Non-Pecuniary Benefits from Biotechnology: Some Preliminary Evidence from a Survey of U.S. Corn Growers[*]

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ABSTRACT: Non-pecuniary benefits may be an important element in farmers' decisions about whether to adopt genetically engineered crop varieties. To investigate this issue, we examine the case of corn rootworm resistant transgenic corn, using data from a national survey of corn growers conducted in 2002. We model farmers' adoption decisions jointly with their valuations of the non-pecuniary characteristics of the new technology in a household production framework. The system of equations representing farmers' willingness to pay for various attributes, and their adoption decisions, is estimated in a seemingly unrelated regressions framework using Gibbs sampling. Some farmers would be willing to pay for non-pecuniary benefits from the new technology. We find evidence of non-separability in profit and utility maximization, both from the estimates of covariate effects and the positive covariance between all choice variables. This suggests that preferences for the non-pecuniary attributes spill into production decisions, providing at least the necessary condition for non-pecuniary benefits to spill off the farm to become external benefits.

1. Introduction

Transgenic cropping technologies have had major impacts on U.S. and global agriculture and they have the potential to do much more. The significance and value of the economic benefits from these technologies has been documented in a number of economic evaluation studies (Marra, Pardey, and Alston, 2002, review the work on farm-level impacts). In spite of the growing evidence of the realized and potential benefits, both to growers and society, genetically engineered crop varieties continue to be controversial. Whilst some opponents seem to be against all modern technologies and anything associated with big business, others have more-specific concerns about the risks of genetic drift, losses of biodiversity, and other environmental and human health risks potentially associated with genetically engineered crops.

These concerns can be seen as perceptions of negative externalities associated with individual farmers adopting the technologies, potentially justifying government intervention. Even in the United States, where the adoption of genetically engineered crops has been greatest, government intervention has been substantial. Before any transgenic cropping technology can be commercialized in the United States it must undergo an expensive process of regulatory approval, which involves exhaustive evaluation of the risks to the environment and human health. These regulatory burdens – combined with intellectual property issues and market resistance associated with negative public perceptions – have severely dampened the enthusiasm of biotech companies for further investment in the development of agricultural biotechnologies.

Transgenic cropping technologies might well pose risks to human health and the environment in ways that mean that farmers and biotechnology companies will not have appropriate incentives from a broader perspective of national or global welfare. But the same concerns might well apply with equal or greater force to the conventional technologies that the transgenic technologies are designed to replace. It is appropriate to assess any new technology – transgenic or otherwise – relative to the next-best alternative, or relative to the current practice, taking into account all market and non-market effects of the alternatives. Curiously, most of those who voice concern about the potential risks to the environment and human health posed by genetically engineered crop varieties have not shown much appreciation for the benefits from replacing the chemical technologies for which the risks are more easily demonstrable.

These observations have implications for the economic evaluation of transgenic cropping technologies, in terms of the types of benefits and costs to be considered, and how to evaluate them. In a conventional analysis, the benefits from a new technology – typically measured in the context of a commodity-market model as benefits accruing to producers and consumers of the commodity, biotech and seed companies, and in some cases taxpayers – are all pecuniary private benefits, reflected in the markets for outputs and inputs used to produce the commodity. In addition to these conventional benefit measures we might want to consider a range of other potential benefits or costs to human health or the environment associated with the technology, which we can call "spillovers." Some of these spillover effects are on site, such as consequences for farm worker health and safety. Others are off-site, such as consequences for neighboring farmers, the broader ecosystem, or for food safety. Some of the effects may be non-pecuniary and non-market while others are, at least to some extent, reflected in markets (i.e., farmers are liable to some degree for the safety of their employees and the consumer safety of their products). Many of the on-site elements would be expected to affect private benefits and costs and hence adoption decisions (and they might even be fully internalized to the farm firm decisions), whereas the off-site elements might do so only to the extent that farmers are willing to contribute to the commons voluntarily.

The past evaluation studies of transgenic cropping technologies have included both ex ante and ex post evaluations of both farm-level and aggregative impacts, but to date the studies have emphasized only the private, pecuniary benefits from adoption of the technology. They have not measured any non-pecuniary benefits associated with differences between transgenic cropping technologies and the conventional alternatives that they replace, though in some cases the non-pecuniary aspects might represent an important element of the decision to adopt and might have significant implications for the total net benefits and their distribution.

In this paper we provide the first detailed analysis and quantitative estimates of non-pecuniary benefits and their role in adoption decisions for an important new transgenic technology. The technology in question is a transgenic corn variety developed to be resistant to the corn rootworm, planted with a seed treatment to control other corn insect pests; in short, CRW resistant transgenic corn.[1] Our analysis is based on data from a computer-assisted telephone survey of 601 corn farmers who might adopt the technology, conducted in 2002.[2]

2. Nature and Economic Importance of Corn Rootworm

Corn rootworm (*Diabrotica* spp.) causes extensive economic damage to corn in the United States. Populations of the western corn rootworm (*D. virgifera virgifera*, Le Conte) and the northern corn rootworm (*D. barberi*, Smith and Lawrence) together are estimated to result in annual yield losses and control costs that exceed $1 billion (Metcalf, 1986). The larvae hatch in the spring and feed on corn roots for several weeks. The damage to the roots can result in

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[1] The first introduction of CRW resistant transgenic corn, which is designated as Yieldgard® Rootworm, was developed by Monsanto, and it was approved for limited release in 2002.

[2] Alston, Hyde, and Marra (2002) (see also Alston et al. 2003) conducted an ex ante assessment of the likely economic impacts in the United States of the commercial adoption of this technology. They describe in detail both the technology and the pest problem it is designed to address, and present a preliminary analysis of potential non-pecuniary benefits.

stunted growth of the corn plant, lodging, and eventual yield losses. Most of the damage is caused by the root feeding of the larval stages (Wright, Meinke and Jarvi, 1999).

In general, corn rootworms cannot complete their life cycle without the food supplied by corn plants. A crop rotation with one year of corn has been an effective control strategy. Recently, however, two variants of corn rootworm have developed. The soybean variant (SBV) of the western corn rootworm has adapted its behavior to lay eggs in crops other than corn (Levine and Oloumi-Sadeghi, 1996). In areas where corn/soybean rotations are common, eggs laid in soybean fields will hatch in corn fields in the following spring. The SBV evolved in eastern Illinois and has since spread into Indiana, Michigan and Ohio (Onstad et al., 1999). The extended diapause variant (EDV) of the northern corn rootworm has adapted to two-year corn rotations as well (Kryan, Jackson, and Lew, 1984). While most corn rootworm eggs hatch in the following spring, for the EDV some of the eggs hatch after two winters and, thus, the larval stages are able to feed on corn roots even in rotated corn. The EDV is most prevalent in eastern South Dakota, northeastern Nebraska, northwestern Iowa, and southeastern Minnesota.

Control methods available currently to deal with the corn rootworm problem include (a) crop rotation (in all but the EDV and SBV regions), (b) soil-applied insecticides to control corn rootworm larvae, and (c) insecticide sprays to control corn rootworm adult beetles. Total expenditure for corn rootworm-targeted insecticides topped $171 million in the 2000 crop year (Doane’s Market Research, 2001).

3. Models

Conceptual Framework

We present a stylized agricultural household production model to frame our discussion and offer testable hypotheses. Suppose the farmer can chose from two seed technologies in the production of a final output. The first technology uses a standard variety and the second uses a bio-engineered variety with similar production characteristics and potentially favourable environmental, human health, and convenience-in-use characteristics. The farmer decides the mix of acres to be planted using each of the seed varieties based on the potential (private) pecuniary and non-pecuniary benefits from their use. Because of the potential for non-pecuniary (utility generating) benefits the non-separable agricultural household production model is appropriate.

Suppose the household utility function is defined over consumption of market goods x and local non-market goods q, broadly defined to include health, environmental, and risk factors. Suppose further that q is at least partially determined by the choice of A_1, the number of acres planted using the new technology. The utility function is given by $\mathrm{u}(x, q(A_1)|\Omega_H)$, where Ω_H denotes household characteristics. Technology in the production of the final output is given by $\mathrm{f}(A_0, A_1, z|\Omega_F)$, where A_0 denotes acres planted using the old technology, z denotes the quantities of other inputs, and Ω_F denotes farm characteristics.

The farm household's choice problem is formally given by

$$\begin{aligned} &\max_{x, A_0, A_1, z} \mathrm{u}\left(x, q(A_1) \mid \Omega_H\right) \\ &\text{subject to} \\ &p\,\mathrm{f}(A_0, A_1, z \mid \Omega_F) - r_0 A_0 - r_1 A_1 - wz \geq p_x x - e \end{aligned} \tag{1}$$

where p is output price, r_0 and r_1 are the rental rates for land used to grow conventional and biotech crops, respectively, w is the price of other inputs, p_x is the price of goods (which we normalize as $p_x = 1$), and e is non-farm income. Hence, the optimization problem can be restated as the Lagrangean:

$$\max_{x, A_0, A_1, z} \mathrm{u}\left(x, q(A_1) \,|\, \Omega_H \right) + l \left[e + p\, \mathrm{f}(A_0, A_1, z \,|\, \Omega_F) - r_0 A_0 - r_1 A_1 - wz - x \right] \tag{2}$$

where l is the Lagrange multiplier. The solution to this problem consists of the choices of A_0 and A_1 (i.e., the technology adoption decision) and the quantities of other inputs employed, z. These choices also determine the amount of income and thus spending on market goods, x, the level of q, and the marginal willingness to pay for the non-market characteristics. After some manipulation the first-order Kuhn-Tucker condition with respect to the choice of acres planted using the biotechnology is given by:

$$\begin{gathered} \frac{1}{l} \frac{\partial u(\cdot)}{\partial q} \frac{\partial q(\cdot)}{\partial A_1} + p \frac{\partial \mathrm{f}(\cdot)}{\partial A_1} \leq r_1; \\ A_1 \geq 0; \\ A_1 \times \left[\frac{1}{l} \frac{\partial u(\cdot)}{\partial q} \frac{\partial q(\cdot)}{\partial A_1} + p \frac{\partial \mathrm{f}(\cdot)}{\partial A_1} - r_1 \right] = 0. \end{gathered} \tag{3}$$

This condition has an intuitive interpretation and suggests several testable hypotheses. First, the non-separability between consumption and production caused by the non-market spill-overs from the new seed variety suggests that the decision to adopt the new technology and its level of employment are based on two components: the dollar value of marginal utility from non-market improvements due to the last acre planted with the new seed variety (the first term in the first equation above), and the value of the marginal product from the last acre planted with the new seed (the second term in the same equation). The technology will be employed on the farm if the sum of these values for the first acre is greater than the input price. Thus, if the farm household has preferences for the non-pecuniary benefits of the new technology the decision to adopt the new technology will be based on both production and utility characteristics.

Testing this notion is the primary focus of this paper. We are interested first in investigating whether farmers value the non-pecuniary benefits of the new seed variety and second, the degree to which these values influence the adoption decision. These questions are of interest for a variety of reasons. First, it is important to know whether the non-pecuniary benefits matter to farmers and influence their adoption choices as a basis for understanding the farmers' choices and their consequences. Perhaps more importantly, farm inputs with favourable non-market characteristics can be thought of as mixed private/public goods, for which private choices might not achieve economically efficient outcomes. To pursue these questions we apply recent developments in Bayesian econometrics, while drawing on established methods from the literature on the application of stated preference methods for estimating the value of environmental amenities, and literature related to the adoption of farm technology, as recently reviewed by Sunding and Zilberman (2001).[3]

While it is reasonable to assume farmer's decisions are based primarily on private well being, it is also possible that utility-generating aspects of new technologies will spill off the farm, providing external as well as private benefits. Huang et al. (2003) document this possibility by showing that adoption of Bt cotton in China led to substantial reductions in pesticide use among sampled farmers. Knowing the degree to which external benefits may occur first requires understanding the degree to which farmers' own preferences will influence their choices of technology. Some evidence exists that altruistic motivation may, in part, account for farmers' actions. Lynne, Shonkwiler and Roja (1988) use the notion of "environmental effort" as a proxy for the intensity of favorable attitudes to the environment. Environmental effort is measured as

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[3] Eliciting consumers' willingness to pay for environmental amenities using contingent valuation survey methods is now the standard for evaluation of most non-market goods, although it still has some unresolved questions and pitfalls. Mitchell and Carson (1993) provide the foundation upon which our stated preference survey is designed, and Freeman (2003) provides extensive discussion on stated preference models in general.

the sum of indicator variables for various conservation practices undertaken by the farmer. Environmental effort is then used as the dependent variable in a tobit regression with a set of regressors grouped into private and altruistic categories. The authors found that altruism was correlated with environmental effort on the part of the farmers surveyed. Weaver (1996) develops a joint model of utility and production that includes both private and public (altruistic) motivations. He finds that, by and large, the producers surveyed chose inputs based on profit potential. Some evidence for public motivation is present, although it is relatively weak.

Econometric framework

Our data provide information on the willingness to pay per acre for several non-pecuniary aspects of the new technology and an indication of whether the farmer would adopt the new technology. Our conceptual model suggests that if the farmer holds preferences for the non-pecuniary characteristics of the technology the willingness to pay values and adoption decision will be jointly determined. The econometric model is designed to test this notion. In particular we consider a reduced form model in which equations representing elements of willingness to pay and adoption choices are stacked into a seemingly unrelated regressions (SUR) system. By jointly estimating the coefficients of the system and specifying a full variance/covariance matrix we are able to draw inferences about the sources of simultaneity in the endogenous outcomes.

A system of p willingness-to-pay equations for any individual farmer, i, represents his valuations of the p non-pecuniary characteristics associated with the adoption of the technology. These equations are defined as

$$y_{ij}^{*} = X_{ij}b_{j} + e_{ij}, \quad j = 1,..., p, \quad i = 1,..., n, \tag{4}$$

where X_{ij} is a matrix of explanatory variables for equation j, b_j is a vector of coefficients for equation j, and e_{ij} is a random error. The econometric model is complicated by the fact that the dependent variables are censored. Censoring arises from the fact that farmers may report zero willingness to pay; the dependent variables in (4) are therefore latent and not fully observed. The observable willingness-to-pay variable, y_{ij} is determined by

$$y_{ij} = \begin{cases} y_{ij}^* \text{ if } y_{ij}^* > 0 \\ 0 \text{ if } y_{ij}^* \leq 0. \end{cases} \tag{5}$$

Define the latent equation for the adoption decision by

$$y_{ia}^* = X_{ia} b_a + e_{ia}, \quad i = 1,..., n, \tag{6}$$

where the farmer adopts the technology if $y_{ia}^* > 0$. In this case the observable variable y_{ia} is given by

$$y_{ia} = \begin{cases} 1 \text{ if } y_{ia}^* > 0 \\ 0 \text{ if } y_{ia}^* \leq 0. \end{cases} \tag{7}$$

We complete the model by assuming that $e_i = (e_{i1},..., e_{ip}, e_{ia})' \sim N(0, \Omega),$ where Ω is a $(p+1)\times(p+1)$ positive definite variance/covariance matrix.

It is convenient to rewrite the equations in stacked notation. Define the model for farmer i by

$$\begin{bmatrix} y_{i1}^* \\ \vdots \\ y_{ip}^* \\ y_{ia}^* \end{bmatrix} = \begin{bmatrix} X'_{i1} & 0 & \cdots & 0 \\ 0 & \ddots & \cdots & 0 \\ \vdots & \vdots & X'_{ip} & \vdots \\ 0 & 0 & \cdots & X'_{ia} \end{bmatrix} \begin{bmatrix} b_1 \\ \vdots \\ b_p \\ b_a \end{bmatrix} + \begin{bmatrix} e_{i1} \\ \vdots \\ e_{ip} \\ e_{ia} \end{bmatrix}, \tag{8}$$

or more compactly by

$$y_i^* = X_i b + e_i, \tag{9}$$

where $y_i^* = (y_{i1}^*,..., y_{ip}^*, y_{ia}^*)'$, $X_i = diag(X'_{i1},...X'_{ip}, X'_{ia}),$ and $b = (b_1,..., b_p, b_a)'$. The observed outcome $y_i = (y_{i1},..., y_{ip}, y_{ia})'$ is related to y_i^* by equations (5) and (7). With this notation and the assumed distribution for the errors, the probability of observing an individual outcome can be stated. For example, if farmer *i* reports a positive willingness to pay for the first *r* characteristics and adopts the technology the contribution to the likelihood function is given by

$$L_i(y_i;b,\Omega)=\int_{-\infty}^{-X_{ir+1}b_{r+1}}\cdots\int_{-\infty}^{-X_{ip}b_p}\int_{-X_{ia}b_a}^{\infty} p(y_i^*;b,\Omega)dy_{ir+1}^*..dy_{ip}^*dy_{ia}^*, \qquad (10)$$

where

$$p(y_i^*;b,\Omega)=(2p)^{-(p+2)/2}\left|\Omega^{-1}\right|^{1/2}\exp\left[-\frac{1}{2}(y_i^*-X_ib)'\times\Omega^{-1}\times(y_i^*-X_ib)\right]. \qquad (11)$$

The likelihood function for the sample is the product of probabilities as given in (10), properly adjusted for the combination of censored outcomes and the adoption decision.

Conventional estimation of the model in equations (8) to (11) is complicated by several factors. Most importantly the calculation of the individual probability in (10) requires computation of a *p*-*r*+1 dimension integral for which no closed form expression exists. Even for relatively low dimension problems this causes difficulty in computing the likelihood function. Also, the variance/covariance matrix Ω is not fully identified due to the lack of scale information in y_{ia}. These two features of the model have severely limited the application of systems of limited dependent variable models as presented here. Exceptions are Huang (2001) who considers a system of tobit equations, and Li (1998) and Lapar et al. (2003) who jointly estimate probit- and tobit-type equations. In each case estimation is carried out using the techniques discussed below. Phaneuf (1999) and Phaneuf et al. (2000) estimate censored models using frequentist methods with highly restrictive error structures.

Recent advances in computational techniques motivated by the challenges of inference in Bayesian analysis provide a surprisingly tractable alternative solution for estimating this model. In particular simulation methods have been developed that allow a researcher to approximate the moments of interest for a posterior distribution (i.e. the means and standard deviations of model parameters) without having to compute the actual posterior distribution. The idea is to accumulate an empirical distribution for the model parameters by sampling from convenient distributions in a way that ensures the draws converge to draws from the target (posterior) distribution. A useful technique for this is Gibbs sampling, which is described in general by Casella and George (1992) and as used in econometrics by Chib and Greenberg (1996). Gibbs sampling exploits that fact that in many models it is much easier to sample from a set of conditional distributions than from the underlying joint distribution. For example, suppose we are interested in obtaining draws from the joint density $f(e_1,e_2)$ with conditional densities $f(e_1|e_2)$ and $f(e_2|e_1)$. Draws from the joint density can be obtained by drawing iteratively from the conditional distributions. That is, for a given e_1^t we draw e_2^{t+1} conditionally, which is followed by drawing an updated e_1^{t+1} conditional on e_2^{t+1}. The sequence begins by choosing arbitrary starting values for the variables, and the process repeats itself many times. After a suitable "burn-in time" the process converges to draws from the joint distribution.

Gibbs sampling as applied in this paper relies on the notion of data augmentation for the limited dependent variables as described by Chib (1992) and applied by McCulloch and Rossi (1994) and McCulloch et al. (2000), among others. Data augmentation involves "filling in" values for the unobserved latent variables as the first step in the Gibbs sampling procedure before sampling the model parameters. Data augmentation is motivated by the fact that estimation is greatly simplified when values for all the latent variables are known. Suppose all elements of the vector $Y^* = (y_1^*,..., y_n^*)$ were observed. In this case the conditional distributions for the parameters b and Ω are given by

$$\begin{aligned} b \,|\, Y^*, \Omega^{-1} &\sim N(\hat{b}, \Sigma) \\ \Omega^{-1} \,|\, Y^*, b &\sim W(n, R_n), \end{aligned} \tag{12}$$

where $\hat{b} = \left(\sum_{i=1}^{n} X_i'\Omega^{-1}X_i\right)^{-1}\left(\sum_{i=1}^{n} X_i'\Omega^{-1}y_i^*\right)$, $\Sigma = \left(\sum_{i=1}^{n} X_i'\Omega^{-1}X_i\right)^{-1}$, W denotes a p+1 dimension Wishart distribution, and $R_n = \left(\sum_{i=1}^{n}(y_i^* - X_i b)(y_i^* - X_i b)'\right)^{-1}$. It is simple to sample from both distributions in (12), given values for Y^*. Diffuse priors are assumed for all parameters in the model.[4] Thus, the main challenge in applying the Gibbs sampler is augmenting the latent variables to allow the parameters of the model to be sampled conditional on the full set of data.

Data augmentation involves drawing realizations for the unobserved latent variables conditional on the structure of the model and the observed data. To illustrate, consider the case in which we observe the first r willingness-to-pay outcomes are zero, and the farmer adopts the technology. In this case we know from (5) and (7) that $y_{i1}^* \le 0, \ldots, y_{ir}^* \le 0$ and $y_{ia}^* > 0$. The augmentation task is to sample values for these latent variables consistent with the observed outcome given the values of the other dependent variables and model parameters. This reduces to sampling from a truncated conditional multivariate normal distribution. We follow Robert (1995) and Huang (2001) and sample each element sequentially using a series of univariate truncated conditional distributions.

The following series of distributions is sequentially sampled given the most recent realization of the conditioning factors to obtain a draw of the latent variables for person i:

$$\begin{gathered}
y_{i1}^* \mid y_{i2}^*, \ldots, y_{ir}^*, y_{ir+1}, \ldots, y_{ip}, y_{ia}^*, b, \Omega \sim TN_{(-\infty,0]}(m_{1|-1}, w_{1|-1}^2) \\
y_{i2}^* \mid y_{i1}^*, y_{i3}^*, \ldots, y_{ir}^*, y_{ir+1}, \ldots, y_{ip}, y_{ia}^*, b, \Omega \sim TN_{(-\infty,0]}(m_{2|-2}, w_{2|-2}^2) \\
\vdots \\
y_{ir}^* \mid y_{i1}^*, \ldots, y_{ir-1}^*, y_{ir+1}, \ldots, y_{ip}, y_{ia}^*, b, \Omega \sim TN_{(-\infty,0]}(m_{r|-r}, w_{r|-r}^2) \\
y_{ia}^* \mid y_{i1}^*, \ldots, y_{ir}^*, y_{ir+1}, \ldots, y_{ip}, b, \Omega \sim TN_{[0,\infty)}(m_{a|-a}, w_{a|-a}^2),
\end{gathered} \tag{13}$$

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[4] A more formal statement of the conditional distributions, including hyperparameters for the prior distributions, is given in Huang (2001).

where *TN* is an appropriately truncated univariate normal distribution with mean and variance $m_{k|-k}$ and $w^2_{k|-k}$. Letting $y^*_{-k} = (y^*_{i1},..y^*_{ik-1}, y^*_{ik+1},..., y^*_{ir}, y_{ir+1},..., y_{ip}, y^*_{ia})'$ the mean and variance are $m_{k|-k} = m_k + \Omega'_{k-k}\Omega^{-1}_{-k-k}(y^*_{-k} - m_{-k})$ and $w^2_{k|-k} = w^2_{kk} + \Omega'_{k-k}\Omega^{-1}_{-k-k}\Omega_{k-k}$ where $m = X_i b$, m_k is the *k*th element of m, and m_{-k} is m with the *k*th element deleted. The term Ω_{-k-k} is the $p \times p$ matrix derived by deleting the *k*th row and column from Ω, and Ω_{k-k} is the $p \times 1$ vector derived by deleting the *k*th row element from the *k*th row of Ω. Each univariate normal variate is sampled using the inversion method as described by Train (2003, p. 210).

The derivations of the conditional distributions in (12) and (13) allow us to formally list the steps in the Gibbs sampler. At iteration *t* we complete the following algorithm to draw from the set of full conditional distributions:

1. Draw the unobserved components of the latent variables from $y^*_{i,t} \mid b_{t-1}, \Omega_{t-1}, y^*_{i,t-1}$ for i=1,…,n using the truncated univariate normal distributions in equation (13). This provides the full set of latent data Y^*_t.
2. Draw a new realization of the parameter vector from $B_t \mid Y^*_t, \Omega_{t-1}$ using the multivariate normal distribution given in the first line of (12).
3. Draw a new realization of the variance/covariance matrix $\Omega_t \mid B_t, Y^*_t$ using the Wishart distribution in the second line of (12).
4. Repeat this sequence many times.

The sequence is initialized by assigning arbitrary starting values for the parameters and latent variables b_0, Ω_0 and Y^*_0. After a "burn-in" period a given sequence of draws can be thought of as a realization from the joint posterior distribution of the parameters in the model given the data and model structure. From a frequentist perspective the Gibbs sampler allows us to produce an empirical distribution of the parameters drawn from the maximized likelihood function.

Summary statistics over the draws provide estimates that are equivalent to their maximum likelihood counterparts (see Train, 2003).

A final point concerns identification of the covariance matrix. In applications of limited dependent variable models involving a dichotomous choice, identification is achieved by normalizing the variance of the latent dependent variable to one. In our case this involves setting the variance for the adoption equation to one. That is, the restriction $\Omega(a,a)=1$ is enforced for identification. We follow McCulloch and Rossi (1994) and Lapar et al. (2003) and impose the restriction by dividing the updated covariance matrix by the (a,a) element before proceeding with the sampler. After step 3 in the sampler the updated variance/covariance matrix is re-scaled such that $\Omega_t = \Omega_t / \Omega_t(a,a)$. This normalization ensures identification, and implies that all of the estimated parameters are conditional on the normalization.[5]

The estimation strategy presented above allows simultaneous estimation of the model parameters and the variance/covariance matrix for the errors. This provides the following tests of our hypotheses. First, systematic, positive estimates of farmers' willingness to pay for the non-pecuniary characteristics, conditional on household-specific covariates, would provide evidence of farmers' preferences for the non-pecuniary characteristics of the seed variety. Second, if the same variables are found to significantly influence both the willingness-to-pay for the non-pecuniary characteristics of the technology and the likelihood of adoption, we can conclude that the non-separable model is appropriate, and that preferences for non-pecuniary characteristics spill into the adoption decisions. Likewise, if the off-diagonal elements of the variance/covariance matrix are non-zero and positive we can conclude that the unobserved factors driving willingness-to-pay and the adoption decision are (positively) correlated, and the

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[5] An informal Monte Carlo experiment confirmed that the identified parameters are consistently estimated using this normalization strategy. Results of the experiment are available upon request.

magnitudes of these effects may suggest which of the non-pecuniary aspects are most important. This would provide further evidence of the simultaneous nature of the decisions. If the actual estimates support these conjectures we can conclude that the necessary conditions exist for the potential positive spillover of benefits from farmers' decisions about adoption of biotechnology.

5. Survey and Data

We identified a total of seven distinct corn production regions (or sub-regions) in the United States, which we treat as separate agroecologies for the purposes of this analysis. The regions are roughly equivalent to the important corn growing Farm Resource Regions as recently defined by the Economic Research Service of USDA (Heartland, Northern Crescent, Northern Great Plains, Prairie Gateway) plus two additional sub-regions within the Heartland where the two corn rootworm variants, the extended diapause variant (the EDV region) and the soybean variant (the SBV region), are currently found. The rest of the country is combined into a region called "other." The sampling was set up with a view toward obtaining one hundred observations chosen randomly from Doanes' Market Research corn producer lists in each of the five initial regions and fifty observations each in the smaller regions where the corn rootworm variants are a problem. The survey was conducted in spring 2002 as a computer-aided telephone survey by Doanes' Market Research. The data were entered by Doanes' personnel and sent to the authors for analysis. The original dataset contains 601 observations.[6]

The survey instrument contains questions typically found on production surveys, including acreage decisions, input use (particularly with regard to corn rootworm control), and current attitudes about corn rootworm control. The new corn rootworm-resistant technology is then described in detail (see the Appendix for the text of the description given to respondents).

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[6] The survey instrument is available from the authors.

Respondents were asked to state the advantages and disadvantages of the new technology from their point of view and indicate how likely they would be to adopt it and, if they adopt, on how many acres the new technology would be planted. The next section of the survey contains questions soliciting farmers' valuation of several potential benefits from the new technology relative to the traditional soil-applied insecticides. They were asked to value attributes such as time savings, equipment savings, risk reductions, and the marginal per-acre safety and environmental benefits of the new technology relative to the corn production technology they were using at the time. The respondents were also asked to place a value on the improved consistency of control and a value on the benefits from a hypothetical 2-5 percent improvement in standability. Finally, respondents were asked their per acre value for the full bundle of the attributes of the technology, and some questions about time allocation.

Responses to the survey questions were used to construct five dependent variables and a set of regressors. For purposes of our empirical analysis we consider systems based on combinations of the following response variables:

- *wtpsafety*: The value per acre (if any) the respondent places on the additional operator and worker safety associated with the new technology.
- *wtpenviron:* The value per acre (if any) the respondent places on the additional environmental benefits provided by the new technology.
- *wtprisk:* The value per acre (if any) the respondent places on more consistent yields because of the weather protection provided by the new technology.
- *wtptotal:* The value per acre (if any) the respondent places on the total bundle of production and utility generating characteristics of the new technology.
- *adopt*: Equal to one if the respondent indicated they were highly likely or likely to adopt the new corn biotechnology, and zero otherwise.

We included the first three variables because they are representative of individual attributes of the technology that may have utility-generating aspects apart from the value of the technology to the farmer from a pure production perspective. The fourth variable is included to allow analysis of the role of the full bundled set of attributes inherent in the technology on adoption, recognizing that farmers are unable to obtain the attributes individually. We hypothesize that the adoption decision is influenced both by the utility-generating and production advantages of the technology. To test this we are interested in the degree to which the preferences for the non-market aspects and the adoption decision are jointly determined.

Table 1 provides summary statistics for the five dependent variables. The magnitudes of the means indicate that risk reduction is the highest-valued component, followed by increased safety and environmental benefits. For each of these there is substantial censoring, with up to 41% of respondents reporting zero willingness to pay for potential environmental benefits. In contrast, only 10% of respondents perceived no (pecuniary or non-pecuniary) benefits from the new technology, suggesting most farmers valued some component of the bundle of attributes contained in the technology.

Descriptions and summary statistics for the regressors chosen for analysis are given in table 2. The variables are constructed to control for production, attitudinal, and other factors that may influence preferences for and adoption of the new technology. Identifying variables primarily associated with the production or utility benefits of the technology allows the hypothesis of non-separability to be tested. The variables *wtpstand*, *costsvgs*, and *work* primarily reflect farmers' beliefs about the potential private pecuniary benefits of the technology. The variables *safe* and *leisure* are utility-related factors that may spill into production decisions under non-separability. Finally, *region* and *percenttrt* are indicative of the degree to which corn rootworm is a problem in the farmer's area, and *biotech* proxies for the farmer's level of experience with transgenic seed varieties and may reflect general attitudes about the attractiveness of biotechnology inputs.

6. Empirical Results

In tables 3 through 5 we present results from the following specifications of the econometric model:

1. Two-equation, intercepts-only model for *wtptotal* and *adopt*
2. Four-equation, intercepts-only model for *wtpsaftey*, *wtpenviron*, *wtprisk*, and *adopt*.
3. Four-equation model for *wtpsaftey*, *wtpenviron*, *wtprisk*, and *adopt* with the full set of common regressors.

Each model is designed to examine a particular hypothesis. The first two specifications examine the unconditional means for the willingness-to-pay measures and how these measures are related to the adoption decision. Specification 1 examines how the bundle of characteristics is valued and influences adoption, while specification 2 breaks out and compares the individual utility-generating components and their influence on adoption. Specification 3 includes covariates that control for heterogeneity and provide a formal test of non-separability between utility and production related factors. We discuss each set of results in turn.

Table 3 presents results for the first specification. With minimal censoring in *wtptotal* this model does not provide new information on the magnitude of the value of the technology beyond what is given in the summary statistics. However, estimating the mean effect jointly with the adoption decision does allow us to draw inferences about the role played by the bundle of attributes contained in the technology in the decision. The positive and significant covariance between the unobserved factors in *adoption* and *wtptotal* suggests positive correlation in the two variables. That is, the more the farmer values the full set of attributes contained in the technology the more likely he is to adopt. This provides preliminary evidence that both the pecuniary and non-pecuniary attributes bundled in the technology matter for adoption.

This is further supported by the results in the second specification, reported in table 4. Here we estimate truncation-corrected means for each of the individual non-pecuniary willingness-to-pay variables jointly with the adoption decision. This model confirms that farmers on average value the increased safety and decreased risk from the technology, but do not on average place significant value on the potential environmental benefits. The covariance matrix between the willingness-to-pay and adoption variables suggests that higher perceived values for the non-pecuniary benefits increase the likelihood that the technology will be adopted. The significant covariance between *adoption* and *wtpenviron* suggests that, even though on average the sample does not value the environmental benefits of the technology, those farmers who do report potential benefits in this area are more likely to adopt the technology. In general these results provide further evidence that some of the non-pecuniary attributes of the new technology are important to farmers, and that they will in some cases influence the use of the new technology.

Results for the final specification are given in table 5. In interpreting these results we caution against attaching much quantitative significance to the estimates given the somewhat ad hoc construction of the covariates. Nonetheless several qualitative findings can be noted. Most importantly, the results provide evidence that production and utility choices are non-separable because of the non-pecuniary benefits from the technology. For example, we find that the utility term *safe* significantly enters the adoption equation, while production terms such as *wtpstand* and *costsvgs* influence the reported willingness to pay for the non-market effects. Several of the control variables have parameters consistent with intuition. For example the coefficient for *region* in the adoption equation confirms that farmers located in the region where corn rootworm can survive crop rotation are more likely to adopt. Likewise farmers' past experience with biotech inputs increases the likelihood that they will adopt this variety, and results in higher perceived benefits for safety and the environment. Interestingly these same farmers report smaller potential benefits associated with risk reduction from the new technology. This is perhaps because the first generation transgenic corn is also yield risk reducing, implying that those farmers who have already adopted the first generation will have smaller incremental willingness to pay for the new technology.

7. Discussion and Conclusion

This paper provides initial evidence on the existence of non-pecuniary benefits from new biotechnologies, and is the first study to jointly examine the role of both pecuniary and non-pecuniary attributes of technologies in the adoption decision. Our econometric approach makes use of contemporary computational techniques to estimate systems of limited dependent variable models that are relatively unique in applied econometrics. Our survey data and modeling approach allow us to draw several preliminary conclusions on the adoption behavior of farmers and the potential for transgenic seed varieties to be viewed as mixed private/public goods.

We find that farmers do hold preferences for the non-pecuniary attributes of the new technology, but that the primarily 'private' benefits from improved safety and reduced yield risk tend to be qualitatively more important than the partially 'public' benefits from improved environmental conditions. Estimates show, however, that the willingness to pay for all non-pecuniary attributes are highly correlated, suggesting the values held for these types of benefits are likely bundled. We find evidence of non-separability in profit and utility maximization, both from the estimates of covariate effects and the positive covariances among all of the choice variables. This suggests preferences for the non-pecuniary attributes spill into production decisions, providing at least the necessary condition for non-pecuniary benefits to spill off the farm to become external benefits. Whether this occurs cannot be answered by this research, but the results suggest farmers are not significantly interested in the commons when making input decisions. Further research is needed to confirm or refute this in general.

Our study is preliminary and leaves several avenues open for further research. We caution that our results are best interpreted as qualitative; we have less confidence in the magnitudes of the effects than in their directions. Also, our analysis of non-market benefits and costs excludes off-site effects perceived by neighbors, consumers, and other far away. Future research might therefore refine the data-gathering process to provide more reliable estimates of the magnitudes of the non-pecuniary and (potential) external effects, and to consider a wider range of cost and benefits.

8. References

Alston, J.M., J. Hyde, and M.C. Marra. *An Ex Ante Analysis of the Benefits from the Adoption of Monsanto's Corn Rootworm Resistant Varietal Technology -- YieldGard*$^{\grave{O}}$ *Rootworm. NSF Center for Integrated Pest Management*. Technical Bulletin 103, 68pp Raleigh, NC, July 2002.

Alston, J.M., J. Hyde, M.C. Marra, and P.D. Mitchell. "An Ex-Ante Analysis of the Benefits from the Adoption of Corn Rootworm Resistant, Transgenic Corn Technology." *AgBioForum* 5(3) (2003): 71-84.

Casella, G. and E.I. George. "Explaining the Gibbs sampler." *American Statistician* 46(1992): 167-174.

Chib, S. "Bayes Inference in the Tobit Censored Regression Model." *Journal of Econometrics* 51(1992): 79-99.

Chib, S. and E. Greenberg. "Markov Chain Monte Carlo Simulation Methods in Econometrics." *Econometric Theory* 12(1996): 409-431.

Doane's Market Research. "Corn Insecticide Product Use." Agro Trak. Data supplied by Monsanto Company, 2001.

Freeman, A. M. *The Measurement of Environmental and Resource Values* (second edition). Washington, DC: Resources for the Future, 2003.

Huang, H.C. "Bayesian Analysis of the SUR Tobit Model." *Applied Economics Letters* 8(2001): 617-622.

Huang, J., R. Hu, C. Pray, F. Qiao, and S. Rozelle. "Biotechnology as an Alternative to Chemical Pesticides: A Case Study of Bt Cotton in China." *Agricultural Economics* 29(2003): 55-67/

Kryan, J. L., J.J. Jackson, and A.C. Lew. "Field Termination of Egg Diapause in *Diabrotica* with New Evidence of Extended Diapause in *D. barberi* (Coleoptera: Chrysomelidae)." *Environmental Entomology* 13(1984):1237-1240.

Lapar, M.L., G. Holloway, and S. Ehui. "Policy Option Promoting Market Participation Among Smallholder Livestock Producers: A Case Study from the Philippines." *Food Policy* 28 (2003): 187-211.

Levine, E., and H. Oloumi-Sadeghi. "Western Corn Rootworm (Coleoptera: Chrysomelidae) Larval Injury to Corn Grown for Seed Production Following Soybeans Grown for Seed Production." *Journal of Economic Entomology* 89(1996):1010-1016.

Li, K. "Bayesian Inference in a Simultaneous Equation Model with Limited Dependent Variables." *Journal of Econometrics* 85(1998): 387-400.

Lynne, G.D., J.S. Shonkwiler, and L.R. Rola. "Attitudes and Farmer Conservation Behavior." *American Journal of Agricultural Economics*, 70 (1988): 12-19.

Marra, M, P. Pardey, and J. Alston. "The Payoffs to Transgenic Field Crops: An Assessment of the Evidence." *AgBioForum*. 5(2002):1-8.

McCulloch, R. and P. Rossi. "An Exact Likelihood Analysis of the Multinomial Probit Model." *Journal of Econometrics* 64(1994): 207-240.

McCulloch, R., G. Polson, and P. Rossi. "A Bayesian Analysis of the Multinomial Probit Model with Fully Identified Parameters." *Journal of Econometrics* 99(2000): 173-193.

Metcalf, R.L. "Forward." *Methods for the Study of Pest Diabrotica*. J. L. Krysan and T. A. Miller, eds. New York: Springer-Verlag, 1986.

Mitchell, R. and T.R. Carson. *Using Surveys to Value Public Goods: The Contingent Valuation Method*. Washington, D.C.: Resources for the Future, 1993.

Onstad, D.W., M. Joselyn, S. Isard, E. Levine, J. Spencer, L. Bledsoe, C. Edwards, C. Di Fonzo, and H. Wilson. "Modeling the Spread of Western Corn Rootworm (Coeloptera: Chrysomelidae) Populations Adapting to Soybean-Corn Rotation." *Environmental Entomology* 28(1999):188-194.

Phaneuf, D.J. "A Dual Approach to Modeling Corner Solutions in Recreation Demand." *Journal of Environmental Economics and Management* 37(1999): 85-105.

Phaneuf, D.J., C.L. Kling, and J.A. Herriges. "Estimation and Welfare Calculations in a Generalized Corner Solution Model with an Application to Recreation Demand." *Review of Economics and Statistics* 82(2000)J: 83-92.

Robert, C. "Simulation of Truncated Normal Variables." *Statistics and Computing* 5(1995): 121-125.

Sunding, D., and D. Zilberman. "The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector." Chapter 4 in B.L. Gardner and G.C. Rausser, eds, the *Handbook of Agricultural Economics*, Volume 1A, Amsterdam: Elsevier, 2001.

Train, K. *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press, 2003.

Wright, R., L. Meinke, and K. Jarvi. "Corn Rootworm Management." Extension Publication EC99-1563-C, Nebraska Cooperative Extension Service, University of Nebraska-Lincoln, 1999. *http://www.ianr.unl.edu/pubs/fieldcrops/ec1563.htm (accessed 1/12/02).*

Weaver, R.D. "Prosocial Behavior: Private Contributions to Agriculture's Impact on the Environment." *Land Economics* 72(2)(1996): 231-247.

Table 1: Summary of Dependent Variables

	Mean	Std. Dev.	Median	% zero
wtpsafety ($/acre)	2.14	3.61	1.00	27%
wtpenviron($/acre)	1.71	3.83	0.50	41%
wtprisk($/acre)	4.17	7.00	2.00	17%
wtptotal($/acre)	7.74	9.53	5.00	10%
adopt (proportion)	0.82	0.38	NA	NA

Table 2: Summary of Regressors

	Description	Mean (std. dev.)
Production related variables		
wtpstand	Per acre production value of a 2-5% improvement in standability from the new technology.	5.67 (7.79)
costsvgs	Farmer's estimate of the value per acre of labor and equipment savings if the new technology is adopted.	4.88 (6.57)
work	Indicator variable equal to one if farmer indicated time savings from the new technology would be used for production activities.	0.52 (0.49)
Utility related variables		
safe	Indicator variable equal to one if 'safety' or 'health' was the first reported advantage of the new technology.	0.73 (1.54)
leisure	Indicator variable equal to one if farmer indicated time savings from the new technology would be used for non-work activities.	0.27 (0.44)
Control variables		
percenttrt	Proportion of corn acreage currently treated for corn rootworm.	0.70 (0.33)
region	Indicator variable equal to one if farm is located in either region where corn rootworm can survive a soybean rotation.	0.17 (0.38)
biotech	Indicator variable equal to one if farmer currently plants a transgenic seed variety.	0.45 (0.49)

Table 3: Mean Total WTP and Adoption[a]

	wtptotal	**adoption**
	Model parameters	
Intercept	7.73 (0.44)	0.92 (0.08)
	Normalized covariance matrix	
wtptotal	93.00	3.63
adoption	3.63	1.00

[a]standard error of marginal posterior in parentheses.

Table 4: Mean Component WTP and Adoption[a]

	wtpsafety	**wtpenviron**	**wtprisk**	**adoption**
		Model parameters		
Intercept	1.35 (0.27)	0.00 (0.21)	3.27 (0.30)	0.93 (0.06)
		Normalized covariance matrix		
wtpsafety	20.03	14.05	13.55	0.85
wtpenviron	14.05	29.01	16.03	1.68
wtprisk	13.55	16.03	63.74	2.18
adoption	0.85	1.68	2.18	1.00

[a]standard error of marginal posterior in parentheses.

Table 5: Component WTP and Adoption with Covariates[a]

	wtpsafety	**wtpenviron**	**wtprisk**	**adoption**
		Model parameters		
intercept	-2.22 (0.95)	-4.12 (0.87)	-1.46 (1.06)	0.06 (0.28)
wtpstand	0.11 (0.11)	0.24 (0.10)	0.56 (0.13)	0.03 (0.04)
costsvgs	0.19 (0.14)	0.21 (0.13)	0.03 (0.20)	0.04 (0.05)
work	0.91 (0.59)	0.94 (0.47)	1.08 (0.61)	0.45 (0.14)
safe	0.40 (0.17)	0.28 (0.14)	0.16 (0.19)	0.06 (0.03)
leisure	0.87 (0.46)	0.37 (0.39)	0.90 (0.51)	0.11 (0.14)
percenttrt	0.55 (0.45)	0.70 (0.51)	0.68 (0.64)	-0.04 (0.20)
region	0.67 (0.63)	0.77 (0.58)	0.01 (0.60)	0.43 (0.20)
biotech	0.27 (0.46)	0.83 (0.39)	-0.87 (0.55)	0.73 (0.17)
		Normalized covariance matrix		
wtpsafety	19.79	9.35	7.89	-0.02
wtpenviron	9.35	23.38	3.44	0.63
wtprisk	7.89	3.44	44.63	1.16
adoption	-0.02	0.63	1.16	1.00

[a] standard error of marginal posterior in parentheses.