Does "Convenience Agriculture" Affect Off-farm Labor Allocation Decisions?

Hiroki Uematsu[1], Ashok K. Mishra[2] and Sachin Chintawar[3]

1. Graduate Student, Department of Agricultural Economics and Agribusiness
   Louisiana State University, Baton Rouge, LA 70803
   E-mail: huemat1@tigers.lsu.edu

2. Professor, Department of Agricultural Economics and Agribusiness
   Louisiana State University AgCenter
   211 Ag. Admin. Bldg.
   Baton Rouge, LA 70803
   Tel: 225-578-0262
   Fax: 225-578-2716
   E-mail: amishra@agcenter.lsu.edu

3. Graduate Student, Department of Agricultural Economics and Agribusiness
   Louisiana State University, Baton Rouge, LA 70803
   E-mail: schint1@tigers.lsu.edu

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Abstract

The objective of this study is to examine the effect of adoption intensity of GM crops on off-farm labor supply by farm households. Using ARMS data in 2004, 2005 and 2006, we estimate a two stage simultaneous Tobit model and find that adoption intensity of GM crops has a negative impact on off-farm labor supply by operators and a positive impact on off-farm labor supply by spouse. This may be due to the comparative advantage of operators and spouses. Our results find that GM crops adoption has different but significant implications on off-farm labor supply by operators and spouses and underscores the importance of understanding farm households' decisions to explain behaviors of farm businesses in the United States.

Keywords: Technology Adoption, Two stage simultaneous Tobit model, GM Crops, Off-farm labor

JEL Classifications: Q10, Q12

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Introduction

Adoption of genetically modified (GM) crop varieties has rapidly been increasing since it was commercially introduced to the U.S. agriculture in 1996, due to the higher expected yields, lower pesticide costs and less labor requirements(Fernandez-Cornejo and Caswell, 2006, Fernandez-Cornejo, et al., 2001). The most widely and rapidly adopted GM crops in the United States are those with herbicide-tolerant (HT) traits that are developed to survive the application of herbicides that previously would have destroyed the crop along with the targeted weeds. The rapid increase in adoption of GM crops is a manifestation that the perceived benefits from adopting GM crops significantly outweigh the additional costs incurred for a wide spectrum of potential adopters.

The diffusion path through which GM crops has taken so far in the United States stand in stark contrast to other recent innovations in agriculture, such as precision farming, integrated pest management (IPM), and soil testing, that substitute management for capital (Smith, 2002). What distinguishes GM crops from these management intensive technologies is their convenience; simplicity and flexibility of what Smith (2002) calls “convenience agriculture,” such as GM crops, relative to conventional technologies, allow farmers to save labor and management time thereby improving efficiency of farming operation.

An important question arises as to how time savings made possible by the adoption of GM crops are allocated by farm households, especially the farm operator and the spouse. Theoretically, rational economic agents allocate their time across various activities so as to maximize their total utility. Thus, a natural consequence of adopting "convenience agriculture" technology, i.e., GM crops, for farm operators and spouses would be either (1) further expanding farm enterprise, (2) increase off-farm labor supply, (3) increase leisure or (4) a combination of two or all of the above.

Empirical evidence, however, on the impact of rapid increase in GM crop adoption on labor allocation decisions by farm households have been scarce and inconsistent at the same time. While earlier studies found no evidence of correlation between GM crops adoption and off-farm labor supply (Fernandez-Cornejo, et al., 2001; Fernandez-Cornejo and McBride, 2002) , more recently, Fernandez-Cornejo et al. (2005) and Fernandez-Cornejo (2007) have found a positive correlation between adoption of herbicide tolerant (HT) crops and off-farm income, postulating that the increase in total income is due to greater off-farm labor supply. However, these studies did not estimate the impact of GM crop adoption and labor allocation decisions of farm operators and spouses jointly. For example, Fernandez-Cornejo (2007) conjectured that increase in off-farm income was a result of increased hours of off-farm work, but did not estimate off-farm hours of operators, spouses or both. Furthermore, empirical evidence (Gould and Saupe, 1989 ; Kimhi, 2004; Kimhi 1994; Tokle and Huffman, 1991; Kwon, Orazem and Otto, 2003) suggests that off-farm labor allocation decisions between operators and spouses were jointly determined.

Herein lies the objective of our analysis. The aim of this study is twofold. First, we expand the scope of existing studies and examine the degree to which intensity of GM crops adoption, in terms of share of GM crops acres (corn, soybeans and cotton) over total operated acres, influences off-farm labor supply by a farm household. In so doing, our analysis allow for the joint process through which farm households allocate labor supply on and off the farm by both operators and spouses as recommended by a number of influential studies (Gould and Saupe, 1989, Kimhi, 1994, Tokle and Huffman, 1991).

The rest of the paper is organized as follows. Section II introduces conceptual framework. Then, Section III and IV describe the data and the empirical model respectively, followed by results and interpretations in Section IV. The final section offers concluding remarks.

I. Conceptual Framework

Farm households' decisions about technology adoption and off-farm labor supply can be well represented in the context of the agricultural household model (Fernandez-Cornejo, et al., 2005, Hallberg, et al., 1991, Sumner, 1982), in which farm households are assumed to maximize utility, U, subject to three constraints: time, budget, and production. The objective function is given by

$$Max\ U = U(G, \boldsymbol{T_L}, \boldsymbol{H}, \boldsymbol{\Phi}), \quad (1)$$

where G is a composite good purchased by the farm household for direct or indirect consumption, $\boldsymbol{T_L}$ is a column vector[1] of leisure time for the operator and the spouse ($\boldsymbol{T_L} = (T_L^O\ T_L^S)'$)[2], $\boldsymbol{H}$ is a vector of human capital for the operator and the spouse

[1] All of the characters in bold font represent a column vector unless otherwise noted.
[2] Post scripts "O" and "S" denote "operators" and "spouses" respectively throughout this paper. $(T_L^O\ T_L^S)'$ indicates that it is a 2×1 column vector.

($\boldsymbol{H} = (H^O\ H^S)'$), and $\boldsymbol{\Phi}$ represents a vector of other exogenous factors that influence household utility such as family characteristics[3]. Time constraint for the household is

$$\boldsymbol{T} = \begin{pmatrix} T^O \\ T^S \end{pmatrix} = \begin{pmatrix} T^O_{on} + T^O_{off} + T^O_L \\ T^S_{on} + T^S_{off} + T^S_L \end{pmatrix} = \boldsymbol{T_{on}} + \boldsymbol{T_{off}} + \boldsymbol{T_L}, \quad (2)$$

where time endowment given to farm households consists of those for operators and spouses, each of which can be distributed among three activities: on-farm work, off-farm work, and leisure[4]. Assuming that all household income is going to be spent, the budget constraint is given by

$$P_g G = P_q Q - \boldsymbol{P}_{\boldsymbol{x}}' \boldsymbol{X} + \boldsymbol{W}'^{\boldsymbol{T}_{off}} + A, \quad (3)$$

where P_g, P_q and P_x are, respectively, price of G, Q, and $\boldsymbol{X}$, Q is composite farm output, and $\boldsymbol{X}$ is a vector of farm inputs, $\boldsymbol{W}$ is the vector of off-farm wage for the operator and the spouse ($\boldsymbol{W} = (W^O\ W^S)'$), $\boldsymbol{T_{off}}$ is the vector of off-farm labor supply by operators and spouses($\boldsymbol{T_{off}} = (T^O_{off}\ T^S_{off})'$), and A is other income such as interests and government transfers. To accommodate the assumption that all farm household income is spent and no savings or investment is made, one can assume that the composite good, G, include a variety of financial services. Note that $P_q Q - \boldsymbol{P_x}'\boldsymbol{X}$ represents net farm household income

[3] Following Hallberg et. al., (1991) we assume that farm household utility is determined by decisions and economic activities by the operator and the spouse. Any contribution to household utility by any other members of the family belongs Φ.
[4] These three activities are denoted by subscripts, "on," "off," and "L."

and $\boldsymbol{W}'\boldsymbol{T}_{\boldsymbol{off}}$ is the total off-farm income for the household[5]. Finally, production technology constraint can be represented as

$$Q = Q[\boldsymbol{X}(\Gamma), \boldsymbol{T}_{\boldsymbol{on}}(\Gamma), \boldsymbol{H}, \Gamma, \mathrm{R}], \quad \Gamma \geq 0, \qquad (4)$$

where Γ is adoption intensity of technology (i.e., share of GM crops in this study), and R is exogenous factors pertinent to the agricultural operation such as site specific environmental factors and climate conditions.

Substituting production technology constraint (4) into (3) to obtain "technology constrained net household income" (Hallberg, et al., 1991), we have

$$P_g G = P_q\{Q[\boldsymbol{X}(\Gamma), \boldsymbol{T}_{\boldsymbol{on}}(\Gamma), \boldsymbol{H}, \Gamma, \mathrm{R}]\} - \boldsymbol{P}_{\boldsymbol{x}}'\boldsymbol{X} + \boldsymbol{W}'^{\boldsymbol{T}_{off}} + A. \quad (5)$$

The first order optimality conditions are obtained by maximizing the Lagrangian function that incorporates the utility function (1), budget constraint that accounts for production function (5) and time constraint (2) given as follows:

$$L = U(G, \boldsymbol{T}_{\boldsymbol{L}}, \boldsymbol{H}, \Phi) + \lambda\big(P_q\{Q[\boldsymbol{X}(\Gamma), \boldsymbol{T}_{\boldsymbol{on}}(\Gamma), \boldsymbol{H}, \Gamma, \mathrm{R}]\} - \boldsymbol{P}_{\boldsymbol{x}}'\boldsymbol{X} + \boldsymbol{W}'\boldsymbol{T}_{\boldsymbol{off}} + A - P_g G\big)$$

$$+\boldsymbol{\gamma}'\big[T - \boldsymbol{T}_{\boldsymbol{on}} - \boldsymbol{T}_{\boldsymbol{off}} - \boldsymbol{T}_{\boldsymbol{L}}\big] \quad (6).$$

Some of the first order conditions are

$$\frac{\partial L}{\partial G} = \frac{\partial U}{\partial G} - \lambda P_q = 0 \quad (7)$$

$$\frac{\partial L}{\partial X} = \lambda\left(P_q \frac{\partial Q}{\partial \boldsymbol{X}} - \boldsymbol{P}_{\boldsymbol{x}}\right) = 0 \quad (8)$$

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[5] $\boldsymbol{W}'\boldsymbol{T}_{\boldsymbol{off}} = (W^O \; W^S)\begin{pmatrix} T_{off}^O \\ T_{off}^S \end{pmatrix} = W^O T_{off}^O + W^S T_{off}^S$.

$$\frac{\partial L}{\partial \Gamma} = \lambda\left\{P_q\left[\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right)'\left(\frac{\partial \boldsymbol{X}}{\partial \Gamma}\right) + \left(\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right)'\left(\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma}\right) + \frac{\partial Q}{\partial \Gamma}\right] - \boldsymbol{W}'\frac{\partial \boldsymbol{X}}{\partial \Gamma}\right\} - \boldsymbol{\gamma}'\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma} \leq 0 \quad (9)$$

$$\frac{\partial L}{\partial \boldsymbol{T_{on}}} = \lambda\left[P_q \frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right] - \boldsymbol{\gamma} \leq 0 \quad (10)$$

$$\frac{\partial L}{\partial \boldsymbol{T_{off}}} = \lambda \boldsymbol{W} - \boldsymbol{\gamma} \leq 0 \quad (11)$$

$$\frac{\partial L}{\partial \boldsymbol{T_L}} = \frac{\partial U}{\partial \boldsymbol{T_L}} - \boldsymbol{\gamma} = 0, \quad (12)$$

where λ and $\boldsymbol{\gamma}$ are Lagrange multipliers[6]. Equality in the first order condition indicates that we a priori expect an interior solution. For example, rearranging equation (10), we obtain

$$\frac{\boldsymbol{\gamma}}{\lambda} \geq P_q \frac{\partial Q}{\partial \boldsymbol{T_{on}}} \quad (13).$$

Since Lagrange multiplier represents the shadow price of corresponding resources at the optimized level, the left hand side of equation (13), which is the ratio of shadow prices of time and net farm household income, represents marginal rate of substitution between time and net farm household income. The right hand side of equation (13) is the marginal value of on-farm labor. Within the range that $\boldsymbol{\gamma}, \lambda$ and $P_q \frac{\partial Q}{\partial \boldsymbol{T_{on}}}$ are all positive, equality in equation (13) assures that optimizing behavior takes place at a point where a positive amount of Q is produced and thus a positive amount of labor is supplied by both the operator and the spouse. Although past literature usually maintains equality in equation

[6] Note that $\boldsymbol{\gamma}$ is NOT a scalar but a 2×1 vector, with each element being a Lagrange multiplier for the operator and the spouse.

(10), we adopt inequality to account for the possibility that there may be some spouses who do not work at all on the farm.

Following Fernandez-Cornejo, et al.,(2005), the optimality condition for technology adoption intensity, Γ, can be obtained by rearranging equation (9).

$$P_q\left[\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right)'\left(\frac{\partial \boldsymbol{X}}{\partial \Gamma}\right)+\left(\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right)'\left(\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma}\right)+\frac{\partial Q}{\partial \Gamma}\right]-\boldsymbol{W}'\frac{\partial \boldsymbol{X}}{\partial \Gamma}-\frac{\boldsymbol{\gamma}'}{\lambda}\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma}\leq 0$$

$$P_q\left[\frac{dQ}{d\Gamma}\right]-\boldsymbol{W}'\frac{\partial \boldsymbol{X}}{\partial \Gamma}-\frac{\boldsymbol{\gamma}'}{\lambda}\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma}\leq 0, \quad (14)$$

where $\frac{dQ}{d\Gamma}=\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right)'\left(\frac{\partial \boldsymbol{X}}{\partial \Gamma}\right)+\left(\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right)'\left(\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma}\right)+\frac{\partial Q}{\partial \Gamma}$. The first term in equation (14) is value of marginal product due to a change in adoption intensity while the second and the third terms represent marginal input cost and on-farm labor cost. When equality holds in equation (14), there is going to be a positive level of technology adoption at the optimal point.

Given the optimal level of technology adoption, Γ^*, off-farm labor supply can be obtained by substituting in optimal levels of on-farm labor and leisure into equation (2). That is,

$$\boldsymbol{T}^*_{\boldsymbol{off}}(\Gamma)=\boldsymbol{T}-[\boldsymbol{T}^*_{\boldsymbol{on}}(\Gamma^*)+\boldsymbol{T}^*_{\boldsymbol{L}}] \quad (15).$$

Equation (15) is the model of our interest and it consists of two-stage off-farm labor supply equations, with the first stage pertaining to the optimal level of technology adoption, Γ^*. Our empirical model, introduced in the next section, will first estimate the adoption intensity, Γ^*, so that its predicted value can be used as an instrument to estimate off-farm labor supply equations by both operators and spouses.

II. Data

The model is estimated using data obtained from a nationwide Agricultural Resource Management Survey 2004-2006, developed by the Economic Research Service (ERS) and the National Agricultural Statistical Service (NASS). The ARMS survey is designed to link data on the resources used in agricultural production to data on use of technologies, including GM crops (Goodwin and Mishra, 2004). The 2004-2006 ARMS survey queried farmers on all types of financial, production, and household activities (such as labor allocation and consumption expenditures). Specifically, it is used to gather information about the relationships among agricultural production, resources, and the environment. The ARMS is also used to determine of production costs and returns of agricultural commodities and measures net farm income of farm businesses. Another aspect of ARMS's important contribution is the information it provides on the characteristics and financial conditions of farm households, including information on input and risk management strategies and off-farm income.

ARMS uses a multi-phase sampling design and allows each sampled farm to represent a number of farms that are similar in the population, the number of which being the survey expansion factor (see Dubman (2000) for more technical detail). The expansion factor, in turn, is defined as the inverse of the probability of the surveyed farm being selected. The survey collects data to measure the financial condition (farm income, expenses, assets, and debts) and operating characteristics of farm businesses, the cost of producing agricultural commodities, and the well-being of farm operator households.

Operators associated with farm businesses representing agricultural production across the United States are the target population in the survey. A farm is defined as an establishment that sold or normally would have sold at least $1,000 of agricultural products (cash grains) during the year. Farms can be organized as sole proprietorships, partnerships, family corporations, nonfamily corporations, or cooperatives. Data are collected from one operator per farm, the senior farm operator, who makes most of the day-to-day management decisions. For the purpose of this study, operator households organized as nonfamily corporations or cooperatives and farms not growing cash grains were excluded. We selected farms that planted corn in 2005 and eliminated observations with missing data. Table 1 provides the definitions of the variables used in our analysis and the mean values.

Since the ARMS data has a complex survey design and is cross-sectional, it raises the possibility that the error terms in both Tobit models are heteroscedastic. Accordingly, all standard errors were adjusted for heteroscedasticiy using the Huber-White sandwich robust variance estimator based on algorithms contained in STATA (Huber, 1967, White, 1980). This type of adjustment for standard errors was used in the regression models in lieu of the Jackknife variance estimation method, which is a method suitable for estimation of standard errors when the dataset has a complex survey design (for further detail in the context of the ARMS, see Dubman (2000)). A similar method to account for heteroscedasticity and complex survey design has been used by Mishra and El-Osta (2008) and Mishra, El-Osta, Shaik (2010).

III. Empirical Model

The empirical model consists of three equations: off-farm hours worked by operators, off-farm hours worked by spouses and adoption intensity of GM crops represented by share of GM crop acres in total crop acres. Based on the theoretical model above, we can express the technology adoption intensity and labor allocation model as follows:

$$y_1 = \alpha\, y_3 + \boldsymbol{\delta}'\mathbf{X_1} + \varepsilon_1 \quad (16)$$

$$y_2 = \beta\, y_3 + \boldsymbol{\eta}'\mathbf{X_2} + \varepsilon_2 \quad (17)$$

$$y_3 = (\gamma_1 \quad \gamma_2)\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} + \boldsymbol{\theta}'\mathbf{X_3} + \varepsilon_3, \quad (18)$$

where y_1 and y_2 are, respectively, hours worked off-farm by operators and spouses and y_3 is share of GM crops acres in total operated acres; α and β are coefficients of share of GM crops in labor supply equations of operators (16) and spouses (17); $\boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\eta}$ and $\boldsymbol{\theta}$ are vectors of unknown parameters to be estimated; finally, $\mathbf{X_1}, \mathbf{X_2}$ and $\mathbf{X_3}$ are vectors of exogenous variables. See Table 1 for complete list of variables, definitions and summary statistics. The error terms, $\varepsilon_1, \varepsilon_2$ and ε_3 are assumed to be normally distributed with zero means but ε_1 and ε_2 are assumed to be correlated with each other at ρ. We first estimate the reduced form equation of (18) in which endogenous variables, y_1 and y_2, are absent. Since the dependent variable, the share GM crop acres in total crop acres, is a censored variable bounded from below at zero and above at one, a double-censored Tobit estimation procedure is used to estimate the model.

The vector of exogenous variables, $\mathbf{X_3}$, contains factors influencing adoption intensity of GM crops. It includes dummy variable for cash grain farms (***cg***), dummy variable for cotton farms (***cotton***), total number of acres (***noacres***), farming efficiency (***effi***), risk aversion (***riskaversion***), dummy variable for hobby farmers (***hobbyfarm***), dummy variable for tenant (***tenant***), dummy variable for part owners (***powner***), dummy variables for levels of formal education completed by the operator (*chs_educ*, *scol_educ*, *ccol_educ*), age (*age*), age squared (*agesq*), direct payment (*direct*), indirect payment (*indirect*), dummy variables for production regions (*heart*, *northc*, *northgp*, *pgate*, *eupland*, *ssboard*, *frim*, *basinr*) and dummy variables for years (*y04*, *y05*). Refer to Table 2 for list of variables in $\mathbf{X_3}$.

We expect cash grain and cotton farmers to be more likely to adopt GM crops. Since GM crops are often considered time saving, we expect farms with efficient operation to adopt GM crops with greater intensity as suggested by Goodwin and Mishra (2004). As with the case in previous literature, we expect highly educated farmers to possess higher analytic capability to assess and analyze information necessary to successfully implement newer technologies. On the other hand, we expect hobby farmers to be less keen to a time saving technology such as GM crops. The expected effect of total number of acres, risk aversion and age are ambiguous. As for total number of acres, larger farms may be more inclined to adopt time saving technology whereas smaller farms, who are more likely to work off-farm, may also have an incentive to adopt GM crops to secure time to work off the farm. As for risk aversion, farmers may see adoption of new technology risky-- but at the same time, empirical evidence that adoption of GM crops leads to higher profit-- may be seen as a tool to mitigate income risk. Younger farmers may be more likely to adopt a new technology, whereas older farmers may be more equipped with knowledge and experience to implement a new technology. The impacts of government payments, regional dummies, and year dummies on adoption intensity of GM crops are also theoretically ambiguous and thus need to be empirically estimated.

Next, we obtain the linear prediction of the latent variable of adoption intensity of GM crops from the first stage double censored Tobit model. Unlike the censored dependent variable of the share of GM acres that ranges from 0 to 1, the linear predication of the latent variable obtained here ranges from -2.75 to 1.96. One way to interpret this latent variable would be the degree to which farm households are willing to and capable of adopting GM crops. In the second stage, a bivariate Tobit model is used to estimate the off-farm hours worked by operators and spouses, the linear prediction of this latent variable serves as an instrument for the share of GM acres, which we suspect and test for endogeneity in the off-farm labor supply equations. This two-stage estimation yield asymptotically consistent estimates of unknown parameters (Nelson and Olson, 1978).

Vectors of exogenous variable $\mathbf{X_1}$ and $\mathbf{X_2}$ in equation (16) and (17) consist of the same set of exogenous variables[7]: dummy variables for age groups for operators (***op_age35***, ***op_age44***, ***op_age54***, ***op_age64***) and spouses (***sp_age35***, ***sp_age44***, ***sp_age54***, ***sp_age64***), years of education for operators (***educ***)and spouses (***sp_educ***), off-farm working experiences for operators (***opowkexp***)and spouses (***spowkexp***), direct payment (***direct***), indirect payment (***indirect***), disaster payment (***dispayment***), dummy variable for dairy farms (***dairy***), dummy variable for large farms according to USDA typology (***large***), share of farm income in total household income (***shincome***), number of children under the age of 6 (***hh_size06_v1***), household net worth (***hhnw1***), distance from household residence to the closest city (***miles***), and dummy variables for years (***y04***, ***y05***).

We expect age to be negatively correlated with off-farm labor supply; younger

[7] The only difference between the two vectors is that $\mathbf{X_1}$ contains age, dummy variables for education and off-farm working experience for operators while $\mathbf{X_2}$ contains those variables for spouses.

farmers (both operators and spouses) would be more likely to work off-farm. Education and prior off-farm experiences should be positively related with off-farm work. More educated and experienced individuals should be able to find relatively more lucrative employment opportunities off the farm. On the other hand, farmers who receive more government payments are expected to be more focused on farming operations and thus less likely to work off-farm. Dairy operation is usually more labor intensive and thus operators/spouses from dairy farms would be less likely to have off-farm employment. Large farm operators and spouses are expected to be more focused on farming operation and thus less likely to work off-farm. We also expect share of farm income in total household income to be negatively correlated with off-farm labor supply as higher share of farm income in total household income indicates higher dependence on farm income relative to off-farm income. The presence of young children should negatively affect off-farm labor supply of farm households due to time required for child care. The distance to the closest city is a proxy for availability of off-farm employment opportunities and we expect that farmers who live closer to the city are more likely to have an off-farm employment. The effect of household net worth is ambiguous. Higher household net worth may reduce necessity of seeking off-farm work whereas having higher off-farm income may increase household net worth. The results from the second stage bivariate Tobit model are presented in Table 3.

IV. Results

Since the focus of the paper is on the effect GM crop adoption on off-farm labor supply and due to brevity we will only discuss the results of off-farm labor supply function.

Table 3 presents the parameter estimates of the bivariate-Tobit model of the latent variables corresponding to the two dependent variables, hours worked off-farm by operators and spouses. These latent variables may be interpreted as ability and desire to work off-farm by operators and spouses. The estimated value of ρ is 0.328 and the associated p-value of 0.000 indicates a strong evidence that error terms in the two equations estimated are correlated at a significant level and supports the use of bivariate Tobit model instead of two separate Tobit models.

Table 4 provides estimates of two different marginal effects from the second stage bivariate Tobit model following McDonald and Moffitt decomposition(McDonald and Moffitt, 1980). Second and sixth columns represent the marginal effects of explanatory variables on the probability of working off-farm by operators and spouses, respectively. Fourth and eighth columns present the marginal effects of the explanatory variables on off-farm hours worked by such operators and spouses, respectively, that have positive off-farm working hours. Marginal effects of dummy variables are based on discrete change from 0 to 1.

In Table 3, Smith-Blundell test statistic and the p-value are provided. Smith-Blundell test examines the null hypothesis that all right hand side variables are exogenous and the residuals from the first stage estimation has no explanatory power (Smith and Blundell, 1986). The test is implemented with STATA command developed by Baum (1999). The p-value of 0.906 indicates strong evidence to maintain the null hypothesis of appropriate model specification.

Our primary interest in this study is how the adoption intensity of GM crops, represented by the share of GM acres, is related to off-farm labor supply by a farm household, represented by off-farm hours worked by operators and spouses. Our second stage bivariate Tobit model (Table 3) shows that the coefficient of share of GM acres is negative and significant for operators whereas it is positive and significant for spouses.

This is not fully consistent with a priori expectation that adoption of a management saving technology such as GM crops will lead to longer off-farm working hours for both operators and spouses. These mixed impacts of adoption of GM crops on off-farm working hours may be due to the comparative advantage of operators and spouses; operators are the primary decision-makers of farming operation and they are likely to have more farming experiences relative to spouses. A plausible explanation is that as farmers adopt time saving technology their spouses who may have spent some time working on the farm (helping with record keeping, seeking contracts, etc) may decide to leave such farming duties to the operator and switch to full-time or increase the number of hours working off the farm.

The marginal effects of the share of GM crop acres on off-farm working hours (Table 4) reveal that a unit increase in ***pshtotgm***, the linear prediction of the share of GM, leads to a 8% decrease and a 6% increase in the probability of working off-farm for operators and spouses, respectively. Point estimates of marginal effects on off-farm working hours for operators and spouses are, respectively, -8.0 hours and 5.9 hours per year. These results suggest that the total household off-farm working hours are decreasing as adoption intensity of GM crops increases. The reduction in off-farm working hours is expected to result in either more on-farm work or leisure to balance the marginal utility of these activities at the household utility maximizing point.

The parameter estimates of other explanatory variables have expected signs.

Coefficients of ***dairy*** are negative and significant for both operators and spouses. Marginal effects indicate that both operators and spouses have lower probability to work off-farm. These results are consistent with our prior expectation that labor intensive dairy production and off-farm labor supply are negatively correlated (Fernandez-Cornejo, 2007, Hallberg, et al., 1991). Our results show that this tendency is more prominent for operators. Dairy farm operators are 22% less likely to work off-farm and, when they do work off-farm, and they work 21 fewer hours per year than their counterparts, whereas dairy farm spouses are 12% likely to work off-farm and work 8.5 fewer hours per year relative to spouses from non-dairy farms.

Large farms are also found to be less likely to work off-farm and work shorter hours. Coefficient estimates from bivariate Tobit as well as marginal effects for ***large***, the dummy variable for large farms according to USDA typology, are all highly negative and significant for both operators and spouses (Table 3). Similar to dairy farms, the negative relationship between large farms and off-farm work is stronger for operators than for spouses. Operators of large farms are 28% less likely to work off-farm while their spouses are 15% less likely to work off-farm. Large farm operators who do work off-farm on average work shorter hours than non-large farm operators by 28 hours per year. The analogous figure for large farm spouses is 15 hours per year (Table 4, column 4 and 8). Findings here are consistent with Fernandez-Cornejo (2007) and Nehring, et al.,(2005).

Not surprisingly, the coefficients of dummy variables for operators' age groups are all positive and highly significant in comparison to the base groups of operator older than 65 years. In fact, the younger the age group is, the larger the coefficient estimates become, indicating that the negative effect of age on off-farm labor supply holds true in the entire range of age considered in this study. This result holds true for the two types of the marginal effects as well. For example, as definitions of age groups become younger by 10 years, off-farm working hours increase by 29 hours, 40 hours, 57 hours and 67 hours per year respectively compared with operators 65 years or older. Younger operators are more likely to work off-farm and work longer hours on average. Findings here are consistent with Sumner (1982).

The effects of age on off-farm working hours by spouses are very similar to those for operators. In comparison to the base group of spouses 65 years or older, younger spouses have higher probability of working off-farm and longer off-farm working hours. Spouses who are between 55 and 64 years old work 41 more hours off-farm per year than spouses older than 65 years old. The analogous figure increases for the younger age groups of spouses and spouses younger than 35 years old work 90 more hours off-farm per year (Table 4, column 4 and 8). These results are consistent with Hallberg, et al., (1991)

Operators' education and off-farm work experience also have positive and significant coefficients but their effect on off-farm working hours are economically insignificant. An additional year of education leads to only 1% increase in probability of working off-farm and increases off-farm working hours by only 1.2 hours a year. Similarly, an additional year of off-farm work experience increases probability of working off-farm by 2% and it enhance off-farm working hours by 2.3 hours a year. However, the effects of education and off-farm work experience are more prominent for spouses. An additional year of education increases probability of working off-farm by 3% and off-farm working hours by 2.9 hours per year, whereas an additional year of off-farm work experience increases probability of working off-farm by 3% and off-farm working hours by 3.2 hours per year. Overall, positive effects of education and off-farm work experience on off-farm labor supply are consistent with the human capital theory as well as empirical findings in literature (Gardner and Rausser, 2001, Goodwin and Mishra, 2004, Huffman, 1980, Huffman and Lange, 1989; Vergara, et al., 2004).

The presence of children under the age of six is found to have a negative and significant impact on off-farm labor supply of spouses. The results confirm the views that childcare negatively affects off-farm labor supply (Fernandez-Cornejo, et al., 2005, Kimhi and Lee, 1996) and that farm operators are predominantly male in the family, off-farm labor supply of spouses, most of whom are females, is expected to be more sensitive to the presence of young children in the family (Fernandez-Cornejo, 2007). The presence of an additional child younger than 6 in the family reduces spouses' probability of working off-farm by 6% and off-farm working hours by 6 hours per year. The negative correlation between the presence of young children and spouses' off-farm labor supply is consistent with the recent finding by El-Osta, et al., (2008).

The distance from farm household residence to the closest city represented by, ***miles***, has negative and significant impact on off-farm labor supply of operators. Results indicate that operators who live far from the city are less likely to work off-farm, and that an additional mile decreases the probability of off-farm work by operators by 0.6%, which confirms previous findings (Fernandez-Cornejo, 2007, Hallberg, et al., 1991). However, the magnitude of this effect is very small. For example, results indicate that operators reduce annual off-farm labor supply by 0.06 hours or 3.6 minutes per year (Table 4, column 4).

Government payments (***direct***, ***indirect***, and ***dispayment***) variables mostly obtained significant and expected results. Directs payments are found to be negatively correlated with off-farm labor supply by operators and spouses, while indirect payments has a negative but marginally insignificant effect on operators' labor supply (p-value-0.13) and no significant effect on spouses' off-farm labor supply. Disaster payment also has a negative and significant effect on operators' off-farm labor supply but not for spouses'. Overall, the negative correlation between government payments and off-farm labor supply is consistent with existing literature (Howard and Swidinsky; 2000, Mishra and Goodwin, 1997) , but it is partially inconsistent with the recent findings by El-Osta, et al.,(2008) who found the negative correlation between government payments and off-farm labor supply by both operators and spouses.

Finally, dummy variables that represent observations in 2004 and 2005 relative to 2006 are significant and their marginal effects are negative for both operators and spouses. This underscores the increasing trend in off-farm labor supply in U.S. farm sector within the three-year period on which this study is based.

V. Conclusions

The introduction of genetically modified (GM) crop varieties to the U.S. agriculture in 1996 and the sharp increase in its adoption thereafter has dramatically changed the landscape of agricultural production. The convenient features of GM crops, higher expected yields, lower pesticide costs and lower labor requirements stand in stark contrast to other management and capital intensive technologies. An important question that entails is how time savings made possible by the introduction of convenient technology such as GM crops are reallocated by farm household. This study builds on the existing literature and expands the scope of analysis by including three types of GM crops, corn, soybeans and cotton, and jointly estimating off-farm labor supply decisions by farm operators and spouses due to changes in intensity of GM crops adoption.

Our analysis demonstrated that the adoption intensity has a positive impact on off-farm labor supply by spouses whereas it has a negative impact on off-farm labor supply by operators. Since farm operators are, by definition, the primary decision-makers of farm operation, they are likely to have comparative advantages in farming operation to spouses, who tend to have less farming experience. Therefore, it is plausible that time savings made possible by adoption of GM crops allow each member of the household to pursue an activity at which he/she has comparative advantage, allowing operators to work more on farm and spouses to work more off the farm. Marginal effects estimates showed that a unit increase in the adoption intensity of GM crops results in an 8% decrease and a 6% increase in the probability of working off-farm by operators and spouses, respectively. For those operators and spouses who do work off-farm, the same increase in adoption intensity of GM crops changes off-farm labor supply by -8.0 hours for operators and 6 hours for spouses annually, respectively.

It is important to note, however, that diffusion of a new technology is a dynamic process (Rogers, 2003) and thus results from this study can be specific to the timeframe of the data analyzed. Studies using more recent data may provide a different picture of how farm households are adjusting their time allocation as they gain more experience with GM crop varieties. It is of great interest for agricultural and labor economists to study how the impact of a "convenient" technology on labor allocation decisions by farm household may change in a dynamic setting as the technology undergoes different diffusion stages.

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Table 1: Variable Definitions and Basic Statistics

Variables	Definitions	Mean	Std. Dev
gmcornacres	acres in which GM corns are planted	45.876	194.17
gmcottonacres	acres in which GM cottons are planted	39.549	275.39
gmsbeansacres	acres in which GM soybeans are planted	79.596	323.13
Totalgm	Total acres in which GM crops are planted	165.022	543.74
shgmcornacres	share of GM corn acres in total corn acres	0.038	0.11
shgmcottonacres	share of GM cotton acres in total cotton acres	0.018	0.10
shgmsbeansacres	share of GM soybean acres in total soybean acres	0.058	0.16
Shtotgm	share of GM crops acres planted in total planted acres	0.114	0.24
pshtotgm	predicted value of shtotgm	-.385	0.47
Cg	= 1 if cash grain farms	0.160	0.37
Cotton	= 1 if growing cotton	0.028	0.16
Noacres	total number of acres	653.012	3876.89
Effi	farming efficiency (gross cash farm income divided by working capital)	-11.733	1525.91
riskaversion	share of crop insurance premiums in total variable cost	0.010	0.04
hobbyfarm	= 1 if farming as a hobby	0.333	0.47
Tenant	= 1 if operator is tenant	0.103	0.30
Powner	= 1 if operator is part owner	0.455	0.50
Dairy	= 1 if farm has dairy operation	0.103	0.30
Large	= 1 if farm is classified as large farm according to USDA farm typology	0.412	0.49
h_offop	hours worked off-farm by operator	49.474	78.88
Opowkexp	operator's off-farm work experience	3.260	8.28
Educ	operator's education in years	12.964	1.75
chs_educ	= 1 if operator completed high school	0.463	0.50
scol_educ	= 1 if operator had some college education	0.264	0.44
ccol_educ	=1 if operator completed college	0.154	0.36
op_age35	= 1 if operator is younger than 35 years old	0.046	0.21
op_age44	= 1 if operator is older than 35 years old and younger than 44 years old	0.145	0.35
op_age54	= 1 if operator is older than 45 years old and younger than 54 years old	0.293	0.46
op_age64	= 1 if operator is older than 55 years old and younger than 64 years old	0.286	0.45
h_offsp	hours worked off-farm by spouse	59.440	77.83
spowkexp	spouse's off-farm experience	3.386	7.51
sp_educ	spouse's education in years	13.243	2.11
sp_age35	= 1 if spouse is younger than 35 years old	0.200	0.40

Table 1 continued.

Variables	Definitions	Mean	Std. Dev
sp_age44	= 1 if spouse is older than 35 years old and younger than 44 years old	0.144	0.35
sp_age54	= 1 if spouse is older than 45 years old and younger than 54 years old	0.336	0.47
sp_age64	= 1 if spouse is older than 55 years old and younger than 64 years old	0.192	0.39
hh_size06_v1	number of household members younger than 6 years old	0.113	0.54
shincome	share of farm income in total household income	0.364	34.97
hhnw1	household net worth	172.312	599.78
Miles	distance to closest city in miles	24.705	25.51
Direct	direct payments received in dollar	7508.885	23241.59
Indirect	indirect payments received in dollar	11338.52	69055.45
dispayment	disaster payments received in dollar	1386.61	11511.58
Heart	= 1 if farm located in the Heartland region	0.129	0.34
Northc	= 1 if farm located in the Northern Crescent region	0.158	0.36
Northgp	=1 if farm located in the Northern Great Plains region	0.050	0.22
Pgate	=1 if farm located in Prairie Gateway region	0.108	0.31
Eupland	=1 if farm located in Eastern Upland region	0.111	0.31
Ssboard	=1 if farm located in Southern Sea Board region	0.140	0.35
Frim	=1 if farm located in Fruitful Rim region	0.173	0.38
Basinr	=1 if farm located in Basin and Range region	0.056	0.23

Source: Agricultural Management Survey, 2004, 2005 and 2006

Table 2: Parameter Estimates from Reduced Form Equation for Share of GM Acres

Variable	Coefficients	P-value	95% Confidence Interval	
intercept	-0.27	0.00	-0.40	-0.13
Cg	0.55	0.00	0.53	0.58
cotton	0.79	0.00	0.75	0.83
noacres	0.00	0.24	0.00	0.00
effi	0.00	0.06	0.00	0.00
riskaversion	0.67	0.00	0.29	1.05
hobbyfarm	-0.19	0.00	-0.22	-0.17
tenant	0.25	0.00	0.22	0.29
powner	0.28	0.00	0.26	0.30
opowkexp	0.00	0.00	0.00	0.00
chs_educ	-0.01	0.56	-0.04	0.02
scol_educ	-0.01	0.45	-0.04	0.02
ccol_educ	-0.05	0.01	-0.08	-0.01
op_age	0.00	0.31	-0.01	0.00
agesq	0.00	0.90	0.00	0.00
direct	0.000002	0.00	0.0000015	0.0000024
indirect	0.0000003	0.01	0.00000008	0.00000044
heart	0.17	0.00	0.13	0.20
northc	0.04	0.01	0.01	0.08
northgp	-0.32	0.00	-0.38	-0.26
pgate	-0.25	0.00	-0.29	-0.21
eupland	-0.22	0.00	-0.26	-0.17
ssboard	-0.08	0.00	-0.11	-0.04
frim	-0.42	0.00	-0.46	-0.37
basinr	-0.54	0.00	-0.62	-0.46
y04	-0.04	0.00	-0.06	-0.02
y05	-0.05	0.00	-0.08	-0.03

Log pseudolikelihood = -6702.1667

Pseudo $R^2 = 0.448$

$F(26, 20004) = 407.79$

Prob > F = 0.000

Table 3: Parameter Estimates from Bivaraite Tobit Model

Variable	Operators				Spouses			
	Coefficients	*p*-value	95% Confidence Interval		Coefficients	*p*-value	95% Confidence Interval	
intercept	-146.48	0.00	-170.20	-122.77	-179.33	0.00	-195.98	-162.67
pshtotgm	-27.33	0.00	-34.37	-20.28	16.97	0.00	11.34	22.60
ofwkexp	8.44	0.00	8.14	8.74	8.85	0.00	8.57	9.14
age35	159.55	0.00	143.35	175.75	165.72	0.00	152.55	178.90
age44	150.82	0.00	140.74	160.90	155.92	0.00	146.46	165.38
age54	120.92	0.00	112.50	129.33	135.25	0.00	126.77	143.74
age64	84.37	0.00	75.96	92.79	97.06	0.00	88.23	105.90
Educ	5.41	0.00	3.66	7.15	8.06	0.00	7.00	9.12
direct	-0.00045	0.00	-0.00067	-0.00023	-0.00013	0.03	-0.00025	-0.000014
indirect	-0.00009	0.13	-0.00021	0.000027	-0.000002	0.95	-0.00007	0.000062
dispayment	-0.00074	0.00	-0.00118	-0.0003	0.000028	0.81	-0.00019	0.000248
dairy	-86.50	0.00	-97.92	-75.09	-32.81	0.00	-40.60	-25.03
large	-100.13	0.00	-107.00	-93.25	-40.55	0.00	-45.80	-35.31
shincome	0.13	0.10	-0.02	0.28	0.01	0.84	-0.09	0.11
hh_size06_v1	-1.74	0.54	-7.36	3.87	-17.43	0.00	-22.36	-12.50
hhnw1	-0.02	0.00	-0.03	-0.01	-0.04	0.00	-0.05	-0.03
miles	-0.14	0.01	-0.25	-0.03	0.05	0.25	-0.04	0.14
y04	-55.51	0.00	-63.03	-47.98	-53.16	0.00	-59.53	-46.79
y05	-59.23	0.00	-66.35	-52.10	-48.59	0.00	-54.58	-42.59
Rho	0.38	0.02	0.29	0.37				

Log likelihood = -70168.625
$\hat{\rho}$ =0.328
Prob ($\hat{\rho} = \mathbf{0}$) =0.000

Smith Blundell Test of Exogeneity=0.014
P-value = 0.9061

Wald chi2(18) = 5761.67
Prob > chi2 = 0.0000

Table 4: Marginal Effects

Variables	Operators				Spouses			
	Pr(h_offop>0)		E(h_offoph|offop>0)		Pr(h_offsp>0)		E(h_offsph|offsp>0)	
	Estimates	*p*-value	Estimates	*p*-value	Estimates	*p*-value	Estimates	*p*-value
Pshtotgm	-0.08	0.00	-8.00	0.00	0.06	0.00	5.89	0.00
Owkexp	0.02	0.00	2.34	0.00	0.03	0.00	3.20	0.00
age35*	0.49	0.00	67.27	0.00	0.46	0.00	90.09	0.00
age44*	0.47	0.00	57.50	0.00	0.48	0.00	76.43	0.00
age54*	0.39	0.00	40.84	0.00	0.46	0.00	55.05	0.00
age64*	0.29	0.00	29.39	0.00	0.33	0.00	40.97	0.00
educ	0.01	0.00	1.22	0.00	0.03	0.00	2.88	0.00
direct	-0.0000013	0.00	-0.00012	0.00	-0.0000005	0.03	-0.00005	0.03
indirect	-0.0000003	0.05	-0.00003	0.06	0.00000004	0.73	0.000004	0.73
dispayment	-0.0000014	0.02	-0.00013	0.02	0.0000001	0.79	0.00001	0.79
dairy*	-0.22	0.00	-21.54	0.00	-0.12	0.00	-11.16	0.00
large*	-0.28	0.00	-27.67	0.00	-0.15	0.00	-14.58	0.00
shincome	0.00	0.21	0.01	0.21	0.00	0.86	0.00	0.86
hh_size06_v1	-0.01	0.32	-0.63	0.32	-0.06	0.00	-6.44	0.00
hhnw1	-0.00007	0.01	-0.007	0.01	-0.00016	0.00	-0.016	0.00
miles	-0.0006	0.00	-0.058	0.00	0.00017	0.26	0.017	0.26
y04*	-0.16	0.00	-15.54	0.00	-0.19	0.00	-18.35	0.00
y05*	-0.16	0.00	-15.70	0.00	-0.18	0.00	-17.41	0.00

(*) Estimate is for discrete change of dummy variable from 0 to 1