Net Effect of Education on Technology Adoption by U.S. Farmers

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Abstract

The objective of this study is to estimate the net effect of education on technology adoption for U.S. farmers. Using 2006 Agricultural Resource Management Survey data, this study develops a simultaneous equations model to integrate farmers' labor allocation decision with adoption of both time saving and management intensive technologies.

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

JEL Classifications: Q10, Q12

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I. Introduction

Adoption of technology is an extensively studied topic in agricultural economics. A large volume of empirical literature has identified a wide range of factors that influence technology adoption decisions by farmers. Among such factors, education may be one of the most frequently used variables in empirical models perhaps because it also is one of the most theoretically uncontroversial factors to positively influence technology adoption. In general, 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 be the early adopters who can take advantage of new technology and profit most from it (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 theoretically possible that education could potentially have a negative effect on technology adoption in agriculture. Education increases farmers' human capital and gives them more lucrative employment opportunities off the farm, which in turn decreases the managerial time on farm to implement new technologies and realize the expected results. This is particularly true for management intensive technologies. This study empirically examines this theory.

Considering the facts that the number of farmers with college education has been steadily increasing 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 net 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 offer 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 in a single model to explain simultaneous decision making process through which farmers allocate their time between off-farm and on-farm labor, including technology adoption.

1) Education and Adoption

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), 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.

At the same time, there are also some empirical studies that found 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, with which education found to be negatively correlated.

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 constant of other factors such as the proportion of off-farm work time to on-farm work time, among others. 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 sensible if highly educated farmers, who are more reliant on off-farm income, have fewer incentives to spend time and effort for 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 consensus consistent with the economic theory. Nonetheless, little attention has been paid to explore the 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. Highly educated farmers are expected to work more off the farm, ceteris paribus, as human capital accumulated through longer years of formal education becomes an advantage to find more lucrative 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 more attractive 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). 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 annual off-farm labor supply by fifteen hours. 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. 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 these two seemingly distinctive topics into a single model had been largely nonexistent until recently, exceptions are Fernandez-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 technology: herbicide tolerant (HT) 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.

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:

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

, 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 $= (\boldsymbol{y_1} \quad \cdots \quad \boldsymbol{y_J})$, $X = (\boldsymbol{x_1} \quad \cdots \quad \boldsymbol{x_K})$ 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, (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 (2) yields a $T \times J$ matrix. We can rewrite (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 (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

$$\boldsymbol{y_j} = \sum_{\substack{j=1 \\ j \neq j}}^{J} \boldsymbol{y_j} \gamma_{j1} + (\boldsymbol{x_1} \beta_{11} + \cdots + \boldsymbol{x_K} \beta_{1K}) + \boldsymbol{e_1}. \quad (4)$$

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}[1] and solve for Y

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

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

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

, where $\Pi = -\mathrm{B}\Gamma^{-1}$ and $V = -E\Gamma^{-1}$. (5) represents reduced form equations of simultaneous equations in (1). Estimating (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

[1] We assume that Γ is invertible.

predicted values from reduced form equations in (5) also yields consistent estimates of unknown parameters Γ and Β (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 three equations: adoption of precision farming, adoption of GM crops and allocation of labor between on and off the farm. Based on the general results above, we can express the technology adoption and labor allocation model as follows:

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

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

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

$$\mathrm{y}_3 = \mathrm{h}(\mathrm{y}_3^*) = \max(0, \mathrm{y}_3^*) \quad (9)$$

, 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 is off-farm working hours for ith farm operators and y_3^* is the latent variable of y_3. α and β are unknown constants and γ, $\boldsymbol{\delta}$, $\boldsymbol{\eta}$ and $\boldsymbol{\theta}$ are vectors of unknown parameters to be estimated. $\mathbf{X_1}$, $\mathbf{X_2}$ and $\mathbf{X_3}$ are vectors of exogenous variables. Note that (6), (7) and (8) are equivalent to the set of structural equations solved for endogenous variables, represented by (4) and the system of these three 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 equation of (8) in which endogenous variables, y_1 and y_2, are absent. We employ Tobit model as the dependent variable, annual off-farm working hours by operators, is a censored variable bounded from below at zero. Then, we obtain linear prediction of the latent variable, $\widehat{y_3^*}$, which is used as an instrument 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 sizes. 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 (11) into (10), we have

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

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

(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 (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 quartile of ***gcfi***. Then we multiply each of the four dummy variables with education to create four interaction variables each of which represents different levels of farm size in terms of farm income. We include three dummy variables, each representing second, third and fourth quartile of farm size, into the regression model and assume coefficient of each dummy variable is associated with education as in (11)[2].

For the lowest quartile interaction variable, for example, we expect the sign of coefficient to be smaller than those for higher quartile 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 quartile, on the other hand, we expect the sign of coefficient to be more elusive[3]. The point we wish to clarify here is that we expect the

[2] We exclude interaction between 1st quartile of total acres and education from the model to avoid multicollinearity. This excluded group will be the base group to be compared with other groups.

[3] 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

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 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 6,457 which when properly expanded using survey weights yielded populations of farm operator households totaling 387,651. 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

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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.

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. 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[4]. 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

[4] 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.

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 estimate of the first stage Tobit model of off-farm working hours is provided in Table 2. The results show that farm operators' off-farm labor supply is positively correlated with education, age, and whether the operator is a part owner (***powner***). These findings are consistent with the human capital theory and empirical findings in the literature. The effect of age on off-farm labor supply, however, is increasing at decreasing rate, as the coefficient of age squared is negative and significant. The negative coefficient on ***dairy*** indicates that operators from farms specializing in dairy are less likely to work off-farm due to the high labor requirement for dairy operation (Fernandez-Cornejo (2007) and Hallberg, et al., (1991)). The number of household members between 7 and 13 years old is also found to have a negative effect on operators' off-farm labor supply. Although this is consistent with the view that the presence of young children requires more childcare (Fernandez-Cornejo, et al., 2005, Kimhi and Lee, 1996), the need for childcare may have a bigger impact on off-farm labor supply by spouses rather than operators (Fernandez-Cornejo, 2007). The negative coefficient on ***farmin*** is consistent with the expectation that a farm operator who report farming as their main occupation is less likely to work off-farm. Direct and indirect farm program payments are also negatively correlated with hours of off-farm labor participation, which is consistent with recent findings by El-Osta et al., (2008) and Dewbre and Mishra (2007).

Next we estimate second stage bivariate probit model of technology adoption (precision farming and GM crops) using the predicted value of off-farm working hours, ***ph_offop***, as an instrument to off work by farm operators. 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 or GM crops. 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.

The predicted value of operator's off-farm labor supply is not significantly correlated with adoption of precision farming, contrary to our expectation that adoption of management intensive technology like precision farming reduces off-farm labor supply. This may be due to the relatively broad definition of precision farming in our data. The 2006 version of ARMS asks respondents if they adopt any precision farming practices to reduce production costs. 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 precision farming by respondents in this study and this may have obscured the relationship between off-farm labor supply and adoption of precision farming.

On the other hand, the predicted value of operator's off-farm labor supply, ***ph_offop,*** is negatively correlated with adoption of GM crops, which is also inconsistent with a priori expectation that adoption of management saving technology such as GM crops would increase off-farm labor supply. Although this result seems contradictory, it may not simply indicate that GM crops are not management saving. It can perhaps be attributed to the fact that our model does not take into account off-farm labor supply by family members. Even if adoption of GM crops is indeed 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 have the highest opportunity cost of working off the farm of all family members[5]. If this is the case, adoption of GM crops may increase off-farm labor supply by other family members, allowing the operator to focus more on farming resulting in shorter off-farm working hours.

Coefficients of education and interaction between education and farm size are partially inconsistent with our expectation but they nonetheless provide interesting results. First, for adoption of precision farming, coefficient of education (***educ***) is found to be insignificant in explaining adoption of precision farming (table 3). Note that this coefficient represents the effect of education on adoption of precision farming for farms whose gross cash farm income belongs to the first quartile (benchmark group). This means that, for small farms whose income is lower than the 25th percentile, education has no significant effect on adoption of precision farming. Coefficients of three interaction terms (***educ_q2, educ_q3, educ_q4***) are all positive and significant and the coefficients increase with farm size (gross cash income). In other words, holding constant of off-farm working hours by farm operator, education has no effect on adoption of precision farming for small farms, but, for larger farms, the effect becomes positive and large. Marginal effects estimates in Table 4 shows that, for farms in the second, third and fourth quartile income, an additional year

[5] Joint estimation of off-farm labor supply by operators and family members is an important empirical question as suggested by Goodwin and Mishra (2004). However, the primary focus of this study is to estimate the net effect of education on technology adoption and it is beyond the scope of this study to address such an issue.

of education has 0.5%, 0.9% and 1.2% higher probability of adopting precision farming in comparison to the farmers in the first income quartile.

The effect of education on adoption of GM crops is similar but different in one important aspect. For farm operators in the first income quartile, the effect of education is unexpectedly negative and significant. The marginal effect in Table 4 shows that an additional year of education leads to a 1% decrease in probability of GM crop adoption. For farms whose gross cash income falls in the second, third and fourth quartile, an additional year of operator's education increase probability of adopting GM crops increases by 0.5%, 0.95% and 1%, respectively, compared to the farmers in the first income quartile. This indicates that, after controlling for off-farm labor supply, education has almost no effect on probability of adopting GM crops for farms whose income is above 75th percentile and the probability becomes negative for smaller farms.

In order to examine the robustness of our specification of farm size (proxy via gross cash farm income), we estimated the same two stage models using interaction between education and total operated acres instead of gross cash farm income, following Mishra and Park (2005). Parameter estimates and marginal effects of education for two models are summarized in Table 5. The results are similar when we replace farm income by total operated acres except that the effect of education on precision farming adoption becomes positive and significant for the first quartile income farms. The fact that all but one interaction terms have significant coefficients and marginal effects in two different specifications of farm size 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 varies 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.

For both precision farming and GM crops, age has positive and age squared has negative coefficients, as expected. For precision farming, the effect of age continues to be positive until 50 years old and it becomes negative afterward. The turning point for GM crops occurs approximately 10 years earlier at 39 years. Total operated acres in operation has no significant impact on adoption of precision farming but has a negative and significant impact on adoption of GM crops.

The degree of risk aversion[6] (***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 effect is more prominent for GM crops, which suggests that GM crops can be seen as a risk reducing tool. This gives us another insight into the unexpected negative effect of 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.

It is not surprising that farm specializing in dairy operations is less likely to adopt precision farming and GM crops. Farmers with dairy operation are 4.7% less likely to

[6] 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).

adopt precision farming and 6.7% less likely to adopt GM crops. On one hand, this is consistent with a priori expectation that dairy farming is so labor intensive that dairy farmers are less likely to adopt management intensive technology such as precision farming, but on the other hand, the negative effect of dairy operation is unexpectedly larger for GM crops which we assumed as management saving.

Estimates for ***powner*** and ***tenants*** represents effects of respective variables relative to the effect of the excluded base group of full-owners who own all of the land they operate. 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 marginal effects of ***powner*** and ***tenants*** are all positive and significant 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 when considering adoption of precision farming and GM crops than full-owners.

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 4% more likely to adopt precision farming and 25% 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. Note that the Mississippi Portal region serves as a base group and thus it is excluded from the model. For precision farming, farmers in all of the eight production regions have higher probability of adoption relative to farmers in the Mississippi Portal region except that the effect is not significant for the Northern Great Plains region. For GM crops, farmers in all but the Heartland region have a lower probability of adoption relative to the base group and coefficient estimates are all significant at 1%. 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 net effect of education on technology adoption varies across farm sizes and it can be negative for small farms.

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 net 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.

Finally, some limitations this study has encountered have to be noted. First, our model did not yield expected results on adoption of GM crops. Although this was not our primary objective, it would be necessary to expand our model to incorporate labor supply of family members and address the risk reducing aspect of GM crops to obtain more accurate estimates of the relationship between GM crops and off-farm labor supply. Second, 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. 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 first attempt to estimate the net effect of education on technology adoption.

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Table 1: Variable Definitions and Descriptive Statistics

Variables	Definitions	Mean	Std. Dev
pfarm	= 1 if farm adopts any precision farming technologies	0.13	0.33
gm	= 1 if farm adopts genetically modified (GM) crops	0.25	0.44
offwork	annual hours worked off-farm by operator	46.23	75.59
educ	operator's years of education	13.45	1.91
age	operator's age	55.76	12.54
agesq	operator's age squared	3266.84	1425.88
acres	total number of acres	1276.53	5264.86
gcfi	gross farm cash income	619716.30	1676277.00
dairy	= 1 if farm has dairy operation	0.09	0.29
risk	share of crop insurance premiums in total variable cost	0.01	0.03
tenant	= 1 if operator is tenant	0.11	0.31
powner	= 1 if operator is part owner	0.45	0.50
adarat2	debt to asset ratio	0.18	1.95
farmin	= 1 if farming is the primary occupation of the farm operator	0.73	0.44
hhnw	household net worth	202.41	659.00
hh_size6	number of household members younger than 6 years old	0.13	0.47
hh_size13	number of household members between 7 and 13 years old	0.48	0.95
metro	1 if farm is located in county classified as metro area	0.34	0.47
direct	direct payments received in dollar	12902.82	39801.16
indirect	indirect payments received in dollar	2434.23	11273.81
disaster	disaster payments received in dollar	757.80	9109.48
govtpmt	= 1 if farm receives any government payments	0.55	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	0.15	0.36
northgp	= 1 if farm located in the Northern Great Plains region	0.05	0.22
pgate	= 1 if farm located in Prairie Gateway region	0.11	0.31
eupland	= 1 if farm located in Eastern Upland region	0.10	0.30
ssboard	= 1 if farm located in Southern Sea Board region	0.15	0.35
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
educ_q1	interaction between educ and first quartile of farm income	3.32	5.84
educ_q2	interaction between educ and first second of farm income	3.31	5.82
educ_q3	interaction between educ and first third of farm income	3.37	5.91
educ_q4	interaction between educ and first fourth of farm income	3.44	6.03
educ_a_q1	interaction between educ and first quartile of total acres	3.33	5.86
educ_a_q2	interaction between educ and first second of total acres	3.30	5.79
educ_a_q3	interaction between educ and first third of total acres	3.35	5.87
educ_a_q4	interaction between educ and first fourth of total acres	3.47	6.07

Observations = 6457 Source: Agricultural Resource Management Survey, 2006

Table 2: First Stage Tobit Estimates of Off-Farm Working Hours

Variables	Coefficient	Robust Std. Err.	P-value
constant	-93.53	36.04	0.01
educ	3.12	0.99	0.002
age	10.24	1.28	0.00
agesq	-0.12	0.01	0.00
acres	0.00	0.00	0.42
dairy	-56.87	10.21	0.00
tenant	0.54	6.47	0.93
powner	12.54	4.09	0.00
risk	53.53	53.82	0.32
farmin	-213.24	3.72	0.00
hhnw	-0.02	0.01	0.02
hh_size13	-5.75	1.95	0.00
hh_size6	-2.72	3.87	0.48
metro	-2.03	3.92	0.61
direct	0.00	0.00	0.00
indirect	0.00	0.00	0.02
dispayment	0.00	0.00	0.89
Observations = 6457			Pseudo R^2 = 0.1125
Log pseudolikelihood = -14346.627			F(16, 6441) = 343.53
			Prob > F = 0.000

Table 3: Parameter Estimates from Bivaraite Probit Model

	Adoption of Precision Farming			Adoption of GM Crops		
Variable	**Coefficient**	**Std. Err.**	**p-value**	**Coefficient**	**Std. Err.**	**p-value**
constant	-3.44	0.41	0.00	-1.33	0.47	0.00
ph_offop	-0.0008	0.0008	0.30	-0.0082	0.0028	0.00
educ	0.01	0.01	0.53	-0.05	0.02	0.00
educ_q2	0.03	0.01	0.00	0.03	0.01	0.00
educ_q3	0.06	0.01	0.00	0.05	0.01	0.00
educ_q4	0.08	0.01	0.00	0.05	0.01	0.00
age	0.04	0.02	0.02	0.07	0.03	0.03
agesq	-0.0004	0.0001	0.01	-0.0009	0.0004	0.01
acres	-0.000003	0.000003	0.33	-0.00004	0.00001	0.00
farmin	0.08	0.18	0.67	-1.74	0.61	0.00
risk	2.54	0.72	0.00	6.41	1.18	0.00
adarat2	0.00	0.01	0.77	-0.01	0.01	0.34
dairy	-0.36	0.09	0.00	-0.40	0.19	0.04
tenant	0.28	0.07	0.00	0.53	0.08	0.00
powner	0.24	0.05	0.00	0.64	0.06	0.00
govtpmt	0.25	0.05	0.00	1.29	0.07	0.00
heart	0.24	0.11	0.03	0.24	0.09	0.01
northc	0.47	0.11	0.00	-0.18	0.09	0.05
northgp	0.13	0.13	0.31	-1.11	0.12	0.00
pgate	0.21	0.12	0.06	-0.68	0.10	0.00
eupland	0.34	0.12	0.01	-0.73	0.10	0.00
ssboard	0.29	0.11	0.01	-0.24	0.09	0.01
frim	0.31	0.10	0.00	-1.39	0.10	0.00
basinr	0.34	0.13	0.01	-1.54	0.18	0.00

Log pseudolikelihood = -4319.5428
Wald chi2(46) = 1933.12
Prob > chi2 = 0.0000

Wald Test of $\rho = 0$
chi2(1) = 18.8296
Prob > chi2 = 0.0000

Table 4: Marginal Effects on Probability of Adoption

	Adoption of Precision Farming			Adoption of GM Crops		
Variable	**dy/dx**	**Std. Err**	**p-value**	**dy/dx**	**Std. Err**	**p-value**
ph_offop	-0.0001	0.0001	0.31	-0.0017	0.0006	0.01
educ	0.0015	0.0023	0.53	-0.0100	0.0034	0.00
educ_q2	0.0050	0.0011	0.00	0.0054	0.0013	0.00
educ_q3	0.0092	0.0011	0.00	0.0095	0.0014	0.00
educ_q4	0.0127	0.0012	0.00	0.0103	0.0017	0.00
age	0.0057	0.0024	0.02	0.0140	0.0066	0.03
agesq	-0.0001	0.0000	0.01	-0.0002	0.0001	0.01
acres	0.0000	0.0000	0.33	0.0000	0.0000	0.00
farmin*	0.0123	0.0278	0.66	-0.4935	0.1959	0.01
risk	0.4081	0.1164	0.00	1.3113	0.2506	0.00
adarat2	-0.0004	0.0014	0.77	-0.0012	0.0012	0.35
dairy*	-0.0469	0.0094	0.00	-0.0667	0.0268	0.01
tenant*	0.0510	0.0154	0.00	0.1347	0.0225	0.00
powner*	0.0394	0.0090	0.00	0.1353	0.0146	0.00
govtpmt*	0.0395	0.0084	0.00	0.2504	0.0105	0.00
heart*	0.0435	0.0221	0.05	0.0553	0.0217	0.01
northc*	0.0924	0.0259	0.00	-0.0338	0.0158	0.03
northgp*	0.0234	0.0246	0.34	-0.1226	0.0080	0.00
pgate*	0.0384	0.0229	0.09	-0.1003	0.0102	0.00
eupland*	0.0658	0.0272	0.02	-0.1041	0.0102	0.00
ssboard*	0.0537	0.0229	0.02	-0.0438	0.0145	0.00
frim*	0.0567	0.0213	0.01	-0.1768	0.0094	0.00
basinr*	0.0659	0.0305	0.03	-0.1386	0.0074	0.00

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

Table 5: Summary of Interaction between Education and Farm Size

Version 1: Interaction between Education and Farm Income

	Adoption of Precision Farming				Adoption of GM Crops			
Variable	**Coefficient**	**p-value**	**dy/dx**	**p-value**	**Coefficient**	**p-value**	**dy/dx**	**p-value**
educ	0.009	0.53	0.0015	0.53	-0.049	0.00	-0.0100	0.00
educ_q2	0.031	0.00	0.0050	0.00	0.027	0.00	0.0054	0.00
educ_q3	0.058	0.00	0.0092	0.00	0.047	0.00	0.0095	0.00
educ_q4	0.079	0.00	0.0127	0.00	0.050	0.00	0.0103	0.00

Version 2: Interaction between Education and Total Acres

	Adoption of Precision Farming				Adoption of GM Crops			
Variable	**Coefficient**	**p-value**	**dy/dx**	**p-value**	**Coefficient**	**p-value**	**dy/dx**	**p-value**
educ	0.051	0.00	0.0086	0.00	-0.068	0.00	-0.0136	0.00
educ_aq2	0.014	0.02	0.0024	0.02	0.037	0.00	0.0074	0.00
educ_aq3	0.022	0.00	0.0038	0.00	0.052	0.00	0.0104	0.00
educ_aq4	0.036	0.00	0.0060	0.00	0.064	0.00	0.0128	0.00