Can Education Be a Barrier to Technology Adoption?

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Abstract

The objective of this study is to test the widely-held belief that the effect of education has a positive impact on technology adoption. Using 2006 Agricultural Resource Management Survey (ARMS) data, we estimate a simultaneous equations model to integrate farmers' labor allocation decision with adoption of GM crops and precision farming. We confirm that the marginal effect of education on technology adoption is significantly larger for large farms for both GM crops and precision farming and it is unexpectedly negative for GM crops at all levels of farm size. These results suggest that formal education can be a barrier to technology adoption, especially for small scale farmers who have higher tendency to work off-farm.

Keywords: Education, Technology Adoption, Off-farm Labor Supply, Precision Farming, Genetically Modified Crops, Simultaneous Equations Model

JEL Classifications: Q10, Q12

I. Introduction

Adoption of technology is an extensively studied topic in agricultural economics. A plethora of empirical literature has identified a wide range of factors that influence technology adoption decisions by farmers. Among such factors, and being consistent with the human capital theory, education may be one of the most frequently used variables in empirical models. Research points out that education is positively correlated with technology adoption. In agriculture, farmers with higher education have better access to information and knowledge that are beneficial to farming operation. They also tend to possess higher analytic capability of the information and knowledge necessary to successfully implement new technology and realize expected results. Hence, higher education allows farmers to make efficient adoption decision (Rahm and Huffman, 1984) and early adopters who can take advantage of new technology are likely to extract maximum profit (Gardner and Rausser, 2001). Highly educated farmers also tend to adopt technology with greater intensity (Saha, et al., 1994).

The objective of this study, however, is to challenge this conventional brief. We believe that it is possible that education could potentially have a negative effect on technology adoption in agriculture. Take the case of education and labor supply, both on and off-farm. Education increases farmers' human capital and gives them more lucrative incentives for employment opportunities off the farm, which in turn decreases the managerial time on farm to implement new technologies and realize the expected results[1]. This is particularly true for management intensive technologies. This study empirically examines this theory.

[1] Results may vary with occupation of the farm operator and also the size of the farming operation.

Considering the facts that the number of farmers with college education has been increasing steadily over the last 50 years (Mishra, et al., 2009) and increasing share of farm household income is from off-farm sources (Fernandez-Cornejo, 2007), it is crucial to accurately assess the effect of education on technology adoption in the context of labor allocation between on and off the farm by farm households. In so doing, we estimate a simultaneous equations model that coalesce labor allocation and technology adoption models using 2006 Agricultural Resource Management Survey (ARMS) data. Technologies considered in this study are precision farming as a representative of management intensive technology and genetically modified (GM) crops as a representative of management saving technology. We estimate this model following the procedure suggested by Nelson and Olson (1978) to obtain asymptotically consistent estimates of parameters of our interest.

The rest of the paper is organized as follows. Section II reviews existing literature on the relationship between education, technology adoption and off-farm labor supply in agriculture. Section III provides analytical framework, followed by empirical results in Section IV. The final section offers concluding remarks.

II. Literature Review

In order to lay a comprehensive theoretical foundation about the net effect of education on technology adoption, we attempt to unite findings from three different topics in agricultural economics literature. We first review empirical findings about the effect of education on technology adoption, followed by the effect of education on off-farm labor supply. Finally, we shed light on recent studies that account for these two effects into a single model to explain simultaneous decision making process through which farmers allocate their time between off-farm and on-farm activities, including technology adoption.

1) **Education and Adoption**

In agriculture, human capital of farm operators can be represented by a number of different ways, with formal education and farming experiences being two of the most commonly adopted measures. Although farming experience can be a preferred measure in a static environment in which accumulated knowledge in farming operation or on-the-job training experiences do not depreciate or become obsolete, formal education is widely considered to be the most important form of human capital (Becker, 1994) in a dynamic political and economic environment where new technology and information are regularly developed (Gardner and Rausser, 2001). In such a more realistic setting, formal schooling will play a more prominent role than farming experience for farm operators to constantly update their knowledge and farming practices to stay competitive.

A number of empirical studies have shown the positive effect of education on adoption of various types of technology in agriculture. For example, education is found to have a positive impact on adoption of forward pricing methods (Goodwin and Schroeder, 1994), computer technology (Huffman and Mercier, 1991; Putler and Zilberman, 1988), use of the internet (Mishra and Park, 2005; Mishra, et al., 2009), reduced tillage (Rahm and Huffman, 1984), recombinant bovine somatotropin (rbST) (Klotz, et al., 1995), precision farming (Roberts, et al., 2004), genetically engineered corn (Fernandez-Cornejo, et al., 2001), soil nitrogen testing (Fuglie and Bosch, 1995), conservation practices (Traore, et al., 1998) and the level of participation in government-supported conservation programs

(Lambert, et al., 2007), to name a few.

On the other hand, there are also some empirical evidences of insignificant or even negative effect of education on technology adoption. Farmers' education has insignificant effect on adoption of variable rate technology (Khanna, 2001) and GPS guidance system for cotton farmers (Banerjee, et al., 2008). Nyaupane and Gillespie (2009) identified factors affecting adoption of best management practices (BMP) for Louisiana crawfish producers, but education was found to be insignificant for adoption of all but one BMP, where education was found to be negatively correlated with BMP adoption. There are studies that discovered mixed effects of education on different technologies; Soule, et al., (2000) found that education positively affected adoption of conservation tillage whereas it had no significant impact on adoption of medium term practices such as contour farming, strip cropping, and grassed waterway; Wozniak (1984) found a positive impact of education on adoption of cattle feeding technology but not such impact is found for implanting technology.

Gould et al. (1989) studied factors affecting adoption of conservation tillage for Wisconsin farmers. They unexpectedly found that education is negatively correlated with adoption, holding other factors (such as the proportion of off-farm work time to on-farm work time, among others) constant. This implies that highly educated farmers are less likely to adopt conservation tillage, given the same proportion of off and on farm work time. Because highly educated farmers are more likely to earn higher wages from off-farm work, they are expected to have a higher proportion of off-farm income to on-farm income given the same proportion of on and off farm work time. Therefore, it seems plausible if highly educated farmers, who are more reliant on off-farm income, have fewer incentives to spend time and effort on farming, including adoption of technology such as conservation tillage.

As these examples show, the effect of education on technology adoption in empirical literature has yet to reach a consensus consistent with the economic theory. Although the mixed empirical evidence might to some extent be explained by factors such as type of technology and diffusion process of the technology (Gardner and Rausser, 2001), relatively little attention has been paid to explore underlying reasons for such incoherent findings perhaps because the underlying theory seems intuitively too appealing to refute.

2) Education and Off Farm Labor Supply

One possible explanation for the inconsistent empirical results about the effect of education on technology adoption may be attributed to the relationship between education and off-farm labor. The recent trend of increasing off-farm labor supply by U.S. farm households can be attributed to (1) relative increase in non-farm sector real wage, (2) decrease in demand for farm labor and family labor (housework) due to development of labor saving technologies (Gardner and Rausser, 2001). Highly educated farmers have higher incentives to work more off the farm, ceteris paribus. As human capital accumulated through longer years of formal education becomes an advantage to find more off-farm employment opportunities, which makes farming relatively less attractive. Theoretically, however, the effect of education on off-farm labor supply is ambiguous; while higher education increases employment opportunities off the farm, farms with highly educated operator may realize higher productivity in farming operation and thus reservation wage to work off-farm for such operators may be high ((Hallberg, et al., 1991; Huffman and Lange, 1989)(Hallberg, et al., 1991, Huffman and Lange, 1989). The existing literature has mostly found that education is positively correlated with both off-farm labor participation and the intensity of off-farm work (Huffman, 1980; Huffman and Lange, 1989), indicating that the marginal effect of education on off-farm wage is higher than the marginal effect of education on the reservation wage. For instance, Goodwin and Mishra (2004) found a strong and positive effect of education on off-farm labor participation; an additional year of education leads an increase in off-farm labor supply by fifteen hours annually. Huffman (1980) estimated the effect of education on the odds ratio of off-farm work participation and the number of days worked off-farm by farm operators. The study found a positive and significant effect of education on both the odds ratio and the number of days working off-farm by operator.

From theoretical standpoint, there are two seemingly contradicting effects of education on technology adoption. On one hand, higher education leads to more technology adoption, but on the other hand, higher education increases off-farm labor supply, which inevitably affects on-farm labor supply available for technology adoption[2]. The mixed findings about the effect of education on technology adoption in empirical literature can perhaps be attributed to the fact that conventional technology adoption models do not fully account for the role of off-farm labor supply.

3) Technology Adoption and Labor Allocation

Although studies that have combined technology adoption and labor allocation into a single model had been largely nonexistent until recently, exceptions are Fernandez-

[2] Although it is theoretically possible that increased off-farm labor income provides farmers with financial flexibility to implement a new technology, Wozniak (1993) concluded that the negative impact of reallocation of operators' time away from farming on technology adoption seems to be more significant than the financial flexibility due to off-farm income.

Cornejo et. al. (2005) and Fernandez-Cornejo (2007). The former explored the simultaneous process through which operators and spouses allocate their time between on and off farm work and its relation to adoption of herbicide tolerant (HT) soybean as a representative of time saving technology. The study found a positive correlation between education and off-farm work for operators but not for spouses. Also, the impact of education on adoption of HT soybeans was not statistically significant. The study by Fernandez-Cornejo (2007) employed a model similar to Fernandez-Cornejo et. al. (2005) but it included adoption of yield monitors, which is required for precision agriculture, as a representative of management intensive technology. The study confirmed a negative correlation between adoption of yield monitor and off-farm income. However, they did not specify if education has a significant effect on adoption of yield monitor as it was not their primary interest.

In this study, we extend models developed by Fernandez-Cornejo (2007) and Fernandez-Cornejo et. al. (2005) to estimate the net effect of education on adoption of two different technologies: GM crops and precision farming. We do so by including in our model the interaction between farm size and education. The correlation between adoption, education and farm size is of particular interest because small farms are more likely to work off-farm (Fernandez-Cornejo, 2007) and less likely to adopt management intensive technology (Fernandez-Cornejo, et al., 2001; Saha, et al., 1994). Therefore, one can capture the net effect of education that varies across farm sizes. Further, in order to test the robustness of our findings we use two measures of farm size—namely value of agricultural sales and total acres operated.

III. Analytical Framework

1) General Representation of Simultaneous Equations Model

Following Judge et al., (1984), a system of simultaneous equations that consists of J equations (representing J endogenous variables) each with T observations can be generally expressed as follows:

$$Y\Gamma + X\mathrm{B} + E = \underline{0}, \quad (1)$$

where Y is a $T \times J$ matrix of observations on endogenous variables, Γ is a $J \times J$ matrix of unknown parameters for endogenous variables, X is a $T \times K$ matrix of observations on exogenous variables, B is a $K \times J$ matrix of unknown parameters for exogenous variables, E is a $T \times J$ matrix of error terms, and $\underline{0}$ is a $T \times J$ matrix all of whose elements are zero. For the purpose of exposition, we partition $Y = (\boldsymbol{y_1} \quad \cdots \quad \boldsymbol{y_J})$, $X = (\boldsymbol{x_1} \quad \cdots \quad \boldsymbol{x_K})$ and $E = (\boldsymbol{e_1} \quad \cdots \quad \boldsymbol{e_J})$ where $\boldsymbol{y_j}, \boldsymbol{x_k}$ and $\boldsymbol{e_j}$ represents jth and kth column of corresponding matrix. We also express elements of Γ and B in corresponding lower case letters. Then, equation (1) can be rewritten as follows:

$$(\boldsymbol{y_1} \quad \cdots \quad \boldsymbol{y_J}) \begin{pmatrix} \gamma_{11} & \cdots & \gamma_{1J} \\ \vdots & \ddots & \vdots \\ \gamma_{J1} & \cdots & \gamma_{JJ} \end{pmatrix} + (\boldsymbol{x_1} \quad \cdots \quad \boldsymbol{x_K}) \begin{pmatrix} \beta_{11} & \cdots & \beta_{1J} \\ \vdots & \ddots & \vdots \\ \beta_{1K} & \cdots & \beta_{JK} \end{pmatrix}$$

$$+(\boldsymbol{e_1} \quad \cdots \quad \boldsymbol{e_J}) = \underline{0} \quad (2)$$

Multiplying and summing up matrices on LHS of equation (2) yields a $T \times J$ matrix. We can rewrite equation (2) as

$$\begin{bmatrix} (\boldsymbol{y_1}\gamma_{11} + \cdots + \boldsymbol{y_J}\gamma_{J1}) \\ (\boldsymbol{y_1}\gamma_{12} + \cdots + \boldsymbol{y_J}\gamma_{J2}) \\ \vdots \\ (\boldsymbol{y_1}\gamma_{1J} + \cdots + \boldsymbol{y_J}\gamma_{JJ}) \end{bmatrix}^T + \begin{bmatrix} (\boldsymbol{x_1}\beta_{11} + \cdots + \boldsymbol{x_K}\beta_{1K}) \\ (\boldsymbol{x_1}\beta_{12} + \cdots + \boldsymbol{x_K}\beta_{2K}) \\ \vdots \\ (\boldsymbol{x_1}\beta_{1J} + \cdots + \boldsymbol{x_K}\beta_{JK}) \end{bmatrix}^T + (\boldsymbol{e_1} \quad \cdots \quad \boldsymbol{e_J}) = \underline{0}.$$

Further rearranging,

$$\begin{bmatrix} (\boldsymbol{y_1}\gamma_{11} + \cdots + \boldsymbol{y_J}\gamma_{J1}) + (\boldsymbol{x_1}\beta_{11} + \cdots + \boldsymbol{x_K}\beta_{1K}) + \boldsymbol{e_1} \\ (\boldsymbol{y_1}\gamma_{12} + \cdots + \boldsymbol{y_J}\gamma_{J2}) + (\boldsymbol{x_1}\beta_{12} + \cdots + \boldsymbol{x_K}\beta_{2K}) + \boldsymbol{e_2} \\ \vdots \\ (\boldsymbol{y_1}\gamma_{1J} + \cdots + \boldsymbol{y_J}\gamma_{JJ}) + (\boldsymbol{x_1}\beta_{1J} + \cdots + \boldsymbol{x_K}\beta_{JK}) + \boldsymbol{e_J} \end{bmatrix}^T = \underline{0}. \quad (3)$$

Each element in the matrix on LHS of equation (3) is a $T \times 1$ vector. For the purpose of normalization, we set $\gamma_{ii} = -1$ and solve jth element in the matrix for jth endogenous variable to obtain J equations

$$\boldsymbol{y_j} = \sum_{\substack{j=1 \\ j \neq j}}^{J} \boldsymbol{y_j}\gamma_{j1} + (\boldsymbol{x_1}\beta_{11} + \cdots + \boldsymbol{x_K}\beta_{1K}) + \boldsymbol{e_j}. \quad (4)$$

Estimating each equation in (4) by OLS or any appropriate form of limited dependent variable models yields biased and inconsistent estimates because of endogenous regressors. Also note that, in order for this system of equations to be identified, there must be at least as many number of excluded exogenous variables as right hand side endogenous variables in each equation (Kennedy, 2008).

In order to obtain consistent estimates for the system of equation, we post-multiply (1) by Γ^{-1}[3] and solve for Y

$$(Y\Gamma)\Gamma^{-1} + (X\mathrm{B})\Gamma^{-1} + E\Gamma^{-1} = \underline{0}$$

[3] We assume that Γ is invertible.

$$Y = -\mathrm{X}\mathrm{B}\Gamma^{-1} - E\Gamma^{-1}$$

$$Y = \mathrm{X}\Pi + V, \quad (5)$$

where $\Pi = -\mathrm{B}\Gamma^{-1}$ and $V = -E\Gamma^{-1}$. Equation (5) represents reduced form equations of simultaneous equations in (1). Estimating equation (5) by OLS or any appropriate form of limited dependent variable models yields unbiased estimates as endogenous regressors are no longer present. Replacing endogenous variables in the structural equations in (1) with predicted values from reduced form equations in (5) yields consistent estimates of unknown parameters Γ and B (Nelson and Olson, 1978).

2) Empirical Model

The purpose of this study is to build an empirically estimable system of simultaneous equations that incorporates farmers' labor allocation decisions into technology adoption model. The system we consider here consists of four equations: adoption of precision farming, adoption of GM crops, and off-farm labor supply by farm operators and spouses. Based on the general results above, we can express the technology adoption and labor allocation model as follows:

$$\mathrm{y}_1 = \alpha\, \mathrm{y}_3^* + \boldsymbol{\delta}'\mathbf{X_1} + \varepsilon_1 \quad (6)$$

$$\mathrm{y}_2 = \beta\, \mathrm{y}_3^* + \boldsymbol{\eta}'\mathbf{X_2} + \varepsilon_2 \quad (7)$$

$$\mathrm{y}_3^* = (\gamma_1 \quad \gamma_2)\begin{pmatrix}\mathrm{y}_1 \\ \mathrm{y}_2\end{pmatrix} + \boldsymbol{\theta}'\mathbf{X_3} + \varepsilon_3 \quad (8)$$

$$\mathrm{y}_4^* = (\gamma_1 \quad \gamma_2)\begin{pmatrix}\mathrm{y}_1 \\ \mathrm{y}_2\end{pmatrix} + \boldsymbol{\theta}'\mathbf{X_4} + \varepsilon_3 \quad (9)$$

$$y_3 = h(y_3^*) = \max(0, y_3^*) \qquad (10a)$$

$$y_4 = h(y_4^*) = \max(0, y_4^*) \qquad (10b)$$

, where y_1 is a dummy variable that takes 1 if the farm employs precision farming and 0 otherwise, y_2 is also a dummy variable that takes 1 if the farm adopts GM crops and 0 otherwise. y_3 and y_4 are off-farm working hours for ith farm operators and spouses with y_3^* and y_4^* being the latent variable of y_3 and y_4, respectively. α and β are unknown constants and $\gamma, \boldsymbol{\delta}, \boldsymbol{\eta}$ and $\boldsymbol{\theta}$ are vectors of unknown parameters to be estimated. $\mathbf{X_1}, \mathbf{X_2}, \mathbf{X_3}$ and $\mathbf{X_4}$ are vectors of exogenous variables. Note that equations (6), (7), (8) and (9) are equivalent to the set of structural equations solved for endogenous variables, represented by equation (4) and the system of these four equations satisfies identification condition mentioned earlier. The error terms, $\varepsilon_1, \varepsilon_2$ and ε_3 are assumed to be normally distributed with zero means but we assume that ε_1 and ε_2 are correlated with each other at ρ.

We first estimate the reduced form equations of (8) and (9) in which endogenous variables, y_1 and y_2, are absent. We employ Tobit model as the dependent variables, annual off-farm working hours by operators and spouses, are censored variables bounded from below at zero. Then, we obtain linear prediction of the latent variable, $\widehat{y_3^*}$ and $\widehat{y_4^*}$, which are used as instruments in the second stage estimation of adoption of GM crops and precision farming by bivariate probit model.

3) Interaction between Education and Farm Size

The primary interest of this study lies in estimating the effect on technology adoption of the interaction between education and farm size as an approximation of the tendency for farm operators and spouses to work off-farm. A common approach to incorporate an interaction of two variables into a regression model is to assume that the coefficient of one variable is dependent on the other variable. Following Ramanassan (2002), suppose we have a simple regression model given by

$$Y = \beta_0 + \beta_1 X + \varepsilon \quad (10)$$

and assume that β_1 is dependent on another variable, Z. That is,

$$\beta_1 = (\gamma_0 + \gamma_1 Z). \quad (11)$$

Substituting equation (11) into equation (10), we have

$$Y = \beta_0 + (\gamma_0 + \gamma_1 Z)X + \varepsilon$$

$$Y = \beta_0 + \gamma_0 X + \gamma_1 (XZ) + \varepsilon. \quad (12)$$

Equation (12) shows that Y is now dependent on X as well as a new regressor that is a product of the two variables of interest, X and Z.

However, following this method and creating a product of education and farm size would not allow us to fully capture the potential interaction between education and farm size. This is because we expect that the coefficient of the interaction term, equivalent to γ_1 in equation (12) in the above example, will not be a constant.

Therefore, instead of simply creating a product of the two variables, we employed the following steps to estimate the interaction between the two variables. First, as a measurement of farm size, we select gross cash farm income (***gcfi***). Next, we create dummy variables for each quintile of ***gcfi***. Then we multiply each of the five dummy variables with education to create five interaction variables each of which represents different levels of farm size in terms of farm income. We include four of the five dummy variables created, each representing first, second, fourth and fifth quintile of farm size, into the regression model and assume coefficient of each dummy variable is associated with education as in equation (11)[4].

For the lowest quintile interaction variable, for example, we expect the sign of coefficient to be smaller than those for higher quintile interactions. This is because, for smaller farms, more educated operators are likely to work more off-farm and thus adopt fewer technologies. For the highest quintile, on the other hand, we expect the sign of coefficient to be more elusive[5]. The point we wish to clarify here is that we expect the effects of interaction between farm size and education to be different for small farms with higher education and large farms with lower education. If this is the case, simply multiplying education and farm size does not capture such conflicting effects.

4) Data

This study employs 2006 Agricultural Resource Management Survey (ARMS) data. ARMS is conducted annually by the Economic Research Service and the National Agricultural Statistics Service. The ARMS, which has a complex stratified, multiframe design, is a national survey conducted annually by the Economic Research Service (ERS) and the National Agricultural Statistics Service (for more detail, see

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[4] We exclude interaction between 3rd quintile of gross cash farm income and education from the model to avoid the dummy variable trap. This excluded group will be the base group to be compared with other groups.

[5] Large farms are less likely to work off-farm and more likely to be focused on farm operation. This implies, for operators of large farms, that opportunity cost of farming is relatively unimportant for labor allocation decisions as farming tend to be the most attractive employment opportunity. At the same time, the degree to which large farm operators commit to farming may be even stronger for those operators with lower education as they will not have as many attractive off-farm employment opportunities as highly educated counterparts do.

http://www.ers.usda.gov/Briefing/ARMS/). Each observation in the ARMS represents a number of similar farms, the particular number being the survey expansion factor (or the inverse of the probability of the surveyed farm being selected for surveying), and is referred to henceforth as survey weight, or w_i ($i = 1, \ldots, n$, where n denotes sample size). To demonstrate, the size of the samples considered in the analysis was 4,674 which when properly expanded using survey weights yielded populations of farm operator households totaling 345,241. The ARMS collects data to measure the financial condition (farm income, expenses, assets, and debt) and operating characteristics of farm businesses, the cost of producing agricultural commodities, and the well-being of farm operator households. The 2006 ARMS also collected information on farm households; in addition to farm economic data, the survey contains detailed information on off-farm hours worked by spouses and farm operators, the amount of income received from off-farm work, net cash income from operating another farm/ranch, net cash income from operating another business, and net income from share renting.

The target population of the survey is operators associated with farm businesses representing agricultural production in the 48 contiguous states. A farm is defined as an establishment that sold or normally would have sold at least $1,000 of agricultural products during the year. Due to the nature of the study dairy farms are excluded from the sample. Farms can be organized as sole proprietorships, partnerships, family corporations, non-family corporations, or cooperatives. Data are collected from one operator per farm, the senior farm operator. A senior farm operator is the operator who makes the majority of the day-to-day management decisions. For the purpose of this study, operator households organized as nonfamily corporations or cooperatives and farms run by hired managers were excluded. Table 1 provides the complete list of variables used in this study, their definitions and descriptive statistics.

Finally, following Goodwin and Mishra (2004) we adopt a bootstrapping approach that consistently accounts for the stratification inherent in the survey design[6]. The ARMS database contains a population-weighting factor that indicates the number of farms in the population (i.e., all U.S. farms) represented by each individual observation. We utilize the weighting (population-weighting factor) factor in a probability weighted bootstrapping procedure. Specifically, the data (selecting N observations from the sample data) are sampled with replacement. The models are estimated using the pseudo sample of data. This process is repeated a large number of times and estimates of the parameters and their variances are given by sample means and variance of the replicated estimates. We utilize 2,000 replications in the application that follows.

IV. Results and Discussion

Maximum likelihood estimates of the first stage Tobit models of off-farm labor supply by operators and spouses are provided in Table 2. The results show that, for both operators and spouses, off-farm labor supply is positively correlated with education and age. Highly educated operators and spouses are more likely to work off-farm as suggested by past literature (Hallberg, et al., 1991; Huffman, 1980; Huffman and Lange, 1989). The effect of age on off-farm labor supply, however, is increasing at a decreasing rate, as the coefficients of age squared (*opage2* and *spage2*) are negative and significant. Unlike the

[6] Goodwin, Mishra and Ortalo-Magne (2003) point out that the jackknife procedure may suffer from some limitations and they propose bootstrapping procedure as an alternative.

concave relationship between age and off-farm labor supply, acreage (*acres*) and off-farm labor supply, for both operators and spouses, have a convex relationship; acreage has a negative impact on off-farm labor supply, but the positive and significant coefficients of squared acreage (*acres2/1000*) indicates that its impact on off-farm labor supply is decreasing at an increasing rate for both operators and spouses. Financial position of the farm household as represented by debt-to-asset ratio (*dta*) and farm net worth (*ntw*) are also correlated with farm household off-farm labor supply; higher debt to asset ratio is positively correlated with off-farm work by operators and higher net worth is negatively correlated with off-farm labor supply by both operators and spouses.

Farm tenure exhibits mixed results for operators and spouses. For operators, being a full owner is positively correlated with off-farm labor supply and being a tenant is negatively correlated with off-farm labor supply, relative to the base group of part owners who, on average, operate the largest farms and account for the largest share of farm sales in the United States (USDA, 1998). For spouses, on the other hand, being a full owner or a tenant relative to a part owner is negatively correlated with off-farm labor supply. Since part owners tend to operate larger farms, it may be the case that they have second and third operators (who are not the primary operator's spouse) who have higher comparative advantages in agricultural operation to spouses (who tend to have fewer farming experiences), thereby allowing spouses to work off-farm more than full owner or tenant counterparts.

The presence of children in family (***hh6***, ***hh7-13***, and ***hh14-17***) has no significant impact on operators' off-farm labor supply, whereas it has negative and significant impact on spouses, who are mostly female. The younger the children, the larger the negative impact on off-farm labor supply for spouses, however, presence of children between age 14 and 17, has no significant impact on spouses' off-farm labor supply. This is consistent with the views that the presence of young children requires more childcare (Fernandez-Cornejo, et al., 2005; Kimhi and Lee, 1996) and the need for childcare may have a bigger impact on off-farm labor supply by spouses rather than operators (Fernandez-Cornejo, 2007).

Geographical location of farms (***urban*** and ***metro***) also shows significant effect on off-farm labor supply. Operators whose farm is located in urban area are more likely to work off-farm compared to their counterparts. Contrary to a priori expectation, on the other hand, spouses whose farm is located in either urban or metro are less likely to work off-farm relative to the base group and the negative impact is even stronger for spouses in metro area. Government payments also have significant impact on off-farm labor supply by farm household. Direct and indirect payments both have negative impact on operators' off-farm labor supply, which is consistent with recent findings by El-Osta et al., (2008) and Dewbre and Mishra (2007).

For spouses, however, only direct payment has a negative impact on off-farm labor supply. Payments from Conservation Reserve Program (***crp***) exhibits a positive and significant impact on operators' off-farm labor supply, whereas payments from Working Land Conservation Programs (***wlcp***) has negative and significant impact on off-farm labor supply for spouses. These are consistent with a priori expectations that participation in long-term land retirement programs such as CRP frees up operators' time that would have otherwise been expended in farming while Working Land Conservation programs such as Environmental Quality Incentives Programs increases labor requirement on the farm as suggested by Lambert, et al., (2006).

Overall, results from Table 2 underlie the importance of including spouses in the analysis of off-farm labor supply by farm households (Goodwin and Mishra, 2004). The effects of tenure, presence of young children in the family, farm location and government payments are all found to be significant but signs of the coefficients may be different on off-farm labor supply by operators and spouses.

Next we estimate the second stage bivariate probit model of technology adoption for precision farming (PF) and GM crops using the predicted values of off-farm labor supply by operators and spouses (***ools_hat*** and ***sols_hat***)[7] obtained in the first stage as instruments. Parameter estimates and summary statistics are presented in Table 3, while Table 4 presents the marginal effects of explanatory variables on probability of adopting precision farming (PF) or GM crops[8]. The Wald test statistic suggests that the null hypothesis of no correlation between two error terms can be rejected at 1% significance level, which supports the use of bivariate probit model instead of two separate probit models.

In the case of precision farming (PF) adoption, the predicted value of operators' off-farm labor supply (***ools_hat***) has a marginally insignificant coefficient estimate (p-value of 0.13) while coefficient of ***sols_hat***, the predicted value of spouses' off-farm labor supply, is not significant. This is contrary to our expectation that adoption of management intensive technology like PF is negatively correlated with off-farm labor supply. This may be due to the relatively broad definition of precision farming in our data. The 2006 version of ARMS queried respondents on adopt any precision farming practices that reduce production costs.

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[7] Strictly speaking, ***ools_hat*** and ***sols_hat*** are the predicted value of *the latent variable of* off-farm labor supply by farm operators and spouses, repectively. However, we refer to them as "predicted value of off-farm labor supply" or simply "off-farm labor supply" to keep the notation simple and to avoid wordiness.

[8] GM crops included in the analysis presented in Table 3 and 4 are corn, soybeans and cottons. We have also conducted analysis using only GM corn and soybeans. See Table 5 for partial results.

Because precision farming can involve a wide range of technologies such as Global Positioning System (GPS), Geographical Information System (GIS) and yield monitors, to name a few, some farmers may leave a positive response when they practice relatively less management intensive technologies. We are not able to capture the potentially heterogeneous perceptions about PF by respondents in this study and this may have obscured the relationship between off-farm labor supply and adoption of PF.

On the other hand, the predicted value of operators' off-farm labor supply, ***ools_hat,*** is negatively correlated with adoption of GM crops and the predicted value of spouses' labor supply yields an insignificant coefficient estimate, which is also inconsistent with a priori expectation that adoption of management saving technology such as GM crops would increase off-farm labor supply. As unexpected as it may seem, it may not simply indicate that GM crops are not management saving. Adopting a relatively new technology such as GM crops may be a manifestation of commitment to farming business by itself, which could be why the adoption is found to be negatively correlated with operators' off-farm labor supply. Even if adoption of GM crops is management saving, operators' off-farm labor supply is least likely to increase in the family since operators are the primary decision-makers of farm operation with comparative advantage in farming and thus they would have the highest opportunity cost of working off the farm of all family members. If this is the case, adoption of GM crops may allow operators to focus more on farming resulting in shorter off-farm working hours while possibly increasing off-farm labor supply by other family members. However, our results do not confirm this argument as we obtained a positive but insignificant coefficient of off-farm labor supply by spouses.

Coefficients of interaction between operators' education and total acres are partially inconsistent with our expectation but they nonetheless provide interesting results. First of all, note that coefficient of education (***educ***) represents the effect of education on technology adoption (either precision farming or GM crops) for the base group farmers whose total operated acres belong to the third quintile (from 41st percentile to 60th percentile). For precision farming, ***educ*** is found to be positive and significant whereas it is negative and significant for GM crops. Coefficient estimates of interaction between operators' education and total acres (***oeduc*ac1*** ~ ***oeduc*ac5***) relative to the base group are negative and significant for farms with smaller acreages (***oeduc*ac1*** and ***oeduc*ac2***) and positive and significant for farms with larger acreages (***oeduc*ac4*** and ***oeduc*ac5***) for both precision farming and GM crops. Marginal effects estimates evaluated at means of explanatory variables shows that the absolute values of marginal effects become larger as the total acreage deviates away from the base group of the third quintile, again for both precision farming and GM Crops. In other words, the effect of education on technology adoption is dependent on farm size represented by total acres and the larger the total acres are, the stronger the effect of education on adoption of both precision farming and GM crops. For instance, the marginal effect of 0.0096 for the base group farmers (whose total acres belong to the third quintile) means that an additional year of education for farm operators increases probability of precision farming adoption by 0.96%. The corresponding probabilities become even larger for farms with larger acreage (***oeduc*ac4*** and ***oeduc*ac5***); probability of precision farming adoption in increased by 1.1% (=0.0096 + 0.0018) for farms with fourth quintile total operated acres and by 1.4% (=0.0096 + 0.0044) for farms with fifth quintile total operated acres. On the other hand, farms with smaller acreage has lower probabilities of adopting precision farming; the marginal effect of operators' education is 0.56% (=0.0096 - 0.0038) and 0.55% (=0.0096 - 0.0039) for farms with second and first quintile total operated acres, respectively. In summary, marginal effect of education on probability of precision farming adoption is positive for farms at all levels of farm size, but the effect is larger for farms with large total operated acres.

Although the increasing marginal effect of education according to total acres also holds true for GM crops, the notable difference from precision farming is that the marginal effects of operators' education on GM crops adoption are negative at all levels of total acres. An additional year of education decreases probability of GM crops adoption by 1.2% (=-0.0063 – 0.0057) for farms whose total acres classified into the first quintile, and analogous probabilities for farms with second through fifth quintiles are, respectively, -0.88%, -0.63%, -0.44%, and -0.28%.

It is surprising that education has a negative impact on technology adoption, however, several explanations could be for this unexpected results. First, precision farming is more human capital intensive whereas GM crops are considered a time-saving and convenient technology (Smith, 2002). Different labor and human capital requirements of the two technologies might have caused smaller marginal effects estimates of education on adoption of GM crops relative to precision farming. Second, and perhaps more importantly, the controversy over manipulation of gene structures in GM crops might have discouraged its adoption, especially for highly educated farmers, leading to negative marginal effects. Note that marginal effects of education on GM crops adoption are negative regardless of the size of farming operation, but they become less negative as the farm size increases. However, farmers' risk perceptions about GM crops are not observed in 2006 versions of

ARMS data and thus we are unable to verify such claim in this study.

In order to examine the robustness of our specification of farm size (proxy via total acres), we also estimated the same two stage models using interaction between education and gross cash farm income, following Mishra and Park (2005). We also estimated each model with another definition of GM crops that only includes corn and soybeans in addition to the original definition that includes corn, soybeans and cotton, which was reported in Table 3 and 4. Estimates of marginal effects of education for these four models are summarized in Table 5. The results are similar when we replace total operated acres by farm income and for alternate definitions of GM crops. The fact that all but two marginal effect estimates have significant coefficients and marginal effects in four different models validates inclusion of the interaction between education and farm size in our model. It also confirms our expectation that the effect of education on technology adoption do vary across farm sizes, holding off-farm labor supply by farm operators constant. As we expected, the effect of education is smaller for small farms for adoption of both precision farming and GM crops and, contrary to our expectation, it becomes negative for adoption of GM crops.

Now we turn back to results in Table 3 and 4 to interpret coefficients and marginal effects of other explanatory variables. For precision farming, operators' age (***opage***) has positive and age squared (***opage2***) has negative coefficients, as expected, but they are not significant for GM crops. Total operated acres in operation divided by 1,000 (***acres/1,000***) has no significant impact on adoption of precision farming but has a positive and significant impact on adoption of GM crops; an increase in total operated acres by 1,000 acres increases probability of GM crops adoption by 0.69%.

Household net worth and average interest rates charged on loans are two variables that represent financial status of farm households (***netw*** and ***interest***) and they are included only in precision farming equation on the assumption that precision farming is capital intensive while GM crops are not. While new worth is not found significant, interest rate has a positive impact on probability of precision farming adoption. This supports the above claim that adoption of precision farming is capital intensive and those who have higher probability of adopting it would be willing to take on loans with higher interest rates.

The degree of risk aversion[9] (***risk***), measured by ratio of crop insurance expenses to total variable costs, as proposed by Goodwin and Rejesus (2008), has positive and significant effect for both precision farming and GM crops. The positive coefficient of ***risk*** indicates that as risk aversion increases operators are more likely to adopt these technologies. This gives us another insight into the unexpected negative effect of operators' off-farm labor supply on adoption of GM crops. Because off-farm labor is often seen as a means to diversify income risk, farmers may perceive risk reducing technologies such as GM crops as a substitute of off-farm labor to manage risks, and thus having more of one leads to less of the other as it may have been the case in our estimation.

Estimates for ***fowner*** and ***ftenant*** represent effects of being a full owner or tenant relative to the effect of being in the excluded base group of part owners. Descriptive statistics in Table 1 shows that part owners and tenants explain 45% and 11% of the sample respectively and the rest of the 44% is represented by full-owners. Coefficients and

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[9] We use the share of crop insurance expense to total farm operating expenses as a measure of risk aversion-higher share of crop insurance expense imply risk aversion (Goodwin and Mishra, 2004; Goodwin and Rejesus, 2008).

marginal effects of ***fowner*** are negative while marginal effects of ***ftenants*** are not significant relative to the base group of part owners for both precision farming and GM crops. Although one might expect the degree of land ownership to be positively correlated with technology adoption, the results need to be interpreted with caution. Our results is consistent with the fact that it is part owners who operate the largest farms and account for the largest share of farm sales, followed by tenants in the U.S. agriculture (USDA, 1998); part owners and tenants may face higher profit opportunities and/or longer time horizon (and thus ***ftenants*** are not significant) when considering adoption of precision farming and GM crops than full-owners.

Another variables that was only included in precision farming equation is ***internet***, a dummy variable that takes a value of one if the household has an internet connection. It has a positive and significant impact on probability of adopting precision farming. Marginal effect estimate of 0.04 (Table 4) indicates that having an internet connection increases probability of adopting precision farming by 4%, which is a very significant effect considering the fact that an additional year of education increases the probability of adoption by only 1.4% at most. It appears that knowledge and experiences in computer and the internet important factor for precision farming adoption and this is evidence that precision farming is a human capital intensive technology.

Government payment is also found to be positively correlated with adoption of both technologies. A possible explanation of this finding is that farm program payments may provide farmers with additional source of income that can be used to purchase newer technologies and adopt newer practices (Caswell, et al., 2001; Lambert, et al., 2006; Lambert, et al., 2007). Results indicate that farmers who receive any type of government payments are 2.3% more likely to adopt precision farming and 17% more likely to adopt GM crops. The higher marginal effect of government payments on GM crops can be attributed to the fact that farm program payments are tied to production of corn, soybean, cotton and other cash grain crops.

Literature indicates that technology adoption is affected by regional location of the farm (Mishra, et al., 2009). Parameter estimated in Table 3 and marginal effects in Table 4 show that most of the coefficients of regional dummy variables were statistically significant for GM crops but only four of them are significant for precision farming. Note that the Mississippi Portal region serves as a base group and thus it is excluded from the model. For precision farming, farmers in Heartland, Northern Crescent, Southern Sea Board and Fruitful Rim regions have higher probability of adoption relative to farmers in the Mississippi Portal region. For GM crops, farmers in all but the Heartland region have a lower probability of adoption relative to the base group, although the effect of Fruitful Rim region is not significant. Higher probability of GM crop adoption in the Heartland region where crop production is active is also expected as found by (Fernandez-Cornejo, et al., 2005).

V. Conclusions

While the economic theory suggests that education has a positive influence on technology adoption for farmers, existing studies on technology adoption have yielded mixed results. We hypothesize that this is because conventional technology adoption models do not account for the potentially negative effect of education on technology adoption through labor allocation between on and off the farm.

The purpose of this study is to fill the gap between the economic theory and empirical findings in agricultural economics. We built a simultaneous equations model that coalesce labor allocation and technology adoption decisions following Fernandez-Cornejo et al. (2005) and Fernandez-Cornejo (2007) and included interactions between education and farm size to estimate the net effect of education. The results confirm our expectation that the marginal effect of education on technology adoption is significantly higher for large farms. Contrary to a priori expectation, however, the marginal effects of education on GM crops adoption are found to be negative at all levels of farm size. These results suggest that formal education can be a barrier to technology adoption, especially for small scale farmers who have higher tendency to work off-farm.

Given the increasing federal spending on agri-environmental programs that encourages farmers to adopt environmentally benign practices over the last two decades, a precise assessment of the effect of education on technology adoption is of great importance for policy makers. Our findings suggest that simply targeting highly educated farmer to adopt new farming practices on the basis of the conventional theory is not sufficient to achieve an efficient outcome. This is primarily because highly educated operators who have small operations are usually more dependent on off-farm income and thus their opportunity cost of farming is higher than that for relatively less educated counterparts.

Finally, some limitations this study has encountered have to be noted. First, the definition of precision farming in our data is more broadly defined than previous studies such as Banerjee, et al. (2008) and Roberts, et al. (2004). This may have obscured the relationship between off-farm labor supply and adoption of precision farming. Second, our results showed that the marginal effect of education on adoption of GM crops were negative regardless of farm size. As mentioned earlier, this unexpected result could be attributed to the controversy over the genetically modified crops, especially for highly educated farmers who would be more aware of the latest discussion and findings about the risk and safety of GM crops. Third, we have employed Nelson and Olson's procedure to estimate a simultaneous equations model with endogenous limited dependent variables. The simplicity of this procedure is a tremendous advantage for practitioners. Although this procedure allows us to obtain consistent estimates of unknown parameters, there exists an asymptotically efficient, but relatively more complicated, estimator suggested by Amemiya (1979). Future researches will address these limitations to build on our early attempt to estimate the true effect of education on technology adoption in the context of labor allocation between on and off the farm.

VI References

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Table 1: Variable Definitions and Descriptive Statistics

Variables	Definitions	Mean	Std. Dev
op_educ	operator's years of education	13.50	1.91
opage	operator's age	55.96	12.14
opage2	operator's age squared	3279	1380
sp_educ	spouse's years of education	13.68	1.86
spage	spoues's age	53.33	12.00
spage2	spouse's age squared	2988	1302
acres	total number of operated acres	1396	5864
acres2	total number of operated acres squared	36328871	8060777
dta	debt to asset ratio	0.19	2.20
netw	household net worth	2011206	7709863
interest	Average interest rates charged on farm loans	1.28	1.80
risk	share of crop insurance premiums in total variable cost	0.01	0.03
fowner	= 1 if operator is full owner	0.45	0.50
powner	= 1 if operator is part owner	0.44	0.50
ftenant	= 1 if operator is a tenant	0.11	0.31
hh5	number of household members younger than 6 years old	0.15	0.49
hh6_13	number of household members between 6 and 13 years old	0.28	0.66
hh14_17	number of household members between 14 and 17 years old	0.24	0.55
internet	= 1 if household has an internet connection	0.74	0.44
urban	= 1 if farm is located in urban county	0.46	0.50
metro	= 1 if farm is located in metro county	0.41	0.49
direct	direct payments received in dollar	14238	43812
indirect	indirect payments received in dollar	1258	11054
crp	CRP payments received in dollar	1.02	7.82
wlcp	WLCP payments received in dollar	0.80	7.46
govpay	= 1 if farm receives any government payments	0.52	0.50
HEART	= 1 if farm located in the Heartland region	0.12	0.33
NORTHC	= 1 if farm located in the Northern Crescent region	0.11	0.31
NORTHGP	= 1 if farm located in the Northern Great Plains region	0.05	0.23
PGATE	= 1 if farm located in Prairie Gateway region	0.12	0.32
EUPLAND	= 1 if farm located in Eastern Upland region	0.10	0.30
SSBOARD	= 1 if farm located in Southern Sea Board region	0.16	0.37
FRIM	= 1 if farm located in Fruitful Rim region	0.20	0.40
BASINR	= 1 if farm located in Basin and Range region	0.06	0.24
MPORTAL	= 1 if farm located in Mississippi Portal region	0.07	0.26

Observations =4676 Source: Agricultural Resource Management Survey, 2006

Table 2: First State Tobit Estimates of Off-Farm Labor Supply by Operators and Spouses

Operator			Spouses		
Variables	Coefficient	P-value	Variables	Coefficient	P-value
constant	-103.0257	0.000	constant	-88.40325	0.000
op_educ	2.082749	0.000	sp_educ	4.388557	0.000
opage	3.730851	0.000	spage	3.178093	0.000
opage2	-0.043907	0.000	spage2	-0.0428509	0.000
acres	-0.0007988	0.010	acres	-0.000806	0.000
acres2/1000	0.0000075	0.000	acres2/1000	0.0000033	0.042
dta	0.5896203	0.025	dta	0.0029975	0.989
netw	-0.000004	0.000	netw	-0.000006	0.000
fowner	8.647161	0.000	fowner	-2.242776	0.059
ftenant	-10.31768	0.000	ftenant	-2.465392	0.171
hh6	1.141448	0.480	hh6	-7.730682	0.000
hh7_13	-1.810035	0.118	hh7_13	-4.727877	0.000
hh14_17	0.1782719	0.891	hh14_17	-1.334393	0.169
urban	5.589422	0.015	urban	-2.777317	0.092
metro	3.491241	0.139	metro	-6.129276	0.000
direct	-0.0002973	0.000	direct	-0.0000714	0.000
indirect	-0.000634	0.000	indirect	0.0000361	0.460
crp	0.4317853	0.000	crp	0.025968	0.789
wlcp	-0.1941671	0.170	wlcp	-0.1744061	0.058
Observations		4715	Observations		4676
Log-Likelihood		-10010.733	Log-Likelihood		-12622.118
LR(chi18)		906.76	LR(chi18)		1132.66
Prob>chi		0.00	Prob>chi		0.00

Table 3: Parameter Estimates from Bivaraite Probit Model

Variable	Precision Farming Coefficient	Precision Farming P-value	GM Crops Coefficient	GM Crops P-value
ools_hat	-0.0021	0.134	-0.0039	0.006
sols_hat	-0.0023	0.322	0.0017	0.458
opage	0.0547	0.003	-0.0013	0.942
opage2	-0.0005	0.003	-0.0001	0.669
op_educ	0.0548	0.000	-0.0446	0.005
oeduc_ac1	-0.0221	0.002	-0.0398	0.000
oeduc_ac2	-0.0213	0.002	-0.0179	0.012
oeduc_ac4	0.0105	0.063	0.0135	0.018
oeduc_ac5	0.0249	0.000	0.0244	0.001
acres	-0.000005	0.330	-0.00005	0.001
netw	-0.000000004	0.547	Not Included	
interest	0.0719	0.000	Not Included	
risk	2.4983	0.002	2.9186	0.002
fowner	-0.1794	0.008	-0.5295	0.000
ftenant	0.1010	0.203	-0.0155	0.842
internet	0.2697	0.000	Not Included	
govpay	0.1330	0.037	1.1874	0.000
heart	0.2187	0.070	0.2722	0.005
northc	0.4482	0.000	-0.1335	0.209
northgp	-0.1030	0.474	-1.2145	0.000
pgate	0.0695	0.574	-0.8054	0.000
eupland	0.1390	0.305	-0.8828	0.000
ssboard	0.2599	0.029	-0.4627	0.000
frim	0.4692	0.000	-1.4238	0.000
basinr	0.1887	0.190	-1.4372	0.000
_cons	-3.8685	0.000	-0.2357	0.645

Log pseudolikelihood =-3040.0852	**Wald Test of ρ = 0**
Wald chi2(47) = 1347.38	**chi2(1) = 14.0663**
Prob > chi2 = 0.0000	**Prob > chi2 = 0.0000**

Table 4: Marginal Effects on Probability of Adoption

	Precision Farming		GM Crops		
variable	dy/dx	P>z	dy/dx	P>z	Mean
ools_hat	-0.0004	0.135	-0.0006	0.007	-16.06
sols_hat	-0.0004	0.322	0.0002	0.459	2.13
opage	0.0096	0.003	-0.0002	0.942	56.01
opage2	-0.0001	0.003	0.0000	0.669	3285.87
op_educ	0.0096	0.000	-0.0063	0.006	13.57
oeduc*ac1	-0.0039	0.002	-0.0057	0.000	2.75
oeduc*ac2	-0.0038	0.002	-0.0025	0.012	2.61
oeduc*ac4	0.0018	0.063	0.0019	0.019	2.77
oeduc*ac5	0.0044	0.000	0.0035	0.001	2.81
acres	0.0000	0.330	0.0000	0.001	1378.98
netw	0.0000	0.603	Not Included		1700000
interest	0.0126	0.000	Not Included		1.31731
risk	0.4396	0.002	0.4147	0.003	0.01
fowner*	-0.0312	0.007	-0.0732	0.000	0.45
ftenant*	0.0187	0.225	-0.0022	0.841	0.11
internet*	0.0435	0.000	Not Included		0.751872
govpay*	0.0233	0.036	0.1705	0.000	0.53
heart*	0.0426	0.099	0.0446	0.014	0.13
northc*	0.0971	0.003	-0.0176	0.178	0.11
northgp*	-0.0171	0.447	-0.0806	0.000	0.06
pgate*	0.0126	0.586	-0.0741	0.000	0.12
eupland*	0.0262	0.337	-0.0764	0.000	0.10
ssboard*	0.0510	0.048	-0.0526	0.000	0.16
frim*	0.0991	0.001	-0.1147	0.000	0.18
basinr*	0.0368	0.233	-0.0857	0.000	0.06

*** dy/dx is for discrete change of dummy variable from 0 to 1**

Table 5: Marginal Effects of Interaction between Education and Farm Size

Version 1: Interaction between Educatin and Farm Income

	Version 1a: GM Corn and Soybeans				Version 1a: GM Corn, Soybeans and Cotton			
	Precision Farming		GM Crops		Precision Farming		GM Crops	
Variable	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value
oeduc*fi1	-0.007	0.000	-0.004	0.001	-0.007	0.000	-0.004	0.001
oeduc*fi2	-0.003	0.005	-0.001	0.187	-0.003	0.005	-0.001	0.180
op_educ	0.005	0.039	-0.006	0.005	0.005	0.043	-0.006	0.018
oeduc*fi4	0.005	0.000	0.002	0.034	0.005	0.000	0.002	0.004
oeduc*fi5	0.008	0.000	0.000	0.727	0.008	0.000	0.002	0.053

Version 2: Interaction between Educatin and Total Acres

	Version 2a: GM Corn and Soybeans				Version 2b: GM Corn, Soybeans and Cotton			
	Precision Farming		GM Crops		Precision Farming		GM Crops	
Variable	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value
oeduc*ac1	-0.004	0.00	-0.005	0.00	-0.004	0.002	-0.006	0.000
oeduc*ac2	-0.004	0.00	-0.003	0.01	-0.004	0.002	-0.003	0.012
op_educ	0.010	0.00	-0.007	0.00	0.010	0.000	-0.006	0.006
oeduc*ac4	0.002	0.06	0.001	0.09	0.002	0.063	0.002	0.019
oeduc*ac5	0.004	0.00	0.002	0.02	0.004	0.000	0.003	0.001