Off-Farm Work and the Economic Impact of Adopting Herbicide-Tolerant Crops

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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, 1999). Adoption of HT crops 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 rose quickly to about 17 percent of soybean acreage in 1997, expanded to 75 percent in 2002 (Fernandez-Cornejo and McBride, 2002), and is expected to reach 80 percent in 2003 (USDA, NASS, 2003).

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). Moreover, rapid adoption of herbicide-tolerant crops (particularly soybeans) by U.S. farmers was seen as evidence that the perceived benefits of these technologies outweighed the expected costs.

However, recent research showed that there is essentially no difference between the net returns (both at the enterprise and whole farm level) 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

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[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. 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 a small yield advantage associated with farmers adopting herbicide-tolerant soybeans, but, on average, variable profits (revenues minus variable costs) were not statistically significantly affected by adoption.

herbicide-tolerant soybeans is driven by the relative simplicity and flexibility of the 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” (Gianessi and Carpenter, 1999). In addition, using HT soybeans is said to make harvest “easier.” (Duffy, 2001).

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 reduced management time employed to supervise production, freeing time for other uses. One 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 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, 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. (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; income from 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 examine the hypothesis that farmers may be induced to adopt HT crops by the simplicity and flexibility of the weed control program, freeing management time (of the operator and spouse) for other uses. We develop an econometric model to analyze the interaction of off-farm work and adoption of HT crops and the impact of adopting on various measures of farm household income after controlling for such interaction, and estimate the model for the case of HT soybean adoption using a nationwide farm survey for 2000.

The Theoretical Model

Comparison of means is sometimes used to analyze results from experiments in which factors other than the item of interest are "controlled" by making them as similar as possible. 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 crop 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. In "uncontrolled experiments," such as farm surveys, conditions other than the "treatment" are not equal. Thus, differences between mean estimates from survey results cannot necessarily be attributed to the use of herbicide tolerance technology since the results are influenced by many other factors not controlled for, including operator characteristics, management practices, and others. 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.

In this paper we control statistically for factors considered relevant, and for which there are data, by using multiple regressions in a econometric model framework. That is, differences in other factors are held 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, due to unmeasured variables correlated with both adoption and participation. The model also corrects for self-selection to prevent biasing the results (Greene, 1997). To account for simultaneity and self-selectivity we use a two-stage model. The first stage consists of the *decision model* --for the adoption of herbicide-tolerant crops as well as off-farm employment decisions. The adoption decision model is estimated by multivariate probit analysis. The second stage is the *impact model* that provides estimates of the impact of using herbicide-tolerant crops on household income, both, on farm and off farm.

Following Maddala and Greene we obtain consistent parameter estimates regarding self-selection as a source of endogenity. Thus, there are two sources for the endogeneity, namely the simultaneity discussed earlier (farmers' off-farm work participation and adoption decisions may be simultaneous) and self-selection. Because of this endogeneity, we can not use the actual adoption values in the impact model. For this reason, the impact model (second stage) uses as instrumental variables the predicted probabilities of off-farm work participation and HT adoption, obtained from the multivariate probit.

The Decision Model

Using the agricultural household model as a framework (Singh et al., 1986), 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 current household's 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) $P_g\, Q_g = P_q Q - W_x X + W_o M_o + W_s M_s + V$ (income constraint)

(3) $Q = f(X, F_o, F_s, H_o, H_s, R)$ (production constraint)

(4) $T_i = F_i + M_i + L_i,\ \ M_i \geq 0$ (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 represents 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 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 on the amount of off-farm work (Huffman and Lange, 1989; Huffman, 1991; Tokle and Huffman, 1991), the (off-farm) market labor demand functions are $W_i = W_i\ (H_{i,}\ \Omega,\ \psi))$, ($i = o,\ s$).

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

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

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; Tokle 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; Tokle and Huffman, 1991). In our case, however, the decision to work off farm and the decision to adopt herbicide-tolerant soybeans 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

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

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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).

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 decision model is estimated by a multivariate probit analysis because the disturbances for the operator and spouse are likely to be correlated (bivariate probit models have been used to model the off-farm decision by the operator and spouse but, in our case, these two decisions must be modeled jointly with the adoption decision; thus, a multivariate probit model is necessary). 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, the empirical decision model is specified as:

(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 $[\varepsilon_o, \varepsilon_s, \varepsilon_o] \sim$ 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, the estimation has been made possible with Montecarlo simulation techniques (Greene, 1997; Geweke et al., 1994).

The Impact Model

The second stage is the *impact model,* which provides estimates of the impact of using herbicide-tolerant crops on household income. The impact model is estimated by regressing a set of predetermined explanatory variables, plus instrumental variables obtained from the decision model, on alternative measures of farm household income. To obtain consistent regression parameter estimates, we follow Maddala and Greene, regarding self-selection as a source of endogenity.

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. In this model the observed indicator variable *I,* indicates the presence or absence of some treatment (e.g., use of herbicide-tolerant crops) (Greene, 1995).

Formally, given the unobserved or latent variable $I^* = \delta' Z + \mu$ and its observed counterpart I (such that $I = 1$ if $I^* > 0$ and $I = 0$ if $I^* \leq 0$), the treatment effects equation, which is the basis for our impact model is,

$$Y = \beta' X + \alpha I + \varepsilon. \qquad (10)$$

Following Maddala (p. 260) and Greene (1995, p. 642, 643) we can obtain consistent estimates of β and α by regarding self-selection as a source of endogenity. Thus, there are two sources for the endogeneity of the variable I, namely the simultaneity discussed earlier (off-farm work participation and HT adoption decisions are simultaneous) and self-selection. Because of this endogeneity (of *I*), we can not use the actual adoption values *I* in the impact model. For this reason, we use the three predicted probabilities of adoption, obtained from the multivariate probit equations of the decision model, as instrumental variables for *I*.

Three measures of household income are used to examine the impact of using herbicide-tolerant soybeans on household income (Y in equation 10): farm household income (*Y_FARMHHI*), off-farm household income (*Y_TOTOFI*), and total household income (*Y_TOTHHI*).

Farm household income includes farm business household income, operator paid onfarm, income, household members paid onfarm income, and net income from farmland rentals (see detailed definitions in table 1.1). Off-farm income equals the sum of off-farm business income, income from operating other farm business, off-farm wages and salaries, interest and dividend income, other off-farm income, including social security and other passive income, and rental income.

In addition to the predicted probability of adoption of herbicide tolerant soybeans, the impact model includes other variables to control for other factors that may influence household income. The variables used, that is the components of vector ***X*** in equation 10, include farm typology, operator age, education and experience, number of children, a proxy for risk, a measure of specialization on soybean production, and a measure of the extent of livestock operations (table 1.2). In addition, the off-farm income equation includes variables related to local market conditions.

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 Statistics Service (NASS) of USDA and conducted in 2000 (USDA, ERS, 2003). 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 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.

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 2258 observations available for analysis. Table 1.2 shows the definitions as well as the sample averages of the main variables used in the model.

Results

Decision Model Results

The maximum likelihood estimates of the first stage, 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 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 (pvalue = 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 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 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 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 (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 the spouse 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.

Mean Household Income for Adopters and Nonadopters of HT Soybeans

Actual mean household incomes, obtained directly from 2000 USDA survey data, differ for adopters and nonadopters of herbicide-tolerant soybeans. As shown in the table below, total household income is much higher for adopters than for non adopters. Moreover, most of the difference is due to off-farm income, as expected under the hypothesis discussed at the introduction.

	Adopters	Non-adopters	Difference
Farm Household Annual Income, $	14,150	12, 140	2,010
Off-Farm Household Annual Income, $	52,903	41,340	11,563
Total Household Annual Income, $	67,053	53,480	13,573

However, while illustrative, this comparison of means can lead us to a valid conclusion only in an ideal experimental setting where factors other than adoption are "controlled" by making them as similar as possible. Unlike controlled experiments, conditions other than the "treatment" are not equal in farm surveys. Thus, these differences in household income cannot necessarily be attributed to adoption of HT soybeans since survey results are influenced by many other factors not controlled for, including operator characteristics and management practices. For these reasons, we proceed directly to the results of the econometric impact model, which statistically control for factors considered relevant, by holding them constant, so that the effect of adoption can be estimated.

Impact Model Results

The results of the impact model are shown in table 3. Regression 1 shows the impact of HT soybean adoption on total household income, regression 2 presents the impact on farm income and regression 3 provides the impact on off-farm household income. The impact model has a total of 31 estimated parameters and more than 50 percent of them are significant at the 5 percent level.

Focusing on the impact of the adoption of herbicide-tolerant soybeans on total household income, this impact is positive and statistically significant at the 5 percent level (table 3). The 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 percent increase in the probability of adoption of herbicide-resistant soybeans would increase total household income by 6.4 percent.[4]

The impact of the adoption of herbicide-tolerant soybeans on off-farm household income is also positive and statistically significant at the 1 percent level (table 3). The elasticity of total 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 percent increase in the probability of adoption of herbicide-resistant soybeans would increase off-farm household income by 8.4 percent.

On the other hand, adoption of herbicide-tolerant soybeans did not have a significant effect on farm household income (table 3).

Conclusions and

Among preliminary findings, we show that there is a definite tradeoff between time spent working on-farm and off-farm. There is a statistically significant relationship between off-farm work by the operator/spouse and technology adoption, as well as structural characteristics, such as farm size. Off-farm work by the operator is negatively associated with that of the spouse; the spouse's off-farm work is positively associated with the adoption of HT soybeans. Households

[4] Results are typically expressed as a unitless measure, an elasticity -- the percent change in a particular effect (herbicide use, yields, or profits) relative to a small percent change in adoption of the technology from current levels. The results can be viewed in terms of the aggregate effect (across an entire agricultural region or sector) from aggregate increases in adoption (as more and more producers adopt the technology). 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. Moreover, as with most cases in economics, elasticities examine small changes (say, less than 10 percent) away from a given, e.g., current level of adoption.

operating small farms (lacking economies of scale) are more likely to work off-farm and more likely to adopt a management-saving technology, such as HT soybeans. For these farms, economies of scope (derived from engaging in multiple income-generating activities, on and off the farm) can substitute for economies of scale. Thus, these findings appear to provide empirical confirmation to Kitty Smith's (2002) observation that, like the economists' perceived link between capital-intensity and scale-dependency of technologies, *"perhaps management intensity should also be viewed as a potential source of scale bias."*

This paper also finds that adoption of herbicide-tolerant soybeans significantly increases off- farm household income for U.S. soybean farmers. In addition, while on-farm household income is not significantly affected by adoption, total household income does increase significantly. Thus, this paper provides an empirical confirmation of the hypothesis that farmers are induced to adopt herbicide tolerant soybeans by the simplicity and flexibility of the weed control program, freeing management time.

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Table 1.1—Household Income Variable Definitions

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1. **Household Income From Farming (Y_FARMHHI) =**
   Farm Business Income (FARMBUSI) * (Household Share of Farm Business Income)
   + Operator Paid on Farm + Household Members Paid on Farm + Net Income from Rented Land

Where:

Farm Business Income (FARMBUSI) = Cash Farm Income – Depreciation
- Gross Income from Rented Land
- Operator Paid Onfarm

Net Cash farm Income = Gross Cash Farm Income - Total Cash Operating Expenses

Gross cash farm income = **Crop and livestock income including cc loans + Other farm income** (includes government 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 farm operating expenses = **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)
+Non cash expenses for paid labor (excludes family labor)
+Depreciation on farm business assets

2. **Off-Farm Household Income (Y_TOTOFI)** = Off-farm business income
   \+ Income from operating other farm business
   \+ Off-farm wages and salaries (ADJWAGE)
   \+ Interest and dividend income
   \+ Other off-farm income, including SS and other passive
   \+ Rental income

3. **Total Household Income (Y_TOTHHI) = Farm Income to Household (FARMHHI)**
   + Off-farm Household Income (TOTOFI)

Table 1.2 Variable Definitions

Variable	Definition	Mean
FARMSIZE	Size of the farm, acres	491.2
NO_COMOD	Number of commodities produced (used as a proxy for complexity of the operation)	3.028
OP_AGE	Age of the operator, years	51.32
OP_AGESQ	Square of the age of the operator	2801
HIGHPLUS	Education, dummy = 1 if operator has at least high school	0.898
OP_EXP	Years of operator experience	25.56
CHILDREN	Number of children	1.110
SP_DECID	Spouse decides on farm day-to-day decisions (dummy var.)	0.365
CHG_IN_UNEMPL	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 - residential farm dummy var.	0.240
RETIREDU	Farm typology variable - retirement farm dummy var.	0.042
LIMITEDD	Farm typology variable - limited resources farm dummy var.	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
ADARAT	Debt-to-assets ratio	2.630
PCTSOY	Share of farm revenues from soybeans	0.372
PCTLIV	Percent revenues from livestock	0.225
Y_ TOTHHI	Total household income, thousand $ per household	61.215
Y_TOTOFI	Off-farm household income, thousand $ per household	47.930
Y_ FARMHHI	Farm income to household, thousand $ per household	13.285

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

Variable	Parameter Estimate	Standard Error	Parameter/Std. Error	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
CHG_IN_UNEMP	-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
PCTLIV	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
OP_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
OP_EXP	0.1784630E-01	0.423418E-02	4.215	0.0000
CHILDREN	-0.1061715E-01	0.264434E-01	-0.402	0.6880
SP_DECID	-0.1178829	0.649632E-01	-1.815	0.0696
CHG_IN_UNEMP	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
PCTLIV	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	Parameter Estimate	Standard Error	Parameter/Std. Error	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
PCTLIV	-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
PSEED	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.

Table 3. Parameter Estimates of Weighted Least Squares Regression

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
1. Dependent Variable: Total household income (Y_TOTHHI)				
Intercept	-54.8759	29.2853	-1.87	0.061
Probability of HT Adoption	69.066	32.4816	2.13	0.034
OP_AGE	-0.6232	0.3522	-1.77	0.077
HIGHPLUS	10.9737	8.9315	1.23	0.219
OP_EXP	0.6664	0.2991	2.23	0.026
CHILDREN	0.8720	1.8780	0.46	0.643
OP_OCUP	30.4483	3.4922	8.72	<.000
ADARATC2	-9.6770	3.2037	-3.02	0.003
FM_TYPOL	17.9716	2.9771	6.04	<.000
PCTLIV	-21.2260	9.8092	-2.16	0.031
PCTSOY	-47.4808	12.1618	-3.90	<.000
Adjusted R-square	0.06			
2. Dependent Variable: Off-farm household income (Y_TOTOFI)				
Intercept	6.1011	24.2706	0.25	0.802
Probability of HT Adoption	90.5545	26.6914	3.39	0.001
OP_AGE	-0.6296	0.2888	-2.18	0.029
HIGHPLU	8.6177	7.3124	1.18	0.239
OP_EXP	0.6797	0.2453	2.77	0.006
CHILDREN	2.6606	1.5381	1.73	0.084
OP_OCUP	18.1954	2.8682	6.34	<.0001
ADARATC2	2.3492	2.6589	0.88	0.377
RURALAREA	-0.9193	0.8348	-1.10	0.271
CHG_IN_UNEMPL	4.0363	2.2522	1.79	0.073
FM_TYPOL	-5.4410	2.4375	-2.23	0.026
PCTLIV	-22.5563	8.0545	-2.80	0.005
PCTSOY	-45.7883	9.9819	-4.59	<.0001
Adjusted R-square	0.06			
3. Dependent Variable: Farm income to household (Y_FARMHHI)				
Intercept	-26.1348	16.4472	-1.59	0.112
Probability of HT Adoption	-1.6429	19.3768	-0.08	0.932
OP_AGE	0.0375	0.2117	0.18	0.860
HIGHPLUS	3.8503	5.3695	0.72	0.473
OP_EXP	-0.1287	0.1785	-0.72	0.471
CHILDREN	-1.2542	1.1280	-1.11	0.266
ADARATC2	-11.5446	1.9283	-5.99	<.0001
FM_TYPOL	16.8218	1.3742	12.24	<.0001
PCTLIV	3.6478	5.8969	0.62	0.536
PCTSOY	-0.5881	7.3173	-0.08	0.936
Adjusted R-square	0.10			