A Trait Specific Model of GM Crop Adoption among U.S. Corn Farmers in the Upper Midwest

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1. Introduction

The advent of genetic engineering techniques has transformed how scientists can manipulate and change the characteristics of plants by giving them the ability to add specific and unique traits to already existing seeds. This makes genetically modified (GM) seeds different from standard technological advances in agriculture which typically involve wholesale replacement of one input or seed with another. In this case GM seeds involve adding specific traits into a plant in a manner similar to how a food company might add a trait to a food, for example sugar coating to corn flakes breakfast cereal. Such a difference implies a different type of adoption logic for GM seeds than has been the standard for such new technologies as hybrid seeds or new products such as rBST (bovine growth hormone).

Models of farmer adoption of new technology typically emphasize farm and farmer characteristics rather than the characteristics of the technologies themselves. For instance, two reviews of adoption studies in developing countries (Feder et al.,1985; Feder and Umali, 1993) fail to identify any study that analyzes the implications of farmers' assessments of agricultural technology characteristics for adoption decisions. In the same review, Feder and Umali (1993) emphasize the importance of distinguishing the effects of different farmer characteristics on adoption depending on the stage of the adoption process. Other later studies, like Fernandez-Cornejo and McBride (2002), similarly focus on the role of farm size on the adoption of GM crop varieties and use probit techniques to distinguish this effect from the effect of farmer wealth and credit access. Barham et. al. (2004, 1996) use a multinomial approach to analyze the adoption of rBST[1] in terms of farmer education and age, use of specialized machinery, herd size and farmer attitude towards biotechnology. Finally, (Fernandez-Cornejo et al., 2001;

[1] Recombinant bovine somatotropin.

Napier et al., 2000; Roberts et al., 2002) focus on determining the characteristics of GM crop adopters using limited dependent variable or discriminant analysis. Yet, there are compelling reasons inherent to the GM technology innovations to extend these models to incorporate their traits. Consumer demand analysts have accumulated considerable evidence illustrating the significance of product characteristics for consumer demand (Nevo 2001, 2000; Revelt and Train 1998, Berry 1994). These studies have amply shown how consumer perceptions of different product attributes or traits may significantly affect product demand.

Probits, logits, and their multinomial versions are the standard empirical methods used in estimating technology adoption models. The multinomial specifications in particular provide insights into the manner in which changes in farm and farmer characteristics push the individuals in and out of different adoption categories. However, they are not explicit in modeling the underlying behavioral choice that the farmer faces, especially in the presence of options with distinctive and perhaps multiple traits. Indeed, anthropologists and sociologists have played a lead role in this area arguing through qualitative methods that farmers' assessments of the attributes of agricultural technologies influence adoption behavior (Kivlin and Fliegel, 1966, 1967; Nowak, 1992; Rogers, 1962). Previous models, especially multinomial techniques mentioned above, also impose restrictions, such as independence of irrelevant alternatives, which limit the between-choices substitution patterns. But, if farmers adopt crop varieties based on their traits and according to their preferences for each of these traits, then the introduction of new varieties -in particular those with stacked traits- might imply substitution among choices based on the similarity of the traits. In this case, traditional empirical models are not likely to capture the important features of the trait differences that govern crop adoption, leaving classic economic approaches to technology adoption poorly specified analyses of the actual farmer choice problem.

This work develops a new approach to the adoption of GM crop varieties that draws from the characteristics-based demand literature (Nevo 2001, 2000; Revelt and Train 1998). Characteristics-based techniques describe the adoption/purchase of a good as a function of the traits of the good purchased, in addition to accounting for individual specific characteristics or individual specific experiences. These techniques have been widely applied in labor economics and studies of transportation and recreational demand and product-variety purchase and could pose a useful set of tools for analyzing technology adoption, the willingness of farmers to pay for traits, and the potential attractiveness of different "bundled" varieties which combine the available traits.

The underlying choice model is based on a random utility framework (Marschack ,1960; McFadden and Train, 2000) that rests on the idea that consumers (or farmers) seek to maximize stable preferences whose domain is the vector of quantities and attributes of the commodities they consume. In this theory of rational choice the farmer collects information on alternative varieties and uses the rules of probability to convert this information into perceived attributes. The farmer then undertakes a cognitive process which might be represented as an aggregation of the perceived attribute levels into a stable one-dimensional utility index. Maximizing this index constitutes the decision whether to adopt.

This model encompasses the more traditional adoption context of previous studies, which views profitability and relative advantage as the most important factors determining the adoption of new crops and new technologies (Qaim and Zilberman 2003, Ameden and Zilberman 2003 , Jovanovic and Stolyarov 2000, 1995, Griliches 1957). However, we emphasize the choice process of utility-maximizing farmers, allowing for variations in demand across individuals without making any explicit assumptions as to which are the intermediate steps in which goods are transformed by these individuals (farmers) to produce satisfaction, e.g., yield transformed in profit, or family labor transformed to household production. Thus, our model does not incorporate farm/household behavior with risk considerations in the standard sense. Moreover, rather than focusing on the adoption of new crops and technologies, we consider our main objective to be the analysis of the adding of traits to existing high-yielding seeds, which is the very direction of the first round of innovation in GMO technology. Our main contribution here then is to illustrate how an adoption model may center on traits, rather than individual characteristics. For simplicity, this paper will only exploit the trait-aspect of the adoption decision, leaving the more encompassing model for the next stage of work.

As the first generation of GM crops incorporates agronomic traits like herbicide tolerance (Ht) or insect resistance (Bt), commercial farmers in developed countries have been the primary target-group of the biotech and seed industries. Reducing herbicide or insecticide applications and volumes has the potential of lowering farmers costs (depending on the seed price), increasing farmers' yields, and saving them labor. However, potential yield effects could be rather small for farmers who already use advanced weed and pest management techniques, and thus may not have much an influence on adoption.[2] This is, of course, an empirical issue, and is explored below, but noting this prospect is another way of motivating this paper's focus on the traits associated with the technologies and moving beyond the standard yield-profit nexus to the full set of traits associated with the first generation of GM crops.

The model developed below centers on recovering a farmer's <u>willingness-to-pay</u> for specific improved characteristics of a crop. Obviously, a high willingness to pay for a certain trait should lead to increased demand for the new technology,[3] while a low willingness-to-pay (WTP) for other traits may prevent them from adopting the technology. Similarly, high or low <u>price elasticities of demand for traits</u> might determine the commercialization strategies used by agbiotechnology and seed firms.[4] Overall, these types of estimates of farmers' willingness-to-pay for traits shapes the type of transgenic varieties offered in the market including the potential value to farmers of "stacked" or "bundled" traits. Thus, in order to understand the economics of GM crops and variety adoption in the context of genetically modified seeds, it is necessary to develop flexible economic models, capable of providing consistent estimates of farmer's WTP and price elasticities of demand for traits, and which allow for non-fixed patterns of substitution among crop varieties. It should also be noted, however, that a full treatment of the "bundling" issue requires consideration of the strategic

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[2] (like in the US, Argentina and Canada).

[3] (and higher amounts of royalties demanded by agbiotechnology firms)

[4] See Huso, S. and W. Williams (2005) for a model of industry strategies. Also, Lemarie and Ramani(2003) find that final form of vertical control accompanying the commercialization of GM seeds is greatly influenced by final market demand.

reasons related to market structure and pricing, which will not be treated here (see Nalebuff, 2004).

This work estimates farmers' WTP and price elasticities for different crop traits associated with GMO corn, applying characteristic-based techniques in conditional (CL) and mixed multinomial logit (MMNL) models of crop-variety choice. The application of the model is based on U.S. corn farmers in the Upper Midwest. The study investigates the degree of heterogeneity in farmers' sensitivity to the attributes of the choices, which is related to both their observed and unobserved characteristics. Since correlation across alternatives is allowed for in the MMNL, and is based on the similarity of the attributes of the choices, flexible substitution patterns among the choice alternatives are accounted for in the estimation approach. The study focuses on farmer adoption choices of a variety of trait-differentiated corn varieties: Ht, Bt, combined Ht/Bt, and non-GMO. The data, collected from corn farmers in Minnesota and Wisconsin in 2003-2004, provide information on crop characteristics as well as farm characteristics and individual demographics. This enables us to control for the influence that these variables might have on the effect of crop attributes on the farmer's choice. In addition, data on previous year's experiences with the performance of the choices are used to control for endogeneity of the traits to producer experiences.

The rest of the paper is divided into six sections. In the following two sections, the model is formulated and the specifications and estimation strategy are described. Then, in section 4, the data on GMO crop adoption are introduced along with some selective basic descriptive statistics. Section 5 presents the results, and section 6 concludes.

2. Model Formulation

As in many adoption studies, (Zepeda, 1990; Barham, 1996), the farmer choice model utilizes a random utility framework (Marschack ,1960; McFadden and Train, 2000). Farmers seek to maximize stable preferences whose domain is the vector of quantities and traits of the commodities they adopt/consume. In the context of the farmer's rational choice problem, they are assumed to collect information on alternative varieties, use the rules of probability to convert this information into perceived traits, and then go through a cognitive process that can be represented as aggregating the perceived trait levels into a stable one-dimensional utility index which is then maximized.

We assume that a farmer faces a choice set consisting of J alternative crop varieties.[5] The utility that farmer i receives from alternative j is denoted by U_{ij}, which is the sum of a linear-in-parameters systematic component V_{ij} and a stochastic component e_{ij}. The latter allows for some ignorance of the econometrician with respect to the exact choice process. Let the systematic component of the utility be a function of farmer's marginal monetary gain/loss from the variety, denoted as income net of the cost of the variety, $(\pi_{ij} - p_j)$, and the expected levels of K observed attributes of the variety j, $E\,(x_{ij} | I_{ik})$, which the farmer predicts, given her information set I_{ik}. The income term considers two components: the budget that the farmer assigns for farm production and a risk premium if the variety that s/he grows is non-transgenic: $\pi_{ij} = \pi_i^* + P_j$.[6]

Assuming a linear shape for V_{ij}, this systematic component, conditional on the type of information about characteristics that the farmer has can be written as:

$$V_{ij} | I_{ik} = \alpha_i(\pi_{ij} - p_j) + E\,(\mathbf{x}_{ij} | I_{ik})^* \beta_i \qquad (1)$$

Where (α_i, β_i) is a vector of parameters to be estimated, which vary over individuals. In particular, we let

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Sigma v_i \qquad (2)$$

with v_i being a stochastic component of unobserved characteristics, with distribution $P_v(v)$, and Σ a (K+1)*(K+1) matrix of parameters. If we assume that $P_v(v)$ is a standard multivariate normal distribution, as we do in the application below, then the matrix Σ

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[5] Here we deal with varieties of a single crop, however, the model can be generalized to different crops. The only difference would be that crop specific effects would have to be accounted for.

[6] In the following analysis, we do not address formally how households allocate total income to their production budgets.

allows each component of v_i to have a different variance and allows for correlation between these (unobserved) characteristics.

The farmer chooses the variety that gives him the highest expected utility:

$$\max_j E\left[U_{ij} \mid I_{ik}\right] = \max_j \int \left[U_{ij}\left(\beta, e\right) \mid I_{ik}\right] dP(e,v) \qquad \text{i=1,…,I; j, k =1,...,J}$$

Correlation of unobservables across alternatives

With non-zero values for the components of the matrix Σ , correlation of unobservables across alternatives is included. Furthermore, this correlation depends on the similarity of the traits across the choices. Letting $\varepsilon_{ij} = E\, \mathbf{x}_{ij} * \sigma_\beta\, v_i + e_{ij}$ the covariance among unobservables for alternatives j and k is:

$$Cov\ (\varepsilon_{ij}\, \varepsilon_{ik}) = E\, \mathbf{x}_{ij}\, \mathbf{x}_{ik} * \sigma_\beta$$

Sources of Information: *Learning-by-doing, learning from neighbors, advertisement and other exogenous information*

The farmer builds her expectations about the traits of the alternatives that are available to her, based on her own experience with the crop varieties, on the information from her "neighbors", and also uses the information that is provided by extension agents, companies, media, local opinion leaders, on-farm trials and experiment station visits. In the case of having to decide about a very new variety or a variety the farmer has never grown, access to information about an innovation is a key factor in determining adoption decisions [7].

In this work, we assume that the farmer forms her expectations of attributes in the following way:

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[7] See Argarwal (1983)

$$Ex_{ijt} = \begin{cases} x_{ijt-1} & \text{, if } \max_j U_{ijt} = \max_k U_{ikt-1} \\ (1/n_i)\sum_{l \in N_i} x_{ilt-1} & \text{, if widely used technology, but not grown before by the farmer} \\ x_{aj} & \text{, if not widely used, and not grown before by the farmer} \end{cases}$$

where x_{ijt-1} is the value of the set of attributes of alternative *j* in the previous period, experienced by farmer *i*, x_{ilt-1} is the value of the set of attributes of alternative *j* , for a neighbor farmer *l*, in the previous growing period, x_{aj} is the value of the set of attributes of alternative *j* as advertised by the media, seed sellers and extension agents, and N_i is the set of (n_i) neighbors of farmer *i.* [8]

Thus, if a farmer plans to grow the same variety that she grew the previous growing season, she uses her experience with the crop in that previous season as a proxy for the traits that she will expect, for that same variety, in the next season. If the farmer has never used the technology before, she looks at the experiences of other farmers in her county and agricultural district, in order to make inferences about the expected levels of the attributes of the new variety. Finally, if adoption is not pervasive in the neighborhood where this farmer grows the selected variety, the farmer obtains the information from extension agents, media and seed sellers.[9]

3. Model Specification and Estimation

In order to analyze the relevance of different traits for the choice of corn variety and to investigate the importance of individual unobserved heterogeneity in adoption choices, we estimate two classes of choice-specific attribute models: a conditional logit (CL) (McFadden, 1974) and a mixed multinomial logit (MMNL). We also investigate how the

[8] The neighborhood used in this case was a geographical neighborhood, at the county level. Ideally, this neighborhood should be defined in a much tighter sense and distinguish indivduals with whom the individual exchanges information, from the ones he does not exchange information from.

[9] However, we also assume that the level of some traits is always adjusted e.g. yield is adjusted by expectations of pest infestations, and prices, adjusted according to market expectations. In addition, unlike recent papers by Foster and Rosenzweig (1995) and Conley and Udry (2004), this paper does not consider the potential for “social effects” of neighbors.

results may differ if we were to use a standard multinomial logit approach to agricultural technology adoption in this traits-based modeling approach.

The conditional logit model (CL) is mathematically equivalent to the standard multinomial logit, which is typically used in the adoption literature, however, it is derived from a behavioral model in which unobserved components enter into the subject's choices. Assuming the disturbances for the J separate alternatives are iid standard extreme value, the conditional logit choice probabilities are:

$$P_{ij} = \frac{\exp(V_{ij})}{\sum_k \exp(V_{ik})} \qquad \text{for i} = 1,\ldots\text{I, j, k} = 1,\ldots,\text{J}$$

from which a linear specification of the systematic component of utility implies:[10]

$$P_{ij} = \frac{\exp(\beta' x_{ij})}{\sum_k \exp(\beta' x_{ik})} \qquad \text{for i} = 1,\ldots\text{I, j, k} = 1,\ldots,\text{J} \qquad (3)$$

Notice that the β coefficients are the same as in the underlying utility model. They are interpreted as measuring preferences for the traits x_{ij}. These traits vary across alternatives for a single individual (repeated choices). The necessary assumption is that the unobserved components are i.i.d. extreme value. Setting the variance of the disturbances at the standard value of $\pi^2/6$ is enough to identify the coefficients, meaning that the scale of the effects differs from that of models of unit variance, such as probit. The logit effects are about 1.6 to 1.8 times as large.

In the standard multinomial logit, the characteristics of the agent making the choices generally replace the traits of alternatives, and the coefficient estimates are not the same as in the underlying utility model. They, rather, capture how changes in one agent characteristic push the individual in and out of each specific choice category. Thus, each coefficient estimate is specific to an alternative, and each explanatory variable is specific to an individual. Even if this variable is a characteristic of the choice, it will be specific to

[10] For simplicity of the illustration we ommit expectation operators in the previous section and generalize the notation of all covariates as $\boldsymbol{x}_{ij}$.

the choice of the individual *i*, and it will vary across individuals necessarily. The choice probabilities in the standard MNL are as follows:

$$P_{ij} = \frac{\exp(\beta_j ' x_i)}{\sum_k \exp(\beta_k ' x_i)} \qquad \text{for i} = 1,\ldots\text{I, j, k} = 1,\ldots,\text{J}$$

In this model, adding a constant to all coefficients, for any constant, produces an identical set of probabilities as above. This is a source of indeterminancy, which is generally solved by setting the coefficients of all explanatory variables for one of the alternatives to be equal to zero. Thus, all other coefficients are interpreted only relative to the baseline category and the choice probabilities become:

$$P_{ij} = \frac{\exp(\beta_j ' x_i)}{1 + \sum_k \exp(\beta_k ' x_i)} \qquad \text{for i} = 1,\ldots\text{I, j, k} = 2,\ldots,\text{J} \qquad (4)$$

Although the basic CL model makes choice probabilities depend on the traits of the alternatives, they can also depend on the characteristics of subjects (which are constant across alternatives, but vary across subjects). These characteristics can be interacted with the traits of the choices, making preferences for a trait different for each level of the subject-specific characteristic and/or by adding them to the set of covariates in a linear fashion. The latter case requires baseline constraints to identify the effect, such that:

$$P_{ij} = \frac{\exp(\beta ' x_{ij} + \gamma_j y_i)}{\sum_k \exp(\beta ' x_{ik} + \gamma_j y_i)} \qquad \text{for i} = 1,\ldots\text{I, j, k} = 1,\ldots,\text{J}$$

where setting γ_1=0 identifies the other γ_i coefficients.

Since the CL model assumes independently and identically distributed error terms, it cannot account for differences in tastes that are linked to unobserved individual traits or characteristics (taste variation in the CL is related only to observed traits or characteristics). The mixed multinomial logit (MMNL) model can be seen as a generalization of the CL which relaxes these assumptions and allows for the influence of unobserved heterogeneity in adoption choice. Also, the CL model assumes independence of irrelevant alternatives, which restricts the relative odds of choosing a crop variety to be independent of other available varieties (and their attributes):

$\frac{P_{ij}}{P_{ik}} = \exp\left[\beta'\left(x_{ij} - x_{ik}\right)\right]$, depends only on the characteristics of the two alternatives (*j* and *k*).

Independently distributed error terms also imply the restriction that the similarity of the choices does not matter, when looking at the substitution between them, which is rather unrealistic and also unnecessary given the MMNL option. The resulting coefficients of the CL model might be better understood as an approximation of average preferences when the unobservable portion of utility is thought to be correlated across alternatives (Train, 2003). The MMNL model relaxes the independence of irrelevant alternatives assumption, thus allowing more realistic inferences about, e.g., the effects of the introduction of new varieties, or the effects of policies that regulate levels or commercialization of traits, on the adoption of unchanged crop varieties.

The MMNL choice probabilities are:

$$P_{ij} = \int \frac{\exp(\beta' x_{ij})}{\sum_k \exp(\beta' x_{ik})} f(\beta)\, d\beta \qquad \text{for i} = 1,\ldots\text{I, j, k} = 1,\ldots,\text{J} \qquad (5)$$

where the β coefficients vary across individuals. In order to estimate these coefficients, we specify a normal distribution: $\beta \sim N(\text{b}, \Sigma)$, with Σ diagonal and individual elements equal to σ_h (h denoting the specific trait). Notice that if $\sigma_h = 0$ for all h, the distribution collapses to its average level and the choice probability is the same as in equation (3), the CL one. Therefore, the CL, when compared to the MMNL, provides an appropriate baseline for testing the significance of unobserved heterogeneity in GM adoption.

While both the CL and the standard multinomial logit models can be estimated through maximum likelihood, the MMNL choice probabilities cannot be calculated exactly because the integral does not have a general closed form. Therefore, the integral is approximated through simulation. For a given value of the parameters (b, Σ), a value of β is drawn from $f(\beta \mid \text{b}, \Sigma)$. Using this draw (*r*), the conditional logit formula

$L_{ij}(\beta) = \frac{\exp(\beta_i' x_{ij})}{\sum_{k=1}^{J} \exp(\beta_i' x_{ik})}$ is calculated. This process is repeated for many draws, and the average of the resulting $L_{ij}(\beta)$'s is taken as the approximate choice probability:

$$\overline{P_{ij}} = \frac{1}{R} \sum_{r=1}^{R} L_{ij}(\beta^r) \qquad (6)$$

3.1. Willingness To Pay for Traits

Although the direct effect of a trait on utility cannot be identified separately from the variance parameter of the *iid* error component in these models, the willingness-to-pay for each trait in the model can be calculated by the ratio of the coefficient of the trait of interest, with respect to the cost coefficient. To see this more clearly, recall that the general form of utility in matrix notation (the equations of the utilities of all alternatives stacked) is:

$U = \alpha\, p + \beta x + e$, where $\alpha = \alpha^*/\sigma$, $\beta = \beta^*/\sigma$ and $e = e^*/\sigma$,

Where α^* stands for the cost coefficient and β^* for the trait coefficient.
Diferentiating, $dU = \alpha\, dp + \beta\, dx$, and keeping utility constant, $dU = 0$.
Therefore, $dp/dx = -(\beta^*/\sigma)/(\alpha^*/\sigma) = -\beta/\alpha$, is the willingness-to-pay for a one-unit change in the level of the trait that leaves the individual's utility unchanged.

Price elasticity calculation at the means of the traits is directly derived from the WTP values. This provides a unit-less measure of the value of the traits:

$E_{px} = (dp/dx) * (x/p) = wtp * (x/p)$

4. Data

Since 1998 the University of Wisconsin-Madison's Program on Agricultural Technology Studies (PATS) along with researchers from the Universities of Minnesota and Nebraska, have surveyed Wisconsin producers about their practices and experiences with genetically engineered corn. We analyze the survey data of the Minnesota and Wisconsin farmer samples. Additional information from several sources was used to complement the survey data: US Agricultural Census information on yields and agrochemical use, Wisconsin seed sellers information on seed prices, Wisconsin and Minnesota Agricultural Statistics Services information on insect and weed infestation, and trial information on price and yield from different sources.

Survey information for 1257 randomly selected corn growers was collected by the research team. Farmers were interviewed about their choices of corn varieties and their individual characteristics and experiences in the 2003 growing season. Furthermore, the late winter 2004 questionnaire also asked the farmers about their planting choices for the 2004 growing season (most farmers would have ordered their seeds by the time of the survey). Variety characteristics, at the individual level, were obtained for four main corn types: herbicide tolerant (Ht), insect resistant (Bt), “stacked” (corn varieties with traits of both Ht and Bt technologies in the same seed), and conventional, non-GM, corn.

Given the low rates of adoption of stacked varieties in the first year (due partially to lack of availability), we concentrate on the estimation of the most widely commercialized corn varieties and their traits (Ht, Bt and regular corn). We consider four exclusive alternatives faced by farmers when deciding about which corn varieties to grow in 2004, given the experience they had in the 2003 growing season and the information available: (1) to purchase some Ht but non Bt-corn seeds, (2) to purchase some Bt- but non Ht-corn seeds, (3) to purchase, both Ht and Bt-corn seeds, and (4) to grow only conventional (non-GM) varieties. While conventional corn was the most common choice for 2004 (32%), the second most common was the combination of Ht and Bt (22%). Then was Bt (15%) and finally Ht (11%). 19% of individuals did not answer the question or were undecided.

Five main traits are considered in the econometric model of adoption: yields, aggregate seed and pesticide costs, insecticide savings, herbicide savings, and labor savings. Yield was measured in terms of bushels per acre, costs in terms of dollars per acre, agrochemical use in terms of acres of corn treated, and labor in terms of workers per farm.[11] Expected values for all of these traits were calculated for each specific variety. The survey only asked for a categorical measure of previous experience with the traits (5 categories for each trait), corresponding to whether the farmer faced a much higher-, higher-, same-, lower-, or much lower level of the trait compared to the level that would have been obtained if conventional varieties were grown. Thus, we calculate the levels of most of these traits based on purely exogenous information provided by different sources as described below. However, conclusive and detailed information does not exist for the labor-saving or herbicide-use traits. Thus, we combine our survey data, at the individual level, with the distributions of labor and herbicide used obtained from the 2002 Agricultural Census, for each county in Wisconsin and Minnesota, which allows us to translate our categorical information into levels and obtain some variability in these measures.

The calculated yield trait is based on per county levels of the 2002 Census, but also accounts for the fact that farmers adjust their expectations of yield according to expected pest infestation levels in their county. Yield losses due to local insect and weed infestation were calculated on the basis of infestation levels reported by the Minnesota and Wisconsin Agricultural Statistical Services. An average was calculated for the last three years for each agricultural district. The relationship between infestation levels and the percentage yield loss was established with UW-Extension and Pioneer information.[12] Aggregate seed costs including technology fees were calculated based on actual prices reported by seed dealers in Wisconsin (Renk, Dahlco, etc.). Pesticide costs per-acre were based on the information available on Monsanto's web page and on the studies by Benbrook (2001) and Gianessi et al. (2002). Insecticide costs were assumed to be zero

[11] It is very difficult to separate work according to crop, but since our sample consists of corn farmers only, we assume that labor at the farm level varies accordingly to labor for corn growing. Variation by variety is introduced according to survey information (revealed preference data), as well as for herbicide use. The latter is necessary, given that it is not clear from exogenous data (industry advertisement, experimental trials, etc.) what predicted increases/decreases in labor and herbicide should be. This is done in a way such that the assumption is implicit that individuals base their expectations about labor and herbicide use for each variety, according to their own experience or the experience of their neighbors, if they never used the variety.

[12] http://www.uwex.edu/ces/cty/calumet/ag/documents/, http://www.pioneer.com/usa/agronomy/insects/, http://www.ipm.iastate.edu/ipm/icm/1997/4-14-1997/cbloss.html

for Bt varieties, along with insecticide use. Otherwise, levels of insecticide and herbicide use were calculated from information of the 2002 Agricultural Census. Finally, we control for the minimum and maximum yield levels of each trait, such that none of them is higher or lower, respectively, than the levels reported in the Agricultural Census.

Descriptive statistics are presented in Tables A and B in the appendix. In summary, the per acre average yield level across all varieties was 146 bushels, per acre aggregate cost was $65, average acres of corn treated with insecticide where 6.5 and with herbicide where 54. Average number of workers was 4. While on average, Ht corn had the highest per acre yield, Bt corn and the mixture of Ht and Bt achieved the absolute maximum. While the lowest herbicide use, on average, was for Ht corn varieties, the conventional varieties had the lowest price. Labor force, on average, was not very different across varieties, but conventional varieties achieved absolute maximum levels.[13]

Our survey asked farmers specifically for reasons why they adopted or did not adopt each variety in 2003. Tables 1 and 2 below present the results of these questions for the herbicide tolerant variety. All varieties display similar ranking (in terms of percent of farmers who consider this aspect relevant) of the importance of characteristics that lead farmers to adopt/not adopt a particular type of seed. The only notorious difference is displayed by the ranking of yield expectations, between Ht and Bt corn. While Table 1 shows that this variable is ranked fourth for Ht adopters, it is the number one for Bt adopters (see Tables C-D in the appendix). These tables show that the major characteristics of the variety that are considered by farmers in their decision of which variety to plant are: pest control, pesticide use, production costs, yield levels, labor savings, marketability and environmental/safety issues. These traits are all included in the regression specification given below.

[13] Survey information contained categorical information of the characteristics, which was translated into levels according to the actual distribution of the variables that was calculated on the per county basis, from the Agricultural Census of 2002.

Table 1. Why Farmers Planted HT Corn in 2003

Reasons	% of Respondents
To allow better weed control	81.4
To reduce overall herbicide use	43.3
To reduce overall corn production costs	39.0
To increase corn yields	37.2
To reduce the labor required to grow corn	25.1
Recommendation from seed dealers/consultants	24.2
Fits well with existing corn production practices	16.9
Other*	10.8
Recommendation from neighbors	4.8
Recommendation from university or extension agents	0.9

* Written comments included: planted for trial purposes, use no-till cropping.

Table 2. Why Farmers Did Not Plant HT Corn in 2003

Reasons	% of Respondents
Price of HT seed corn is too high	54.8
Do not currently use Roundup or Liberty herbicides	32.2
Did not anticipate having weed problems	20.0
Concerned about having trouble selling HT corn	19.3
Concerned about possible environmental or safety issues	18.3
Concerned about having to segregate HT corn from non-HT corn	17.3
Other*	13.8
Concerned about weed resistance	16.9
Not satisfied with the net return of HT corn	9.8
Concerned about getting a lower price for HT corn	8.6
Not satisfied with HT corn yields	7.1
Experienced increased weed resistance to herbicide	1.2

* Written comments included: organic farm, use Roundup to kill corn in rotation with Roundup Ready soybeans, no interest, unfamiliar with HT corn, corn used for silage.

Nonetheless, there are two major aspects potentially influencing the decision of not growing GM varieties, for which we do not directly construct trait measures: environmental or safety issues and marketability or commercialization concerns, including the risk premium potentially associated with non-GM varieties. Instead, we include in our specifications of the model an alternative-specific component for conventional versus transgenic varieties, which is intended to capture both of these aspects. Finally, the survey information asked for the experiences with Ht and Bt varieties, separately, even if farmers where combining them in the same field or farm. Thus, our measure of traits for the Ht-Bt alternative might not capture unobserved complementarities or economies of scope due to their combination (e.g., no need to segregate GM from non-GM varieties). The last specification of our empirical model also takes this aspect into account.

5. Results

5.1. Estimated Model

The empirical model estimates expected utility from the expected traits:

$$EU_i(Ht\text{-}corn)=\alpha_{i1}\pi_{i,ht} - \alpha_{i2}\, p_{ht}+\beta_{i1}EY_{ht}+ \beta_{i2}E\, I_{ht}+\beta_{i3}E\, H_{ht}+\beta_{i4}E\, Lab_{ht}$$

$$EU_i(Bt\text{-}corn) = \alpha_{i1}\, \pi_{i,bt} - \alpha_{i2}\, p_{bt} +\beta_{i1}EY_{bt}+\beta_{i3}E\, H_{bt}+\beta_{i4}E\, Lab_{bt}$$

$$EU_i(Ht\&Bt) = \gamma_{hb} +\alpha_{i1}\, \pi_{i,bh} - \alpha_{i2}\, p_{bh}+\beta_{i1}EY_{bh}+ \beta_{i2}E\, I_{bh}+\beta_{i3}E\, H_{bh}+\beta_{i4}E\, Lab_{bh}$$

$$EUi(conventional)=\gamma_{ng}+\alpha_{i1}\, \pi_{i,ng} -\alpha_{i2}\, p_{ng} + \beta_{i1}EY_{ng}+ \beta_{i2}E\, I_{ng}+\beta_{i3}E\, H_{ng}+\beta_{i4}E\, Lab_{ng}$$

where π = the individual's variety revenue per acre outcomes including a variety risk premium for non-GM, p=cost of seed and pesticide per acre, Y=yield in bushels per acre, I=corn-acres treated with insecticide, H=corn-acres treated with herbicide and Lab = number of workers used.

Notice that π budget drops out of the estimation due to the specified shape of the choice probabilities. Also, the risk premium offered in the market corresponds to a premium for conventional varieties as opposed to transgenic varieties. This premium is constant across individuals, thus we cannot identify this effect separately from the effect of the unincluded-factors component (γ_{ng}) for non-GM corn (see next sub section below for an explanation about this component).

5.2. Model Specifications

Estimates for three basic CL (fixed-effects) models are reported in Table 3. The first model (I) only includes the traits of the crop varieties. The second one (II) accounts for the average effect of the unincluded factors, which influence the choice between growing conventional varieties as opposed to growing GM-varieties, through the inclusion of an alternative specific intercept for non-GM crops. This binary variable captures the average effect of unincluded factors for this alternative with respect to all others. Finally, as the option of a combination of Ht and Bt might be driven by economies of scope or complementarities of the individual varieties, which we also do not observe, the third model accounts for these factors through another alternative-specific intercept.

The coefficient estimates reveal the effect of each observed factor relative to the variance of the *iid* extreme value error term e_{ij} . This parameter is used to normalize the scale of utility and is not separately identified from the effect of the corresponding observed factor. Thus, even though the signs of the coefficients are meaningful, their absolute value cannot be interpreted in the usual way. The ratio of coefficients, however, is not affected by the scale parameter, and it generally provides economically meaningful information, as described above.

A quick look at Table 3 allows us to see the importance of controlling for average unobserved factors in the specification. The signs of almost all coefficients are consistent with *a priori* expectations in all three models and they are significant: As the cost of a variety of corn increases in one dollar per acre, all other factors remaining the same, the probability of that corn type being chosen decreases. The same is the case for increases in the amount of pesticide and labor use. The lower the pesticide- and labor-saving levels that a variety induces, the lower is the probability of choosing it.

In specification II of the CL model, we see that there exists a strong unincluded component in the utility that explains the choice to cultivate non-GM crops, which distinguishes this variety from transgenic crops. Judging from the survey information presented in tables 2 and D (the latter in the appendix), this term probably captures the potential effects of environmental and marketability traits of the crops, including the risk premium component of conventional varieties. Controlling for this term changes the significance of the coefficient estimate on yield, which shows that the negativity of this coefficient in the first CL model may be spuriously driven by the fact that 32% of the individuals in the sample choose to grow conventional crops, in spite of their potentially lower yield trait. Instead, that first yield coefficient estimate shows that these individuals have motives to grow this crop, which are different from the observed traits included in the model, and not that they 'dislike' higher yielding varieties.

Insignificant yield effects in model II can be explained as follows: first, potential yield effects of GM crops might not have an influence on adoption choices of farmers who already used advanced weed and pest management techniques, and second, farmers may not base their decisions on yield because of uncertainty regarding this factor. Not only do they need to adjust their expectations of yield by the predicted level of pest infestations, but also to weather conditions. These predictions might prove very difficult and not trustworthy. Added to this uncertainty is the informational uncertainty, for individuals with no experience with GM-crops. Moreover, multiple studies present contradicting findings about the yield advantage of GM-crops, and some firmly assess that "comparative trials on Bt corn and cotton have not demonstrated a statistically significant yield drag".[14] Similarly, specification III indicates that growing Ht&Bt combined has positive unincluded factors also, with respect to growing any of them alone. We also notice in model III a larger magnitude for the coefficient estimate for the alternative of growing conventional varieties as compared with the estimate in model II.

[14] Benbrook, C. (2003)

Table 3. Conditional (Fixed Effects) Logit

Explanatory Variable	Coefficient I	Coefficient II	Coefficient III
Yield Advantage	-0.042**	-0.013	-0.011
	(0.01)	(0.013)	(0.013)
Cost seed+pesticide	-0.115**	-0.09**	-0.097**
	(0.011)	(0.014)	(0.014)
Insecticide use (Ht& HB)	-0.044**	-0.047**	-0.053**
	(0.005)	(0.005)	(0.005)
Herbicide use	-0.010**	-0.011**	-0.012**
	(0.002)	(0.002)	(0.002)
Labor	-0.150**	-0.149**	-0.135**
	(0.05)	(0.05)	(0.05)
Non gm average effects of unincluded factors	--	0.388**	0.63**
	--	(0.14)	(0.14)
Combine Ht&Bt Avge. Unobserved Effects		---	0.60**
		---	(0.08)
Log likelihood [a]	-1520	-1516	-1486
Prob> Chi2	0	0	0
Obs	4768	4768	4768

[a] The log-likelihood with only alternative specific constants and an iid error term is –1615.

In Table 4, the mean and standard deviation of each coefficient were estimated thus allowing each coefficient to be different for each individual. Table 4 shows the estimated parameters for two different specifications. Model IV is equivalent to model II, in the CL version; i.e., it includes only an alternative-specific component for conventional varieties. However, it allows for unobserved heterogeneity in the tastes for attributes in the MMNL, as opposed to the CL. The second model, V, corresponds to the CL III specification, again, including unobserved taste-heterogeneity.

Similar to Bhat (1998) and Revelt and Train (1997), we find that the magnitudes of the significant parameters increases from the CL to the MMNL. This is an expected result, since the variance before scaling is larger in the CL model compared to the mixture model. The signs of all coefficients are the same as in the CL and are expected, as discussed above.

Of particular interest is the significance of the standard deviation of the coefficients for some of the traits, indicating that individuals' tastes significantly differ from the average taste and vary across the population. For example, the preference for work savings is not positive for all individuals. That is, some individuals do not care about choosing a variety that requires them to use more work, as long as the cost and the herbicide use are lower and/or factors like marketability or environmental protection are better. The coefficient of labor is normally distributed with mean -.22 and standard deviation .50. The share of people with coefficients below zero can be easily computed by calculating the value of the cumulative probability of a standardized normal deviate evaluated at .22/.5. Thus, we find that the share is .67. This means that 67% of the population is estimated to dislike varieties which are more labor using. The other factor whose value is heterogeneous among the population is insecticide use. However, the standard deviation is not big enough to reverse the sign of the coefficient for practically any farmer.

Table 4. Mixed Multinomial Logit

Explanatory Variable	Average β IV	StdDev β IV	Average β V	StdDev β V
Yield advantage	-0.02 (1.44)	0.004 (2.7)	-0.02 (1.49)	0.004 (3.0)
Cost of seed+pesticide	-0.092** (0.02)	-0.001 (0.03)	-0.092** (0.02)	-0.001 (0.03)
Insecticide use (Ht& HB)	-0.057** (0.07)	0.019** (0.07)	-0.068** (0.09)	0.029** (0.08)
Herbicide use	-0.012** (0.003)	0.0004 (0.003)	-0.013** (0.003)	0.0001 (0.004)
Labor	-0.29** (0.09)	0.748** (0.24)	-0.22** (0.08)	0.50** (0.22)
Non gm average effects of unincluded factors	0.43** (0.15)	0.037 (0.26)	0.65** (0.08)	- -
Combine Ht&Bt Avge. Unobserved Effects	--- ---	--- ---	0.53** (0.16)	- -
Log-likelihood	-1508		-1476	
Number of cases	4768		4768	

The robustness of the five alternative models in Tables 3 and 4 can be evaluated formally using conventional likelihood ratio tests. A statistical comparison of the CL models among themselves and with respect to the MMNL model is shown in Table E in the appendix. The comparison leads to rejection of the CL models against the corresponding MMNL models.

A different way of testing for the validity of the CL model is to test the independence of irrelevant alternatives (IIA) assumption with the Hausman test. This provides a way of testing the IIA assumption without specifying any particular alternative model. The test is based on the idea that excluding one or more categories from the dependent variable should not affect the remaining estimates. We performed this test with different possibilities for exclusion of alternatives. The estimates did, in fact, change in all cases. This result further supports the rejection of the IIA assumption and the value of the MMNL approach to examining trait-based adoption decisions.

Finally, we estimated a standard multinomial logit model including the traits of the crop alternatives as explanatory variables rather than the typical approach using the characteristics of the farmers. As explained in section 3, these traits enter as specific for each farmer. Thus, if all traits of all alternatives are to be taken into account, they all have to enter as covariates in the systematic part of the utility of any single alternative. This creates a proliferation of parameter estimates, severe problems of multicollinearity, instability in the parameters, and difficulties in the interpretability of the model. Moreover, all parameters have to be interpreted with respect to a baseline alternative (here the conventional varieties). Table F in the appendix shows the estimated coefficients of the standard multinomial logit model using traits. No coefficient estimates are shown for four traits (insecticide use of Bt, Ht&Bt and conventional varieties, and herbicide use by conventional corn), because they drop out from the estimation due to multicollinearity. The same problem seems to be the source of the reversed sign for the price coefficients for all alternatives, which are highly significant and positive. Other significant results show high substitutability between Bt and Ht&Bt yield and consistent negative effects of unincluded factors of GM with respect to conventional varieties. Clearly, the alternative specifications used above dominate the standard multinomial logit for examining the importance of crop traits in farmer adoption choices.

5.3. Willingness-to-Pay and Price Elasticity Estimates of Demand for Traits

As mentioned in section 3, the estimated coefficients of cost and of the various traits provide information on the value of the traits. Table 5, below, presents these estimates for the CL and MMNL models, in columns 4 and 6. Column 4 presents the average WTP derived from the CL model III, while column 6 presents the estimates for the corresponding MMNL model (V).

WTP for traits in both models rank them similarly; however, the magnitudes of WTP for insecticide and labor are higher for the MMNL, and the WTP for herbicide is lower. We discuss the MMNL values, since we rejected the CL model against the MMNL in the previous section. The WTP for a one-corn-acre reduction in insecticide use is .6. Thus, the average farmer is willing to pay $.60 (ie., 60 cents) more per acre in higher seed and pesticide cost in order to reduce insecticide use on corn by one acre. Similarly, s/he is willing to pay $.11 per acre to reduce herbicide amount on one acre of the corn s/he grows. Finally, the value of one less worker in the farm is $1.93. i.e., the average farmer will be willing to pay 1 dollar and 93 cents per acre, if s/he can save the labor of one worker.

Price elasticity estimates are shown in columns 5 and 7 for the CL and MMNL, correspondingly. While the CL model predicts that the highest price elasticity corresponds to the herbicide use(.11) characteristic, the MMNL estimates a highest elasticity for labor (.13). The price elasticity of demand for insecticide remains the same in both models (.06). We showed that the MMNL is superior to the CL in this setting, so we concentrate on column 7 for the discussion below.

Table 3. WTP and Price Elasticities

Variable	Unit	Mean	WTP CL	Price Elasticity CL	WTP MMNL	Price Elasticity MMNL
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price seed+pesticide	$/Acre	64.9	---	---	---	---
Yield	bushel/Acre	145.7	---	---	---	---
Insecticide	corn acres treated	6.5	-0.55	-0.06	-0.6	-0.06
Herbicide	corn acres treated	53.6	-0.13	-0.11	-0.11	-0.09
Labor	# workers	4.0	-1.40	-0.09	-1.93	-0.13

Overall, these results suggest that labor saving technologies have a much wider potential to be adopted. Potentially the high value for this trait may reflect the fact that family farms, where labor constraints are more likely to be binding, are adopting GM technologies, particularly in Wisconsin.

Although, it is difficult to unbundle the effects of input- and labor-saving traits, there are important factors that cause them not to be correlated necessarily. For example, even though Bt-corn reduces the amount of insecticide used, its refuge planting requirements might offset any possible labor saving effect of Bt corn varieties and make them less desirable from a labor-savings perspective. In Wisconsin, Bt requires that farmers plant a minimum of 20 percent of total corn acres to a non-Bt refuge in a separate field within 0.5 mile of Bt corn fields or in blocks within the cornfields; that they do not use microbial Bt insecticides to treat target insects in the corn refuge and that they use other insecticides only if economic thresholds are reached. This result highlights the importance of allowing for correlation among the parameters in future studies, and testing for its significance.

The high price elasticity estimates for labor and herbicide savings suggest that the strategy to charge royalties for these traits by agricultural biotechnology firms may be more adequately margin ones (as opposed to volume charges).[15] It also suggests that final form of vertical control accompanying the commercialization of GM seeds is greatly influenced by the labor saving trait. [16]

The higher price elasticity for herbicide with respect to insecticide is probably driven by three facts: 1. More widespread weed problems in the region (wider areas of corn are treated with herbicides as opposed to insecticides –see Graphs1-2 in the appendix), 2. Many herbicide resistant cultivars are resistant to glyphosate, 3. New technologies allow for a more flexible use of broad-spectrum herbicides, but they do not necessarily decrease their volume.[17,18] Development of corn varieties which enable a shift from relatively high field rates (glyphosate or atrazine) to low dose herbicides (imidazolinone or sulfonylurea families) should therefore favor their adoption, relative to other varieties.

Given that the standard deviation of the price coefficient is shown to be non-significant in the MMNL , we also calculate the previous estimators based on a more parsimonious version of model (V), which constrains the standard deviation of the price coefficient to be zero. In other words, we do not allow the price coefficient to vary, which amounts to having one less parameter to estimate. The result is an even higher estimates of WTP and price elasticity for labor (wtp=2.5, elasticity=.16) , and a slightly higher elasticity WTP and elasticity for herbicide use, as well (wtp=.13, elasticity =.10).

If we were to estimate a willingness-to-pay and price elasticity for factors like environmental-friendly characteristics or marketability, it would be very high. However, given the difficulties we face in measuring these factors, we would not know at which 'mean' or level of these factors to evaluate the estimates.

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[15] Huso, S. (2005).
[16] Lemarie and Ramani (2003) indicates that demand enhancing innovations give rise to incentives for mergers.
[17] Op. Cit.
[18] Independent research and USDA studies show that there has been on average about a 5% increase in herbicide pounds applied per acre in GM soybeans in contrast to conventional varieties.

6. Conclusion

This work offers a new approach to the adoption of GM crop varieties by adopting the econometric methodology of the characteristics-based demand literature. A random utility framework was implemented through different specifications of a conditional (CL) and a mixed multinomial logit (MMNL) model of crop-variety choice. Willingness-to-pay and price elasticity estimates for traits were calculated. All specifications of the CL were rejected with respect to the equivalent MMNL specifications. However, there is some degree of consistency in the regression coefficient, willingness-to-pay, and price elasticity estimates and results of both models in terms of sign and magnitude. The attempt to estimate alternative specific coefficients through a standard MNL model including the characteristics of the alternatives as explanatory variables results in an unparsimonious model plagued with problems of multicollinearity, instability of the parameters, and problems of interpretability.

The coefficients of the MMNL model allowed us to measure preferences of U.S. farmers, in the Upper Midwest, for the traits of Bt-, herbicide tolerant, and conventional, non-transgenic, corn varieties. We find significant, expected signs for preferences for cost, pesticide and labor-saving traits; specifically, as the cost of a variety of corn increases one dollar per acre, all other factors remaining the same, the probability of that corn type being chosen decreases. The same is the case for increases in the amount of pesticide and labor use. The lower the pesticide- and labor-saving levels that a variety induces, the lower is the probability of that it will be chosen by a farmer. Yield effects, however, are insignificant on average. This might be explained in the following way: first, potential yield effects might not have an influence on adoption choices of farmers who already used advanced weed and pest management techniques, and second, farmers do not base their decisions on yield because of the high uncertainty regarding the impact of this factor. This uncertainty is underscored by the multiple studies that present contradicting findings about the yield advantage of GM-crops.

Individuals in the sample who chose to grow conventional corn varieties have motives to grow non-transgenic, crop varieties, which are different from the typical economic factors included in standard adoption regressions. Traits related to environmental concerns and marketability, particularly a risk premium component of conventional varieties, are in explaining the choice of non-GM varieties. Growing Ht and Bt combined has also positive complementarities, which are not captured from either of these GM varieties alone.

The MMNL approach also demonstrates that individuals' tastes can significantly differ from the average taste and vary significantly across the population. In particular, the value that individuals have for labor-savings varies widely across farmers. The value of the insecticide-saving trait is also significantly heterogeneous among the population; however, the range of variation is smaller than the one for labor-saving traits.

Overall, the results regarding the willingness-to-pay for traits and their price elasticity estimates suggest that labor saving technologies have a much wider potential to be adopted. Interestingly, the high value for this trait suggests the possibility that many family farms, where labor constraints are tight, are adopting GM technologies, particularly in Wisconsin. The difficulty in unbundling the effects of input- and labor-saving traits highlights the importance of allowing for correlation among the parameters in future studies, and testing for its significance. This would help, for example, to disentangle the labor-saving effect of insecticide reduction versus the labor-using effect of refuge planting requirements for Bt-corn. High price elasticity estimates for labor and herbicide savings suggest that the strategy to charge royalties for these traits by agricultural biotechnology firms may be more adequately margin ones (as opposed to volume charges).[19] It also suggests that final form of vertical control accompanying the commercialization of GM seeds is greatly influenced by the labor saving trait. [20] Factors like widespread weed problems, herbicide resistance and lack of technologies reducing herbicide

[19] Huso, S. (2005).

[20] Lemarie and Ramani (2003) indicates that demand enhancing innovations give rise to incentives for mergers.

amounts with certainty, might be the ultimate reason for the high price elasticity of demand estimates for herbicide-saving traits.

New technologies can bring new economic issues to the forefront. That is the case in GM crops, with their emphasis on adding traits to existing high yield seeds. Our use of a trait-based model to examine the adoption patterns of GM crop varieties among corn farmers in Minnesota and Wisconsin reveals a new set of results and lessons that classic adoption models cannot provide. Further elaboration of this traits-based approach holds considerable promise for deepening our understanding of this new area of agricultural technology, but will also require some reorientation in the design of surveys and the types of information gathered from farmers and other sources associated with GM crops.

APPENDIX

Table A. Descriptive statistics for all varieties, by trait

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield (bu/A)	4579	145.7	14.9	104.0	177.3
Cost of Seed and Pesticide ($/A)	4928	64.9	3.7	53.7	77.7
Insecticide Use (Acr CornTreated)	4850	6.5	14.8	0.0	242.0
Herbicide Use (Acres CornTreated)	4772	53.6	90.8	0.0	990.1
Labor (Number of workers per farm)	4928	4.0	0.9	1.4	11.2
Variety choice	1232	2.93	1.06	1	4

Table B. Descriptive statistics of traits, by variety

Variable	Obs	Mean	Std. Dev.	Min	Max
yht	1197	149.7	14.2	110.6	174.5
ybt	1195	146.2	15.1	107.1	177.3
yhb	1196	147.8	14.5	107.1	177.3
yng	1197	141.6	14.3	104.0	167.4
yst	1195	154.2	14.9	113.8	183.9
ps_ht	1197	63.6	2.2	53.7	66.7
ps_bt	1197	68.7	3.4	60.2	77.7
ps_hb	1197	66.0	2.7	53.7	77.7
ps_ng	1197	61.1	0.0	61.1	61.1
ps_st	1197	75.3	0.0	75.3	75.3
iht	1193	10.5	19.1	0.0	242.0
ibt	1197	0.0	0.0	0.0	0.0
ihb	1197	5.3	9.5	0.0	121.0
ing	1193	10.5	19.1	0.0	242.0
ist	1197	0.0	0.0	0.0	0.0
hht	1193	49.0	80.0	0.0	790.0
hbt	1193	56.5	97.6	0.0	990.1

hhb	1193	52.6	86.8	0.0	799.8
hng	1193	56.5	97.6	0.0	990.1
hst	1193	49.0	80.0	0.0	790.0
wht	1197	4.0	0.8	1.4	8.4
wbt	1197	4.1	0.7	1.8	7.7
whb	1197	4.0	0.8	1.4	8.4
wng	1197	4.1	1.3	2.0	11.2
wst	1197	4.0	0.8	1.4	8.4

Table C. Why Farmers Planted Bt-ECB Corn in 2003[21]

Reasons	% of Respondents
To increase corn yields	71.9
To allow better insect control	68.1
Anticipated having corn borer problems	46.4
Recommendation from seed dealers/consultants	44.3
To reduce overall insecticide use	34.9
Fits well with existing corn production practices	17.9
To reduce overall corn production costs	13.6
To reduce the labor required to grow corn	9.8
Anticipated having corn rootworm problems	8.9
Other*	7.7
Recommendation from neighbors	7.2
Recommendation from university or extension agents	3.4

* Written comments included: planted for trial purposes, only way to get desired variety

Table D. Why Farmers Did Not Plant Bt-ECB Corn in 2003

Reasons	% of Respondents
Price of Bt seed corn is too high	57.6
Did not anticipate having corn borer problems	39.5
Did not anticipate having corn rootworm problems	34.0
Concerned about possible environmental or safety issues	18.1
Concerned about having trouble selling Bt corn	16.0
Other*	14.8
Concerned about having to segregate Bt corn from non-Bt corn	13.3
Not satisfied with the net return of Bt corn	9.5
Concerned that insect resistance management requirements would be too much trouble or complicated	8.4
Concerned about insect resistance	8.0
Not satisfied with Bt corn yields	7.0
Concerned about getting a lower price for Bt corn	6.3

*Written comments included: use crop rotation, no interest, organic farm, corn used for silage, unfamiliar with Bt corn

[21] Note: Tables C,D,E,F were calculated by Merrill et. al. (2005) with the same data set used in the present study.

Table E. Likelihood Ratio Tests

		df	Xsq(.025)
LR I-II	8	1	5.02
LR II-III	60	1	5.02
LR IV-II	16	6	14.5
LR V-III	20	5	12.8

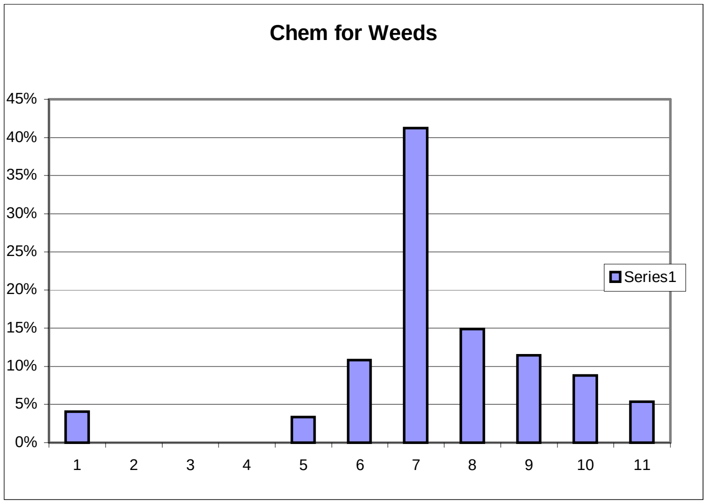
Table F. Standard Multinomial Logit

By variety choice Explanatory Variable	Coefficient		Std. Err.
HT			
Yht	-0.144		(0.09)
Ybt	-0.027		(0.04)
Yhb	0.038		(0.08)
Yng	0.121		(0.09)
Iht	0.009		(0.02)
Hht	0.006		(0.01)
Hbt	-0.005		(0.01)
Hhb	0.000		(0.02)
ps_ht	0.575	**	(0.13)
ps_bt	0.215	**	(0.07)
ps_hb	-0.463	**	(0.13)
ps_ng	-0.304	**	(0.01)
Wht	-0.689		(0.57)
Wbt	0.045		(0.30)
Whb	0.583		(0.60)
Wng	0.052		(0.09)
Ng	-1.760	**	(0.45)
BT			
Yht	-0.006		(0.08)
Ybt	0.175	**	(0.06)
Yhb	-0.241	**	(0.08)
Yng	0.080		(0.09)
Iht	0.020		(0.02)
Hht	0.003		(0.01)
Hbt	-0.023	*	(0.01)
Hhb	0.029		(0.02)
ps_ht	-0.348	**	(0.09)
ps_bt	-0.694	**	(0.09)
ps_hb	0.779	**	(0.12)
ps_ng	0.292	**	(0.09)

	Wht	-0.222		(0.31)
	Wbt	-0.019		(0.42)
	Whb	0.134		(0.50)
	Wng	0.037		(0.09)
	Ng	-2.008	**	(0.41)
HtBt				
	Yht	-0.150	*	(0.08)
	Ybt	-0.042		(0.05)
	Yhb	0.065		(0.07)
	Yng	0.130		(0.08)
	Iht	0.011		(0.02)
	Hht	0.004		(0.01)
	Hbt	0.005		(0.01)
	Hhb	0.003		(0.02)
	ps_ht	-0.162	**	(0.08)
	ps_bt	-0.231	**	(0.06)
	ps_hb	0.268	**	(0.08)
	ps_ng	0.187	**	(0.08)
	Wht	-1.100		(0.37)
	Wbt	-0.023		(0.31)
	Whb	0.820	*	(0.46)
	Wng	-0.064		(0.09)
	Ng	-4.721	**	(0.38)

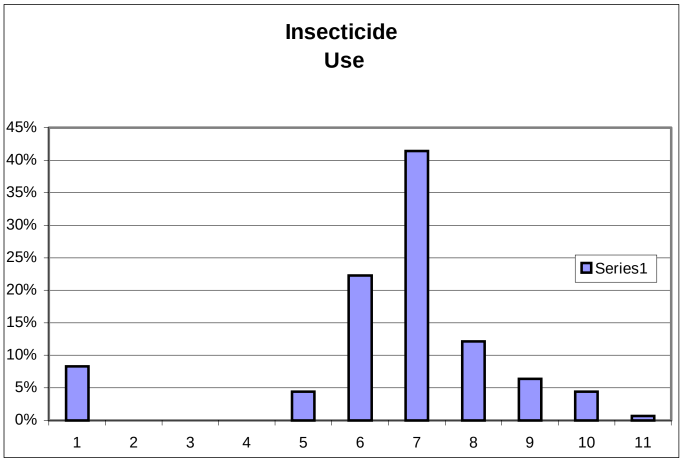
(Outcome typeb04==4 is the comparison group)

Graphs 1. Herbicide Use in Counties of Minnesota and Wisconsin (acres treated/farm)



Source: Agricultural Census, 2002
*See graph categories below

Graphs 2. Insecticide Use in Counties of Minnesota and Wisconsin (acres treated/farm)



Source: Agricultural Census, 2002
*See graph categories below

Acres Categories in Graph 1. and 2.

1	**<25**
2	**25<= x <35**
3	**35<= x <50**
4	50<= x <100
5	100<= x <200
6	200<= x <300
7	300<= x <400
8	400<= x <500
9	500<= x <600
10	600<= x <700
11	700<= x

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