Journal of Agricultural and Applied Economics, 37,3(December 2005):549–563

Technology Adoption and Off-Farm Household Income: The Case of Herbicide-Tolerant Soybeans

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We model the interaction of off-farm work and adoption of agricultural technologies and the impact of adopting these technologies on farm household income from on farm and off-farm sources after controlling for such interaction, and estimate the model for the case of adoption of herbicide-tolerant (HT) soybeans using a nationwide survey of soybean farms for 2000. We find that adoption of HT soybeans is positively and significantly related to off-farm household income for U.S. soybean farmers, after controlling for other factors. In addition, while on-farm household income is not significantly related to adoption, total household income increases significantly with adoption.

Key Words: agricultural household model, biotechnology, herbicide tolerant soybeans, off-farm income, technology adoption

JEL Classifications: O33, Q12.

Herbicide-tolerant (HT) 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 (Gianessi and Carpenter). Adoption of HT crops has risen dramatically, particularly for HT soybeans, since commercial availability in 1996. HT soybeans use rose quickly to about 17% of U.S. soybean acreage in 1997 and reached 81% in 2003 (Fernandez-Cornejo and McBride; U.S. Department of Agriculture, National Agricultural Statistics Service).

A major element in assessing the farm-level impacts of HT 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). In particular, rapid adoption of HT soybeans by U.S. farmers was seen as evidence that the perceived benefits of this technology outweighed the expected costs.

However, recent research showed no statistically significant differences between the net returns (both at the enterprise and whole-farm level) from using HT and conventional soybeans (Fernandez-Cornejo and McBride). This suggests that other considerations may be

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The views expressed are those of the authors and do not necessarily represent the views or policies of ERS or the U.S. Department of Agriculture.

[1] The most common HT 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 HT crops include corn resistant to glufosinate ammonium.

driving adoption. In particular, some researchers believe that adoption of HT soybeans is driven by the relative simplicity and flexibility of the weed-control program. HT programs allow growers to apply one herbicide product over the soybean crop at any stage of growth instead of using several herbicides to control a wide range of weeds "without sustaining crop injury" (Gianessi and Carpenter). In addition, using HT soybeans is said to make harvest "easier" (Duffy).

While difficult to measure, simplicity and flexibility translate into reduced management time employed to supervise production, freeing time for other uses (Fernandez-Cornejo and McBride). An obvious important alternative use of operators' time (and their spouses', if married) is off-farm employment. However, despite the likelihood of a strong interaction between 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. Moreover, as Smith observed, standard measures of farm profitability, such as net returns (to management), give an incomplete picture of economic returns because they exclude the value of management time.

Using the appropriate measure of economic performance for farm households is essential, given the importance of off-farm income in U.S. agriculture. Made possible by alternative employment opportunities and facilitated by labor-saving technological progress, such as mechanization, off-farm work by farm operators and their spouses has risen steadily over the past decades, becoming the most important component of farm household income. As Mishra et al. 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), soared to about $120 billion in 1999. Moreover, as Mishra et al. 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.

This article has two main objectives: (1) to develop an econometric model to examine the interaction of off-farm work and adoption of agricultural technologies and the impact of technology adoption on farm household income (from on-farm and off-farm sources) after controlling for such interaction and (2) to estimate the model for the case of adoption of HT soybeans using data from a nationwide survey of soybean farms for 2000. The main research question is whether or not HT adoption has a significant effect on each of the components of household income.

Mean Household Income for Adopters and Nonadopters of HT Soybeans

The household income measure used to examine the impact of adopting HT soybeans on household income has two components: household income from farming and off-farm household income. Actual mean household income, calculated directly from a nationwide U.S. Department of Agriculture (USDA) survey of soybean farmers in 2000, differs for adopters and nonadopters of HT soybeans. As shown in the table below, total household income is much higher for adopters than for nonadopters. Moreover, most of the difference is due to the off-farm income component.

	Adopters	Non-adopters	Difference
Household income from farming, $/y	14,150	12,140	2,010
Off-farm household income, $/y	52,903	41,340	11,563
Total household income, $/y	67,053	53,480	13,573

These results are consistent with the notion that the management time saved by the adoption of HT soybeans is used to increase household off-farm activities, as discussed in the introduction. Thus, it appears that, to measure the economic benefits from HT soybean adoption, one also needs to look off the farm.

However, while illustrative, a comparison of means can only lead to a definite conclusion in an ideal experimental setting, where factors other than adoption are controlled by making them as similar as possible.[2] Unlike controlled experiments, conditions other than the treatment are not equal in farm surveys. Thus, these differences in mean household income cannot necessarily be attributed to adoption of HT soybeans because survey results are influenced by many other factors, including operator characteristics and management practices. Moreover, farmers are not assigned randomly to the two groups (adopters and nonadopters of the HT technology), but make the adoption choices themselves. Therefore, adopters and nonadopters may be systematically different and these differences may manifest themselves in farm performance and could be confounded with differences due purely to adoption. This situation, called self-selection, would bias the statistical results, unless it is corrected.

For these reasons, an econometric impact model is specified, which statistically controls for factors considered relevant, and for which there are data, by holding them constant, so that the effect of adoption can be estimated. The model developed takes into consideration that farmers' adoption and off-farm employment participation decisions may be simultaneous. The model also corrects for self-selection to prevent biasing the results (Greene).

The Conceptual Framework

The theoretical foundation is the agricultural household model (Huffman 1980, 1991; Kimhi 1994, 2004; Lass et al.; Lass and Gempesaw; Singh et al.). This model is appropriate because it combines in a single framework all important economic decisions of the farm household. The following presentation borrows from the farm household model offered by Huffman (1991), with several additions to allow for technology adoption. According to the agricultural household model, farm households maximize utility, U, subject to income, production technology, and time constraints. Household members receive utility from goods purchased for consumption, G, leisure (including home time), $\boldsymbol{L} = (L_o, L_s)$ for the operator and the spouse, and from factors exogenous to current household decisions, such as human capital, $\boldsymbol{H} = (H_o, H_s)$, and other factors, ψ (including household characteristics and weather). Thus,

$$(1) \qquad \text{Max } U = U(G, \boldsymbol{L}, \boldsymbol{H}, \psi).$$

subject to the constraints

$$(2) \qquad P_g G = P_q Q - \boldsymbol{W}_x \boldsymbol{X}' + \boldsymbol{W}\boldsymbol{M}' + A \quad \text{(income constraint)}$$

$$(3) \qquad Q = Q[\boldsymbol{X}(\Gamma), \boldsymbol{F}(\Gamma), \boldsymbol{H}, \Gamma, \boldsymbol{R}], \qquad \Gamma \geq 0 \quad \text{(technology constraint)}$$

$$(4) \qquad \boldsymbol{T} = \boldsymbol{F}(\Gamma) + \boldsymbol{M} + \boldsymbol{L}, \qquad \boldsymbol{M} \geq 0 \quad \text{(time constraint)},$$

where P_g and G denote the price and quantity of goods purchased for consumption, respectively; P_q and Q represent the price and quantity of farm output, $\boldsymbol{W}_x$ and $\boldsymbol{X}$ are the price and quantity (row) vectors of farm inputs; $\boldsymbol{W} = (W_o, W_s)$ represents off-farm wages (net of commuting costs) paid to the operator and spouse; $\boldsymbol{M} = (M_o, M_s)$ is the amount of time working off-farm by the operator and spouse; $\boldsymbol{F} = (F_o, F_s)$ is the amount of time working on the farm by the operator and spouse; A is other income, including income (from interest, dividends, annuities, private pensions, and rents) and government transfers (such as Social Security, retirement, disability, and unemployment); $\boldsymbol{R}$ is a vector of exogenous factors that shift the production function, and $\boldsymbol{T} = (T_o, T_s)$ denotes the (annual) time endowments for the operator and spouse. The production function is concave and has the usual regularity characteristics. As discussed in the introduction, some technologies offer simplicity and flexibility in the operations that translate into reduced management time employed to supervise production, freeing time for other uses. In these cases, the amount of time working on

[2] For example, means can be compared for yields of two groups of soybean plots that are equal in soil type, rainfall, sunlight, and all other respects, except that one group receives a treatment (e.g., uses HT varieties) and the other group does not. As an alternative to controlled experiments, the subjects that receive treatment and those that don't can be selected randomly.

the farm by the operator and the spouse $\boldsymbol{F}$ (and possibly the use of other farm inputs $\boldsymbol{X}$) are a function of Γ, the adoption intensity (extent of adoption) of the technology. A technology-constrained measure of (cash) household income is obtained by substituting Equation (3) into Equation (2) (Huffman 1991),

$$(5)\quad P_g G = P_q Q[\boldsymbol{X}(\Gamma), \boldsymbol{F}(\Gamma), \boldsymbol{H}, \Gamma, \boldsymbol{R}] - \boldsymbol{W}_x \boldsymbol{X}(\Gamma)' + \boldsymbol{W}\boldsymbol{M}' + A.$$

The first-order conditions for optimality (Kuhn–Tucker conditions) are obtained by maximizing the Lagrangian expression $\mathcal{L}$ over $(G, \boldsymbol{L})$ and minimizing it over the Lagrange multipliers $(\lambda, \boldsymbol{\mu})$, where $\boldsymbol{\mu} = (\mu_0, \mu_s)$,

$$(6)\quad \mathcal{L} = U(G, \boldsymbol{L}, \boldsymbol{H}, \psi) + \lambda\{P_q Q[\boldsymbol{X}(\Gamma), \boldsymbol{F}(\Gamma), \boldsymbol{H}, \Gamma, \boldsymbol{R}] - \boldsymbol{W}_x \boldsymbol{X}(\Gamma)' + \boldsymbol{W}\boldsymbol{M}' + A - P_g G\} + \boldsymbol{\mu}[\boldsymbol{T} - \boldsymbol{F}(\Gamma) - \boldsymbol{M} - \boldsymbol{L}].$$

The off-farm participation and adoption decisions may be obtained from the following Kuhn–Tucker conditions:

$$(7)\quad \partial\mathcal{L}/\partial\boldsymbol{X} = \lambda[P_q(\partial Q/\partial\boldsymbol{X}) - \boldsymbol{W}_x] = \boldsymbol{0}$$

$$(8)\quad \partial\mathcal{L}/\partial\boldsymbol{F} = \lambda P_q(\partial Q/\partial\boldsymbol{F}) - \boldsymbol{\mu} = \boldsymbol{0}$$

$$(9)\quad \partial\mathcal{L}/\partial\Gamma = \lambda\{P_q[(\partial Q/\partial\boldsymbol{X})(d\boldsymbol{X}/d\Gamma)' + (\partial Q/\partial\boldsymbol{F})(d\boldsymbol{F}/d\Gamma)' + \partial Q/d\Gamma] - \boldsymbol{W}_x(d\boldsymbol{X}/d\Gamma)'\} - \boldsymbol{\mu}(d\boldsymbol{F}/d\Gamma)' \le 0, \quad \Gamma \ge 0, \quad \Gamma(\partial\mathcal{L}/\partial\Gamma) = 0$$

$$(10)\quad \partial\mathcal{L}/\partial\boldsymbol{M} = \lambda\boldsymbol{W} - \boldsymbol{\mu} \le 0, \quad \boldsymbol{M} \ge \boldsymbol{0}, \quad \boldsymbol{M}(\lambda\boldsymbol{W} - \boldsymbol{\mu}) = \boldsymbol{0}$$

$$(11a)\quad \partial\mathcal{L}/\partial G = U_G - P_g\lambda = 0,$$

$$(11b)\quad \partial\mathcal{L}/\partial\boldsymbol{L} = \boldsymbol{U}_L - \boldsymbol{\mu} = \boldsymbol{0}$$

$$(12)\quad P_q Q[\boldsymbol{X}(\Gamma), \boldsymbol{F}(\Gamma), \boldsymbol{H}, \Gamma, \boldsymbol{R}] - \boldsymbol{W}_x\boldsymbol{X}(\Gamma)' + \boldsymbol{W}\boldsymbol{M}' + A - P_g G = 0$$

$$(13)\quad \boldsymbol{T} - \boldsymbol{F}(\Gamma) - \boldsymbol{M} - \boldsymbol{L} = \boldsymbol{0},$$

where $\boldsymbol{U}_L$, U_G are the partial derivatives of the function U. Without loss of generality, both the operator and spouse are assumed to have positive optimal hours of leisure and farm work, i.e., Equations (8) and (11b) are equalities.

The off-farm participation decision conditions for the operator and the spouse may be obtained from the optimality conditions for off-farm work, Equation (10), together with Equations (8) and (11b) as

$$(14)\quad \boldsymbol{W} \le \boldsymbol{\mu}/\lambda = P_q(\partial Q/\partial\boldsymbol{F}),$$

where $\boldsymbol{\mu}/\lambda$ is equal to the marginal rate of substitution between leisure and consumption goods (from Equations from [11a] and [11b]) and $P_q(\partial Q/\partial\boldsymbol{F})$ represents the value of the marginal product of farm labor for the operator and the spouse. Examining the components of Equation (14), $W_i < \mu_i/\lambda$ (strict inequality) indicates that the total time endowment for the operator ($i = o$) or spouse ($i = s$) is allocated between farm work and leisure; optimal hours of off-farm work are zero (corner solution), i.e., $M_i^* = 0$. On the other hand, if $W_i = \mu_i/\lambda$, optimal hours of off-farm work may be positive ($M_i^* \ge 0$) and $W_i = \mu_i = (\partial Q/\partial F_i)$ (interior solution) (Lass et al.; Huffman 1991; Kimhi 1994; Huffman and El-Osta). In this case, the value of the marginal product of farm labor is equal to the off-farm wage rate.[3]

When an interior solution for $\boldsymbol{M}$ occurs, Equations (7) and (8) can be solved together, independently of the rest of the Kuhn–Tucker conditions, to obtain the demand functions for on-farm labor, i.e., the optimal production and consumption decisions can be separated because the off-farm wage determines the value

[3] The marginal value of time of the farm operator (or spouse) when all his/her time is allocated to farm work and leisure and none is allocated to off-farm work ($P_q(\partial Q/\partial F_i)|_{M_i=0}$), represents the shadow value of farm labor and is called the reservation wage for off-farm work for the operator ($i = o$) or spouse ($i = s$). In this context, the operator (or spouse) will work off-farm when his/her reservation wage is less than the anticipated off-farm wage rate and will not work off-farm otherwise. Note also that assuming that both the operator and spouse face wages that are dependent on their marketable human capital characteristics $\mathbf{H}$, local labor market conditions and job characteristics Ω, but not on the amount of off-farm work (Huffman, 1991; Huffman and Lange, 1989; Tokle and Huffman, 1991), the off-farm market labor demand functions are $W_i = W_i(\mathbf{H}, \Omega)$ ($i = o, s$).

of the operator's and spouse's time ($\boldsymbol{W} = \boldsymbol{\mu}/\lambda$) (Huffman 1991; Huffman and Lange).[4]

The demand function for on-farm labor is then $\boldsymbol{F}^* = F(\boldsymbol{W}, \boldsymbol{W}_x, P_q, \boldsymbol{H}, \Gamma, \boldsymbol{R})$ and the demand for purchased farm inputs $\boldsymbol{X}^* = X(\boldsymbol{W}, \boldsymbol{W}_x, P_q, \boldsymbol{H}, \Gamma, \boldsymbol{R})$. These optimal input demand functions are substituted in the production function to obtain the supply of farm output, $Q^* = S(\boldsymbol{W}, \boldsymbol{W}_x, P_q, \boldsymbol{H}, \Gamma, \boldsymbol{R})$, and the maximum net household income may be expressed as

$$(15)\quad NI^* = P_q S(\boldsymbol{W}, \boldsymbol{W}_x, P_q, \boldsymbol{H}, \Gamma, \boldsymbol{R}) - \boldsymbol{W}_x \boldsymbol{X}^{*\prime} + \boldsymbol{W}\boldsymbol{M}' + A.$$

Solving jointly Equations (10), (11), and (15), we obtain the demand for leisure $\boldsymbol{L}^* = L(\boldsymbol{W}, P_g, NI^*, \boldsymbol{H}, \psi, \boldsymbol{T})$, and for consumption goods, $G = G(\boldsymbol{W}, P_g, NI^*, \boldsymbol{H}, \psi, \Gamma, \boldsymbol{T})$. The supply function for off-farm time is obtained by substitution of the optimal levels of leisure hours and farm work hours (Huffman 1991),

$$(16)\quad \boldsymbol{M}^* = \boldsymbol{T} - \boldsymbol{F}^* - \boldsymbol{L}^* = M(\boldsymbol{W}, \boldsymbol{W}_x, P_q, P_g, NI^*, \boldsymbol{H}, \psi, \Gamma, \Omega, \boldsymbol{R}, \boldsymbol{T}).$$

Finally, a reduced-form expression of total household income is obtained by

$$(17)\quad NI^* = NI(\boldsymbol{W}_x, P_q, P_g, A, \boldsymbol{H}, \psi, \Gamma, \boldsymbol{R}, \boldsymbol{T}).$$

As Huffman (1991) notes, when optimal hours for off-farm hours for the operator or the spouse are zero, the decision process is not recursive and production and consumption decisions must be made jointly. In this case, the arguments for the reduced-form expression of household income are the same as those in Equation (17) but exclude the exogenous variables related to the job characteristics and labor marketability.

The technology adoption decision condition is obtained from the optimality conditions, Equation (9) and Equations (8) and (11b), noting that the expression in brackets in Equation (9) is the total derivative $dQ/d\Gamma$. Thus, we obtain

$$(18)\quad P_q(dQ/d\Gamma) - \boldsymbol{W}_x(d\boldsymbol{X}/d\Gamma)' - (\boldsymbol{\mu}/\lambda)(d\boldsymbol{F}/d\Gamma)' \leq \boldsymbol{0}.$$

But from Equations (11a) and (11b), $\boldsymbol{\mu}/\lambda = P_g(\boldsymbol{U}_L/U_G)$, then

$$(19)\quad P_q(dQ/d\Gamma) - \boldsymbol{W}_x(d\boldsymbol{X}/d\Gamma)' - P_g(\boldsymbol{U}_L/U_G)(d\boldsymbol{F}/d\Gamma)' \leq \boldsymbol{0}.$$

The left-hand side of this expression may be interpreted as the marginal benefit of adoption, $P_q(dQ/d\Gamma)$ minus the marginal cost of adoption, which includes the marginal cost of the production inputs, $\boldsymbol{W}_x(d\boldsymbol{X}/d\Gamma)'$, and the marginal cost of the farm work, $P_g(\boldsymbol{U}_L/U_G)(d\boldsymbol{F}/d\Gamma)'$ (of the operator and the spouse), brought about by adoption (could be negative if adoption saves managerial time), valued at the marginal rate of substitution between leisure and consumption goods (which, when off-farm work hours are positive, equals the off-farm wage rate). It will not be optimal to adopt if the inequality is strict (corner solution), i.e., the marginal benefit of adoption falls short of the marginal cost of adoption. Optimal extent of adoption (interior solution) will occur when the equality is strict, i.e., when the value of the marginal benefit of adoption is equal to the marginal cost of adoption.

Based on the above theoretical discussion and given the cross-sectional nature of the data, one can use the implicit function theorem to deduce expressions for off-farm labor supply for farm operator and spouse and technology adoption (which affects off-farm labor supply of farm of operators and spouses) that are functions of wages, prices, human capital, nonlabor income, and other exogenous factors. These factors are replaced in reduced-form representations of labor supply and adoption by observable farm, operator, and household characteristics, including human capital. Ambient variables (family size, access to urban

[4] Moreover, when an interior solution occurs, from Equations (10), (11a), and (11b), we obtain $\boldsymbol{U}_L/U_G = \boldsymbol{W}/P_g$; that is, the marginal rate of substitution of between consumption goods and leisure is equal to the ratio of the wage rate and the price of the consumption goods.

areas), which might affect the productive capacity of the farm operator and the spouse, are also included. The following section outlines the empirical model and estimation method used to conduct the analysis.

The Empirical Model

A two-stage econometric model is specified. The first stage, the decision model, examines the off-farm work participation decisions and the technology adoption decision. The second stage is used to estimate the impact of adoption on household income.

The Decision Model

A simplified reduced-form approach is followed (Goodwin and Holt; Goodwin and Mishra) to specify the empirical model rather than explicitly estimating a structural model of labor supply. In this approach, the reduced-form model is obtained by specifying the endogenous variables ($\boldsymbol{M}$, $\boldsymbol{F}$, Q_g, $\boldsymbol{X}$) in terms of the exogenous variables, including ($\boldsymbol{W}_x$, P_q, P_g, $\boldsymbol{H}$, ψ, ξ_i, Ω, $\boldsymbol{R}$, $\boldsymbol{T}$). Equation (14), implied by the Kuhn–Tucker conditions, is central for the off-farm work participation decision of the operator and the spouse, and Equation (19) is central for the adoption decision. Thus, considering a first-order approximation (linear terms) and adding the stochastic terms, the empirical representation of the off-farm participation of the operator, Equation (20a), and the spouse, Equation (20b), and the technology adoption decision, Equation (20c), are

$$\text{(20a)} \quad \boldsymbol{\beta}_o \boldsymbol{Z}_o' + \varepsilon_o \leq 0$$

$$\text{(20b)} \quad \boldsymbol{\beta}_s \boldsymbol{Z}_s' + \varepsilon_s \leq 0$$

$$\text{(20c)} \quad \boldsymbol{\beta}_a \boldsymbol{Z}_a' + \varepsilon_a \leq 0,$$

where the (row) vectors $\boldsymbol{Z}_o$, $\boldsymbol{Z}_s$, and $\boldsymbol{Z}_a$ include all the factors or attributes influencing linearly the off-farm participation for the operator and spouse and the adoption decision, respectively, and $\boldsymbol{\beta}_o$, $\boldsymbol{\beta}_s$, and $\boldsymbol{\beta}_a$ are vectors of parameters. Assuming that the stochastic disturbances are normally distributed, each of these equations may be estimated by probit. However, because the disturbances (ε_o, ε_s, ε_a) are likely to be correlated, univariate probit equations are not appropriate. Bivariate probit models have been used to model the off-farm employment decisions by the operator and spouse (Huffman and Lange; Lass et al.; Tokle and Huffman). Because the decisions to work off farm and the technology adoption decision may be related, all three decisions are modeled together in a multivariate probit model (Greene). Formally, [ε_o, ε_s, ε_a] $\sim$ trivariate normal (TVN) [0, 0, 0; 1, 1, 1; ρ_{12}, ρ_{13}, ρ_{23}], with variances ρ_{ij} ($i = j$) equal to 1 and correlations ρ_{ij} ($i \neq j$), where i, j = 1, 2, 3.

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, the estimation has been made possible with Monte Carlo simulation techniques (Geweke et al.; Greene).

The vector $\boldsymbol{Z}_i$ includes: (i) farm factors, such as farm size and complexity of the operations, (ii) human capital (operator age/experience and education), (iii) household characteristics (such as the number of children), (iv) 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, (v) farm typology, (vi) government payments.[5,6] The factors or attributes influencing adoption of HT soybeans, included in the vector $\boldsymbol{Z}_a$ include farm factors, human capital, farm typology, a proxy for risk (risk-averse farmers are less likely to adopt agricultural innovations,

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[5] Following Goodwin and Holt (2002), some prices are not included in our empirical models because prices are approximately constant across households when data consist of cross-sectional observations taken at a point in time.

[6] Farm typology classification is based on the occupation of the farm operator and includes mutually exclusive typology categories, such as limited-resource, retirement, residential lifestyle, or a nonfamily 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.).

Fernandez-Cornejo et al., 1994), as well as crop and seed prices.

The Income Impact Model

The second stage is the income impact model, which provides estimates of the impact of adoption on household income after controlling for other factors. The empirical representation of this model based on Equation (17), the reduced-form expression of household income, is $NI^* = NI(\boldsymbol{W}_x, P_q, P_g, A, \boldsymbol{H}, \psi, \Gamma, \boldsymbol{R}, \boldsymbol{T})$.

After linearizing this reduced form, separating out explicitly the adoption indicator variable, and appending a random disturbance ε, assumed to be normally distributed, we have

$$(21) \quad NI^* = \boldsymbol{\theta}\boldsymbol{V}' + \alpha I + \varepsilon,$$

where NI^* represents household income, $\boldsymbol{V}$ is a (row) vector of observable explanatory variables that may influence household income (other than technology adoption), such as prices, human capital, and ambient variables (family size, access to urban areas), that may affect the productive capacity of the farm operator and the spouse; I is an indicator variable for adoption ($I = 1$ if adoption takes place and $I = 0$ otherwise), $\boldsymbol{\theta}$ and α are appropriately dimensioned parameters. The impact of adoption on household income is measured by the estimate of the parameter α. However, as noted by Stefanides and Tauer, if α is to measure the impact of adoption on income of a representative farm, farmers should be randomly assigned among adopters and nonadopter categories. This is not the case because farmers are not assigned randomly to the two groups (adopters and nonadopters) but make the adoption choices themselves. Therefore, adopters and nonadopters may be systematically different and these differences may manifest themselves in farm performance and could be confounded with differences due purely to adoption. This situation, called self-selection, would potentially bias the statistical results unless it is corrected (Fernandez-Cornejo et al. 2002).

To correct for self-selection bias, we follow Maddala (p. 260) and Greene (p. 642, 643) and obtain consistent estimates of the parameters $\boldsymbol{\theta}$ and α by regarding self-selection and simultaneity (discussed earlier) as sources of endogeneity. Because the dummy variable I cannot be treated as exogenous, instrumental variable techniques are used to purge the dependence of I. The predicted probability of adoption, obtained from the decision model, is used as an instrument for I in Equation (21).

Note that, unlike the traditional selectivity model, in which the effects are calculated (separately) using the subsamples of adopters and nonadopters, the impact model uses all the observations and is known as a treatment-effects model, used by Barnow, Cain, and Goldberger, and others. The treatment-effects model consists of the regression $Y = \boldsymbol{\theta}\boldsymbol{V}' + \alpha I + \varepsilon$, where the observed indicator variable I ($I = 1$ if $I^* > 0$ and $I = 0$ if $I^* \leq 0$), indicates the presence or absence of some treatment (adoption of HT crops in this case) and the unobserved or latent variable I^* is given by $I^* = \boldsymbol{\delta}\boldsymbol{Z}_a' + \nu$ (Greene).

Total household income (NI^*), as represented in Equation (17), has two components: household income from farming (*FARMHHI*) and off-farm household income (*TOTOFI*). Household income from farming includes farm business household income, operator-paid farm income, household members paid farm income, etc. (see detailed definitions in Table 1). Off-farm household income includes off-farm business income, income from operating other farm business, off-farm wages and salaries, etc. (Table 1).

The components of vector $\boldsymbol{V}$ include farm location and typology, operator age, education and experience, number of children, price of soybeans, a measure of specialization on soybean production, a measure of the extent of livestock operations, farm size, and proxies for local labor market conditions.

Data and Estimation

The model is estimated using data obtained from the nationwide Agricultural Resource Management Survey (ARMS) developed by the Economic Research Service (ERS) and the

Table 1. Household (HH) Income Variable Definitions

1. Household income from farming (FARMHHI) = farm business income HH share
+ operator paid on farm
+ household members paid on farm
+ net income from rented land

where

Farm business income HH share = net cash farm business income
− depreciation
− gross income from rented land
− operator paid onfarm
− income due to other households

Net cash farm income = gross cash farm income − cash operating expenses

Gross cash farm income = crop and livestock income including cc loans
+ other farm income (includes goverment payments, income from custom work and machine hire, income from livestock grazing, other farm-related income, income from farm rented to others, fee income from crops removed under production contract, fee income from livestock removed under production contract)

Total cash operating expenses (hired labor, contract labor, seed, fertilizer, chemicals, fuel, supplies, tractor and other equipment leasing, repairs, custom work, general business, real estate and property taxes, insurance, interest, purchased feed, purchased livestock)

2. Off-farm household income (TOTOFI) = off-farm business income
+ income from operating other farm business
+ off-farm wages and salaries
+ interest and dividend income
+ other off-farm income
+ rental income

3. Total household income (TOTHHI) = household income from farming (FARMHHI)
+ off-farm household income (TOTOFI)

National Agricultural Statistics Service (NASS) of USDA and conducted in 2000 (USDA, ERS). The ARMS 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 multiframe, 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.

The data set includes 17 soybean producing states: Arkansas, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Mississippi, Michigan, Minnesota, Missouri, Nebraska, North Carolina, Ohio, South Dakota, Tennessee, and Wisconsin. After selecting those farms that planted soybeans in 2000 and eliminating those observations with missing data, there were 2,258 observations available for analysis. Table 2 shows the definitions as well as the sample averages of the main variables used in the model.

Because of the complexity of the survey design, a weighted least squares (WLS) technique is used to estimate the parameters using full-sample weights developed by the NASS of the USDA.

Two methods are used for the calculation of variances (and standards errors). The standard

Table 2. Variable Definitions

Variable	Definition	Mean
SIZE	Size of the farm, acres	474
NO_COMOD	Number of commodities produced (used as a proxy for complexity of the operation)	3.021
OP_AGE	Age of the operator, years	51.32
HIGHPLUS	Education, dummy = 1 if operator has at least high school	0.898
OP_EXP	Years of operator experience	25.57
CHILDREN	Number of children	1.110
SP_DECID	Spouse decides on farm day-to-day decisions (dummy variable)	0.365
CHANGE_IN_U	Change in unemployment (between 2001 and 2000)	0.811
RURALARE	Rural area continuum (metro = 0, completely rural = 9)	5.373
HEARTLAN	Regional dummy variable, heartland	0.647
NORTHERN	Regional dummy variable, northern crescent	0.156
RESIDEND	Farm typology variable, residental farm dummy variable	0.240
RETIREDU	Farm typology variable, retirement farm dummy variable	0.042
LIMITEDD	Farm typology variable, limited resources farm dummy variable	0.020
FM_TYPOL	Farm typology index	4.357
PERCENTO	Percent cropland owned by the operator	0.812
SBPRICE	Soybean price, $/bushel	4.497
RISKLOVE	Risk attitude (risk avoiding = 4, risk loving = 20)	10.24
PCTSOY	Share of farm revenues from soybeans	0.372
PCTLIV	Percentage revenues from livestock	0.225
TOTOFI	Off-farm household income, thousand $	47.930
FARMHHI	Household income from farming, thousand $	13.285
TOTHHI	Total household income, thousand $	61.215

procedure is simple but does not account for the effect of stratification. However, as Carrington et al. note, "... ignoring stratification in the estimation of variances is not likely to cause substantial bias." The alternative method of variance estimation accounts for the survey design and involves a delete-a-group jackknife method. While this alternative method "can be used meaningfully in a remarkably broad range of settings" in complex survey designs, such as ARMS (Kott 1998), it has also a drawback. It is overly conservative (estimated variances and standard errors are higher than the true variances and standard errors; Kott, 1998), which may underestimate the significance of a variable under some circumstances.

The alternative method follows the logic of the standard jackknife method except that a group of observations is deleted in each replication. It consists of partitioning the sample data into r groups of observations ($r = 15$ in this survey) and resampling, thus forming 15 replicates and deleting one group of observations in each replicate (Kott; Kott and Stukel; Rust). A set of sampling weights is calculated by NASS for each replicate. The model is run first with the full-sample weights to obtain the parameter estimates. The model is then run 15 additional times (using each of the 15 replicate weights) and the vector of parameters obtained in each case is compared with the full-sample parameter vector to calculate the standard errors.[7]

Results

Decision Model Results

The maximum likelihood estimates of the decision model, i.e., the three-equation multivar-

[7] The standard errors se(b) are calculated by se(b) $= \sqrt{c \cdot \Sigma^k[\mathbf{b}(k)-\mathbf{b}][\mathbf{b}(k)-\mathbf{b}]'}$ where $k = 1, 2, \ldots, 15$; $c = 14/15$; $\mathbf{b}(k)$ is the vector of parameters obtained in each replication and $\mathbf{b}$ is the full-sample parameter vector.

Table 3. Parameter Estimates of the Decision Model (Multivariate Probit)

Variable	Parameter estimate	Using standard procedures: Standard error	Using standard procedures: Coefficient/ standard error	Using the delete-a-group jackknife: Standard error	Using the delete-a-group jackknife: Coefficient/ standard error
A. Index function for operator off-farm work (Equation [20a])					
Constant	−1.9381	0.6813	−2.845	1.4263	−1.359
SIZE	−0.0008	0.0001	−5.890	0.0002	−3.821
NO_COMOD	−0.2418	0.0373	−6.482	0.0638	−3.787
OP_AGE	0.0709	0.0293	2.421	0.0634	1.119
OP_AGESQ	−0.0011	0.0003	−3.161	0.1210	−0.009
HIGHPLUS	1.0193	0.2191	4.652	0.4142	2.461
OP_EXP	−0.0040	0.0056	−0.720	0.0118	−0.341
CHILDREN	−0.0752	0.0365	−2.060	0.0997	−0.754
SP_DECID	0.1855	0.0975	1.902	0.1941	0.955
CHANGE_IN_U	−0.1012	0.0479	−2.112	0.0722	−1.402
RURALARE	0.0100	0.0200	0.503	0.0317	0.317
HEARTLAN	0.0040	0.1112	0.036	0.2273	0.017
NORTHERN	0.2049	0.1540	1.331	0.2023	1.013
VPLIVRAT	0.1118	0.1548	0.722	0.2754	0.406
RESIDEND	2.1028	0.1058	19.883	0.1991	10.561
RETIREDU	−0.3052	0.3550	−0.860	6.7441	−0.045
LIMITEDD	0.5512	0.2406	2.291	0.5503	1.002
PERCENTO	−0.0898	0.0614	−1.462	0.1626	−0.553
B. Index function for operator's spouse off-farm work (Equation [20b])					
Constant	−4.1253	0.5240	−7.873	0.7955	−5.186
SIZE	−0.0002	0.0001	−3.163	0.0001	−2.889
NO_COMOD	−0.0070	0.0281	−0.248	0.0454	−0.153
OP_AGE	0.1590	0.0225	7.058	0.0350	4.541
OP_AGESQ	−0.0019	0.0002	−7.810	0.0004	−4.942
HIGHPLUS	−0.0672	0.1192	−0.564	0.2377	−0.283
OP_EXP	0.0178	0.0042	4.215	0.0095	1.886
CHILDREN	−0.0106	0.0264	−0.402	0.0466	−0.228
SP_DECID	−0.1179	0.0650	−1.815	0.0998	−1.182
CHANGE_IN_U	0.0206	0.0357	0.577	0.0412	0.500
RURALARE	0.0405	0.0137	2.957	0.0256	1.584
HEARTLAN	−0.0012	0.0816	−0.014	0.1258	−0.009
NORTHERN	−0.0266	0.1172	−0.227	0.2175	−0.122
VPLIVRAT	0.1223	0.1095	1.117	0.1898	0.644
RESIDEND	0.2459	0.0810	3.034	0.1439	1.709
RETIREDU	−0.0083	0.2145	−0.039	0.5077	−0.016
LIMITEDD	−0.3158	0.2766	−1.142	0.3808	−0.829
PERCENTO	−0.0919	0.0399	−2.302	0.0774	−1.187
C. Index function for adoption of herbicide-tolerant soybeans (Equation [20c])					
Constant	−1.6644	0.4118	−4.042	0.8044	−2.069
SIZE	−0.0002	0.0001	−2.676	0.1801	−0.001
NO_COMOD	−0.0030	0.0253	−0.119	0.1315	−0.023
OP_AGE	0.0461	0.0145	3.185	0.0289	1.594
OP_AGESQ	−0.0004	0.0001	−2.708	0.0002	−1.629
HIGHPLUS	0.1542	0.0985	1.565	0.2187	0.705
OP_EXP	−0.0040	0.0035	−1.156	0.0054	−0.748

Table 3. (Continued)

Variable	Parameter estimate	Using standard procedures: Standard error	Using standard procedures: Coefficient/ standard error	Using the delete-a-group jackknife: Standard error	Using the delete-a-group jackknife: Coefficient/ standard error
CHILDREN	−0.0443	0.0241	−1.837	0.0395	−1.121
SP_DECID	0.0145	0.0591	0.246	0.1134	0.128
HEARTLAN	0.1203	0.0606	1.987	0.0816	1.474
VPLIVRAT	−0.0051	0.1062	−0.048	0.1511	−0.034
RESIDEND	0.0556	0.0779	0.714	0.1669	0.333
RETIREDU	−0.2950	0.1528	−1.931	0.3095	−0.953
LIMITEDD	−0.2898	0.1968	−1.472	0.3912	−0.741
PERCENTO	−0.0869	0.0331	−2.622	0.6390	−0.136
SBPRICE	0.1284	0.0352	3.652	0.1351	0.951
SEEDP	0.00002	0.0000	6.840	0.00000	4.292
RISKLOVE	−0.0081	0.0085	−0.952	0.0154	−0.527

iate probit model (Equations [20a]–[20c]) are shown in Table 3. This decision model is mainly used to estimate the predicted probabilities of adoption, accounting for the interaction with off-farm employment decisions. Table 3 also shows the standard errors and *t*-statistics calculated using the standard variance calculation procedure and the delete-a-group jackknife variance calculation procedure.

Beginning with the operator's off-farm work participation decision and considering the significant variables under the standard variance calculation procedure, the operator's decision to work off-farm 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, the operator's decision to work off-farm 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. The operator's off-farm work decision is also negatively related to the share of the farm's land owned by the operator, but this relationship is not statistically significant (p-value = 0.14). The operator's off-farm work decision is not significantly related to the farm being located in a particular region of the country.

The off-farm work participation decision of the operator's spouse 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 decision is also positively related to operating residential farms (typology variable). The spouse's off-farm work decision 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 decision 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 decision is not significantly related to location in a particular region of the country.

Adoption of HT 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 neg-

Table 4. Parameter Estimates of the Impact Model

Variable	Parameter estimate	Using standard procedures: Standard error	Using standard procedures: *t*-value	Using the delete-a-group jackknife: Standard error	Using the delete-a-group jackknife: *t*-value
1. Dependent variable: Off-farm household income (TOTOFI)					
Intercept	56.080	18.386	3.05	25.761	2.18
PROBABILITY OF ADOPT	133.438	34.354	3.88	66.981	1.99
HIGHPLUS	12.379	7.424	1.67	5.087	2.43
OP_EXP	0.090	0.154	0.58	0.115	0.78
CHILDREN	4.589	1.527	3.01	2.032	2.26
RURALAREA	−0.941	0.842	−1.12	1.062	−0.89
CHANGE_IN_U	3.193	2.276	1.40	4.061	0.79
HEARTLAND	−0.134	4.764	−0.03	8.661	−0.02
SBPRICE	−4.213	3.005	−1.40	2.477	−1.70
FM_TYPOL	−12.336	2.406	−5.13	8.570	−1.44
PCTLIV	−26.675	8.529	−3.13	17.778	−1.50
PCTSOY	−46.037	10.099	−4.56	51.107	−0.90
SIZE	−14.119	8.563	−1.65	5.907	−2.39
SIZE_SQ	2.639	1.696	1.56	1.159	2.28
2. Dependent variable: Farm income to household (FARMHHI)					
Intercept	−57.662	13.151	−4.38	14.262	−4.04
PROBABILITY OF ADOPT	−30.446	25.140	−1.21	29.794	−1.02
HIGHPLUS	5.853	5.437	1.08	4.309	1.36
OP_EXP	0.085	0.113	0.75	0.121	0.70
CHILDREN	−1.944	1.118	−1.74	1.175	−1.65
HEARTLAND	6.207	3.435	1.81	4.567	1.36
SBPRICE	1.950	2.200	0.89	2.063	0.95
FM_TYPOL	16.313	1.761	9.27	1.223	13.34
PCTLIV	5.360	6.232	0.86	6.742	0.80
PCTSOY	1.827	7.385	0.25	6.723	0.27
SIZE	−7.630	6.216	−1.23	11.035	−0.69
SIZE_SQ	3.534	1.238	2.86	2.976	1.19

atively related to farm size, to the number of children in the household, to operating retirement farms (typology variable), and to the percent of land owned by the operator.

Under the most strict, although perhaps too conservative, delete-a-group jackknife variance calculation procedure, the operator's decision to work off-farm is negatively related to farm size and complexity (as measured by the number of commodities produced) and positively related to the operators' education and to farm typology variables (retirement, residential, and limited-resource farms). The operator's spouse's off-farm work participation decision is negatively related to farm size, but, unlike the operator's case, it is not significantly related to farm complexity. The spouse's off-farm work decision is also positively related to operating residential farms. On the other hand, the spouse's off-farm work is positively related to age and negatively related to age squared, indicating that the spouse's off-farm work increases with age but only up to a certain point.

Impact Model Results

The results of this model are shown in Table 4. The relationship of adoption of HT soybeans with *off-farm* household income is positive and statistically significant under both the standard and jackknife variance calculation procedures (Table 4). The elasticity of off-farm household income with respect to the probability of adoption of herbicide-resistant soybeans (calculated at the mean) is +0.843. That is a 10% increase in the probability of adoption of HT soybeans is associated with an increase in off-farm household income of 8.4%.[8] On the other hand, adoption of HT soybeans did not have a significant effect on household income from farming under either the standard or jackknife variance calculation procedures (Table 4).

Adoption of HT soybeans is positively and significantly associated with total household income (from off-farm and on-farm sources). The calculated elasticity of total household income with respect to the probability of adoption of herbicide-resistant soybeans (calculated at the mean) is +0.643. This means that a 10% increase in the probability of adoption of herbicide-resistant soybeans is associated with an increase in total household income of 6.4%.

Regarding the influence of farm size on off-farm household income, we find that, after controlling for other factors, both the linear and quadratic coefficients are significant for farm size (Table 4), implying that income from off-farm sources increases with size, but only up to a certain point, at which off-farm income reaches a maximum, and then declines as size increases further. This maximum was reached at a size of about 2,670 acres, which is five times the average farm size in the sample. On the other hand, the relationship between size and income from on-farm sources was not significant after controlling for other factors (Table 4). Because of the predominance of off-farm income, total household income increases with size but up to a maximum of 1,846 acres, which is lower than the size at which the maximum for off-farm income was obtained.

Concluding Comments

This article develops a model that incorporates the technology-adoption decision into the agricultural household. Two contributions to traditional research on technology-adoption analysis are introduced in this article: the unit of analysis is the household rather than the farm business and the metric for economic performance is household income rather than farm profits.

This article finds statistically significant relationships between off-farm income, adoption of HT soybeans, and structural characteristics, such as farm size. U.S. farm operators and their spouses are more likely to work off-farm and together are more likely to obtain a higher household income from off-farm sources when they operate small soybean farms (lacking economies of scale). Adoption of HT soybeans is significantly and positively associated with off-farm household income for U.S. soybean farmers, after controlling for other factors. In addition, while on-farm household income is not significantly affected by adoption, there is a significant relationship between adoption and total household income. Thus, our findings also suggest a rationale for the rapid HT adoption by U.S. farmers. Farmers may adopt herbicide-tolerant soybeans because the simplicity and flexibility of the weed-control program permits them to save management time, allowing farmers to obtain a higher income from off-farm activities.

Interpreted in a broader sense, our findings illustrate the importance of accounting for household and firm interactions in modeling farmer adoption decisions. In particular, our findings suggest that the tradeoff between the time spent working on the farm and off the farm translates into a substitution of economies of scope (derived from engaging in multiple income-generating activities, on and off the farm) for economies of scale. Thus, our findings appear to provide empirical confirmation to Kitty Smith's observation that, like the economists' perceived link between capital

[8] Results are typically expressed as elasticity—the percentage change in a particular effect (e.g., income) relative to a small percentage change in adoption of the technology from current levels. The results can be viewed in terms of the aggregate effect (across a region or sector) from aggregate increases in adoption. However, in terms of a typical farm—that has either adopted or not, the elasticity is usually interpreted as the (marginal) farm-level effect associated with an increase in the probability of adoption, away from a given, e.g., current level of adoption.

intensity and scale dependency of technologies, ". . . perhaps management intensity should also be viewed as a potential source of scale bias."

[Received January 2005; Accepted March 2005.]

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