The Impact of Adoption of Genetically Modified Corn on the Off-Farm Labor Supply in the United States

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Abstract

With the production and cropping efficiency gains from adoption of Genetically Modified (GM) corn, the number of acres planted has increased steadily over the past decade. Also, the adoption of GM crops in general has an impact on the labor allocation decisions of farm operators. Using a large sample of Agricultural Resource Management Survey (ARMS) data, we estimate a two-stage left-censored simultaneous Tobit model to estimate the impact of adoption of GM corn on the off-farm labor supply of farm operators. Results indicate that the adoption of GM corn has had a negative and significant impact on the off-farm labor supply.

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

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Introduction

The adoption of Genetically Modified (GM) corn in the United States has seen a steady increase since its introduction in 1998. Corn hybrids that are resistant to targeted pests have reduced insecticide usage in corn production. Other genetically engineered corn resistant to glyphosate, a herbicide effective on many species of grass and broad leafed weeds, has become prominent in the United States. Adoption of GM corn has increased steadily since its introduction in 2000. The percent of GM corn acreage nearly doubled in 5 years (26 percent in 2001 to 52 percent in 2005, figure 1) second to only Herbicide Tolerant (HT) soybean in the United States.

These changes in production technology have had farm-level impacts on resource allocation and the availability of farm operators for off-farm labor. Biotechnology, in a low commodity price scenario, was perceived to be a cost-reducing, yield-increasing measure by farmers, thus improving the financial performance of farmers (Fernandez-Cornejo, Dabercow and McBride, 2000). The rapid adoption of GM corn is seen as evidence of the perceived benefits of the technology outweighing the additional costs incurred.

One externality resulting from the adoption of this new production technology in corn that has been largely ignored is the change in the availability of farm labor for other uses. The adoption of technology has been shown to increase farm efficiency (Goodwin & Mishra, 2004). The authors suggest that increased farm efficiency decreases the amount of hours spent off the farm. The phenomenon of diversification of income sources for farm households created by working off the farm has been observed in both developed and developing countries (Mishra, Morehart, El-Osta, Johnson and Hopkins, 2002; Chang and Mishra, 2008). Extensive literature has evolved that investigates the involvement of farm households in nonfarm labor markets. Mishra and Goodwin (1997) noted the importance of off-farm employment as a means of decreasing financial risks. Lamb (1996) observed that the decision of farm households to use an off-farm labor supply to mitigate the effects of production shocks leads to more efficient production choices (use of fertilizers) on the part of farmers. Fernandez-Cornejo, Chad and Mishra, (2005), studied the causal effects of farm households adopting new technologies on increased income through off-farm labor.

Literature Review

An abundance of literature has evolved to investigate the determinants of farm labor involvement in non-farm labor markets in the U.S. Yang (1997) studied the returns to education and the spillover effects of knowledge contributing to farming while participating in off-farm employment. Yang's research indicated that higher household schooling contributed to increased farm allocative efficiency and increased off-farm labor wages. Huffman (1980) considered education and agricultural research and extension as variables representing human capital which have efficiency effects on farm production, while changing the time allocated to farming. The changes in types of government payments (direct and indirect) since 1996 and their effects on off-farm labor supply have been studied in various papers. Ahearn, El-Osta and Dewbre (2006) provided evidence suggesting that policy changes with regards to payments since the 1996 FAIR act have not affected the availability of off-farm labor and that these payments increased the opportunity cost of price of leisure. They concluded that payments, irrespective of their nature, have a negative impact on the off-farm labor supply. The paper also showed evidence from Agricultural Resource Management Survey (ARMS) data that suggested that cash grain operations received payments and their operators were less likely to work off the farm. Various other studies have considered the effects of demographic factors on the availability of off-farm labor including age, household size, experience, and size of farms (Lass, Findeis & Hallberg, 1991; Huffman, 1980; Goodwin and Mishra, 2004; and Sumner, 1982).

Numerous studies have analyzed the environmental, agronomic, and economic effects of adopting GM corn. Fernandez-Cornejo et al. (2001) studied the effects of GE corn and factors influencing its adoption; Fernandez-Cornejo and McBride (2000) suggested that adoption was highly correlated to net returns and change in yields of corn. Fernandez-Cornejo and Ingram (1998) estimated the effects of herbicide-tolerant corn adoption on yields, profits and herbicide use and concluded that lower herbicide use was significantly related to the adoption of new corn varieties. Marra, Pannell and Ghadim (2003) confirmed earlier studies that GM corn significantly decreased pesticide use while significantly increasing the net returns and average yields.

This paper addresses two major objectives. First, it investigates the determinants of adoption of GM corn and second, it identifies the relationship between the number of hours worked off the farm and the adoption of new technology, specifically the share of acres planted of GM corn. An important component of our modeling method includes developing a two-stage left censored Tobit model, unlike a single Tobit equation, accounting for the endogeneity of the share of acres of GM corn planted in the U.S.

Furthermore, the study tests for endogeneity using the Smith and Blundell (1986) test by testing for exogeneity of the share of GM acres planted in the off-farm labor equation. To better understand the intensity of the effect of adoption of the acres allocated to GM corn, this paper investigates the impact of this adoption on the number of hours worked off the farm for farmers who have already adopted and those who switched to these new varieties of corn using the McDonald and Moffitt (1980) decomposition.

Economic Model

The theoretical model is based on the labor supply model of low-income households developed by Snow et al. while modifying it for off-farm availability of agricultural labor and allowing for technology adoption. The farmer maximizes his utility based on consumption *C*, the decision of whether to incorporate technologies *p* (*p*=1 to accept new technologies), the human capital *h*, and other factors (including household characteristics).

(1) $$MaxU = U(c, p, h, \varphi)$$

Farmers maximize utility subject to constraints

(2) $$C = I + S + W$$ (Income Constraint),

which requires that the consumption expenditure C equals the sum of farm income I, subsidies S, and off-farm income W. In this case,

(3) $$C = P_s G$$ The Price and Quantity vector of consumed goods
$$I = P_q Q$$ The Price and Quantity vector of farm outputs

(4) $$Q = Q\left[X(\Gamma), F(\Gamma), H, \Gamma, R\right]$$ (Technology Constraint)

Where X represent the quantity of farm inputs, F represents the quantity of on farm work, R is a vector of all other exogenous variables, and H is the human capital.

(5) $T = F(\Gamma) + M + L$ (Time Constraint)

Where L is the time allocated for leisure (Fernandez-Cornejo et al.),

Off-farm wage W can be represented as

(6) $W = K - w(I + p + T)$

Where K is the market value of on farm labor, T is the transportation costs, and *w* is the wage rate. Combining 2 through 6, we can write the income constraint as

(7) $C = P_q Q + S + (K - w(I + p + T))$

Rearranging

(8) $wp = P_q Q + S + K - wI - wT - C$

is the consumer's off-farm labor income conditional to the adoption of new technology. The decision to adopt GM corn is dictated by comparing the utilities between adopting and otherwise. Thus, let the indirect utility be defined as

(9) $V = (p, (1-w), Y(p))$

defining *p** as the difference between the utility due to adopting the GM corn,

(10) $p^* = V(1, (1-w), Y(1)) - V(0, (1-w), Y(0))$

Thus, the farmer chooses to adopt the new GM corn when the *p** is positive.

Thus, supply of off-farm labor H conditional to the adoption of GM corn is given by

(11) $h^* = H(p, (1-w)W, Y(p))$.

Hence, the model yields two-stage dependent off-farm labor supply equations, one pertaining to the farmers who choose to grow GM corn (p=1) and the other pertaining to farmers who do not adopt GM corn (p=0), while adoption p depends on other factors (equation 10).

Econometric Model

The off-farm labor supply for farmers using GM corn and for those who do not plant GM corn are estimated. The labor supply and GM corn are treated as left-censored variables in our empirical specification. The resulting system is a simultaneous equation Tobit model of off-farm labor supply and adoption of GM corn. Because the censoring precludes unique or sensible solutions for the reduced forms, a condition must be imposed in a system of censored dependent variables (Heckman, 2001). The structural form of the model is given by

(12) $y_2^* = \beta_2 y_1^* + \delta_2 X_2 + \varepsilon_2$

(13) $y_1^* = \beta_1 y_2^* + \delta_1 X_1 + \varepsilon_1$

where y_2^* is the off-farm labor supply, X_2 is a vector of exogenous variables determining y_2^*, y_1^* is the adoption of GM corn, X_1 is a vector of exogenous variables determining y_1^*, δ_1 and δ_2 are the vectors of parameters associated with the variables X_1 and X_2, β_1 and β_2 are scalar parameters, and ε_1 and ε_2 are distributed as bivariate normal random variables with correlation ρ. The random variables y_2 off-farm labor supply, and y_1, adoption of GM corn, are thus the observed realizations of their latent counterparts, y_2^* and y_1^* (Amemiya, 1974). They are left censored at zero such that

(14) $y_1 = y_1^*$ if $y_1^* > 0$ and $y_1 = 0$ (Baum, 1999)

and similarly for y_2. One can conclude that the model from equations 12 and 13 implies that the off-farm labor supply and adoption of GM corn are simultaneously determined.

To avoid transmission of a possible misspecification of the equation determining off-farm labor, we use the two-stage estimation as proposed by Newey (1987). The model defined is estimated in two stages. In the first stage, equation 13 is estimated by Tobit. The reduced form coefficient estimates are then used to create an instrument, $\hat{y}_1^*$, which is asymptotically uncorrelated with the error term in equation 12 (Greene). The second stage uses the $\hat{y}_1^*$ predictor value in equation 12 to develop the off-farm labor supply equation. Endogeneity tests of acres of GM corn planted and hours worked off the farm are considered. We use the Smith Blundell test to determine exogeneity as proposed by Baum (1999) who computes a test for exogeneity based on the Smith and Blundell's test where, under the null hypothesis, the models are appropriately specified with all explanatory variables as exogenous.

Under the alternative hypothesis, the suspected endogenous variables are expressed as linear projections of a set of instruments, and the residuals from the first-stage regressions are added to the model. MacDonald and Moffitt (1980) proposed the use of the decomposition of the marginals in Tobit models to determine the changes in the probability of being above the limit and changes in the value of the dependent variable if it is already above the limit. We use this decomposition to understand the effects of changes in the second stage dependent variable (hours of off-farm work) due to the independent variables. To understand the effects of the independent coefficient on the dependent variable (in our case the time spent off the farm), the expectation of this $y*$ (the unobserved latent variable) can be expressed as

$$(15) \qquad \partial E(y^*) / \partial x_j = P(y^* > 0) \, \partial E(y^* | y^* > 0) / \partial x_j + \partial E(y^* | y^* > 0) \, \partial P(y^* > 0) / \partial x_j$$

implying that the total change in the unconditional expected value of hours worked off the farm is decomposed into two intuitive parts.

a) The change in the expected value of hours worked off the farm (y*) of those above zero, weighted by the probability of being above zero

b) The change in the probability of being above zero, weighted by the conditional expected value of y* (McDonald & Moffitt, 1980).

Considerable literature has evolved in the use of the simultaneous equation limited dependent variable model. Amemiya (1974) considers a model in which all endogenous variables are truncated to zero, revealing certain necessary restrictions on the model and suggesting a method of estimation using the indirect least squares method. Nelson and Olson (1978) proposed a two-stage least squares procedure for Tobit analysis proving that the estimates are asymptotically normal. More recent studies have applied these models for specifying effects on adoption of technologies including Blundell and Smith (1989) who compared estimates of marginal and marginal and new conditional maximum likelihood procedures. Goodwin and Mishra (2004) used the simultaneous equation framework to determine multiple job holdings and resulting effects on farming efficiency. McDonald and Moffitt (1980) suggested that decomposition of the marginal effects provided more substantive economic and policy implications.

While many studies have considered the importance of off-farm labor and net income gains due to technology adoption, the off-farm labor supply changes that have resulted from these new technologies has hardly been explored. Smith (2002) notes that GM crops are management-saving and affect the off-farm labor supply, mainly due to the wage differential. The model developed in this paper considers the adoption of GM corn and the supply of off-farm labor jointly. Following MacDonald and Moffitt (1980), we decompose the total effect of a change in the dependent variable for those farmers who work off-farm, weighted by the probability of being farmers who work off-farm and the change in the probability of farmers who work off the farm weighted by the expected value of the dependent variable.

Variables

Table 2 provides a description of the variables and their mean values. For a better understanding, we discuss some of the explanatory variables in detail. The risk aversion (*RISKAVERSION*) measure is the ratio of crop insurance payment to the total farm operating expenditures as defined by Goodwin and Mishra (2004). We hypothesize that risk-averse farmers would adopt new proven technologies that increase productivity while guaranteeing a higher yield and therefore be positively correlated with a higher share of GM (*SHGMACRES*) acres on their farms. Higher costs of adoption may lead these risk-averse farmers to spend fewer hours off the farm (*H_OFFOP*) to protect their investments; hence, they may be more likely to work off the farm. Farmers who are part-owners (*POWNER*) and lease more land (*TENANT*) tend to adopt new technologies that provide higher yield and, therefore, would show a positive relation to the share of GM acres planted.

Government payments were disaggregated into three groups based on the type of payments: direct payments (decoupled, *DIRECT*), indirect payments (*INDIRECT*), and CRP payments (*CRPPAYMENT*). El-Osta, Mishra and Ahearn, (2005), suggest that since direct payments have only wealth effects while indirect and CRP payments have both wealth and substitution effects, there may be differences in the effect of these payments on off-farm labor considerations by farmers. Because the effects of direct payments may be different from other types of subsidy payments, we try to capture these effects in our off-farm labor supply model. Chang et al. (2008) suggest that CRP payments could affect savings, consumption, and income differently for different households based on their income and consumption distribution. Irrespective of any kind of payment, we expect that they have a significant negative impact on the number of hours worked off the farm. To better understand the intensity with which these payments affect the number of hours worked off the farm, we divide them into three categories as discussed above. Cash grain payments (*CG*) would positively affect the share of GM acres planted by the farmer.

The cropping efficiency (*CROP_EFF*) factor was calculated as the ratio of gross cash farm income to total variable costs. Goodwin and Mishra (2004) suggest that the adoption of new technologies tends to increase cropping efficiency and, therefore, these two factors are positively correlated. Since corn is largely grown in the heartland and northern-crescent regions (as defined by ERS), we expect to see a significant positive impact on the share of acres planted under GM corn for these areas.

The ARMS solicits education information by asking individuals to indicate which category (e.g., less than high school, high school, college, and graduate school) represents their educational achievement. We impute the years of education from these responses, assigning a level of education for each of the qualitative category (e.g., less than high school = 10 years; four-year college degree = 16 years). Literature (Lass, et. al., 1991; Fernandez-Cornejo et.al., 2005) suggests that, while age plays an important role in both adoption of new technologies (positively correlated) and the number of hours spent working off the farm (positively correlated), it tends to show a decline over longer periods of time. We capture the effect by adding the age-squared variable, which provides an intuitive way of calculating the age at which farmers tend to adopt fewer new technologies and also work off the farm. The off-farm work experience of the farm operator was believed to have an impact on the decision to work off the farm. Farmers with certain off-farm labor experience may show a higher tendency to work off the farm.

Farmers with a higher household net worth would tend to allocate more time to leisure (Dewbre and Mishra, 2007), which would negatively affect the number of hours they work off the farm. The share of income from farming would have a negative effect on the hours spent off the farm by a farm operator.

The Data

The model is estimated using data obtained from the nationwide Agricultural Resource Management Survey (ARMS) developed by the Economic Research Service (ERS) and the National Agricultural Statistical Service (NASS) conducted in 2005 (USDA, ERS). The ARMS survey is designed to link data on the resources used in agricultural production to data on use of technologies, including GM crops (Mishra & Goodwin, 2004). The 2005 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. It also helps in the determination of production costs and returns of agricultural commodities and in the measurement of net farm income of farm businesses. Another aspect of ARMS' important contribution is the information it provides on the characteristics and financial conditions of farm households, including information on 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 (see 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)

Empirical Results and Analysis:

The two-stage simultaneous Tobit model estimates are presented in table 2. The joint significance for the independent variables included in the model are significant at the 1 percent level of significance. Table 2 shows that pseudo-R^2 indicating a good fit[2] is 0.27 for the adoption model and 0.12 for the hours worked off the farm model,. Table 2 also shows the robust standard errors and the t-statistics for the model. The coefficients and their *p* values merely suggest the direction of the coefficients and its significance.

The share of acres planted under GM corn was positively and significantly affected by the mean productivity index of the county, the amount of cash grain payments, the risk averseness of the farmer, and the fact that a farm is located in the North Central and Heartland areas. This conforms to all earlier literature on adoption of new technologies (Dewbre and Mishra, 2007;. Fernandez-Cornejo, et.al., 2000; Fernandez-Cornejo, et.al., 2005; Yang, 1997). Cropping efficiency, number of acres of corn, age of the farmer, and the age-squared variable show no significant impact on the adoption of GM corn in our analysis.

Interpreting the regression coefficients in the tobit model is complicated due to the presence of censoring (Tansel and Bircan, 2006). Since the regression coefficient would overestimate the effect on the dependent variable because a proportion of the sample is censored, marginal effects provide unbiased estimates as they take into account the probability of being in the nonlimit portion of the sample (Hobbs, 1997). The

[2] A rule of thumb among practitioners is that the regression model is deemed to have excellent predictive power if the computed value of McFadden Pseudo-R^2 falls between 0.10 and 0.30.

decomposition of the marginal effects of the two-stage Tobit model provides a richer and better understanding of the magnitude of the effect of the independent variables on the dependent variable, since coefficients from the Tobit model depict both changes in the probability of being above limit and changes in the value of the dependent variable if it is already above limit (McDonald & Moffitt, 1980). Following earlier literature we present the unconditional marginal effects and the marginal effects conditional on the dependent variable being positive for the two stages in Table 3 and 4 respectively. The tables also provides probability of being uncensored according to equation 15.

The first stage decomposition of the marginal effects on the share of acres of GM corn planted by farmers are presented in table 3. The marginal effects on the share of adoption of GM corn suggests that higher degree of risk-averseness (*RISKAVERSION*) tends to increase the share of GM corn by nearly an acre for all farmers and over an acre and a half for those who already have a share of their farms in GM corn, an increase in the mean productivity index of the county (*MEANPI*) tends to increase the share of GM corn by 0.02 acres for all farmers and by 0.03 acres for those who have already adopted this new technology, the cash grain (*CG*) payments to farmers shows that an unit increase in these payments increases the share of GM corn by 0.04 acres for all farms, tenant farmers. Tenant farmers (*TENANT*) and part owners (*POWNER*) tend to increase their profitability in farming through adoption of new technologies and show similar magnitude of effects on the share of GM corn planted. Tenant farmers and part-owners tend to increase the amount of GM corn planted by 0.03 acres for all farms and by 0.04 acres for those who already have adopted this technology. The Corn Belt dummies (*HEART* and *NORTHC*) show a positive significant effect on the adoption GM corn, with the share of acres in GM corn showing a significant increase by 0.05 acres if it is in heartland area, and 0.04 acres if it is in the Northern Crecent area, which is not surprising as these are primary corn producing regions in the U.S.

In the second stage predicted value of the adoption of GM corn is used to account for the interaction with the off-farm labor supply equation. Results are presented in table 4. The effect of the share of acres planted with GM corn on the hours worked off the farm showed a negative significant influence. This suggests that an increased number of acres of GM corn decreases the farmer's willingness to work off the farm. This may be due to the extra care that farmers who invest in higher priced seeds take to protect their investments. Smith (2002) points to the fact that off-farm labor offsets efficient farming; therefore, adopting new technologies has a potentially negative impact on the off-farm labor supply. Our results show empirically that this is true for farmers who plant GM corn. The proportion of time worked off-farm by the farm operator or spouse was shown by Fernandez-Cornejo et al. (2001) to have a negative impact on the adoption of Bt. Corn – a genetically modified variety of corn. Our study substantiates this finding in the two-stage simultaneous model for all GM corn varieties.

The test for exogeneity as proposed by Smith and Blundell (1986) was conducted following Baum (1999) to test the endogeneity of acres planted under GM corn and the number of hours worked off the farm. Results from table 2 suggest that we reject the null hypothesis that the two variables are exogeneous and that GM corn should be considered endogenous in our two-stage Tobit model.

The off-farm work experience and education show positive significant impacts on the number of hours worked off the farm by farm operators. Results from our model conforms to earlier literature suggesting that number of hours worked off the farm is affected by the share of income from farming **()**, all types of government payments **()**, net household worth (),age squared of the farm operator (), and risk aversion factor () have a negative significant impact on the hours worked off the farm, which conforms to earlier literature (Dewbre and Mishra, 2007; El-Osta, Mishra, and Ahearn, 2004; Huffman, 1980; Lamb, 1996; Lass D., 1991; Ahearn, et. al., 2006; Mishra and Goodwin, 1997; Sumner, 1982). Adoption of GM corn has a negative significant impact on the number of hours worked off the farm. This suggests that farmers adopting this new technology tend to work on the farm. Smith (2002) observed that off-farm work may hinder "smart" farming techniques and that capital intensive technology may scale dependent. Goodwin and Mishra (2004) showed an inverse relation to farm efficiency and hours worked off the farm.

The age of the operator (*OPAGE*) and age squared (*AGESQ*) variables have positive and negative signs, respectively. Results indicate that farmers tend to increase the number of hours worked off the farm at a decreasing rate, consistent with the life-cycle work pattern of farm operators. The coefficient for age 2.078 represents the age elasticity of the unobserved hours of off-farm labor. The coefficients suggest that farmers tend to start decreasing spending time off the farm at approximately age 38.

The coefficient of operator's educational attainment (OPEDUC) is positive and statistically significant. The marginal effect for all farm households suggests that an additional year of schooling increases the number of annual hours worked off the farm by 207 hours; for those farmers who already work off the farm, the number of annual hours worked off the farm increases by 179 hours.

Farm operators receiving direct farm program payments show a negative impact on the number of hours worked off the farm. The marginal effect of direct payments on the number of hours worked off the farm suggests that a one dollar increase in direct payment decreases the number of annual hours worked off the farm by three hours for all farm operators. Further, for operators who are already working off the farm, the number of hours worked off the farm decreases by two and half hours annually (table 4). Our results are consistent with the findings of Ahearn et. al. (2006). The coefficient of share of income from farming to total household income (SHINCOME) is negative and statistically significant at the 1 percent level of significance. Results suggest that a one percent increase in the share of income from farming tends to decrease annual hours worked off the farm by 20 percent for farmers who work off the farm, while it decreases by 23 percent for all farm operators in general.

Farm operators' off-farm work experience (OPOWEXP) has a significant positive impact on the number of annual hours worked off the farm. This result is in agreement with all earlier studies on the effect of off-farm work experience on off-farm labor supply and off-farm income (Huffman, 1980; Lamb, 1996; Lass, 1991; and Mishra and Goodwin, 1997). Results indicate that an additional year of off-farm work experience increases the number of annual hours worked off the farm by 3 percent, while for those farmers who are already working, the increase is about 2.5 percent.

Concluding Remarks

Sustained corn price increases in the past four years coupled with an increase in demand for alternative use of corn has made it critical for policymakers to understand the factors affecting the adoption of genetically modified corn and GM crops in general.

While the introduction of GM corn has been viewed as a time-saving technology, it may also be inducing farm operators to work off the farm; however, other factors, including the risk preference of farmers adopting this new technology and its cost intensiveness outweigh the increased number of hours farmers tend to work off the farm.

Using a national farm-level dataset, this study develops a model to estimate the impact of adoption of GM corn on the off-farm labor supply by farm operators. The study draws inferences about how different attributes of new technology influence its adoption and how its adoption has structural effects on the basic economic unit – the farm household. The study incorporates the endogeneity of adoption of GM corn and its effect on the number of hours worked off the farm by farm operators using a two-stage left censored Tobit model. Marginal effects are decomposed based on the MacDonald Moffitt decomposition of the Tobit model to better understand the differences and implications on all corn farms and those who have planted GM corn.

The study finds a. negative and a highly significant relationship between adoption of GM corn and the number of hours worked off the farm by farm operators. A number of farm and socio-economic characteristics, including size of farms, age, off-farm work experience of farm operators, and share of income from farming operations are significant factors that affect the off-farm labor supply of farm operators who adopt new technology such as GM corn. Our analysis concludes that increased efficiency measures by farmers through adoption of new technologies, such as GM corn, tend to decrease off-farm labor supply of farm operators, as hypothesized by Smith (2002).

Limitations and Future Research Directions

While the research has incorporated the share of farm income to control for the effects of large farms in the model for adoption of GM corn, an explicit 'large' farm has not been defined. As an ongoing research project we plan to address this limitation to our study. Further, to better understand the effects of a higher share of GM crops planted by farmers on the number of hours worked off the farm, we plan to extend this model to include GM cotton and soybean. To increase the robustness of our model we plan to use multiple year ARMS data (2004, 2005, and 2006) to test our current model and add year dummies to capture effects over these three years.

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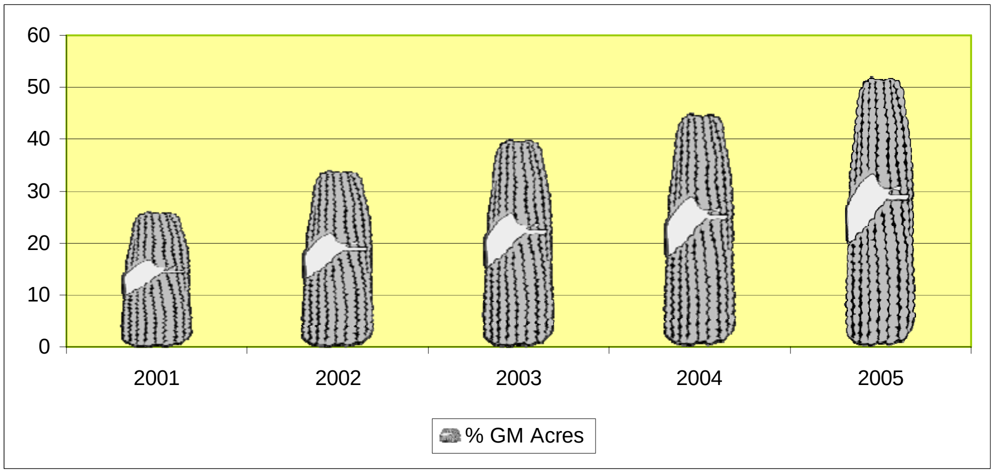
Figure1: Percent Acres of GM Corn in the US



Source: USDA, ERS

Table 1: Variable Definitions and Basic Statistics

Variable	Description	Mean
CROP_EFF	Cropping Efficiency (gross cash income/total variable cost)	2.6314
TENANT	Dummy tenant = 1	2.6314
POWNER	Dummy if Part Owner = 1	0.4648
MEANPI	Mean County Yield	76.3241
CG	Cash Grain Dummy	0.1663
HEART	Heartland Region Dummy	0.1262
NORTHC	North Crescent Region Dummy	0.1663
OP_AGE	Operator's Age	55.2259
AGESQ	Age Squared in ‘00	3210.0100
OP_EDUC	Operator's Education	12.3027
DIRECT	Direct Payments Received (Dollars)	8445.6500
INDIRECT	Indirect Payments Received (Dollars)	10412.6000
CRPPAYMENT	CRP Payments Received (Dollars)	1749.7700
SHINCOME	Share of Income from Farming	13.5803
RISKAVERSION	Ratio of Crop Insurance Premium to Variable Inputs	0.0097
OPOWKEXP	Operator's Off-farm Work Experience	4.5726
HH_SIZE	House Hold Size	2.8604
HHNW1	House Hold Net Worth ('00000 Dollars)	17.4628
NONMETRO	Miles to the Nearest Town of 10,000 or more	0.5105
SHGMACRES	Share of Number of Acres Planted under GM Corn	
H_OFFOP	Annual Hours Worked Off the Farm (00’s Hours)	

Table 2: Parameter Estimates of the Two Stage Tobit Model

Variable	Estimate	Robust Std. Err	t	P>|t|
		Share of GM Acres		
OPOWKEXP	-0.00473	0.000953	-4.96	0.0000
NOACRES	0.000002	0.000003	0.74	0.4600
CROP_EFF	-0.0033	0.002053	-1.61	0.1080
RISKAVERSION	0.872445	0.235036	3.71	0.0000
TENANT	0.227024	0.026106	8.70	0.0000
POWNER	0.248849	0.018668	13.33	0.0000
MEANPI	0.001835	0.000689	2.66	0.0080
EDUC	0.009797	0.006055	1.62	0.1060
OP_AGE	-0.00376	0.003850	-0.98	0.3290
AGESQ	0.000010	0.000034	0.30	0.7620
CG	0.25325	0.018234	13.89	0.0000
HEART	0.28724	0.018975	15.14	0.0000
NORTHC	0.249139	0.017396	14.32	0.0000
_CONS	-0.77712	0.132523	-5.86	0.0000
sigma	0.353364	0.00974		
Pseudo R^2	0.2646			
F(13, 6786)	76.25			
Prob > F	0.00000			
		Hours worked off the Farm		
OP_AGE	2.07739	1.41660	1.47	0.1430
AGESQ	-0.05626	0.01362	-4.13	0.0000
EDUC	6.61062	1.59250	4.15	0.0000
DIRECT	-0.00090	0.00029	-3.06	0.0020
INDIRECT	-0.00051	0.00019	-2.72	0.0070
CRPPAYMENT	-0.00060	0.00035	-1.72	0.0850
SHINCOME	-0.07590	0.03662	-2.07	0.0380
RISKAVERSION	-47.65096	83.17441	-0.57	0.5670
OPOWKEXP	9.59955	0.19721	48.68	0.0000
HH_SIZE	-2.12355	1.31557	-1.61	0.1070
HHNW1	-0.40967	0.20795	-1.97	0.0490
NONMETRO	9.73724	3.84159	2.53	0.0110
PSHGMCORNACRES	-35.02029	9.22520	-3.8	0.0000
_CONS	-109.86490	39.72623	-2.77	0.0060
sigma	119.923	2.352707		
Pseudo R^2	0.1108			
F(14.6785)	267.84			
Prob > F	0.0000			
Smith-Blundell test of exogeneity: 0.9633193 F(1,6784) P-value = 0.3264				

Table 3: Marginal Effects of the First Stage Tobit Model

variable	Probability Uncensored	Conditional on being Uncensored	Unconditional Expected Value
OPOWKEXP	-0.00235***	-0.00080***	-0.000474***
	(0.00046)	(0.00016)	(0.00009)
NOACRES	0.000001	0.00000034	0.0000001
	(0.0000)	(0.0000)	(0.0000)
CROP_EFF	-0.001641	-0.0005581	-0.000331
	(0.00102)	(0.00035)	(0.0002)
RISKAVERSION	0.43411***	0.14768***	0.0875***
	(0.11778)	(0.0398)	(0.0237)
TENANT	0.15163***	0.0448***	0.03558***
	(0.0209)	(0.0053)	(0.00561)
POWNER	0.1292***	0.0431***	0.0272***
	(0.0094)	(0.00314)	(0.00211)
MEANPI	0.000913***	0.000311***	0.000184***
	(0.00034)	(0.0012)	(0.00007)
EDUC	0.004875	0.00165	0.0009822
	(0.0030)	(0.0010)	(0.0006)
OP_AGE	-0.001871	-0.00064	-0.00037
	(0.0019)	(0.00065)	(0.0004)
AGESQ	0.000005	0.0000018	0.000001
	(0.00002)	(0.00001)	(0.0000)
CG	0.16656***	0.0496***	0.03901***
	(0.01515)	(0.0041)	(0.00411)
HEART	0.2011***	0.0586***	0.0491***
	(0.01648)	(0.00445)	(0.00468)
NORTHC	0.1632***	0.04871***	0.03811***
	(0.0137)	(0.00377)	(0.0036)

Table 4: Marginal Effects of the Second Stage Tobit Model

Variable	Probability Uncensored	Conditional on being Uncensored	Unconditional Expected Value
OP_AGE	0.061395	0.5623	0.0651
	(0.0042)	(0.3822)	(0.44125)
AGESQ	-0.00017***	-0.015229***	-0.01763***
	(0.00004)	(0.0037)	(0.0042)
EDUC	0.01954***	1.789415***	2.0711***
	(0.0047)	(0.4046)	(0.4973)
DIRECT	-0.0000027**	-0.0002439***	-0.0002823***
	(0.0000)	(0.00008)	(0.00009)
INDIRECT	-0.0000015**	-0.0001369***	-0.0001585***
	(0.0000)	(0.00005)	(0.00006)
CRPPAYMENT	-0.0000017*	-0.0001613*	-0.0001867*
	(0.0000)	(0.00009)	(0.00011)
SHINCOME	-0.0002243**	-0.0205456**	-0.023781**
	(0.00011)	(0.0099)	(0.01144)
RISKAVERSION	-0.1408	-12.89854	-14.9297
	(0.2459)	(22.525)	(26.084)
OPOWKEXP	0.02837***	2.5984***	3.0076***
	(0.0006)	(0.0565)	(0.08376)
HH_SIZE	-0.00627*	-0.57482*	-0.66533*
	(0.0039)	(0.3559)	(0.41187)
HHNW1	-0.001211**	-0.1109**	-0.128355**
	(0.0006)	(0.056)	(0.0646)
*NONMETRO**	0.02875**	2.63466***	3.0483***
	(0.0113)	(1.038)	(1.201)
PSHGMCORNACRES	-0.10349***	-9.4795***	-10.9723***
	(0.02725)	(2.50419)	(2.911)