A Joint Framework for Analysis of Agri-Environmental Payment Programs

by

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Abstract

This paper presents an approach for simultaneously estimating farmers' decisions to accept incentive payments in return for adopting a bundle of environmentally benign management practices. Using the results of a multinomial probit analysis of surveys of over 1,000 farmers facing ten adoption decisions in an EQIP-type program, we show how the farmers' perceptions of the desirability of various bundles changes with the offer amounts and with which practices are offered in the program.

Key words: incentive payments, EQIP, simulated multivariate normal, multinomial probit, simulated maximum likelihood estimation, best management practices

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Introduction

Agri-environmental payment programs can accomplish the task of improving the environmental performance of agriculture, with 'green payment' programs adding the additional goal of providing an alternative source of farm income relative to traditional commodity programs (Claassen and Horan; Batie; Lynch and Smith; Smith; Feather and Cooper; Claussen et al.). Interest in developing these programs is currently strong. For example, in Fall 2000, Senator Harkin and Congressman Minge introduced the 'Conservation Security Act' as a bill in the U.S. House and Senate (S.3223, HR.5511), and the Clinton Administration proposed the Conservation Security Program (Clinton Administration's FY 2001 budget proposal). Each of these programs would introduce one form of 'green payments', which can accomplish the dual tasks of improving the environmental performance of agriculture and providing an alternative source of farm income relative to traditional commodity programs. This paper focuses on voluntary programs designed along the lines of the USDA's Environmental Quality Incentives Program (EQIP), which provides incentive payments to encourage producers to perform land management practices such as nutrient management, manure management, and integrated pest management.

For policymaking purposes, it would be useful to know the sensitivity of the producer's decision to enroll in response to a schedule of potential incentive payments and to which practices are bundled together. Such information can be used to assess the costs of encouraging farmers to try various environmentally benign management practices (commonly known as Best Management Practices, or BMPs).

EQIP offers the farmer a suite of BMPs to choose from. Existing published research (Cooper and Keim) modeled the probability of farmer adoption of BMPs as a function of the incentive payment, with each practice being modeled independently in a bivariate probit analysis of actual adoption and hypothetical adoption. Khanna (2001) also conducts a bivariate probit analysis of technology adoption, but between two technologies at a time.

Logically, there is no reason to believe that the farmer's decision to adopt each of these practices should be treated independently; these BMP should be considered in fact, as a bundle of inter-related practices (Amacher and Feather). If each adoption decision is treated independently in estimation, then valuable economic information may be lost. If the available set of BMP options does indeed influence the farmer's decision as to which practices to adopt, then the adoption decision follows a multivariate distribution. The multinomial probit (MNP) model, which makes use of the multivariate normal (MVN) distribution, is the appropriate econometric tool for modeling multiple adoption decisions in a joint fashion such that the correlations of the error terms across the practices are nonzero.

Unfortunately, the MVN becomes computationally intractable and develops serious shortcoming in numerical accuracy as the number of random variables increases past three when using traditional Gaussian quadrature techniques. This is the reason why econometric applications greater than the trivariate probit are rarely seen. The goal of this paper is to simultaneously model ten discrete choice adoption decisions. The alternative to quadrature methods that makes this possible is to appeal to Monte Carlo methods to simulate the MVN, in our case using the GHK (Geweke, Hajivassiliou and Keane) simulator.

Simulation of standard normal variables is a relatively well-studied problem (see Gouriéroux and Montfort for an overview of simulation-based methods), although applications in the applied economics area are still rare. Dorfman (1996) provides the only published example of application of the simulated normal probability density function (with a Gibbs sampling approach) to modeling a single-stage farmer decision making process. He estimated his MNP using the method of simulated moments (MSM) for three possible decisions. This paper, on the other hand, uses the simulated maximum likelihood estimation (SMLE) approach, which with its direct correspondence to the MLE approach, is more intuitive to most applied economists, and applies it to a multiple-stage decision process with ten decisions.

In the numerical illustration, a dataset is drawn from surveys of over 1,000 farmers in four US regions, and is used to simultaneously model ten discrete choices in an EQIP-like cost sharing program. Because cost sharing programs such as EQIP only accept farmers who are not currently using the desired BMPs, to avoid sample selection bias and make use of all available information, the model combines actual and hypothetical users of the BMPs. Namely, using a multiple-bound approach in the multivariate setting, the model simultaneously considers the decision to adopt the BMPs without an incentive payment and the hypothetical decision (i.e., the farmers' responses to survey questions) to adopt as a function of the offered incentive payments. To the best of the author's knowledge, this is the first application of a multiple-bounded simulated MNP model. By modeling the decision making process jointly across the offered BMPs, the resulting estimate of the correlations across both the current use decisions and the hypothetical use decisions allow us to examine which BMPs the farmers consider as bundles (both among current users of the BMPs and among the hypothetical users) and to calculate conditional probabilities, which can be of policy significance in the design of the type of agri-environmental payment program discussed here. Before turning to the econometric model and then to the numerical illustration of the approach, in the next section, we provide the theoretical basis for addressing the incentve payment program as a bundle of technologies to be adopted.

The Theoretical Model

Consider a farmer who is faced with a set of decisions on what combination of $j = 1,\ldots,J$ BMPs to choose from under a incentive payment program. Assume that she has a land constraint and that she is risk averse with utility function $U(\cdot)$ with $U > 0$ and $U \leq 0$ defined on wealth. We can derive the theoretical model by modifying Just and Zilberman's (1983) model of farmer adoption of one practice to a farmer adoption of a bundle of practices given government incentive payments. Assuming that land is denoted as L, and supposing that wealth at the end of the season is defined by the sum of the land value, $p_L L$ and the return from production. The farmer must either allocate all his land to his current technologies (denoted by subscript "0") or the new technologies, or BMPs (denoted by subscript "1") for which she incurs fixed set-up costs, k^j, for the new technologies. The farmer can allocate his land into any proportions between the BMPs. Hence, each acceptance decision is a discrete choice and the land-allocation decision is a continuous choice. Denoting stochastic profits per acre as $\boldsymbol{p}$, the decision problem is

$$(1)\quad \max_{\substack{I^j=0,1 \\ L_0, L_1^j \\ \forall\, j=1,\ldots,J}} \quad \mathrm{E}U\left\{\left[p_L L + \boldsymbol{p}_0 L_0 + \sum_j I^j\left(\boldsymbol{p}_1^j(\mathbf{I}, \tilde{\mathbf{A}})L_1^j - k^j + g^j\right)\right], \mathbf{I}, \mathbf{s}\right\}$$

$$\text{s.t.} \qquad L_0 + I^j L_1^j \le \overline{L}, \quad \forall j$$

$$L_0, L_1^j, \ldots, L_1^J \ge 0$$

where $\overline{L}$ is total acres, the 0/1 subscript references nonadoption/adoption, L_0 is the acres of land on which no BMPs are adopted, L_1^j is the acres upon which the jth BMP is adopted, k^j is the fixed costs associated with adopting the BMP, g^j is the incentive payment the farmer receives in return for adopting the practice, and I^j is 1 if the farmer adopts practice j and 0 otherwise. The profit associated with the adoption of each practice is a function of which set of practices are adopted, $\boldsymbol{I} = \{I^1, I^2, \ldots, I^J\}$, and of the interactions between the practices, denoted by the correlation matrix $\tilde{\mathrm{A}}$.[2] In other words, in maximizing his utility, the farmer simultaneously considers the impacts on profits of each adoption decision.

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[2] Fixed costs k may also be a function of I and $\tilde{\mathrm{A}}$ but is not considered further as specifying this function adds little to the conceptual understanding of the problem.

Considering the problem as stated in equation (1) as simply maximizing profits instead of the expected utility of profits would of course ignore the impacts that the farmer's level of risk adversity would have on the decision to adopt. For instance, considering the case of the decision over one BMP, even if $E(\pi_1) - k + g > E(\pi_0)$, a farmer may not choose to adopt the practice if the variance of profits, $\sigma^2(\pi_1)$, is greater than $\sigma^2(\pi_0)$. In addition, in order to account for the possibility that farmers may receive some utility from taking measures that have environmental benefits, EU in equation (1) is also a function of $\boldsymbol{I}$ independently of the profit motivation, and vector $\boldsymbol{s}$ comprises farmer (and farm) attributes other than the change in profits that may explain the adoption decision.

In an empirical application, it is convenient, if not necessary, to separate the EU maximization process above into two steps, the first discrete, the second continuous. In empirical practice, this process could be conducted with a Heckman model. As the evidence suggests that for many BMPs, the discrete adoption decision is of greater policy interest than the continuous land allocation decision (Cooper; Cooper and Keim) – physical or other management constraints are more important factors in deciding on the number of acres to apply the practice to – the paper focuses on the decision to adopt.

The farmer's discrete decision to accept incentive payments in exchange for adopting the BMPs can be modeled using the random utility model (RUM) approach (e.g. Hanemann). From the utility theoretic standpoint, a farmer is willing to accept g^j to switch to a new production practice if the farmer's utility with the new practice and incentive payment is at least as great as at the initial state, i.e., if $U_1(L_1, \pi_1, \boldsymbol{s}, k^j, g^j)$

$\geq U_0(L_0,\ \boldsymbol{p}_0, \boldsymbol{s})$, where 0 is the base state; 1 is the state with the green practice adopted. The farmer's utility function is unknown because some components are unobservable to the researcher, and thus, can be considered a random variable from the researcher's standpoint. The observable portion is V, the mean of the random variable U. With the addition of an error $\boldsymbol{e}$, where $\boldsymbol{e}$ is an independently and identically distributed random variable with zero mean, the farmer's decision to adopt the practice can be re-expressed as $V_1(L_1,\ \boldsymbol{p}_1, \boldsymbol{s}, k^j, g^j) + \boldsymbol{e}_1 \geq V_0(L_0,\ \boldsymbol{p}_0, \boldsymbol{s}) + \boldsymbol{e}_0$.

In practice, V_1 and V_0 are generally not separably identifiable, but their difference (ΔV) is. This is done by expressing the probability of adoption in a probability framework as $\Pr\{\boldsymbol{e}_0 - \boldsymbol{e}_1 \leq V_1 - V_0\}$, and hence, the parameters of which can be estimated through maximum likelihood. Because ΔV is generated directly from the utility model given above, it is compatible with the theory of utility maximization. Many different specifications for ΔV are possible, including semi-nonparametric (e.g., Creel and Loomis). The probability of farmer adoption at g^j is $\mathrm{F}_e\left[\Delta V\left(g^j\right)\right]$, where F_e is a cumulative density function. Given that $\boldsymbol{p}_1^j$ and $\boldsymbol{p}_0$, as well as any nonfinancial motivations for adoption, are unlikely to be known to the researcher, survey approaches (such as those that explicitly ask the farmer whether or not she would adopt for a given incentive payment g) are needed to estimate the parameters of F_e (Cooper; Cooper and Keim; Khanna). According to equation (1), the $\Delta V\left(g^j\right)$, $j = 1,\ldots,J$ are correlated across the practices. Assuming the $\Delta V\left(g^j\right)$ are distributed normally, the multivariate normal distribution is necessary to account for the correlations, where the (Jx1) vector $\boldsymbol{\Delta V}$ is distributed as $\Delta \boldsymbol{V} \sim \mathrm{F}\left(m^{1}, m^{2}, m^{3}, \ldots, m^{J} ; \Sigma\right)$, where Σ is the (J x J) correlation matrix between the practices. The next section presents the empirical model for estimating the parameters of this distribution.

Econometric Model

Two issues require consideration in the econometric analysis. One is the how to treat the adoption decisions as a bundle. The second, as mentioned in the introduction, is how to combine data from actual and hypothetical users (i.e., current nonusers who are asked in a survey whether or not they would adopt the practice for a given incentive payment). Regarding the latter question, government subsidized BMP adoption programs tend to offer incentive payments only to those who do not currently use the offered practices. However, as current users are effectively using the practice at a $0 per acre incentive payment, adding them to the analysis of farmer responses to a range of incentive payments adds additional information to the analysis, and may smooth out potential biases in the set of contingent behavior responses. Furthermore, ignoring the current users in the analysis can instill sample selection bias in the model.

Assume that farmers choose among a set of J practices. Subscript a represents the farmer's current decision to use or not use the BMP. Subscript b represents the farmer's decision to accept or not accept the incentive payment offer. Farmer i's RUM associated with current use practice j is

(2.1) $\Delta V_{ija} = X'_{ija}\boldsymbol{b}_j + \boldsymbol{e}_{ija}$ $\quad$ (j = 1,…,J; i = 1,…,N)

The farmer's RUM associated with the incentive payment offer to adopt the BMP is

(2.2) $\Delta V_{ijb} = X'_{ijb}\boldsymbol{b}_j + \boldsymbol{e}_{ijb}$ $\quad$ (j = 1,…,J; i = 1,…,N)

Where $X_{ija} = \{x_{ij}, C_{ija}\}$ and $X_{ijb} = \{x_{ij}, C_{ijb}\}$, where $Cijb$ is the incentive payment offer to farmer i, and $Cija$ = \$0 is the incentive payment offer currently facing the user or nonuser, i.e., if the farmer is currently using the practice, he is doing so without a subsidy, and where the coefficient vector *â* is equal across the two equations.[3]

The MNP model assumes that the error terms in equations are distributed $\boldsymbol{e}_i \equiv (\boldsymbol{e}_{i1a}, \ldots, \boldsymbol{e}_{iJa}, \boldsymbol{e}_{i1b}, \ldots, \boldsymbol{e}_{iJb})' \sim$ IIDN(0, Σ), $\Sigma = \lfloor \boldsymbol{s}_{ij}^{ab} \rfloor$. The survey data used in the numerical illustration considers the adoption of five BMPs. Hence, it contains five equations on current use and five equations on hypothetical use. Normalizing along the main diagonal, the resulting symmetric correlation matrix is therefore

[3] A full MNP model would have variables in the RUMs in equation 2.1 and 2.2 that vary across the J choices. While explanatory variables that vary across the choices are possible for some datasets, such as those used in recreational site choice, such variables are unlikely to be available to researchers modeling the farmer's technology adoption process. However, convergence of a MNP model with variables that vary across choices as well as across individuals generally requires restrictions on the correlation matrix, such as normalizing the matrix along one row.

(3.1) Σ =

$$\begin{bmatrix}
1 & & & & & \cdots & & & & s^{ab}_{51} \\
s^{aa}_{21} & 1 & & & & & & & & \\
s^{aa}_{31} & s^{aa}_{32} & 1 & & & & & \iddots & & \\
s^{aa}_{41} & s^{aa}_{42} & s^{aa}_{43} & 1 & & & & & & \\
s^{aa}_{51} & s^{aa}_{52} & s^{aa}_{53} & s^{aa}_{54} & 1 & & & & & \vdots \\
s^{ba}_{11} & s^{ba}_{12} & s^{ba}_{13} & s^{ba}_{14} & s^{bb}_{15} & 1 & & & & \\
s^{ba}_{21} & s^{ba}_{22} & s^{ba}_{23} & s^{ba}_{24} & s^{bb}_{25} & s^{bb}_{21} & 1 & & & \\
s^{ba}_{31} & s^{ba}_{32} & s^{ba}_{33} & s^{ba}_{34} & s^{bb}_{35} & s^{bb}_{31} & s^{bb}_{32} & 1 & & \\
s^{ba}_{41} & s^{ba}_{42} & s^{ba}_{43} & s^{ba}_{44} & s^{bb}_{45} & s^{bb}_{41} & s^{bb}_{42} & s^{bb}_{43} & 1 & \\
s^{ba}_{51} & s^{ba}_{52} & s^{ba}_{53} & s^{ba}_{54} & s^{bb}_{55} & s^{bb}_{51} & s^{bb}_{52} & s^{bb}_{53} & s^{bb}_{54} & 1
\end{bmatrix}.$$

It naturally follows that for comparison, we should estimate a subset of the full model, in which it is assumed that farmers consider the adoption decision of each BMP in an independent fashion. The restricted correlation matrix is therefore

(3.2) Σ^{R} =

$$\begin{bmatrix}
1 & & & & & \cdots & & & & 0 \\
0 & 1 & & & & & & & & \\
0 & 0 & 1 & & & & & \iddots & & \\
0 & 0 & 0 & 1 & & & & & & \vdots \\
0 & 0 & 0 & 0 & 1 & & & & & \\
s^{ba}_{11} & 0 & 0 & 0 & 0 & 1 & & & & \\
0 & s^{ba}_{22} & 0 & 0 & 0 & 0 & 1 & & & \\
0 & 0 & s^{ba}_{33} & 0 & 0 & 0 & 0 & 1 & & \\
0 & 0 & 0 & s^{ba}_{44} & 0 & 0 & 0 & 0 & 1 & \\
0 & 0 & 0 & 0 & s^{ba}_{55} & 0 & 0 & 0 & 0 & 1
\end{bmatrix}$$

Since all the correlations except the within practice correlations are zero in equation (3.2), estimating the model subject to this matrix is analogous to performing a bivariate probit regression of current and hypothetical use for each of the five BMPs. Conceivably, one could further restrict Σ^R by setting the five within practice correlations equal to one. Doing so would be equivalent to the individual practice specific multiple bound (specifically, one-way up) models in Cooper (1997). However, some recent evidence suggests imposing an effective correlation of one in multiple bound models, such as those used in contingent valuation, can produce coefficient estimates on the offer amount, that while consistent, can potentially have spurious standard errors.[4]

The MNP log-likelihood function to be estimated is an expanded version of the bivariate model (Greene, 1997):

(4) $$L(\boldsymbol{b},\Sigma) = \sum_{i=1}^{N} \log F\left(\boldsymbol{w}_i, \Sigma^*\right),$$ where

$$\boldsymbol{w}_i \equiv \left(q_{i1a} * z_{i1a}, \ldots, q_{iJa} * z_{iJa}, q_{i1b} * z_{i1b}, \ldots, q_{iJb} * z_{iJb}\right)'$$ and

$$z_{ijt} = x'_{ijt}\boldsymbol{b}\text{ , } t = a,b$$

$$q_{ija} = \begin{cases} 1 \text{ if } i \text{ currently uses practice } j \text{ at } \mathrm{C}_{ij} = \$0 \\ -1 \text{ if } i \text{ currently does not use practice } j \text{ at } \mathrm{C}_{ij} = \$0 \end{cases}$$

[4] Namely, when a correlation of one is imposed between the Δ V's, the bid coefficients can be statistically significant even if the responses are completely random, and the level of significance is some function of the choice of offer amounts. Upon request, the author can provide a computer program that shows this effect. A fruitful line of study may be to investigate why this is the case. At any rate, freeing up the correlation parameters (to anywhere between –1 and 1), may help reduce biases associated with potential misspecification of the RUM and distribution.

$$q_{ijb} = \begin{cases} 1 \text{ if } i \text{ will accept Cij [\$0 for current user, offer amount otherwise] per acre to adopt practice } j \\ -1 \text{ if } i \text{ will not accept Cij [\$0 for current user, offer amount otherwise] per acre to adopt practice } j \end{cases}$$

$$\Sigma^{*} = T_i \Sigma T_i$$

where T_i is a $J \times J$ diagonal matrix with $T_i \equiv \left(q_{i1a}, \ldots, q_{iJa}, q_{i1b}, \ldots, q_{iJb}\right)'$ on the diagonal, and where the unrestricted $J \times J$ covariance matrix has $(J-1) \times J$ free elements (after imposing symmetry conditions).

Leaving out the subscript *i*, the multivariate normal density function in equation (4) is

$$\text{(5)} \quad F\left(\vec{w}, \Sigma^{*}\right) = \frac{1}{\sqrt{\left|\Sigma^{*}\right| (2\boldsymbol{p})^{J}}} \int_{-\infty}^{w_{a1}} \int_{-\infty}^{w_{2a}} \cdots \int_{-\infty}^{w_{Jb}} e^{-\frac{1}{2} q' \Sigma^{*-1} q} \, d\boldsymbol{q} \quad ,$$

where $w_{jt} = (\boldsymbol{w}_{jt}$ - ì$_{jt})/\ \boldsymbol{s}_{jt}$, $\boldsymbol{s}_{jt} = 1$, ì$_{jt} = 0$, and $t = a, b$.

As noted earlier, the computational intractability of the MVN density in equation (5) accounts for why it is rarely used in dimensions higher than J = 2 (bivariate), or increasingly, J = 3 (trivariate). The traditional numerical quadrature methods to calculating F(.) tend not only to be unacceptably slow in more than three or four dimensions, they also suffer from serious shortcoming in numerical accuracy as J increases (e.g., Horowitz *et al.*). An alternative to quadrature methods, namely Monte Carlo methods, is necessary to estimate the CDF *F*(.). Simulation of standard normal variables is a well-studied problem (see Gouriéroux and Montfort for an overview of this simulation based methods), although applications in the applied economics area are rare (e.g. Dorfman's trivariate model). To some extent this state is due to desktop computers only recently having the computational speed to perform this analysis and to a lack of available software. Several simulation techniques for calculating the densities are possible (Gouriéroux and Montfort). For this paper, the GHK (Gweke-Hajivassiliou-Kean) importance sampling technique and a similar technique proposed by Genz (1992) were both tried and gave similar results. The approximation to $F(.)$ using these procedures lies in the unit interval and is a continuous function of the parameters. Hajivassiliou et al. (1992) found the root-mean square-error performance of the GHK measure to be superior to twelve other simulators for normal rectangle probabilities. An extensive discussion of the GHK or Genz simulator is outside the scope of the paper, and we simply note that these methods work by taking recursive draws from a truncated normal CDF. As the Genz approach can be adequately summarized in a few lines, we present a description of it as the example:

1. Input Σ and the number of simulations, *Rmax*
2. Compute lower triangular Cholesty factor C for Σ.
3. Initialize *Intsum* = 0, N = 0, $d_1 = \Phi(a_1 / c_{1,1})$ and $f_1 = \Phi(b_1 / c_{1,1})$ and $f_1 = e_1 - d_1$.
4. Repeat *Rmax* times
   (a) Generate uniform random $w_1, w_2, \ldots, w_{J-1} \in [0,1]$.
   (b) For j =2,3,…,J set $y_{j-1} = \Phi^{-1}\left(d_{j-1} + w_{j-1}\left(e_{j-1} - d_{j-1}\right)\right)$, $d_j = \Phi^{-1}\left(\left(a_{j-1} - \sum_{k=1}^{j-1} c_{j,k} y_j\right) / c_{j,k}\right)$, $e_j = \Phi^{-1}\left(\left(b_{j-1} - \sum_{k=1}^{j-1} c_{j,k} y_j\right) / c_{j,k}\right)$, and $f_j = (e_j - d_j)$-1.
   (c) Set $R = R + 1$, $d = (f_m - Intsum)\ R$, $Intsum = Intsum + d$.

5. Output F = *Intsum*.[5]

For the model in this paper, $a_j = -\infty$ for $j = 1,\ldots,J$ and $b_j = (x_j \beta_j - \mu_j)/\sigma_j$, where $\sigma_j = 1$ and $\mu_j = 0$.

Since the Monte Carlo simulator can approximate the probabilities of the MVN density to any desired degree of accuracy, the corresponding maximum simulated maximum likelihood estimate (SMLE) based on the simulated MVN can approximate the MLE estimator (Hajivassiliou, McFadden, and Ruud). For the results to be consistent, *Rmax* must increase with the sample size at a sufficiently rapid rate (Newey and McFadden, 1993). One hundred repetitions is used here (as suggested by Gweke, Kean, and Runkle for their simulated MNP model).

The method of simulated moments (MSM) is an alternative to SMLE as an approximation to MLE. Each has advantages and drawbacks (Gouriéroux and Montfort). SMLE is more intuitively appealing as it is an approximation to the MLE, which is a much more common form of optimization in applied economics than method of moments estimators. Furthermore, some evidence suggests that MSM works best for models with a smaller number of choices than SMLE. In their Monte Carlo analysis, Hajivassiliou and Ruud found MSM works best for small sample spaces with a number of choices less than six.

[5] Alternatively, the loop can continue until some a priori minimum level of error in the difference between f_m and *Instum* is reached. It tends to be faster in GAUSS to simply generate the vectors in (a) and (b) in parallel fashion for a large Rmax than to do the loop procedure.

Numerical Illustration

The data used for the numerical illustration is taken from a data collection and modeling effort undertaken jointly by the Natural Resource Conservation Service (NRCS), the Economic Research Service (ERS), the U.S. Geological Survey (USGS), and the National Agricultural Statistical Service (NASS). Data on cropping and tillage practices and input management were obtained from comprehensive field and farm level surveys of about 1,000 farmers apiece for cropping practices in each of four critical watershed regions. In the survey, current nonusers of the practices were asked if they would adopt the BMPs with an incentive payment of $[X] per acre, a value which was varied across the respondents in the range $2 to $24. As the data is discussed in detail in Cooper and Cooper and Keim, for brevity and to avoid repetition, we do not discuss the data in detail here. Table 1 lists the BMPs discussed in the surveys, and Table 2 lists the explanatory variables used in the regressions. The decision on which variables to include in the regressions for each of the practices was based on whether or not the variables appear justified from a farm management standpoint (*ibid*).

The SMLE likelihood function and maximization routines were programmed by the author in GAUSS.[6] Regression results are presented in Tables 3 and 4. The coefficient on the offer amount (BIDVAL) is of the expected sign and significant to at least the 10% level, and for most cases, the 1% level, for all five practices in Tables 3 and 4a. As

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[6] The only commercially available program that the author is aware of that performs the MNP using the simulated normal is an optional package in Limdep. However, it is not suitable to the model here for two reasons: 1) it offers no practical way to fix the coefficient vector $\hat{a}$ to be equal between ΔV_{ija} and ΔV_{ijb}; and 2) the author found that modeling just the data on the five current use decisions was too computationally burdensome to be practical.

expected, the within practice correlations are close to one and highly significant in both Table 3 and Table 4b. In the latter table, most of the other correlations are significant to at least the 5% level as well. In general, the correlations between the current use variates (the upper left triangle of values in table 4.b) tend to be less significant than the correlations between the hypothetical use variates (in the bottom right triangle of numbers). This difference in significance is to be expected; whether or not the farmer is a current user of the BMPs is a result of an evolutionary process, while the hypothetical adoption decisions are over a bundle of practices offered to the farmer at one point in time in a survey instrument.

As the restricted model (Table 3) is nested within the unrestricted model (Tables 4a-b), a likelihood ratio test, namely $LR = -2(\ln L_r - \ln L_u)$, can be used to test the null hypothesis that farmers consider each BMP adoption decision as an independent one. Given the log-likelihood values in Tables 3 and 4a, this hypothesis is not accepted for any reasonable level of significance.

Next, given that the restricted model is not accepted, we turn to how the unrestricted MNP results can be used for analysis of bundling. The basic value of the multivariate analysis is it allows us to calculate the joint probabilities as a function of the incentive payments. Figure 1 provides an example of how the joint probability changes as a function of the IPM incentive payment offer. The baseline density is that for a typical respondent who currently uses CONTILL (as around 70% in the sample did), but does not currently use the other BMPs, and refuses to use them at the offered incentive payments. In this case, the joint probability is the probability of a "no" to any practices except CONTILL, i.e., the probability that the farmer will not use any of the practices except CONTILL. In other words, the MVN density function is $F\left(z_{1a}, -z_{2a}, -z_{3a}, -z_{4a}, -z_{5a}; z_{1b}, -z_{2b}, -z_{3b}, -z_{4b}, -z_{5b}; \Sigma \middle| C_{1b}, C_{2b}, \ldots, C_{5b}\right)$, and the slope of the curves in the figure is $\partial F(.)/\partial C_{2b}$, where C_{2b} is the incentive payment for IPM.[7] For the baseline, C_{2b} is varied between \$0 and \$30 per acre, with the other incentive payment set equal to zero. In other words, incentive payments are provided only for the adoption of IPM; other practices are to be adopted purely at the farmer's expense. Scenario 1 is the same except that now, MANTST at a fixed incentive payment of \$10 per acre is bundled with IPM. This bundling shifts the probability of a "no" response downwards, but not by a great amount. However, when LEGCR is bundled with a \$10 per acre IPM incentive payment instead of MANTST (Scenario 2), then the probability shifts downwards by a large amount. Bundling in MANTST, LEGCR, and SMTST (Scenario 3) with IPM has little impact on decreasing the negative response of the farmer compared to Scenario 2 as adding MANTST and SMTST has little impact on the farmer's decision to adopt IPM. In fact, the correlation coefficient between IPM and LEGCR is higher than between IPM and MANTST or IPM and SMTST (Table 4b). Hence, if for the sake of argument, the government's focus is on IPM adoption, it appears from this analysis that bundling LEGCR with IPM is attractive to the farmer and has the potential to be cost effective. A wide variety of scenarios can be examined in the same manner.

[7] The key to the subscripts is CONTILL = 1, IPM = 2, LEGCR = 3, MANTST=4, and SMTST = 5.

Conclusion

This paper develops an econometric model based on the multivariate normal distribution that identifies producer tendencies to bundle types of management practices that may be covered under an incentive payment system. Identifying producer tendencies to bundle these types of practices may increase adoption and lower the costs of voluntary adoption programs. Although the scenario examined here relies on payments to encourage adoption, identifying these producer tendencies can also lower the costs of voluntary adoption programs that rely on the dissemination of information to encourage adoption. Since a critical component of voluntary adoption is producer perceptions, as in the numerical illustration, identifying and packaging BMPs that are perceived to be jointly beneficial, or bundled, may increase adoption and lower the costs of the programs. Alternatively, the identification of producer perceptions regarding bundling preferences that may be considered suboptimal in some fashion can be used in identifying information and extension needs. Thus, jointly modeling the observed adoption data across the BMPs can indicate which practices should be bundled into composite practices. If voluntary agri-environmental programs in the US become more systems-oriented, such as in the EU, the multivariate approach developed this paper can become an increasingly useful tool in optimizing the design of these programs. In fact, as the current EQIP program already takes more of a systems approach than older programs such as WQIP, the program evolution is probably in that direction.

Of course, the multivariate SMLE routine presented here can be applied to other subjects besides technology adoption. For example, it can be directly applied to analysis of multiple bound discrete choice contingent valuation questions, in cases when it is necessary or expedient to ask several sets of questions in the same survey instrument. Future extensions to the approach could be implementations that reduce the potential biases associated with the distributional assumptions of the model. For example, the linear random utility model assumed here could be substituted with a highly flexible functional form, such as the Fourier (e.g., Creel and Loomis). However, practical application of such procedures in the context of the simulated multivariate normal distribution require greater computational power than is currently available to most economists.

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Table 1. Descriptions of the Farm Management Practices Presented in the Survey Instrument.

Conservation Tillage (CONTILL) - Tillage system in which at least 30% of the soil surface is covered by plant residue after planting to reduce soil erosion by water; or where soil erosion by wind is the primary concern, at least 1,000 pounds per acre of flat small grain residue-equivalent are on the surface during the critical erosion period.

Integrated Pest Management (IPM) - Pest control strategy based on the determination of an economic threshold that indicates when a pest population is approaching the level at which control measures are necessary to prevent a decline in net returns. This can include scouting, biological controls and cultural controls.

Legume Crediting (LEGCR) - Nutrient management practice involving the estimation of the amount of nitrogen available for crops from previous legumes (e.g. alfalfa, clover, cover crops, etc.) and reducing the application rate of commercial fertilizers accordingly.

Manure Testing (MANTST) - Nutrient management practice which accounts for the amount of nutrients available for crops from applying livestock or poultry manure and reducing the application rate of commercial fertilizer accordingly.

Soil Moisture Testing (SMTST) - Irrigation water management practice in which tensiometers or water table monitoring wells are used to estimate the amount of water available from subsurface sources.

Table 2. Definitions of the Explanatory Variables.

BIDVAL - Bid Offer ($) in the WTA question.
TACRE - Total acres operated.
EDUC - Formal education of operator.
EINDEX - Sheet and rill erosion index.
FLVALUE - Estimated market value per acre of land.
EXPER - Farm operator's years of experience.
BPWORK - Number of days annually operator worked off the farm.
NETINC - Operation's Net farm income in 1991.
SNT - Soil nitrogen test performed in 1992 (dummy).
TISTST - Tissue test performed in 1992 (dummy).
CTILL - Conservation tillage used in 1992 (dummy).
PESTM - Destroy crop residues for host free zones (dummy).
ANIMAL - Farm type-beef,hogs,sheep (dummy).
ROTATE - Grasses and legumes in rotation (dummy).
MANURE - Manure applied to field (dummy).
HEL - Highly erodible land (dummy).
IA - Sample located in the Eastern Iowa or Illinois Basin Area (dummy).
ALBR - Sample located in the Albermarle-Pamlico Drainage Area (dummy).
IDAHO - Sample located in the Upper Snake River Basin Area (dummy).

Table 3. Multinomial Probit Regression Results for the Multiple Bound Model – Restricted Correlation Matrix (Log-likelihood = -3671.983)

	CONTILL	IPM	LEGCR	MANTST	SMTST
Variable	Coefficient Estimates (Coefficient Estimates/Standard Error)				
CONST	0.2628	-0.8786	-0.7858	-1.4857	-0.4924
	(.981)	-(3.822)	-(2.418)	-(3.405)	-(1.662)
BIDVAL	0.0084	0.0382	0.0208	0.0413	0.0512
	(1.681)	(9.406)	(8.886)	(8.167)	(7.519)
EDUC	-0.0065	0.1704	0.0967	0.0427	-0.0360
	-(.2)	(5.296)	(3.02)	(.999)	-(.869)
CTILL	0.4205	--	--	--	--
	(4.756)				
TISTST	--	--	0.0762	-1.5490	--
			(.288)	-(1.269)	
HEL	-0.0500	--	--	--	--
	-(.465)				
EXPER	-0.0002	-0.0036	-0.0018	-0.0100	-0.0072
	-(.048)	-(1.044)	-(.5)	-(2.048)	-(1.664)
PESTM	0.0733	0.4424	--	--	--
	(.584)	(4.045)			
ROTATE	0.0857	-0.0616	0.4729	--	--
	(.466)	-(.319)	(3.035)		
MANURE	-0.1758	-0.1925	0.0533	0.2625	--
	-(1.7)	-(1.556)	(.497)	(1.996)	
ANIMAL	-0.0327	-0.2798	-0.0841	0.2852	-0.1396
	-(.31)	-(2.46)	-(.808)	(2.233)	-(1.104)
TACRE	-5.58E-06	4.82E-05	-7.41E-06	2.51E-06	4.55E-06
	-(.17)	(1.419)	-(.189)	(.068)	(.148)
FLVALUE	-1.60E-05	-1.63E-05	-0.0001	-7.83E-05	-0.0002
	-(.236)	-(.243)	-(1.47)	-(.772)	-(2.006)
IA	0.2955	0.0805	0.5057	0.6459	-0.2656
	(1.568)	(.43)	(1.892)	(1.831)	-(1.23)
ALBR	0.3955	0.0962	-0.1167	-0.2130	-0.6208
	(1.595)	(.373)	-(.33)	-(.488)	-(1.904)
IDAHO	0.0667	-0.4146	0.2554	0.2878	0.2366
	(.304)	-(1.875)	(.861)	(.717)	(1.047)
BPWORK	-0.0006	-0.0004	-0.0005	-0.0003	-0.0001
	-(1.307)	-(.691)	-(.916)	-(.359)	-(.112)

Table 3. Continued

NETINC	4.31E-07	9.08E-07	-3.87E-06	-2.19E-07	5.73E-06
	(.195)	(.452)	-(1.808)	-(.079)	(2.07)
Within practice correlation coefficients between current and hypothetical use					
	CONTILL		0.8504		
			(24.57)		
	IPM		0.9704		
			(51.59)		
	LEGCR		0.9998		
			(4191.)		
	MANTST		0.9939		
			(165.9)		
	SMTST		0.9318		
			(24.04)		

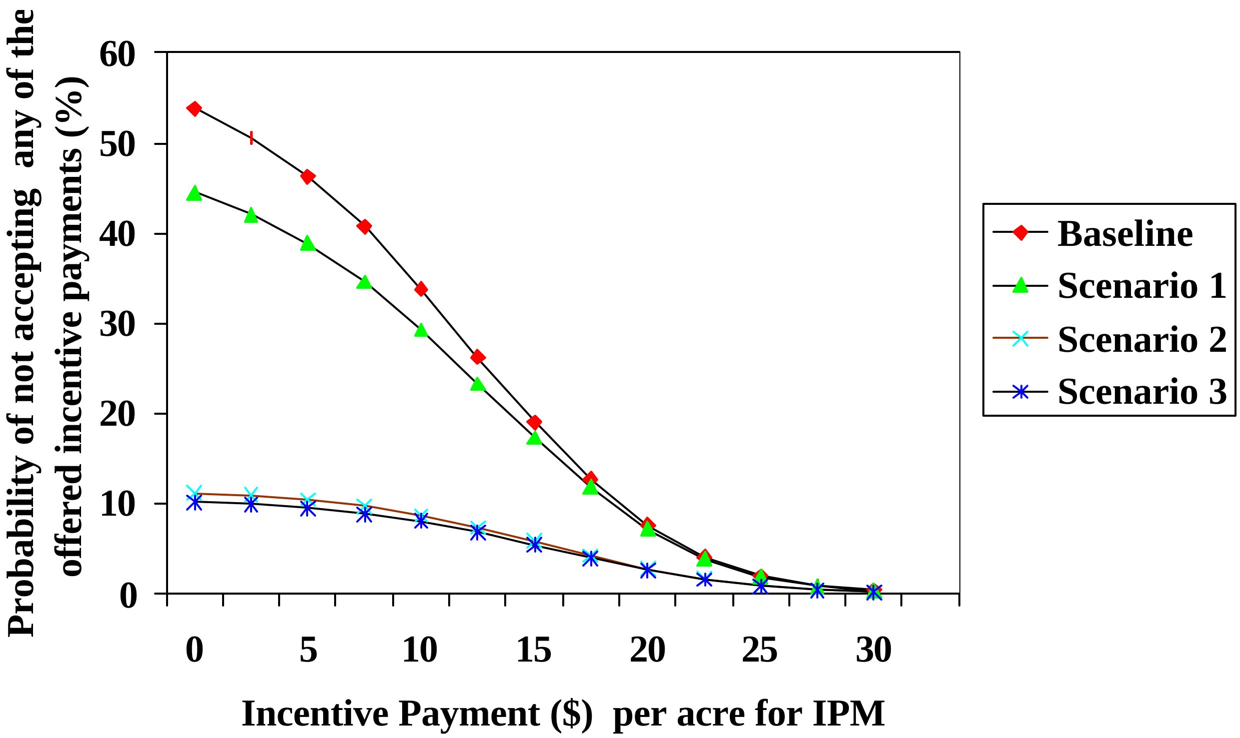
Table 4a. Multinomial Probit Regression Results for the Multiple Bound Model – Unrestricted Correlation Matrix (Log-likelihood = -3485.78223)

	CONTILL	IPM	LEGCR	MANTST	SMTST
Variable	Coefficient Estimates (Coefficient Estimates/Standard Error)				
CONST	0.2501	-1.1187	-2.1961	-3.5710	-3.1764
	(.938)	-(5.202)	-(7.219)	-(9.623)	-(16.02)
BIDVAL	0.0114	0.0266	0.0067	0.0315	0.0285
	(3.035)	(6.413)	(2.624)	(5.311)	(5.985)
EDUC	-0.0104	0.1877	0.1315	0.0879	0.0872
	-(.301)	(6.299)	(4.524)	(2.259)	(2.934)
CTILL	0.4101	--	--	--	--
	(4.476)				
TISTST	--	--	0.2036	-2.4712	
			(.904)	-(3.089)	
HEL	-0.0465	--	--	--	--
	-(.413)				
EXPER	0.0019	-0.0002	0.0051	0.0023	0.0079
	(.549)	-(.078)	(1.562)	(.543)	(2.278)
PESTM	-0.0484	0.4303	--	--	--
	-(.366)	(3.961)			
ROTATE	0.1221	-0.0707	0.4263	--	--
	(.58)	-(.375)	(2.598)		
MANURE	-0.1684	-0.1947	0.1126	0.3311	--
	-(1.53)	-(1.684)	(1.208)	(2.662)	
ANIMAL	-0.0131	-0.2752	-0.1363	0.1576	-0.2484
	-(.116)	-(2.905)	-(1.473)	(1.28)	-(2.322)
TACRE	-2.24E-06	5.48E-05	5.70E-06	-6.12E-06	2.55E-05
	-(.063)	(1.569)	(.169)	-(.151)	(1.185)
FLVALUE	-1.15E-05	3.98E-06	-0.0001	-0.0002	-0.0003
	-(.153)	(.069)	-(1.803)	-(1.662)	-(4.609)
IA	0.1706	0.2230	1.6614	2.4504	1.9161
	(.927)	(1.249)	(6.53)	(8.288)	(13.15)
ALBR	0.3061	0.2389	0.4431	1.6267	1.0059
	(1.204)	(.985)	(1.451)	(4.467)	(3.313)
IDAHO	-0.0371	-0.3045	1.2844	2.1152	2.0153
	-(.17)	-(1.442)	(4.676)	(6.28)	(12.11)
BPWORK	-0.0002	-0.0003	-0.0001	0.0004	0.0002
	-(.4)	-(.713)	-(.154)	(.693)	(.376)
NETINC	2.06E-06	1.51E-06	-1.21E-07	2.51E-06	1.46E-05
	(.861)	(.767)	-(.061)	(1.003)	(7.305)

Table 4b. Correlation Matrix Estimates for Multinomial Probit Regression Results for the Multiple Bound Model – Unrestricted Model

	CONTILL_a	IPM_a	LEGCR_a	MANTST_a	SMTST_a	CONTILL_b	IPM_b	LEGCR_b	MANTST_b	SMTST_b
	Coefficient Estimates (Coefficient Estimates/Standard Error)									
CONTILL_a	--									
IPM_a	-0.0329	--								
	-(.425)									
LEGCR_a	0.2145	0.3036	--							
	(2.988)	(5.03)								
MANTST_a	-0.0114	0.2201	0.2447	--						
	-(.121)	(2.69)	(2.453)							
SMTST_a	0.1503	0.0225	0.1444	0.5696	--					
	(1.945)	(.281)	(1.724)	(9.233)						
CONTILL_b	0.9309	-0.123	0.1817	0.0466	0.1470	--				
	(52.79)	-(1.64)	(2.316)	(.441)	(1.772)					
IPMb	0.0367	0.8833	0.2328	0.2223	-0.0229	0.0830	--			
	(.601)	(37.0)	(4.015)	(2.626)	-(.313)	(1.345)				
LEGCR_b	0.2043	0.2851	0.9617	0.3236	0.1541	0.2687	0.3257	--		
	(3.424)	(5.67)	(111.9)	(3.506)	(1.886)	(4.25)	(6.60)			
MANTST_b	0.0111	0.1297	0.2487	0.9653	0.4807	0.1171	0.2309	0.3633	--	
	(.145)	(1.72)	(3.458)	(65.47)	(6.435)	(1.286)	(2.81)	(5.248)		
SMTST_b	0.1352	0.0393	0.1925	0.5598	0.9202	0.2283	0.1668	0.2805	0.5521	--
	(2.416)	(.664)	(3.18)	(13.41)	(62.79)	(3.786)	(2.73)	(4.64)	(10.21)	

Figure 1. Joint Probability Function with Changes in IPM Incentive Payments



Notes:
- The joint CDF is F(is current user of Conservation Tillage, is nonuser of the other four practices and rejects incentive payment offers on all four)
- Baseline: MANTST, LEGCR, and SMTST incentives are set equal to $0 per acre.
- Scenario 1: MANTST incentive = $10 per acre; LEGCR and SMTST incentives = $0.
- Scenario 2: LEGCR incentive = $10 per acre; MANTST and SMTST incentives = $0.
- Scenario 3: LEGCR, MANTST and SMTST incentives = $10 per acre.