} \times PR\_GOV\ \mathbf{+0.10} \times LAST\_YR\_SALES\ \mathbf{+0.26} \times ENTROPY+..+\mathbf{6.83} \times SOUTH.\ (R\text{-squared: } 0.09).$$

The apparent lack of importance of education with regard to adjusted farm income, unlike in the case of adjusted total farm household income, seems to support the old adage that posits that a higher level of formal education is less important for a farmer involved in the production of commodities than for other occupations because much of the human capital demanded of a farmer comes from farming experience, i.e., "learning-by-doing" (see Luh and Stefanou 1993).

## Summary and Policy Implications

The paper started by noting the scarcity in the literature of studies that dealt directly with the impact of human capital, as proxied by farm operators' years of education, on the incomes of farm households. This was followed by providing a simple economic model that attributes the variation in the distribution of households' economic position, among other variables, to education. Next, a discussion was provided of the 2006 ARMS data and of the inverse hyperbolic-sine transformation of the dependent variable and of the quantile regression procedures used to lessen the adverse impacts of heteroscedasticity and of extreme observations found in the data.

The variations found in the impact of educational attainment and of policy-relevant variables such as those depicting expected earnings from off-farm work and from farm programs, among others, across the quantiles of the adjusted income distribution confirmed the appropriateness of using quantile regressions over conditional-mean regression when examining the incomes of farm households. For example, findings have shown that increases in the educational attainment of farm operators in the 0.05th and the 0.95th quantiles, unlike in the case of a conditional-mean regression, will have no effect on the incomes of these households. In contrast, while increases in government payments are found to be associated with decreases in the adjusted incomes of farm households based on the conditional-mean regression model, such increases are found to have their only positive although statistically insignificant ($p$-value = 0.1363) impact on the incomes of farm households in the 0.95th quantile.

To the extent that current farm policies tie federal support payments to income, it's only prudent to describe the characteristics of those 98,001 farm households that are in the 0.05th quantile of the adjusted (IHS-transformed) income distribution and that are most likely to be impacted by farm programs. These households, based on the sample data from the 2006 ARMS, tend to be heavily involved in farming, as 93 percent of their operators, compared to the national average of 43 percent, report that their main occupation is farming. In the same vein, the average years of operators' farming experience—despite their modest average years of education, which is slightly below the national average of 13.54 years—is 29, compared to a national average of 24 years. While the average farm household in this group has a total farm household income of -\$65,327, which makes them income-poor, they are nevertheless asset-rich, as their average operated acreage (1,693 acres) is the highest when compared to those households in the other quantiles and is more than four times the national average (410 acres). In terms of total household wealth, the average household in this group commands \$1.1 million in net worth, second only to the \$1.5 million for the average household in the top 5 percent of the income distribution and over 1.8 times the national average of \$0.59 million. The heavy involvement in farming by this group of households is further demonstrated by their reported average government payment (\$35,621), which is significantly larger than the reported average payments in all the quantiles of the income distribution, and by their disproportionate share of all payments (26.4 percent).

While findings from the quantile regression show that the income-poor yet asset-rich households in the 0.05th quantile would not benefit from increased levels of schooling or increased government payments, those households are found nevertheless to benefit instead from increases in expected off-farm earnings. For the remaining 95 percent of farm households, while no economic benefit seems to result from increased levels of government payments in contrast to increased levels of schooling, which is found beneficial except for those at the very top of the income distribution, increases in the earnings from off-farm wages and salaries are found beneficial to all farm households across the full spectrum of the income distribution. In light of these findings, a marginal dollar being spent in improving the off-farm earnings capacity of farmers may have a better impact in improving the overall income of farm households than would a marginal dollar being spent on government programs. This finding falls in line with that of Gardner (2000), who pointed toward labor market integration as being by far the most predominant factor, in comparison to factors such as government payments, or growth in agricultural productivity or farm size, in improving the economic conditions of low-income farm households. Similarly, considering the positive impact of farmers' human capital on the incomes of most farm households, and notwithstanding the potential for brain-drain in rural areas (see Weber et al. 2007) and/or for increasing income inequality at least in the medium term (see Green 2007), such findings may be used to buttress the views of those who advocate increased federal spending on education in rural areas.

## References


Adkins, L.C., and R. Carter Hill. 2004. "Bootstrap Inferences in Heteroscedastic Sample Selection Models: A Monte Carlo Investigation. " Paper presented at the 74th meeting of the Southern Economic Association, New Orleans, LA (November 22).

Ahearn, C.M., H.S. El-Osta, and J. Dewbre. 2006. "The Impact of Coupled and Decoupled Government Payments on Off-Farm Labor Participation of U.S. Farm Operators." *American Journal of Agricultural Economics* 88(2): 393–408.

Ahearn, C.M., and R. Gibbs. 2009. "Farm Household Economics and Well-Being: Beginning Farmers, Demographics, and Labor Allocations." Available at http://www.ers.usda.gov/briefing/wellbeing/demographics.htm (accessed July 1, 2009).

____. 2010. "Farm Household Economics and Well-Being: Farm Household Income." Available at http://www.ers.usda.gov/Briefing/WellBeing/farmhouseincome.htm (accessed July 1, 2009).

Ahearn, C.M., J.E. Perry, and H.S. El-Osta. 1993. "The Economic Well-Being of Farm Operator Households, 1988–90." AER No. 666, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Altonji, J.G., and U. Doraszelski, 2001. "The Role of Permanent Income and Demographics in Black/White Differences in Wealth." Working Paper No. 8473, National Bureau of Economic Research, Cambridge, MA.

Angrist, J.D., and A.B. Krueger. 1991. "Does Compulsory School Attendance Affect Schooling and Earnings?" *Quarterly Journal of Economics* 106(4): 979–1014.

Astone, N.M., C.A. Nathanson, R. Schoen, and Y.J. Kim. 1999. "Family Demography, Social Theory, and Investment in Social Capital." *Population and Development Review* 25(1): 1–31.

Baguio, C.B. 2009. "Performance of Median and Least Squares Regression for Slightly Skewed Data." *World Academy of Science, Engineering and Technology* 53: 226–230.

Barnes, M.L., and A.W. Hughes. 2002. "A Quantile Regression Analysis of the Cross Section of Stock Market Returns." Federal Reserve Bank, Boston, MA. Available at http://www.bos.frb.org/economic//wp/wp2002/wp022.pdf (accessed February 8, 2009).

Becker, G.S. 1962. "Investment in Human Capital: A Theoretic Analysis." *Journal of Political Economy* 70(5): 9–49.

____. 1966. "Human Capital and the Personal Distribution of Income: An Analytical Approach." National Bureau of Economic Research, New York.

____. 1975. *Human Capital.* National Bureau of Economic Research, New York.

____. 1994. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education* (3rd edition). Chicago, IL: University of Chicago Press.

____. 1995. "*Human Capital and Poverty Alleviation.*" HRO Working Papers, World Bank, Washington, D.C. Available at http://www-wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/1995/03/01/000009265_3970702134116/Rendered/PDF/multi0page.pdf (accessed February 8, 2009).

Ben-Porath, Y. 1967. "The Production of Human Capital and the Life Cycle of Earnings." *Journal of Political Economy* 75(4): 352–365.

Blank, R.M. 1997. *It Takes a Nation: A New Agenda for Fighting Poverty.* Princeton, NJ: Princeton University Press.

Bound, J., D.A. Jaeger, and R.M. Baker. 1995. "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variables Is Weak." *Journal of the American Statistical Association* 90(430): 443–450.

Box, G.E.P., and D.R. Cox. 1964. "An Analysis of Transformations." *Journal of the Royal Statistical Society* (Series B: Methodological) 26(20): 211–252.

Breusch, T.S., and A.R. Pagan. 1979. "A Simple Test for Heteroscedasticity and Random Coefficient Variation." *Econometrica* 47(5): 1287–1294.

Buchinsky, M. 1994. "Changes in the U.S. Wage Structure 1963–1987: Application of Quantile Regression." *Econometrica* 62(2): 405–458.

____. 1995. "Estimating the Asymptotic Covariance Matrix for Quantile Regression Models: A Monte Carlo Study." *Journal of Econometrics* 68(2): 303–338.

____. 1998. "Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research." *Journal of Human Resources* 33(1): 88–126.

Burbidge, J.B., L. Magee, and A.L. Robb. 1988. "Alternative Transformations to Handle Extreme Value of the Dependent Variable." *Journal of the American Statistical Association* 83(401): 123–127.

Card, D. 1994. "Earnings, Schooling, and Ability Revisited." NBER Working Paper No. 4832, National Bureau of Economic Research, Cambridge, MA. Available at http://www.nber.org/papers/w4832.pdf (accessed July 12, 2009).

Carneiro, P., and J. Heckman. 2003. "Human Capital Policy." In J. Heckman and A. Krueger, eds., *Inequality in America: What Role for Human Capital Policies?* Cambridge, MA: MIT Press.

Carroll, C.D., K.E. Dynan, and S.D. Krane. 2003. "Unemployment Risk and Precautionary Wealth: Evidence from Households' Balance Sheets." *Review of Economics and Statistics* 85(3): 586–604.

Chang, H., D.M. Lambert, and A. Mishra. 2008. "Does Participation in the Conservation Reserve Program Impact the Economic Well-Being of Farm Households?" *Agricultural Economics* 38(2): 201–212.

Chen, M.Y., F.L. Lin, and C.K. Chang. 2009. "Relations Between Health Care Expenditure and Income: An Application of Local Quantile Regressions." *Applied Economics*

*Letters* 16(2): 177–181.

Coad, A., and R. Rao. 2006. "Innovation and Market Value: A Quantile Regression Analysis." *Economics Bulletin* 15(13): 1–10.

Coleman, J.S. 1988. "Social Capital in the Creation of Human Capital." *American Journal of Sociology* 94(S1): S95–S120.

____. 1990. *Foundations of Social Theory*. Cambridge, MA: Belknap Press of Harvard University Press.

Deaton, A.S. 1989. "Rice Prices and Income Distribution in Thailand: A Non-Parametric Analysis." *Economic Journal* 99(395): 1–37.

Deavers, K.L., and R.A. Hoppe. 1992. "Overview of the Rural Poor in the 1980s." In C.M. Duncan, ed., *Rural Poverty in America*. Westport, CT: Auburn House.

De Frahan, B., T. Nkunzimana, R. De Blander, F. Gaspart, and D.A. Sumner. 2008. "Farm Household Incomes and Reforming the CAP." Paper presented at the 109th EAAE seminar, Viterbo, Italy (November 20–21).

Dewbre, J., and A. Mishra. 2002. "Farm Household Incomes and U.S. Government Program Payments." Paper presented at the annual meeting of the American Agricultural Economic Association, Long Beach, CA (July 28–31).

Dooley, D.M., and P. Gottschalk. 1984. "Earnings Inequality among Males in the United States: Trends and the Effect of Labor Growth." *Journal of Political Economy* 92(1): 59–89.

Dubman, R. 2000. "Variance Estimation with USDA's Farm Costs and Returns Surveys and Agricultural Resource Management Study Surveys." Staff Report No. AGES 00-01, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Efron, B., and R.J. Tibshirani. 1994. *An Introduction to the Bootstrap*. New York: Chapman and Hall.

El-Osta, H.S., A.K. Mishra, and M.C. Ahearn. 2004. "Labor Supply by Farm Operator Households under 'Decoupled' Farm Program Payments." *Review of Economics of the Household* 2(4): 367–385.

El-Osta, H.S., A.K. Mishra, and M.J. Morehart. 2007. "Determinants of Economic Well-Being among U.S. Farm Operator Households." *Agricultural Economics* 36(3): 201–304.

Freeman, R.B. 1979. "The Effects of Demographic Factors on Age-Earnings Profiles." *Journal of Human Resources* 14(3): 289–318.

Friedman, M., and S. Kuznets. 1945. *Income from Independent Professions*. New York: National Bureau of Economic Research.

Furtan, W.H., G.C. Van Kooten, and S.J. Thompson. 1985. "The Estimation of Off-Farm Supply Functions in Saskatchewan." *Journal of Agricultural Economics* 36(2): 212–220.

Gardner, B.L. 2000. "Economic Growth and Low Income in Agriculture." *American Journal of Agricultural Economics* 82(5): 1059–1074.

Gisser, M. 1965. "Schooling and the Farm Problem." *Econometrica* 33(3): 582–692.

Goetz, S.J. 1993. "Human Capital and Rural Labor Issues." *American Journal of Agricultural Economics* 75(5): 1164–1168.

Goodwin, B.K, A.K. Mishra, and F.N. Ortalo-Magne. 2003. "What's Wrong with Our Models for Agricultural Land Values?" *American Journal of Agricultural Economics*. 85(3): 744–752.

Green, D.A. 2007. "A Cautionary Discussion about Relying on Human Capital Policy to Meet Redistributive Goals." *Canadian Public Policy* 33(3): 397–418.

Greene, W.H. 2002. *Econometric Analysis* (5th edition). Englewood Cliffs, NJ: Prentice-Hall.

Griliches, Z. 1964. "Research Expenditures, Education and the Aggregate Agricultural Production Function." *American Economic Review* 54(6): 961–974.

Gundersen, C., and S. Offutt. 2005. "Farm Poverty and Safety Nets." *American Journal of Agricultural Economics* 87(4): 885–899.

Hahn, J. 1995. "Bootstrapping Quantile Regression Estimators." *Econometric Theory* 11(1): 105–121.

Hao, L.D., and Q. Naiman. 2007. *Quantile Regression*. Thousand Oaks, CA: Sage Publications.

Harwood, J., R. Heifner, K. Cobble, J. Perry, and A. Somwaru. 1999. "Managing Risk in Farming: Concepts, Research, and Analysis." AER No. 774, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Haveman, R., B. Wolfe, and J. Spaulding. 1991. "Childhood Events and Circumstances Influencing High School Completion." *Demography* 28(1): 133–157.

Heckman, J. 2005. "Inequality in America: What Role for Human Capital Policies." *Focus* 23(3): 1–10.

Hill, M., and G.J. Duncan. 1987. "Parental Family Income and the Socioeconomic Attainment of Children." *Social Science Research* 16(1): 39–73.

Hoppe, R.A., and H. Bluestone. 1987. "Black Farmers and the Economic and Social Conditions Where They Live: Some Policy Implications." *Southern Rural Sociology* 5(1): 41–58.

Huber, P.J. 1967. "The Behavior of Maximum Likelihood Estimates Under Nonstandard Conditions." In L.M. Le Cam and J. Neyman, eds., *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*. Berkeley, CA: University of California Press.

Huffman, W.E. 1972. "The Contribution of Education and Extension to Differential Rates of Change." Unpublished Ph.D. thesis, University of Chicago, Chicago, IL.

____. 1974. "Decision Making: The Role of Human Capital." *American Journal of Agricultural Economics* 55(1): 85–97.

____. 1977. "Allocative Efficiency: The Role of Human Capital." *Quarterly Journal of Economics* 91(1): 59–79.

____. 1980. "Farm and Off-Farm Work Decisions: The Role of Human Capital." *Review of Economics and Statistics* 62(1): 14–23.

____. 1981. "Black-White Human Capital Differences: Impact on Agricultural Productivity in the U.S. South." *American Economic Review* 71(1): 94–107.

____. 1985. "Human Capital, Adaptive Ability, and the Distributional Implications of Agricultural Policy." *American Journal of Agricultural Economics* 67(2): 429–434.

Katchova, A.L. 2005. "The Farm Diversification Discount." *American Journal of Agricultural Economics* 87(4): 984–994.

Key, N., and M.J. Roberts. 2009. "Nonpecuniary Benefits to Farming: Implications for Supply Response to Decoupled Payments." *American Journal of Agricultural Economics* 91(1): 1–18.

Khaldi, N. 1975. "Education and Allocative Efficiency in U.S. Agriculture." *American Journal of Agricultural Economics* 57(4): 650–657.

Kmenta, J. 1986. *Elements of Econometrics*. New York: Macmillan Publishing Company.

Koenker, R., and G. Bassett, Jr. 1978. "Regression Quantiles." *Econometrica* 46(1): 33–50.

Kott, P.S. 1997. "Using the Delete-a-Group Jackknife Variance Estimator in NASS Surveys." National Agricultural Statistics Service, U.S. Department of Agriculture, Washington, D.C.

Kusmin, L. 2007. "Rural America at a Glance." Economic Research Service, U.S. Department of Agriculture, Washington, D.C. Available at http://www.ers.usda.gov/Publications/EIB31/EIB31.pdf (accessed July 1, 2009).

Lass, D.A., J.L. Findeis, and M.C. Hallberg. 1991. "Factors Affecting the Supply of Off-Farm Labor: A Review of the Empirical Evidence." In M.C. Hallberg, J.L. Findeis, and D.A. Lass, eds., *Multiple Job-Holding among Farm Families*. Ames, IA: Iowa State University Press.

Lazear, E. 1980. "Family Background and Optimal Schooling Decisions." *Review of Economics and Statistics* 62(1): 42–51.

Long, J.S. 1997. *Regression Models for Categorical and Limited Dependent Variables.* Thousand Oaks, CA: Sage Publications.

Luh, Y.H., and S. Stefanou. 1993. "Learning-by-Doing and the Sources of Productivity Growth: A Dynamic Model with Application to U.S. Agriculture." *Journal of Productivity Analysis* 4(1): 353–370.

Mallar, C.D. 1977. "The Estimation of Simultaneous Probability Models." *Econometrica* 45(7): 1717–1722.

Manski, C.F. 2000. "Economic Analysis of Social Interaction." *Journal of Economic Perspectives* 14(3): 115–136.

Marchant, M. 1997. "Bargaining Models for Farm Household Decision Making: Discussion." *American Journal of Agricultural Economics* 79(2): 602–604.

Mincer, J. 1962. "On-the-Job Training: Costs, Returns, and Some Implications." *Journal of Political Economy* 70(5): 50–79.

____. 1974. *Schooling, Experience, and Earnings*. New York: Columbia University Press.

Mincer, J., and S. Polacheck. 1974. "Family Investments in Human Capital: Earnings of Women." *Journal of Political Economy* 82(2): S76–S108.

Mishra, A.K., H. El-Osta, and J.D. Johnson. 1999. "Factors Contributing to Earning Success of Cash Grain Farms." *Journal of Agricultural and Applied Economics* 31(3): 623–637.

Mishra, A.K., H.S. El-Osta, M.J. Morehart, J.D. Johnson, and J.W. Hopkins. 2002. "Income, Wealth, and the Economic Well-Being of Farm Households." AER No. 812, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Nelson, R.R., and E.S. Phelps. 1966. "Investment in Humans, Technological Diffusion, and Economic Growth." *American Economic Review* 56(1/2): 69–75.

Neter, J. 1985. *Applied Linear Statistical Models-Regression Analysis of Variance, and Experimental Design* (2nd edition). Homewood, IL: Richard D. Irwin, Inc.

Newbery, D.M.G., and J.E. Stiglitz. 1985. *The Theory of Commodity Price Stabilization.* Oxford: Oxford University Press.

Parker, T. 2005. "Low Earnings But Steady Job Growth in Low-Employment Counties." *Amber Waves* 3(4): 20–27.

Pence, K.M. 2006. "The Role of Wealth Transformations: An Application to Estimating the Effect of Tax Incentives on Savings." *Berkeley Electronic Journal of Economic Analysis and Policy* 5(1): 1–24. Available at http://www.bepress.com/bejeap/contributions/vol5/iss1/art20 (accessed February 20, 2009).

Purdy, B.M., M.R. Langemeier, and A.M. Featherstone. 1997. "Financial Performance, Risk, and Specialization." *Journal of Agricultural and Applied Economics* 29(1): 149–161.

Ramsey, J.B. 1969. "Tests for Specification Errors in Classical Linear Least Squares Regression Analysis." *Journal of the Royal Statistical Society* (Series B: Methodological) 31(2): 350–371.

Ritzen, J.M., and D.R. Winkler. 1977. "The Production of Human Capital Over Time." *Review of Economics and Statistics* 59(4): 427–437.

Rivers, D., and Q.H. Vuong. 1988. "Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models." *Journal of Econometrics* 39(3): 347–366.

Robison, L.J., and P.J. Barry. 1987. *The Competitive Firm's Response to Risk*. New York: Macmillan Publishing Co.

Robison, L.J., and M.E. Siles. 1999. "Social Capital and Household Income Distributions in the United States: 1980, 1990." *Journal of Socio-Economics* 28(1): 43–93.

Roe, T., A. Somwaru, and X. Diao. 2002. *Do Direct Payments Have Intertemporal Effects on U.S. Agriculture?* International Food Policy Research Institute, Washington D.C. Available at http://ageconsearch.umn.edu/bitstream/16308/1/tm020104.pdf (accessed August 5, 2009).

Rousseeuw, P.J., and B.C. van Zomeren. 1990. "Unmasking Multivariate Outliers and Leverage Points." *Journal of the American Statistical Association* 85(411): 633– 639.

Schiller, B.R. 2004. *The Economics of Poverty and Discrimination.* Upper Saddle River, NJ: Prentice Hall.

Schultz, T.W. 1960. "Capital Formation and Education." *Journal of Political Economy* 68(5): 571–583.

____. 1964. *Transforming Traditional Agriculture.* New Haven, CT: Yale University Press.

____. 1972. "The Increasing Economic Value of Human Time." *American Journal of Agricultural Economics* 54(5): 843–850.

____. 1975. "The Value of the Ability to Deal with Disequilibria." *Journal of Economic Literature* 13(3): 827–846.

Smith, R.J., and R.W. Blundell. 1986. "An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply." *Econometrica* 54(2): 679–685.

Smith, A., C.J. Morrison Paul, W.R. Goe, and M. Kenney. 2004. "Computer and Internet Use by Great Plains Farmers." Working Paper No. 04-010, Department of Agricultural and Resource Economics, University of California, Davis, CA.

Theil, H. 1971. *Principles of Econometrics*. New York: John Wiley and Sons.

U.S. Department of Agriculture. 2006. "Agricultural Resource Management Survey, 2006." National Agricultural Statistics Service, U.S. Department of Agriculture, Washington, D.C. Available at http://www.ers.usda.gov/Briefing/ARMS/ (accessed December 10, 2008).

Weber, B., A. Marre, M. Fisher, R. Gibbs, and J. Cromartie. 2007. "Education's Effect on Poverty: The Role of Migration." *Review of Agricultural Economics* 29(3): 437–445.

Welch, F. 1970. "Education in Production." *Journal of Political Economy* 78(1): 35–59.

White, H. 1980. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48(4): 817–838.

Whitener, L., and T. Parker. 2007. "Policy Options for a Changing Rural America." *Amber Waves* 5 (May): 58–65.

Williams, R.L. 2000. "A Note on Robust Variance Estimation for Cluster-Correlated Data." *Biometrics* 56(2): 645–646.

Wilson, K. 2001. "The Determinants of Educational Attainment: Modeling and Estimating the Human Capital Model and Education Production Function." *Southern Economic Journal* 67(3): 518–551.

Wooldridge, J.M. 2002. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

Wozniak, G.D. 1984. "The Adoption of Interrelated Innovation: A Human Capital Approach." *Review of Economics and Statistics* 66(1): 70–79.