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A TRAIT SPECIFIC MODEL OF GM CROP ADOPTION BY MINNESOTA AND WISCONSIN CORN FARMERS

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Advances in the genetic modification of agricultural seeds have allowed a range of new opportunities for manipulating seed traits according to production, market and environmental concerns. As seed varieties continue to become increasingly differentiated, preferences for specific seed traits may be expected to impart significant effects on farmer demand for new seeds. This paper proposes a model of technology adoption that integrates demand for traits of new technologies with the potential for heterogeneity based on farm and farmer characteristics. The model is applied to recent GM corn adoption data from Minnesota and Wisconsin farmers, and uses conditional logit and mixed multinomial logit econometric models to estimate the effects of traits and farm and farmer characteristics on adoption outcomes.

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1. INTRODUCTION

Economic models of agricultural technology adoption have long emphasized the role of farm and farmer characteristics in shaping decisions, with scant attention paid to the role of technology traits themselves (Feder, Just and Zilberman 1985). Recent adoption studies of transgenic or genetically modified (GM) crops have followed in this tradition by focusing on how such factors as farm size, education of farmer, age, and other farm management practices shape adoption decisions (see Fernandez-Cornejo and McBride (2002) for a review). Conventional approaches to modeling adoption ignore the range of choice farmers face and the trade-offs among distinct yet related GM crops. As seed varieties are increasingly differentiated by their traits (such as the potential to reduce herbicide or insecticide inputs, save labor, reduce management demands, affect health and safety outcomes, increase or stabilize yields, affect environmental performance, and the like), farmers assess, for their own situation, the benefits and costs associated with the distinct trait combinations embodied in the various types of GM crops. This paper develops and implements a model of technology adoption that integrates farmer demand for individual traits with the potential for heterogeneity in that demand.

The proposed trait-based adoption model unifies three major lines of adoption research. First, it incorporates the traditional adoption approach of economic studies, which views profitability and relative advantage as the key factors determining the adoption of new crops and new technologies (Qaim and Zilberman 2003; Jovanovic and Stolyarov 2000, 1995; Feder, Just and Zilberman 1985; Griliches 1957). Second, it helps to quantify and put formal structure on conceptual, descriptive, and qualitative research by anthropologists and sociologists that documents the influence of farmer assessments of the attributes or traits of agricultural technologies on their adoption behavior (Ruttan 2003; Nowak 1992, 1987; Kivlin and Fliegel 1966, 1967; Rogers 1962). Third, it exploits recent innovations in consumer demand analysis (Berry, Levinsohn and Pakes 2004; Nevo 2000, 2001; Brownstone and Train 1999; Revelt and Train 1998; Berry 1994) that describe consumer purchase (adoption) of a good as a function of the traits of the good purchased, in addition to the individual specific characteristics of the consumer.

The standard empirical methods used to estimate technology adoption models are probits, logits, and their multinomial versions. The multinomial specifications in particular provide insights into the manner in which changes in farm and farmer characteristics push the individuals into and out of several different adoption categories, and are used to handle multiple choice situations including selection among multiple varieties. However, these models have several shortcomings for the study of multiple traits within a seed variety. As explained in detail below, these models do not readily incorporate traits, the potential heterogeneity of demand for those traits, or the potential substitution possibilities inherent in GM varieties with related traits. The multinomial logit model, for example, breaks down under the burden of incorporating traits because of the proliferation of parameters and problems with multicollinearity. These standard approaches also impose restrictions, such as independence of irrelevant alternatives, which limit the between-choices substitution patterns of related varieties. In other words, traditional empirical adoption models fail to capture the important features of the trait differences that are likely to govern GM crop adoption, leaving the econometric models of technology adoption as poorly specified analyses of the actual farmer choice problem.

This work uses the conditional (CL) and mixed multinomial logit (MMNL) specifications to implement the trait-based adoption models in this paper, with the first being a special and more restrictive case of the second. The models focus on farmer adoption choices of four different corn varieties (Ht, Bt, Ht/Bt, or non-GM). Our specific focus on farmer choices across these trait-differentiated corn varieties enables us to derive willingness-to-pay estimates for different crop traits in corn (herbicide savings, insecticide savings, yield improvements, and labor savings), and to account for farm and farmer heterogeneity in those estimates (both observed and unobserved components). The models allow us to consider all crop traits simultaneously. Obviously, a high willingness to pay (WTP) for a certain trait should lead to increased demand for the new technology, while a low WTP for other traits may reduce demand for adopting the technology.

The economic and econometric approach developed below provides a structure for examining the effect of traits, farm/farmer characteristics, and the interactions between traits, such as farm revenues and seed price, on the adoption decision of farmers. The methodology we demonstrate in this work is sufficiently flexible to allow recovery of estimates for the values of different combinations of traits and to incorporate regional dimensions of the demand for these traits. The empirical results, not surprisingly, confirm that individual traits, heterogeneity of tastes for traits, and farm/farmer characteristics shape adoption decisions. They do so in ways that both verify some well-known outcomes (such as education influences technology adoption) and offer some new insights (such as "family farms", where labor is supplied almost entirely by the owner-operators, are more likely to value GM crops because of their labor-saving traits). The econometric results also demonstrate the superior performance of the more general MMNL model over the CL model.

The rest of this article is divided into six sections. Section 2 introduces key factors (both crop traits and farm/farmer characteristics) that are likely to shape adoption decisions of corn seeds. Section 3 develops the trait-based adoption model, while Section 4 explains the CL and MMNL econometric approaches. Section 5 presents the data and descriptive statistics. Section 6 specifies the econometric models and then explores the results. Section 7 concludes.

2. Factors Likely to Influence Adoption Decision of GM Corn Varieties

The now large literature on the adoption of GM crops has found a number of farm and farmer characteristics which influence adoption decisions. Dynamic diffusion models (Fernandez-Cornejo, Alexander, and Goodhue 2002) and farmer adoption choice models (Qaim et al. 2006; Marra, Piggot, and Carlson 2004; Gouse, Pray and Schimmelpfennig 2004; Marra, Hubbel, and Carlson 2001) have identified farm size, education, age, available market information, as among the key explanatory factors. *Ex ante* descriptive studies and benefit-cost analyses of GM crops have examined several trait-based rationale for farmer adoption beyond yield and input-reduction reasons, such as ease of use (Benbrook 2001a, 2001b; Gianessi and Carpenter 2000), lower harvest costs (Duffy 2001), more convenience (Fernandez-Cornejo and McBride 2002), and compatibility with reduced and no-tillage systems (Fawcett and Towery 2002). While these latter studies investigate trait based differences they have done so without formally incorporating these traits into the adoption models.

In estimating our model, we explore the role of key crop traits of the GM varieties and the characteristics of the farm and farmer in our adoption model. The key traits we investigate in this work are: price differential, yield advantage, and savings in herbicide, insecticide, and labor inputs. Based on standard microeconomic principles, we expect the demand for GM crops to be declining in the price of seeds. We further expect ceteris paribus that the demand for GM crops will be increasing as they increase yields as well as when they decrease herbicide, insecticide and labor use. Based on the literature cited above we expect the following farm and farmer characteristics to favor GM crop adoption. Larger farms will be more likely to adopt, as are better educated farmers and farms facing labor constraints (Fernandez-Cornejo and McBride 2002). Because agricultural biotechnology has been politicized, and farmers have varied views on the environmental and social effects of the technology, we also expect farmers with environmental or safety concerns about the technology to be less likely to adopt it (Barham et al. 2004).

3. Model Formulation

As in many adoption studies (Zepeda 1990; Barham 1996), our farmer choice model utilizes a random utility framework (Marschack 1960; McFadden and Train 2000). Farmers seek to maximize stable preferences for the traits of the crop varieties they plant. 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. Thus, in contrast to classical demand studies (in product space), the data from each farmer is not seen as one observation of purchases when faced with a particular price, rather, as an observation on the likelihood of purchasing J different bundles of attributes.[1]

In this work we assume that a farmer faces a choice set consisting of J alternative corn varieties (e.g. Herbicide tolerant (Ht), *Bacillus Turigensis* (Bt), etc).[2] The utility that farmer i receives from alternative j is denoted by U_{ij}, which is the sum of a linear-in-parameters component V_{ij} and a stochastic component e_{ij}. The stochastic component is assumed to be known by the farmer, but to be unobserved by the analyst. 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 levels of K observed attributes of the variety j, $\mathbf{x}_{ij}$. The income term has two components: the budget that the farmer assigns for farm production (π_i^*) and an environmental-political benefit (γ_j) if the variety that s/he grows is non-transgenic: $\pi_{ij}= \pi_i^* + \gamma_j$.[3] The observed attributes of the varieties are yield advantage, pesticide use, labor savings, and price.

Assuming a linear shape to the utility function, the observed component of utility V_{ij} can be written as:[4]

$$V_{ij}(\alpha_i , \boldsymbol{\beta}_i) = \alpha_i(\pi_{ij} - p_j) + \mathbf{x}_{ij}{}^*\boldsymbol{\beta}_i \qquad (1)$$

Where $(\alpha_i , \boldsymbol{\beta}_i)$ is a vector of parameters to be estimated that give the marginal effect of traits on farmers' utility.[5] Farmer heterogeneity implies that the vector of preference parameters, $(\alpha_i , \boldsymbol{\beta}_i)$, will vary over individuals. In particular, we let

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

v_i be a component of characteristics of the farmer, which influence their preferences for specific traits, but are unobserved by the analyst. This component is assumed to be stochastic and have a distribution, $P_v(v)$. Assuming $P_v(v)$ to be a standard multivariate normal distribution, the vector $(\alpha , \boldsymbol{\beta})$ captures the mean value of the sensitivity of farmers' utility to traits and Σ , a (K+1)*(K+1)

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[1] A variety is defined by a set of traits, which producers and consumers observe. However, the researcher observes only some of them.

[2] 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.

[3] In the following analysis, we implicitly assume a multi-stage budgeting process in which the farm production budget is separable from the other parts of the farm household budget.

[4] V is "observed" conditionally (on α_i and β_i).

[5] Notice that we refer to a marginal effect with respect to utility not with respect to choice probability**.**

matrix of variance parameters σ_k, allows each component of $(\alpha_i , \boldsymbol{\beta}_i)$ to have a different variance.[6]

The model represented by equations (1) and (2) is more flexible than traditional models in two primary aspects. First, it allows farmers' tastes for a trait to deviate from average tastes.[7] Farm and farmer characteristics, which are unobservable to the analyst, are allowed to influence a farmer's valuation for a trait, such that two different farmers facing the same levels of attributes for all alternatives might choose differently.[8] Second, it allows for correlation in the unobservable components of the utility for different alternatives, when the degree of correlation depends on how close the two alternatives are in terms of their attributes.[9] We present the full derivation of the covariance between the unobservable components of the two varieties in Section 4.1. The key point is that two varieties with similar attribute levels are treated by a farmer as closer substitutes than two varieties with very different attribute levels.

3.1 Modeling Farmer Characteristics

The model in (1) and (2) explains farmers' systematic utility from a crop variety in terms of preferences and traits, but it does not explicitly control for the observable characteristics of the farm or the farmer, which will also have effects on technology adoption. For example, previous studies have found that characteristics such as the size of the farm or the education of a farmer can influence adoption patterns (Feder, Just and Zilberman 1985; Feder and Umali 1993). Equations (3) and (4) below present an extension of the basic model that integrates these factors in the analysis.

$$V_{ij}(\alpha_i , \boldsymbol{\beta}_i) = \alpha_i(\pi_{\mathbf{ij}} - p_j) + \mathbf{x}_{ij}{}^*\boldsymbol{\beta}_i + \mathbf{z}_{1i}{}^*\boldsymbol{\delta}_{\mathbf{j}} \quad (3)$$

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Sigma\ v_i + \mathrm{D}\ \mathbf{z}_{2i} \quad (4)$$

where $\mathbf{z}_{1i}$ and $\mathbf{z}_{2i}$ are vectors of observable farm and farmer characteristics influencing farmer's utility for a specific variety. In particular, $\mathbf{z}_{2i}$ might have a direct influence on farmers' preference parameters and capture some or all of the variation that was assumed unobserved in the basic model above. For example, a farmer (or group of farmers) with high farm revenues might not

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6 Recall that a normally distributed variable alfa, with mean *a* and variance *s* can be parameterized as *alfa=a+s*e* , where *e* has a standard normal distribution. However, the model flexibility is not conditional on the normal representation. Many other distributions can be parameterized analogously.

7 The average is the average over all alternatives and over all farmers.

8 Without observations of farmers choices and varietal attributes over time we cannot identify the individual value of (α_i , β_i) but we can estimate the mean and standard deviation of these parameters in the population.

9 The measure of closeness used in this case is mathematically derived by Hausman and Wise (1978).

care about high prices of seeds as much as a farmer who barely makes a living from her crops. An advantage of letting the taste parameters vary with the observed demographics is that it reduces the reliance on parametric assumptions and brings in additional information.

In summary, we can express the farmer's maximization problem as a choice of the variety that gives her the highest utility, given the preference parameters in her utility function (α_i , $\boldsymbol{\beta}_i$) and own characteristics $\boldsymbol{z}_i$. This gives the following utility function for farmer i:

$$U_i = \text{Max}_j\ U_{ij}\ (\boldsymbol{x}_{ij} \,|\, \alpha_i, \boldsymbol{\beta}_i, \boldsymbol{z}_i)\ \text{i=1,…,I; j =1,...,J.}$$

Here the farmer seeks to choose the variety j that yields the highest utility taking into consideration her knowledge of the traits of each variety, her expected profitability of each variety, her tastes for the traits, and her own characteristics. The estimation procedure described below seeks to estimate the preference parameters (α_i , $\boldsymbol{\beta}_i$) given information on the traits, $\boldsymbol{x}_{ij}$, and farmer characteristics, $\boldsymbol{z}_i$.

4. Model Specification, Estimation, and Predictions

Model Specification

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) and a mixed multinomial logit (MMNL). 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 i.i.d. 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]

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

[10] For simplicity of the illustration we omit expectation operators in the previous section and generalize the notation of all covariates as x_{ij}.

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}.[11] 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 addition, conditional on the traits of the alternative varieties, farmer choice probabilities can also depend on the characteristics of subjects (which are constant across alternative varieties, 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:

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

where setting $\gamma_1=0$ identifies the other γ_i coefficients.

Although the CL model presents several advantages for modeling adoption behavior, relative to standard binary and multinomial models, it shares with these models the restrictive "independence of irrelevant alternatives (IIA)" property. This property is better understood as an "independence among alternatives" assumption, which is directly linked to the assumption of independent and identically distributed error terms in the models, a point that is explored next.

The MMNL model relaxes the independence of irrelevant alternatives assumption by allowing for a random deviation of an individual's tastes from the average taste,[12] such that correlation across alternatives is estimated simultaneously. In particular, the MMNL choice probabilities are:

$$P_{ij} = \int \frac{\exp(\beta' x_{ij})}{\sum_k \exp(\beta' x_{ik})} f(\beta)\, d\beta \qquad \text{for i} = 1,\ldots\text{I, j, k} = 1,\ldots,\text{J} \qquad (6)$$

where the β coefficients are distributed across individuals, according to the density $f(\beta)$.[13] The CL model in Equation (5) is a particular case of Equation (6); one where $f(\beta)$ is degenerate and the coefficients β = b, are fixed across individuals.

[11] In contrast for a 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.
[12] This is commonly called unobserved heterogeneity in the literature.
[13] For estimation purposes, this density is parameterized as f (β | b,Σ), where b,Σ are the parameters that describe the density. The latter parameters are estimated, and the random components are integrated out.

In order to illustrate the link between the IIA assumption and the unobserved heterogeneity in terms of our model in Section 3, we should recall that the total utility of an alternative U_{ij}, is the sum of a systematic component with average coefficients ($\bar{U}_{ij}$) and stochastic components ($\varepsilon_{ij} = \eta_{ij} + e_{ij}$). The stochastic components in the model are e_{ij}, the unobserved white noise, and $\boldsymbol{x}_{ij}'\Sigma\, v_i = \eta_{ij}$, the unobserved component determined by the deviation from the average taste parameters that are associated with each specific trait ***x*****.**[14] If two alternatives *j* and *k* are very similar in terms of their attributes, then an individual who places greater value than the sample average on one of them (ε_{ij} is positive) should also place greater value on the other. Thus, for this non-average individual, ε_{ij} and ε_{ik} should be correlated. And this is exactly what the model achieves through the particular specification of ε_{ij} : $Cov\ (\varepsilon_{ij}\ \varepsilon_{ik}) = \boldsymbol{x}_{ij}\,\boldsymbol{x}_{ik} * \sigma^2_{\beta} = Cov\ (U_{ij},, U_{ik},)$.

In particular, the degree of correlation depends on the attributes of both alternatives. At the same time, this specification of ε_{ij} is what allows for non-average, heterogeneous agents, through the term η_{ij} .

The i.i.d. characteristic of the CL error terms results in coefficient estimates which 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, p. 40). This feature of the CL model also means that 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). Likewise, the IIA property also restricts the substitution among alternatives, or relative probability of choosing a crop variety, to be independent of other available varieties (and their attributes). Thus, the expression in equation 7 shows the relative probability of choosing alternative *j* over *k* in the CL model:

$$\frac{P_{ij}}{P_{ik}} = \exp\left[\beta'\left(x_{ij} - x_{ik}\right)\right], \ (7)$$

which depends only on the characteristics of the two alternatives (*j* and *k*).

Unlike the CL, the ratio of MMNL probabilities, P_{ij}/P_{ik}, depends on all the data, including attributes of alternatives other than j or k (the denominators of the logit formula are inside the integrals and therefore do not cancel). Another way of explaining this issue is to observe that a change in an attribute of alternative j changes the probabilities for all other alternatives by the same percent in the CL, while not in the MMNL.[15] Thus, the MMNL model does not exhibit the restrictive substitution patterns of the CL, and different substitution patterns are attained by

[14] In order to simplify the notation, we refer here to all traits jointly as x.

[15] This can be seen by calculating the derivative of Equations 5 and 6 with respect to x_{ik} and multiplying by x_{ik}/P_{ij}. This cross elasticity is the same for all alternatives in the CL model, while in the MMNL it differs across alternatives and depends on the correlation of the likelihood function of j and k.

appropriate specification of the density or mixing distribution *f*. In summary, the MMNL model allows more realistic inferences about substitution patterns among the traits such as the effects of the introduction of new varieties with attribute levels that resemble those of already existing varieties, or the effects of policies that regulate levels of commercialization of traits on the adoption of unchanged crop varieties.

4.2 Model Estimation

In order to estimate the coefficients in equation (6) we specify a normal distribution of $\beta \sim N(\mathrm{b}, \Sigma)$, 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 (5), 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, we need to approximate the integral through simulation techniques. For a given value of the parameters $\Theta = (\mathrm{b}, \Sigma)$, we draw a value of β from the distribution $f(\beta \mid \Theta)$. Using this draw (r), we can then calculate the conditional logit formula

$L_{ij}(\beta) = \dfrac{\exp(\beta_i' x_{ij})}{\sum_{k=1}^{J} \exp(\beta_i' x_{ik})}$. Repeating this process for many draws, one can use the

average of the resulting $L_{ij}(\beta)$'s as the approximate choice probability:

$$\overline{P_{ij}} = \frac{1}{R} \sum_{r=1}^{R} \mathrm{L}_{\mathrm{ij}}(\beta^r) \,. \tag{8}$$

One then inserts the simulated probabilities into the log-likelihood function to give a simulated log-likelihood (SLL) that is maximized. The value of the parameters Θ that maximizes SLL is the maximum simulated likelihood estimator of β and σ, which collectively determine the distribution of preferences for the different traits in the model, across farmers. Estimates of β provide mean values of the sensitivity of the probability of choosing a crop-variety to each specific attribute. Estimates of the standard deviation of β (denoted as σ) measure the degree of heterogeneity of this sensitivity among farmers that is due to individual characteristics, which are unobservable to the researcher.

4.3. Willingness To Pay for Traits

Although the direct effect of a trait on utility cannot be identified separately from the variance parameter of the *i.i.d.* error component in these models, the normalized coefficients can be conveniently interpreted as the average amount that a respondent with median income would be willing to pay for an additional unit of a particular attribute.

We can then calculate willingness-to-pay (WTP) for each trait in the model 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:

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

where α^* stands for the cost coefficient and β^* for the trait coefficient. Taking the total differential of this equation gives, $\mathrm{d}U = \alpha\,\mathrm{dp} + \beta\,\mathrm{d}x$, which at a constant utility, $\mathrm{d}U = 0$, allows us to write the expression for the WTP as: $\mathrm{dp}/\mathrm{dx} = -(\beta^*/\sigma)/(\alpha^*/\sigma) = -\beta/\alpha$. This expression captures the agent's willingness-to-pay for a one-unit change in the level of the trait that leaves utility unchanged.

The utility may also depend upon farm and farmer socioeconomic characteristics, which were suppressed in the above WTP expression. Including these characteristics in our model allows us to also estimate group specific values of the relevant parameters that determine the distribution of tastes for traits in the population. Therefore, we are also able to derive corresponding group specific estimates of willingness-to-pay for traits. Such group specific WTP for traits can help extension agents identify where to focus their outreach efforts and companies to identify potential adopters of new traits.

5. Data

5.1 Data Sources and Data Construction

The empirical analysis uses survey data gathered from 1257 randomly selected corn growers in Minnesota and Wisconsin. The data include information on farmers' choices of corn varieties, demographic and farm characteristics, and experiences with the traits of corn varieties used in 2003 and their planting choices in 2004. The questionnaire was implemented in the winter of 2004 at a time when most farmers would have already ordered their seeds for the 2004 growing season. This analysis uses the data on the farmers experience with corn seed traits from 2003, while the adoption choice is measured using the 2004 data. In addition we combine the survey data with information from the US Agricultural Census on observed county levels of crop traits and from seed dealers on seed prices to construct the dataset used below.

On the basis of the most widely commercialized corn types, we classify farmers' corn choices for 2004 into four categories: (1) herbicide tolerant (Ht), if the farmer decided to purchase some Ht but no Bt-corn seeds in 2004; (2) insect resistant (Bt), if the farmer decided to purchase some Bt- but no Ht-corn seeds in this year; (3) Ht-Bt, if the farmer decided to purchase both Ht and Bt-corn seeds;[16] and (4) Non-GM, if the farmer decided to grow only non genetically modified, conventional varieties. Farm and farmer characteristic data come entirely from the survey instrument and include information on total farm receipts, total acres of operated cropland, share of labor performed by immediate family members (categorized as: all, more than 50%, or less than 50%), highest education level of the principal operator, and an indicator variable related to farmer concerns with environmental or safety issues associated with GM varieties.

We consider five corn seed traits in the model of adoption: yields, seed costs, and savings in insecticide, herbicide, and labor. In order to implement a trait based approach to estimating farmer adoption, we need information on the relative levels for each of the five traits and ideally how they would vary across farmers. Seed costs (conventional, Bt, Ht, Ht/Bt) including the technology fee, because their relative values will not vary across farmers, are most easily calculated. The data we use are averages across corn varieties based on prices reported by Renk seed dealers.[17]

Values of the remaining four traits, yields, and insecticide, herbicide, and labor savings, required more individualized estimates based on both farmer experiences and the information sets available to farmers. For these we combine information contained in the survey with 1997 Agricultural Census data (USDA-NASS, 2004).[18] The survey asked farmers who used GM corn (Bt, Ht, or both) how it performed relative to conventional varieties in terms of these traits on a 5 point scale from "much lower" through "the same" to "much higher." We then calibrated this data using the mean and distribution from agricultural census data for the farmer's county and region for corn yields, dollars of insecticide costs, dollars of herbicide costs, and labor use converted into dollars. For example, a yield trait would get the regional (agricultural district) minimum if it were "much lower", the county average if "the same", and the regional maximum if it were "much higher". Thus for each trait we were able to construct a measure of the relative value of the trait for farmers who had experience with the trait.

For farmers with no recent experience with a GM variety, we needed to make some assumptions about their available information sets. We assume that those farmers observe no trait

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[16] Because the survey questions did not differentiate them, this category also includes any farms that planted stacked Ht/Bt corn. Although stacked Ht/Bt corn was available on the market for the 2004 growing season, both the distribution and adoption of the stacked variety were quite low that year.

[17] We took the average sales price of Renk corn seeds with each of the traits in it, since they sell a number of different corn varieties with those traits. Renk sells primarily in Wisconsin, but its average prices were found to be close to those of other sellers in Wisconsin and Minnesota.

[18] We used the 1997 data, because the use of GMO varieties was minimal in that year, and thus 1997 data provide a cleaner baseline of the traits associated with conventional varieties.

advantages/savings or disadvantages/dissavings relative to GM varieties. Specifically, we assume that they observe those traits to be identical to the traits of conventional varieties.[19] This assumption can be justified on the grounds that Ht and Bt corn varieties were by 2004 relatively mature technologies that Minnesota and Wisconsin farmers have had repeated opportunities to evaluate. Their revealed preference of choosing not to adopt them means that they may be just as likely to perceive the traits of the technology as being worse as better from those of conventional varieties for their particular farm operation. In that sense, our assumption is consistent with the revealed preferences shown by farmers and does not create additional *contamination through imputation* problem as described by Manski (2003).

5.2 Descriptive Statistics on Corn Variety Adoption and Explanatory Variables

Corn variety adoption data for 2003 and 2004 are presented in Table 1 in a transition matrix for survey respondents for whom we had data on both years. The table shows both the overall adoption rates in the total rows and columns as well as how farmers move between adoption choices across the years. Note from the 2004 total row that among these farmers, conventional corn was the most common choice for 2004 (39%). Next most common was the combination of Ht and Bt corn (28%). Then came adoption of Bt corn (19%) and finally Ht corn (14%). The biggest change across the 2003 to 2004 year was the increase in adoption of both Ht and Bt which went from 24% in 2003 to 28% in 2004, and mostly added previous Bt or Ht adopters. Quite noteworthy is that slightly more than three-quarters of the observations are on the diagonal shaded boxes which depict no change in adoption outcome across the two years. This persistence in adoption, along with the movement from single GM varieties into Bt-Ht combinations, implies that most of our sample has information sets that closely match the assumptions we made constructing the data.[20]

Descriptive statistics on the five traits and the farm and farmer characteristics are reported in table 2 below. In summary, the per acre seed cost was $39,with conventional corn the lowest at $25 and Bt the highest at $55, per acre average yield level across all varieties was 125 bushels, average cost of treating one acre with insecticide is $5 and with herbicide is $22. Average per acre labor cost is $43. Yield differences across the varieties, on average, were small, but the GM crops, especially Bt, did have a slightly higher average yield than the others. While the lowest herbicide use, on average, is for Ht corn varieties, the conventional varieties have the lowest seed price. Labor cost, on average, was not very different across varieties, but conventional varieties

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[19] The regression results reported below are stable to changes in the broad neighborhood of changes in this informational assumption, including using information on county averages and years of previous experience with GM crops.

[20] If we drop from the subsequent regression analysis the 14% of respondents for whom we are making larger information assumptions, i.e., those who switched to a new GM variety in 2004, the results do not change significantly.

had higher averages, suggesting some labor savings potential in the GM varieties. In terms of the farm and farmer characteristic data, it is perhaps worth noting that more than half of the corn farms have total revenues that are less than $100,000, more than three-quarters of them have all of the farm labor performed by immediate family members, and that 14% reported serious concerns with possible environmental or safety issues associated with GM varieties.

6. RESULTS

6.1. Estimated Model

The empirical model estimates expected utility from the expected traits as follows:

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

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

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

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

where π is the individual's variety revenue per acre outcomes including a variety specific preference for non-GM, p is the cost of seed per acre, Y is yield in bushels per acre, I is per acre cost of insecticide treatment, H is per acre cost of herbicide treatment, Lab is per acre cost of on-farm labor, and γ_{hb} and γ_{ng} are variety specific constants. The variety specific constants capture the average effect of unincluded factors for this alternative with respect to all others. We include a variety specific constant for the Ht&Bt equation to capture potential synergies (or tradeoffs) between growing Ht and Bt on a farm, which might not be captured by our other measures. With the variety specific constant in the conventional equation, we intend to capture unincluded benefits a farmer receives from growing conventional rather than GM varieties as would be the case if the farmer had ideological reasons for not planting GM varieties. The variety specific constant in the conventional equation might also capture any premium accruing to a farmer if there were added value in selling non-GM corn.

6.2. Model Specifications

In order to illustrate more clearly the trait-aspect of the adoption decision, the first specification of the model will consist of a set of baseline conditional logit (CL) estimations, models I and II. We then estimate a mixed multinomial logit (MMNL), model III, and that we use to test the restrictions of the CL model. These three models include only the traits of the crops as explanatory variables. We then expand the specification to be more encompassing by including farm and farmer characteristics in addition to the crop traits.

6.2.1 Baseline CL Model.

Estimates for two basic conditional logit (fixed-effects) models are reported in table 3. The first model (I) only includes the traits of the crop varieties. The second model (II) includes the variety specific constants γ_{hb} and γ_{ng}, which capture average effects of the non-included factors in the Ht&Bt and conventional equations. The coefficient estimates reveal the effect of each observed factor relative to the variance of the *i.i.d.* 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 provides an economically meaningful estimate of willingness-to-pay.

A perusal of table 3 reveals that the signs of almost all of the coefficient estimates are significant and consistent with *a priori* expectations in all three models. As the cost of a variety of corn increases in dollars per acre, *ceteris paribus*, the probability of that corn type being chosen decreases. The same holds 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 addition, yield has a significant effect; varieties that produce more corn bushels per acre are more likely to be adopted.

Specification II, which includes the two variety specific constants, indicates that growing Ht&Bt combined has positive unmeasured complementarities, with respect to growing any variety alone. In contrast, the constant component capturing average unobserved effects on the probability of adoption of non-genetically modified varieties is not significant. This suggests that there would be no significant effect of a potential risk and marketability premium received by farmers for not growing GM varieties.

6.2.2 Baseline MMNL Model

In table 4, we show the mean and standard deviation for each coefficient from estimating a Multinomial Mixed Logit (MMNL), which allows each coefficient to take different values for each individual. Given the significance of the variety specific constants we show only those results in the table. In contrast to the CL, this MMNL allows for unobserved heterogeneity in preferences for the traits in the crop varieties. Notice that in table 4 we have two different types of standard deviations. One corresponds to the typical standard error calculated for all coefficients (in parentheses below the estimate of β), and the other is the deviation parameter indicating heterogeneity of preferences for each attribute (a diagonal term of the matrix Σ in equation (2) above). The latter is estimated through simulation.

Similar to Bhat (1998) and Revelt and Train (1998), we find that the magnitudes of most parameters increase from the CL to the MMNL. This is an expected result, because the variance before scaling is larger in the CL model compared to the mixture model. In other words, the variance of the stochastic portion of utility is lower for the MMNL model because some of the error has been explained by the other stochastic components. The signs of all coefficients are the same as in the CL and are expected.

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 herbicide savings, while positive for 89% of the farmers, is negative for about 11% of the sample.[21] That is, some individuals do not care about choosing a variety that requires them to use more herbicide, as long as there are other positive traits to the technology such as the seed cost and the labor use being lower. The share with positive willingness to pay is higher for the insecticide-using trait: 94%. The preferences for yield advantage also vary significantly across the population, with 93% of individuals significantly caring about having better yields and reflecting this in their choice of corn variety. The interpretation of the other parameters is the same as in Table 3 above.

Using the MMNL results we can now test the validity of the restricted substitution patterns, restricted preference heterogeneity, and the independence of irrelevant alternatives (IIA) assumptions of the conditional logit. We can use a conventional likelihood ratio test to test the CL versus the MMNL, which amounts to testing the restrictions on the substitution patterns and the heterogeneity of the coefficients. The results of those tests, shown in table 5, soundly reject the CL models in favor of the MMNL. We then test the IIA assumption using the Hausman test which excludes one or more categories from the dependent variable. Because the coefficient estimates change significantly with exclusion of one or more alternatives, the test support rejection of the IIA assumption of the CL model. Thus we can reject the restricted CL model in favor of the MMNL.

6.2.3 Farm and Farmer Characteristics

The MMNL in model III identifies significant heterogeneity across farmers in their preferences among crop traits, but does not help us identify the causes of this heterogeneity. Including demographic variables (farm and farmer characteristics) in the model may help explain this heterogeneity across agents. From previous adoption studies and basic economic theory we expect the following effects in testing how preferences vary with farm and farmer characteristics: 1) that the variation in farmer preferences with respect to the seed price will be a function of farm revenue categories; 2) that preferences toward labor savings will vary with the availability

[21] We calculate this based on the coefficient of herbicide use being normally distributed with mean -0.118 and standard deviation 0.097. 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 0.118/0.097. Thus, we find that the share is 0.89; meaning that 89% of the population is estimated to dislike varieties which are more herbicide using.

of family labor on the farm; 3) that, as suggested in the literature, farm size explains a significant variation in the preferences for different corn varieties; 4) that the level of farmer education also explains a significant variation in the preferences for different corn varieties; and 5) that differences in farmer environmental concerns account significantly for variations in farmer preferences for corn varieties.

In order to evaluate the first two hypotheses, we interact the price variable with dummies reflecting three different total farm revenue categories for the year 2003: lower than $50,000 (41% of farms), between $50,000 and $100,000 (16% of farms), higher than $100,000 (43% of farms).[22] We further interact the labor variable with three different categories of the percentage of total amount of farm labor performed by family labor: all family labor (77% of farms), more than 50% (19% of farms), less than 50% (4% of farms). For the third and fourth hypotheses, we include both the acres operated by the farm and the highest educational level achieved by the person making decisions on the farm. Since the latter variables do not change across alternatives, i.e. they are individual specific, it is required for identification purposes that they be interacted with alternative specific constants. Thus, their effect on one variety is interpreted with respect to their effect on another (base) variety. This is also the case for the fifth hypothesis: Farmers' environmental concerns --a dummy variable equal to 1 if the farmer has concerns about the effect on the environment of any variety-- are included as an individual specific characteristic, whose coefficient indicates the contribution of this farmer characteristic to the utility of adopting one specific variety, relative to adopting the base category (in this case regular non GM corn).[23]

Since the list of explanatory variables is long, we arrange the results in separate tables. Tables 6a and 6b show the results of estimations including farm and farmer characteristics using the MMNL which allows for unobserved heterogeneity of tastes.[24] Coefficient estimates of traits and trait interactions are presented in table 6a, displaying the effects of the different traits on the probability of growing any given corn variety. Part b continues with the effect of farm and farmer characteristics on this probability. However, the latter have to be interpreted in relative terms for identification purposes as noted earlier. Here we specify the effect of each farmer characteristic on the probability of growing a variety "j' (where j is genetically modified) relative to non GM varieties.[25]

The first part of table 6a shows that the price sensitivity decreases with increases in farm revenue. Thus, the likelihood that a farm purchases a corn variety whose price increased one

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[22] Results do not change when using different ordered categories of farm revenues.
[23] Notice the difference between controlling for the fact that many farmers care for the environment, which in turn affects their adoption behavior, versus including an objective trait-measure of environmental damage for each alternative. Because we do not observe the specific level of environmental benefit or damage associated with each specific variety, we cannot explicitly estimate the willingness to pay or the taste for this trait.
[24] As with the previous models a conventional likelihood ratio test shows that the CL model is too restrictive and implies that the MMNL model performs better.
[25] Which category is chosen as the base category is not relevant for the estimation. This is explained below.

unit, when the price of other varieties remained constant, will be higher if it had high rather than low total revenues. A second important result is that the labor savings sensitivity is only significant for farms whose labor force is mostly family labor. In contrast farms that use mostly hired labor are not sensitive to the labor saving trait. This suggests that the value of labor savings technologies accrue primarily to family farms where labor constraints may be more likely to bind.

The second part of table 6a shows that controlling for farm and farmer characteristics helps explain some of the unobserved heterogeneity in yield and insecticide use. Yield and pesticide savings traits continue being highly significant. For the yield trait coefficient, the magnitude of both the mean and standard deviation of the distribution decreases as compared to the coefficients in table 4 without inclusion of individual characteristics. At the same time that the share of the population for whom the yield coefficient is negative is lower than in model III. An analogous change occurs for preferences for the insecticide-use trait. This is not the case for the herbicide-use trait coefficients which increase in magnitudes. Finally, the alternative specific constants have no effect in this model, which suggests that the previously unobserved characteristics are well explained by demographic factors.

Table 6b presents results associated with our third, fourth and fifth hypotheses. The third one, that the size of the farm influences the demand for corn varieties, is confirmed only for varieties that include Bt-corn, relative to conventional varieties. The larger the size of the farm, the higher the probability that a farmer grows Bt-corn or Bt combined with Ht-corn, relative to conventional non-gm varieties. The likelihood of growing Ht alone relative to growing conventional varieties, however, is not influenced by farm size. This provides us with a more nuanced understanding of the commonly found link between farm size and GM crops. Farm size matters to certain but not all technologies and technology traits.

Regarding the fourth hypothesis, the education of the person making decisions on the farm positively influences the likelihood of growing Ht&Bt together only, but is insignificant for the other varieties. In contrast, being concerned about environmental or safety issues of the varieties, hypothesis five, is a determinant negative factor affecting the probability of growing any GM variety, relative to non-GM ones. Most interestingly, the results produce a relative ranking of preferences such that a farmer who is concerned about environmental issues would rather grow Ht corn than Bt corn and Bt more than a combination of Bt and Ht corn on her farm.

6.3. Willingness-to-Pay for Traits

As delineated in section 3, the estimated coefficients of cost and of the various traits provide information on the value of the traits. Since we have rejected the restrictions on the CL model, table 7 presents estimates of the mean willingness to pay for traits derived from the MMNL model. In order to better understand this table, it is important to remember that, in the model in table 6, we interacted the seed price with three different farm revenue categories. Therefore, we have three different, farm-revenue specific, seed price coefficients. Since the WTP for a trait is the ratio of the trait coefficient with respect to the price coefficient, we are able to calculate three different, group-specific, WTP measures for each trait (according to the farm-revenue group).

Let us first analyze the low farm revenue category, which contains about 40% of the households in the sample. These households, on average, are willing to pay the highest amount for seeds of varieties that save them herbicide. For one dollar of herbicide savings related to a specific variety, they would be willing to pay 1.59 more dollars for the seed. For the same amount of savings in terms of insecticide, they are willing to pay 78 cents, and for one dollar of labor savings, they are willing to pay only 40 cents if they use only family labor in their production, and 59 cents if they use both family and hired labor (this, for households whose labor in the farm consists mostly of family labor).

The lower willingness to pay for insecticide savings may be because, even for conventional varieties, small farmers in Minnesota and Wisconsin may prefer to use other management practices or suffer some level of lodging or breakage than use insecticides. Thus, it is more likely that the value placed on insect resistant varieties by this type of farmers accrues to the higher potential yield from lower pest damage, rather than to generated insecticide savings. Similarly for the labor savings trait, small farms using mostly family labor often do not pay the market value for this factor, and thus will likely not want to pay the market value price for a one unit reduction of it. Average willingness to pay related to yield increases for farms with low revenues is 2.44 per extra bushel. This is the amount of dollars that would be paid for a variety which would provide one extra bushel of corn. (since the average price of corn in 2003/04 was 2.40 dollars per bushel (USDA 2004), this reflects a MWTP for the seed that is almost exactly one dollar for an extra dollar in yield).

Farmers in higher farm-revenue groups are willing to pay more for the mentioned traits than their low revenue counterparts. The relative magnitudes of the MWTP for traits in other farm-revenue groups reflect the same ordering as in the low-revenue group, however, willingness to pay for all traits increases monotonically with increases in the farm-revenue category.[26] The same is true for the standard deviation of the MWTP.

In addition, the significant standard deviation of the WTP for the yield, insecticide and herbicide saving traits tells us that, although these are valued traits among most farmers, a minority of them is willing to pay nothing for the traits. For the low revenue farms, these farmers represent about 6% for insecticide, 7% for yield and 11% for herbicide. Low or negative willingness to pay for these traits might be related to the high uncertainty associated with the levels of the traits due to weather variation and difficulty predicting pest infestations. Contradictory information about trait advantages might also be associated with the high heterogeneity in WTP for trait values.

[26] Several thresholds of farm-revenue categories were calculated and the results regarding monotonicity were not

Also, 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, such as might be the case for some of the high revenue farms.

From an opposite point of view, a minority of farmers are willing to pay much more than the average farmer for a dollar of savings in chemical inputs or for a dollar of extra-yield. Unobserved factors that could give rise to a high WTP for input savings include equipment cost savings, human safety, environmental safety and savings in management time (See Alston et. al. (2002) for a study about the WTP for these specific factors). These high WTP estimates also suggest that there might be some correlation among preferences for different factors. For example, savings in herbicide use might be associated with labor force savings. Overall, our results suggest that herbicide saving technologies have a much wider potential to be adopted.

7. CONCLUSION

This work offers a new approach to the adoption of GM crop varieties by adapting the econometric methodology of the characteristics-based demand literature, the mixed multinomial logit. The coefficient estimates of the MMNL model allow 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. Comparing the results from our MMNL model with results from standard adoption models demonstrates the importance of taking farm and farmer heterogeneity into account when estimating the demand for new technologies.

We show that farmers faced with the decision to adopt genetically modified corn seeds display heterogeneous preferences across different seed traits. Although they value herbicide and labor savings the most, the valuation of herbicide savings varies markedly across individuals. The value of the labor-saving trait is also significantly heterogeneous among the population; however, controlling for farm and farmer characteristics this heterogeneity disappears, and is reflected in a higher willingness to pay for this trait among "family farms". The common result that farm size affects technology adoption holds for Bt varieties but not for Ht ones. We further find that the willingness-to-pay for any given seed trait increases monotonically with farm size. The results also show that farmers 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 and marketability concerns are thus also helpful in explaining the choice of non-GM varieties.

Our use of a trait-based model to examine the adoption patterns of GM crop varieties among corn farmers in Minnesota and Wisconsin reveals results and lessons that classic adoption models cannot provide. This method holds considerable promise for deepening our

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sensitive to these changes.

understanding of agricultural biotechnology, or other types of innovations where traits are added to existing technologies. A trait based approach can also be used to identify sub-populations of potential adopters for extension services, to develop predictions of market shares for bundles of traits in a variety not yet on the market, and, because of its capacity to capture flexible substitution patterns among traits, to evaluate potential market power concerns associated with vertical or horizontal mergers of seed and chemical companies.

The traits-based approach needs further research innovation and refinement. For example, the methodology suggests the need for different types of survey questions than those that are commonly used in adoption studies, ones that help to identify more carefully farmer information sets with respect to traits and bundled varieties. In addition, attention to the effects of interactions across traits (e.g., input and labor saving in the case of corn) will be needed both in the modeling design and in the questionnaires. With those and other refinements, the trait-based approach developed in this paper can be a foundation for technology adoption studies that provide a more appropriate and meaningful specification of the many factors influencing adoption outcomes.

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Table 1. Transition Matrix of Corn Variety Adoption – 2003, 2004 Among Minnesota and Wisconsin Grain Producers

		2004				
		HT-Corn	Bt-Corn	Both Ht+Bt	No GMO	Total
2003	HT-Corn	8.9	0.2	2.6	3.0	14.8
	Bt-Corn	0.2	14.3	5.1	1.6	21.2
	Both Ht+Bt	1.6	2.5	19.4	0.7	24.1
	No GMO	2.9	2.2	1	33.7	39.9
	Total	13.7	19.3	28.1	39.0	100

Table 2. Descriptive statistics for all varieties, farm and farmer characteristics

VARIABLE	MEAN	STD. DEV.	MIN	MAX
TRAITS				
SEED PRICE ($/A)	38.8	8.5	25.0	55.0
YIELD (BU/A)	125.0	11.6	72.9	145.9
INSECTICIDE USE ($/A)	5.3	4.0	0.0	80.9
HERBICIDE USE ($/A)	21.5	8.0	0.0	75.0
LABOR USE ($/A)	43.0	30.9	16.2	482.3
TOTAL OPERATED ACRES	363.1	487.7	2.0	6500
SHARE OF TOTAL FARM LABOR BY IMMEDIATE FAMILY				
ALL	0.76	0.43	0.0	1.0
>= 50 %	0.20	0.40	0.0	1.0
< 50 %	0.03	0.18	0.0	1.0
TOTAL FARM RECEIPTS				
< $50,000	0.35	0.48	0.0	1.0
>= $50,000 AND < $100,000	0.16	0.37	0.0	1.0
>= $100,000	0.49	0.50	0.0	1.0
HIGHEST EDUCATIONAL LEVEL ACHIEVED BY PERSON TAKING DECISIONS – SHARE BY LEVEL				
ATTENDED GRADE SCHOOL OR SOME HIGH SCHOOL	0.08	0.27	0.0	1.0
HAS A HIGH SCHOOL DIPLOMA OR EQUIVALENT	0.38	0.49	0.0	1.0
WENT TO A TWO YEAR COLLEGE, TO TRADE SCHOOL OR A FORMAL APPRENTICESHIP PROGRAM	0.39	0.49	0.0	1.0
COMPLETED A 4-YEAR COLLEGE DEGREE	0.11	0.32	0.0	1.0
HAS SOME GRADUATE STUDIES OR GRADUATE DEGREE	0.04	0.18	0.0	1.0
SHARE OF FARMERS HIGHLY CONCERNED ABOUT ENVIRONMENTAL OR SAFETY	0.14	0.34	0.0	1.0

ISSUES OF GM VARIETIES

- *N=1189* Sources: PATS Survey, 2004 and US Agricultural Census, 1997.

Table 3. Conditional (Fixed Effects) Logit

EXPLANATORY VARIABLE [A]	COEFFICIENT I	COEFFICIENT II
SEED PRICE	-0.055**	-0.067**
	(0.003)	(0.014)
LABOR USE	-0.04**	-0.039**
	(0.008)	(0.008)
INSECTICIDE USE	-0.069*	-0.066*
	(0.037)	(0.035)
HERBICIDE USE	-0.045**	-0.043**
	(0.016)	(0.016)
YIELD ADVANTAGE	0.188**	0.189**
	(0.019)	(0.019)
AVERAGE EFFECT OF UNINCLUDED FACTORS ON PROB OF GROWING NON-GM (γ_{NG})	--	-0.034 (0.269)
COMBINED HT&BT AVERAGE UNOBSERVED EFFECTS (γ_{HB})	--	0.485** (0.074)
LOG LIKELIHOOD [B]	-1517.67	-1496.76
PROB> CHI2	0.000	0.000
OBSERVATIONS	1181	1181

[a] Standard errors are in parenthesis underneath each coefficient.

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

Table 4. Mixed Multinomial Logit

EXPLANATORY VARIABLE [A]	AVERAGE B	STDDEV B
	III	III
SEED PRICE	-0.075**	-0.001
	(0.017)	(0.011)
LABOR USE	-0.044**	-0.015
	(0.013)	(0.034)
HERBICIDE USE	-0.118**	0.097**
	(0.039)	(0.049)
INSECTICIDE USE	-0.091**	0.059**
	(0.02)	(0.02)
YIELD ADVANTAGE	0.311**	0.209**
	(0.048)	(0.052)
NON-GM AVERAGE EFFECTS	-0.045	-
OF UNINCLUDED FACTORS (γ_{NG})	(0.306)	-
COMBINED HT&BT AVERAGE	0.433**	-
UNOBSERVED EFFECTS (γ_{HB})	(0.078)	-
LOG-LIKELIHOOD	-1417.20	
OBSERVATIONS	1181	

[a] Standard errors are in parenthesis underneath each coefficient.

Table 5. Log Likelihood Ratio (LR) Tests

MODELS TESTED	LL(I)	LL(II)	LL(III)	LR	DF	X^2 (α=5%)
I – II	1517.67	1496.76	--	41.82	2	5.99
II – III	--	1496.76	1417.20	159.12	5	11.07

Table 6. a.) Mixed Logit with Farm and Farmer Characteristics

EFFECT OF TRAITS ON THE PROBABILITY OF ADOPTION OF A CORN VARIETY	MMNL AVERAGE B	MMNL STDDEV B
SEED PRICE		
PRICE * FARM_RECEIPTS < 50.000	-0.096**	--
	(0.015)	--
PRICE * 50000 >= FARM_RECEIPTS < 100.000	-0.067**	--
	(0.016)	--
PRICE * 100000 >= FARM_RECEIPTS	-0.049**	--
	(0.015)	--
LABOR USE		
LABOR USE * (FARMS WITH ALL FAMILY LABOR)	-0.038**	--
	(0.012)	--
LABOR USE * (FARMS WITH > 50% FAMILY LABOR)	-0.056**	--
	(0.019)	--
LABOR USE * (FARMS WITH < 50% FAMILY LABOR)	0.003	--
	(0.061)	--
YIELD ADVANTAGE	0.234**	0.168**
	(0.039)	(0.041)
INSECTICIDE USE	-0.074**	0.057**
	(0.029)	(0.027)
HERBICIDE USE	-0.152**	0.114**
	(0.042)	(0.049)
NON GMO AVERAGE UNOBSERVED EFFECTS (γ_{NG})	0.432	--
	-0.355	--
HT&BT AVERAGE UNOBSERVED EFFECTS (γ_{HB})	-0.436	--
	(0.263)	--

[a] Standard errors are in parenthesis underneath each coefficient.

Table 6b.) Mixed Logit with Farm and Farmer Characteristics (Continued)

EFFECT OF FARM & FARMER CHARACTERISTICS ON THE ADOPTION OF A GM-VARIETY (RELATIVE TO THE EFFECT ON NON-GM)	MMNL	
	AVERAGE B	**STDDEV B**
OPERATED ACRES ON HT	-0.037	--
	(0.045)	--
OPERATED ACRES ON BT	0.121**	--
	(0.032)	--
OPERATED ACRES ON HT&BT	0.195**	--
	(0.031)	--
EDUCATION ON HT	0.08	--
	(0.09)	--
EDUCATION ON BT	0.11	--
	(0.089)	--
EDUCATION ON HT&BT	0.22**	--
	(0.095)	--
CONCERN ABOUT ENVIRONMENT/SAFETY ISSUES ON HT	-1.277**	--
	(0.332)	--
CONCERN ABOUT ENVIRONMENT/SAFETY ISSUES ON BT	-0.821**	--
	(0.276)	--
CONCERN ABOUT ENVIRONMENT/SAFETY ISSUES ON HT/BT	-2.347**	--
	(0.401)	--
MEAN LOG-LIKELIHOOD	-1382	
NUMBER OF CASES	1181	

[a] Standard errors are in parenthesis underneath each coefficient.

Table 7. Mean Willingness to Pay for Traits

		VARIABLE UNIT	MWTP FOR 1 UNIT	STD. DEV.
IF FARM_REVENUE < $50.000				
WTP FOR ……	YIELD (BUSHELS)	1 BU /ACRE	2.44	1.76
	YIELD ($)	1 $ /ACRE	0.98	0.70
	INSECTICIDE SAVINGS	1 $ /ACRE	0.78	0.59
	HERBICIDE SAVINGS	1 $ /ACRE	1.59	1.19
	LABOR SAVINGS			
	I. FARMS WITH ONLY FAMILY LABOR	1 $ /ACRE	0.40	--
	II. FARMS WITH > 50% FAMILY LABOR	1 $ /ACRE	0.59	
IF $ 50000 >= FARM_REVENUE < $100.000				
WTP FOR ……	YIELD (BUSHELS)	1 BU /ACRE	3.50	2.52
	YIELD ($)	1 $ /ACRE	1.40	1.01
	INSECTICIDE SAVINGS	1 $ /ACRE	1.11	0.85
	HERBICIDE SAVINGS	1 $ /ACRE	2.28	1.71
	LABOR SAVINGS			
	I. FARMS WITH ONLY FAMILY LABOR	1 $ /ACRE	0.57	--
	II. FARMS WITH > 50% FAMILY LABOR	1 $ /ACRE	0.84	
IF $100000 >= FARM_REVENUE				
WTP FOR ……	YIELD (BUSHELS)	1 BU /ACRE	4.75	3.42
	YIELD ($)	1 $ /ACRE	1.90	1.37
	INSECTICIDE SAVINGS	1 $ /ACRE	1.51	1.16
	HERBICIDE SAVINGS	1 $ /ACRE	3.09	2.32
	LABOR SAVINGS			
	I. FARMS WITH ONLY FAMILY LABOR	1 $ /ACRE	0.78	--

II. FARMS WITH > 50% FAMILY LABOR	1 $ /ACRE	1.14

* Assuming price per bushel of corn is 2.5 dollars.