Off-Farm Work and the Adoption of Herbicide-Tolerant Soybeans

Jorge Fernandez-Cornejo
Chad Hendricks

Economic Research Service, USDA
1800 M Street, NW, Room 4052, Washington DC, 20036
Phone 202-694-5537, jorgef@ers.usda.gov.

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Introduction and Objectives

Herbicide-tolerant crops contain traits that allow them to survive certain herbicides that previously would have destroyed the crop along with the targeted weeds.[1] This allows farmers to use more effective postemergent herbicides, expanding weed management options (Carpenter and Gianessi, 1999). Adoption has risen dramatically since commercial availability, particularly for herbicide-tolerant soybeans, which became available to farmers in limited quantities in 1996. Usage of HT soybeans quickly expanded to about 17 percent of soybean acreage in 1997 and reached 75 percent in 2002 (Fernandez-Cornejo and McBride, 2002).

A major element in assessing the farm-level impacts of GE crops is their microeconomic impact. Faced with reduced returns to crop production caused by low commodity prices, farmers were said to have viewed biotechnology as a potential means for reducing costs and/or increasing yields, thereby improving financial performance (Fernandez- Cornejo et al, 2002). Moreover, rapid adoption of herbicide-tolerant soybean varieties by U.S. farmers was seen as evidence that the perceived benefits of these technologies had outweighed the expected costs. However, recent research showed that there is essentially no difference between the net returns to using herbicide-tolerant versus conventional soybeans (Fernandez-Cornejo and McBride, 2002).[2] This suggests that other considerations may be driving adoption. In particular, some researchers believe that adoption of herbicide-tolerant soybeans is driven by the relative simplicity and flexibility of the

[1] The most common herbicide-tolerant crops are resistant to glyphosate, an herbicide effective on many species of grasses, broadleaf weeds, and sedges. Glyphosate tolerance has been incorporated into soybeans, corn, canola, and cotton. Other genetically modified herbicide-tolerant crops include corn resistant to glufosinate-ammonium, and cotton resistant to bromoxynil. There are also traditionally bred herbicide-tolerant crops, such as soybeans resistant to sulfonylurea.

[2] Fernandez-Cornejo et al. (2002) presented the first econometric estimate of the farm-level effects of adopting herbicide-tolerant soybeans based on nationwide farm-level survey data and correcting for self-selection and simultaneity. Their results show that there was a small yield advantage associated with farmers adopting herbicide-tolerant soybeans, but, on average, profits (net returns) are not statistically significantly affected by adoption.

weed control program. Herbicide-tolerant programs allow growers to apply one product over the soybean crop at any stage of growth instead of using several herbicides to "control a wide range of both broadleaf and grass weeds without sustaining crop injury" (Carpenter and Gianessi, 1999). In addition, using HT soybeans is said to make harvest "easier." (Duffy, 2002).

While it is difficult to measure simplicity and flexibility from survey data (Fernandez-Cornejo and McBride, 2002), it is clear that simplicity and flexibility translate into less management time employed to supervise production, freeing time for other uses. One obvious important alternative use of operators' time (and their spouses') is off-farm employment. However, despite the likelihood of a strong interaction between the adoption of management-saving agricultural technologies and off-farm employment by both the operator and his/her spouse, the role of off-farm activities has been largely neglected in studies of technology adoption in agriculture.

Made possible by alternative employment opportunities and facilitated by labor-saving technological progress, off-farm work by farm operators and their spouses has risen steadily over the past decades. As Mishra et al. (2002) show, total net income earned by farm households from farming, grew from about \$15 billion in 1969 to nearly \$50 billion in 1999. However, off-farm earned income, which began at a roughly comparable figure in 1969 (\$15 billion; off-farm wages and salaries alone totaled \$9 billion) soared to about \$120 billion in 1999. Moreover, as Mishra et al. (2002) note, as women's wages have risen, married women have become more likely to work in the paid labor market and household tasks are now shared between spouses.

The objective of this paper is to develop and estimate an econometric model to analyze the interaction of off-farm work and adoption of herbicide-tolerant soybeans using data from a nationwide survey of soybean farms for 2000.

The Theoretical Model

Using the agricultural household model as a framework (Singh et al., 1987), farm households are assumed to maximize utility U subject to income, production, and time constraints (Huffman, 1980, 1991; Lass et al., 1991; Lass and Gempesaw, 1992; Huffman and El-Osta, 1997). Household members receive utility from goods purchased for consumption (G), leisure (Lo for the operator and Ls for the spouse), and from factors exogenous to the household current decisions, such as human capital (H_o and H_s) and other exogenous factors, including household characteristics and weather (ψ). Thus:

(1) $$Max\ U = U(G, Lo, Ls, H_o, H_s, \psi)$$

Subject to the constraints:

(2) $$P_g Q_g = P_q Q - W_x X + W_o M_o + W_s M_s + V \qquad \text{(income constraint)}$$

(3) $$Q = f(X, F_o, F_s, H_o, H_s, R) \qquad \text{(production constraint)}$$

(4) $$T_i = F_i + M_i + L_i, \ \ M_i \geq 0 \qquad \text{(time constraint)}$$

where P_g and Q_g denote the price and quantity of goods purchased for consumption, respectively; P_q and Q represent the price and quantity of farm output, W_x and X are the price and quantity vectors of farm inputs; W_i represent off-farm wages paid to the operator ($i = o$) and spouse ($i = s$); M_i is the amount of off-farm work carried out by the operator ($i = o$) and spouse ($i = s$); F_i is the amount of on-farm work carried out by the operator ($i = o$) and spouse ($i = s$); V is other income, including income (from interest, dividends, annuities, private pensions, and rents) and government transfers (such as Social Security, retirement, disability, and unemployment); R denotes exogenous factors that shift the production function, and T_i denotes the (annual) time endowments for the operator and spouse.

The Decision to Work Off-Farm.

Assuming that both the operator and spouse face wages that are only dependent on their on their marketable human capital characteristics (H_o, H_s), local labor market conditions (including employment opportunities, cost of living and local amenities*)* and job characteristics *(*Ω), but not the amount of off-farm work (Huffman and Lange, 1989; Huffman, 1991; Tolke and Huffman, 1991), the (off-farm) market labor demand functions are $Wi = Wi\ (H_i, \Omega, \psi))$, ($i = o, s$).

From the Kuhn-Tucker optimization conditions we obtain the following off-farm participation rules for the operator and spouse of a married household:

$$(5) \qquad D_i = \begin{cases} 1 \ \ if \ \ W_i^* > 0 \\ 0 \ \ if \ \ W_i^* \leq 0 \end{cases}$$

where $W_i^* = (W_i - P_q\, \partial Q/\partial F_i)|_{Mi = 0}$ is the (unobserved) difference between the market wage and the reservation wage for the operator ($i = o$) and spouse ($i = s$) (Huffman and Lange, 1989; Lass et al, 1989; Tokle and Huffman, 1991). Then the probability of working off-farm is:

$$(6) \qquad P(D_i = 1) = F(W_i^* > 0) = \Phi(W_i > P_q\, \partial Q/\partial F_i|_{Mi = 0})$$

where Φ is a distribution function. The reservation wage for off-farm work for the operator (spouse) is the shadow value of farm labor --that is, the marginal value of time of the operator (spouse) when all his/her time is allocated to farm work and leisure ($M_i = 0$). From equation (6), the probability of working off-farm will depend on the reservation wage (which is a function of prices P_g, P_q, W_x*;* other income V*;* human capital $H_{i,}$*;* local labor market conditions Ω; household characteristics, such as children, and farm factors, such as size and complexity of operation; and other exogenous factors ψ. (Lass et al, 1989; Tolke and Huffman, 1991). Thus, the probability of working off-farm is:

(7) $P(D_i = 1) = F(w_i^* > 0) = \Phi\,(P_g, P_q, W_x, V, H_o, H_s, \Omega, \psi).$

For the empirical model, we append the random disturbance terms ε_i ($i = o,s$) and assume that ε_i is distributed normally. Thus, if F denotes the cumulative normal distribution and the vector Z includes all the factors or attributes influencing linearly the decision to work off-farm (i.e., the variables affecting the probability of working off-farm), equation (7) becomes the probit transformation:

(8) $P(D_i = 1) = F(\delta_i' Zi)$

where the vector Z_i includes: (i) farm factors, such as farm size, complexity of the operations, (ii) human capital (operator age/experience and education), (iii) off-farm employment opportunities, which will depend on the farms' accessibility to urban areas and the change in the rate of unemployment in nearby urban areas, (iv) farm typology, (v) government payments.[3]

Thus, the probit transformation can be used to model the off-farm work decision. However, the disturbances for the operator (ε_o) and spouse (ε_s) are likely to be correlated (Huffman, 1980). Therefore, univariate probit equations may not be used. Bivariate probit models have been used to model the off-farm employment decision by the operator and spouse (Huffman and Lange, 1989; Lass et al, 1989; Tokel and Huffman, 1991). In our case, however, the decision to work off farm and the adoption decision are related. Thus, we need to model the two off-farm employment decisions together with the adoption decision. For this reason, a multivariate probit model is necessary.

[3] Farm typology classification is based on the occupation of farm operator and includes mutually exclusive typology categories such as limited-resource, retirement, residential lifestyle, or a non-family farm. Limited-resource farms are constrained by low levels of assets and household income. Retirement farms are those with operators who report that they are retired (excluding limited resource farms). Residential lifestyle farms are those with operators who report a major occupation other than farming (excluding limited resource farms) (Hoppe et al., 1999).

The Adoption Decision

The adoption of a new technology is essentially a choice between two alternatives, the traditional technology and the new one. Growers are assumed to make their decisions by choosing the alternative that maximizes their perceived utility (Fernandez-Cornejo et al., 1994). Thus, a grower is likely to adopt if the utility of adopting, U_{a1}, is larger than the utility of not adopting, U_{a0}, that is if: $U_a^* = U_{a1} - U_{a0} > 0$. However, only the binary random variable I_a (taking the value of one if the technology is adopted and zero otherwise) is observed, as utility is unobservable. Moreover, because utilities are not known to the analyst with certainty, they are treated as random variables. In the context of adoption of HT soybeans: $U_{aj} = V_{aj} + \varepsilon_{aj}$, where V_a is the systematic component of U, related to the profitability of adopting ($j=1$) and the profitability of not adopting ($j=0$), and the random disturbance (ε_a) accounts for errors in perception and measurement, unobserved attributes and preferences, and instrumental variables.

The probability of adopting HT soybeans is:

$$P_1 = P\,(I_a = 1) = P\,(U_a^* > 0) = P\,(U_{a1} > U_{a0}) = P(V_{i1} - V_{i0} > \varepsilon_{a0} - \varepsilon_{a1}) = P(\varepsilon_{a0} - \varepsilon_{a1} < V_{a1} - V_{a0}).$$

Assuming that the disturbances are normally distributed, their difference will also be normally distributed and the probit transformation can be used to model the adoption decision. Thus, if F denotes the cumulative normal distribution, the probability of adoption of technology a is $P(I_a=1) = F(\delta_a' Z_a)$ and the adoption equation is $I_a = \delta_a' Z_a + \varepsilon_a$, where I_a denotes the adoption of a herbicide-tolerant crop and is usually interpreted as the probability, conditional on Z, that a particular grower will adopt (Fernandez-Cornejo et al., 2002).

The factors or attributes influencing adoption of HT soybeans, included in the vector Z_a, with the rationale to include them in parentheses, are: (i) farm size (other studies show that operators of larger farms are more likely to adopt innovations), (ii) farmer education (more educated farmers are often found to be more eager to adopt innovations), (iii) age (older farmers may be more reluctant to accept newer techniques), (iv) crop price (operators expecting higher prices are also more likely to expect higher margins and are more likely to adopt agricultural innovations), (v) seed price (higher prices reduce margins), (vi) a proxy for risk (as risk-averse farmers are less likely to adopt agricultural innovations), and (vii) farm typology.

The Multivariate Probit

The multivariate model generalizes the bivariate model (Greene, 1997). In the case of three dependent variables, (a) the operator's off-farm work participation decision, (b) the operator's spouse off-farm work participation decision, and (c) the HT soybeans adoption decision, we have:

(9a) $W_o^* = \delta_o' Z_o + \varepsilon_o,\ D_o = 1$ if $W_o^* > 0,\ D_o = 0$ otherwise,

(9b) $W_s^* = \delta_s' Z_s + \varepsilon_s,\ D_s = 1$ if $Ws^* > 0,\ D_s = 0$ otherwise,

(9c) $U_a^* = \delta_a' Z_a + \varepsilon_a,\ I_a = 1$ if $U_a^* > 0,\ I_a = 0$ otherwise.

where $[\varepsilon_o, \varepsilon_s, \varepsilon_o]$ ~ trivariate normal (TVN) $[0,0,0;1,1,1; \rho_{12}, \rho_{13}, \rho_{23}]$. That is, a multivariate normal distribution with variances $\rho_{ij}\ (i = j)$ equal to 1 and correlations $\rho_{ij}, (i \neq j)$, where $i, j = 1,2,3$. Each individual equation is a standard probit model.

The joint estimation of three or more probit equations was computationally unfeasible until recently because of the difficulty of evaluating high-order multivariate normal integrals. Over the past decade, however, new Montecarlo simulation techniques have been developed to carry out the estimation (Greene, 1997; Geweke et al., 1994).

U.S. farm-level data are obtained from the 2000 Agricultural Resource Management

Survey (ARMS) developed by the Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS) of USDA and carried out by NASS. The survey is designed to link data on the resources used in agricultural production to data on use of technologies (including the use of genetically engineered crops), other management techniques, chemical use, yields, and farm financial/economic conditions for selected field crops. The survey includes three phases (screening, obtaining production practices and cost data, and obtaining financial information). The ARMS is a multi-frame, probability-based survey in which sample farms are randomly selected from groups of farms stratified by attributes such as economic size, type of production, and land use. After selecting those farms that planted soybeans in 2000 and eliminating those observations with missing data, there were 2258 observations available for analysis. Table 1 shows the definitions as well as the sample averages of the main variables used in the model.

Results

The maximum likelihood estimates of the 3-equation multivariate probit model (equations 9a-9c) are shown in table 2. Beginning with the operator's off-farm work participation decision and considering the significant variables, the operator's off-farm work is positively related to age but negatively related to age squared, indicating that off-farm work participation increases with age up to a certain point and then declines. Operator's off-farm work is also positively related to his/her education, to the operator's spouse making day-to-day decisions in the farm, and to two farm typology variables (operating residential and limited-resource farms). On the other hand, operator's off-farm work is negatively related to farm size and complexity (as measured by the number of commodities produced), to the number of children in the household, and to increases in unemployment in areas within commuting distance from the farm. Operator's off-farm work is also negatively related to the share of the farm's land owned by the operator but this relationship is not statistically significant (pvalue = 0.14). The operator's off-farm work is not significantly related to the farm being located in a particular region of the country.

The operator's spouse's off-farm work participation decision is positively related to age and negatively related to age squared, indicating that spouse's off-farm work participation also increases with age up to a certain age and then declines. The spouse's off-farm work is also positively related to operating residential farms (typology variable). The spouse's off-farm work is negatively related to the spouse making day-to-day decisions in the farm and it is also negatively related to farm size, but, unlike the operator's case, it is not significantly related to farm complexity, number of children in the household, and changes in unemployment within commuting distance from the farm. Also, the spouse's off-farm work is negatively related to the land ownership share but, unlike the operator's case, this relationship is statistically significant. On the other hand, like the operator's, the spouse's off-farm work is not significantly related to a particular region of the country.

Adoption of herbicide tolerant soybeans is significantly positively related to age (but negatively related to age squared), to location in the heartland, and to the price of soybeans. Adoption is negatively related to farm size, to the number of children in the household, to operating retirement farms (typology variable), and to the percent land owned by the operator.

An important result, made available by the use of the multivariate probit model, are the correlation coefficients among the (the errors of the) three equations. As shown in table 2, the correlation between the operator's off-farm work decision and that of the spouse is significant and positive, indicating that if the operator decides to work off farm, the spouse is also likely to decide to work off farm. The correlation of the decision to adopt herbicide-tolerant soybeans and the decision to work off-farm is positive and significant for the spouse indicating that adoption facilitates working off-farm. However, the correlation between adoption and off-farm work was not significant for the operator. While this result seemed surprising, it is consistent with previous findings that in U.S. farm households the operator is more likely to work off farm than the spouse (Mishra et al., 2002, p. 7), i.e. the spouse's off-farm employment is more likely to be decided at the margin.

Discussion

Among the preliminary significant findings, we show that the operator's decision to work off-farm is positively associated with that of the spouse; the spouse's decision to work off-farm is positively associated with the adoption of HT soybeans. There is also a definite tradeoff between time spent on-farm and off-farm employment. Households operating small soybean farms that lack economies of scale are more likely to devote time to off-farm employment and are more likely to adopt management-saving technologies, such as the herbicide-tolerant soybeans. For these farms, it appears that economies of scope (derived from engaging in multiple income-generating activities, on and off the farm) can substitute for economies of scale. We believe that these findings provide empirical confirmation for Kitty Smith's (2002) observation: "*Economists have become accustomed to considering capital-intensive technologies as scale-dependent. Perhaps management intensity should also be viewed as a potential source of scale bias.*"

Conclusion

There is a tradeoff between time spent working on-farm and off-farm and a statistically significant relationship among off-farm work decisions by the operator, the spouse, and adoption, as well as some structural characteristics, such as farm size. The off-farm work decision by the operator is positively associated with that of the spouse; the spouse's off-farm work decision is positively associated with the adoption of HT soybeans. Households operating small farms are more likely to work off-farm and more likely to adopt a management-saving technology, such as HT soybeans.

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Table 1. Variable Definitions

Variable	Definition	Mean
NARMSIZE	Size of the farm, acres	1070.6
NO_COMOD	Number of commodities produced	3.4269
OP_AGE	Age of the operator, years	50.385
OP_AGESQ	Square of the age of the operator	2678.5
HIGHPLUS	Education, dummy = 1 if operator has at least high school	0.9252
OP_EXP	Years of operator experience	26.122
CHILDREN	Number of children	1.1696
SP_DECID	Spouse decides on farm day-to-day decisions	0.3654
CHANGEIN	Change in unemployment (between 2001 and 2000)	0.8318
RURALARE	Rural area continuum (metro=0, completely rural = 9)	5.5142
HEARTLAN	Regional dummy - Heartland	0.5009
NORTHERN	Regional dummy - Northern crescent	0.1382
VPLIVRAT	Percent revenues from livestock	0.2569
RESIDEND	Farm typology variable - residential farm	0.9920E-01
RETIREDU	Farm typology variable - retirement	0.1639E-01
LIMITEDD	Farm typology variable - limited	0.9300E-02
PERCENTO	Percent cropland owned by the operator	0.5833
SBPRICE	Soybean price	4.4692
PSEED	Seed price	3.5392
RISKLOVE	Risk attitude (risk avoiding = 4, risk loving = 20)	10.238

Table 2. Maximum Likelihood Estimates of the 3-Equation Multivariate Probit Model

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]
Equation 1. Index function for operator off-farm work				
Constant	-1.9380932	0.681314	-2.845	0.0044
FARMSIZE	-0.8305028E-03	0.141003E-03	-5.890	0.0000
NO_COMOD	-0.2417871	0.373004E-01	-6.482	0.0000
OP_AGE	0.7093432E-01	0.292951E-01	2.421	0.0155
OP_AGESQ	-0.1055620E-02	0.333899E-03	-3.161	0.0016
HIGHPLUS	1.0193211	0.219097	4.652	0.0000
OP_EXP	-0.4033875E-02	0.560620E-02	-0.720	0.4718
CHILDREN	-0.7515478E-01	0.364804E-01	-2.060	0.0394
SP_DECID	0.1854702	0.975224E-01	1.902	0.0572
CHANGEIN	-0.1011548	0.478842E-01	-2.112	0.0346
RURALARE	0.1003040E-01	0.199508E-01	0.503	0.6151
HEARTLAN	0.3956655E-02	0.111197	0.036	0.9716
NORTHERN	0.2049156919	0.154007	1.331	0.1833
VPLIVRAT	0.1117590	0.154826	0.722	0.4704
RESIDEND	2.1027722	0.105758	19.883	0.0000
RETIREDU	-0.3052223	0.355017	-0.860	0.3899
LIMITEDD	0.5511946	0.240622	2.291	0.0220
PERCENTO	-0.8983015E-01	0.614414E-01	-1.462	0.1437
Equation 2. Index function for operator's spouse off-farm work				
Constant	-4.1252798	0.524002	-7.873	0.0000
FARMSIZE	-0.1981476E-03	0.626399E-04	-3.163	0.0016
NO_COMOD	-0.6951498E-02	0.280770E-01	-0.248	0.8045
P_AGE	0.1589617	0.225230E-01	7.058	0.0000
OP_AGESQ	-0.1854348E-02	0.237425E-03	-7.810	0.0000
HIGHPLUS	-0.6718197E-01	0.119202	-0.564	0.5730
P_EXP	0.1784630E-01	0.423418E-02	4.215	0.0000
CHILDREN	-0.1061715E-01	0.264434E-01	-0.402	0.6880
P_DECID	-0.1178829	0.649632E-01	-1.815	0.0696
HANGEIN	0.2059969E-01	0.357155E-01	0.577	0.5641
RURALARE	0.4053680E-01	0.137088E-01	2.957	0.0031
HEARTLAN	-0.1167345E-02	0.816455E-01	-0.014	0.9886
NORTHERN	-0.2661796E-01	0.117225	-0.227	0.8204
VPLIVRAT	0.1223026	0.109494	1.117	0.2640
RESIDEND	0.2459152	0.810410E-01	3.034	0.0024
RETIREDU	-0.8322805E-02	0.214543	-0.039	0.9691
LIMITEDD	-0.3158151	0.276633	-1.142	0.2536
PERCENTO	0.9185248E-01	0.398959E-01	-2.302	0.0213

Table 2. Maximum Likelihood Estimates of the 3-Equation Multivariate Probit Model (continued)

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]
Equation 3. Index function for adoption of herbicide-tolerant soybeans				
Constant	-1.6644405	0.411813	-4.042	0.0001
FARMSIZE	-0.1859074E-03	0.694593E-04	-2.676	0.0074
NO_COMOD	-0.3016133E-02	0.252856E-01	-0.119	0.9051
OP_AGE	0.4613829E-01	0.144848E-01	3.185	0.0014
OP_AGESQ	-0.3789020E-03	0.139928E-03	-2.708	0.0068
HIGHPLUS	0.1541777	0.985113E-01	1.565	0.1176
OP_EXP	-0.4008051E-02	0.346753E-02	-1.156	0.2477
CHILDREN	-0.4426462E-01	0.241025E-01	-1.837	0.0663
SP_DECID	0.1454147E-01	0.591046E-01	0.246	0.8057
HEARTLAN	0.1203079	0.605509E-01	1.987	0.0469
VPLIVRAT	-0.5107751E-02	0.106224	-0.048	0.9616
RESIDEND	0.5563322E-01	0.778970E-01	0.714	0.4751
RETIREDU	-0.2950230	0.152814	-1.931	0.0535
LIMITEDD	-0.2897545	0.196826	-1.472	0.1410
PERCENTO	-0.8690686E-01	0.331445E-01	-2.622	0.0087
SBPRICE	0.1284102	0.351599E-01	3.652	0.0003
SEED	0.1667438E-04	0.243765E-05	6.840	0.0000
RISKLOVE	-0.809693E-02	0.850792E-02	-0.952	0.3413
Correlation coefficients				
R(01,02)	0.1806486	0.557698E-01	3.239	0.0012
R(01,03)	-0.3968323E-01	0.555862E-01	-0.714	0.4753
R(02,03)	0.6822406E-01	0.389992E-01	1.749	0.0802

Notes: E+nn or E-nn means multiply by 10 to + or -nn power.
Log likelihood function = -3287.97
Iterations completed = 70
Replications for simulated probs. = 100.