The Effect of Label Information on Farmers' Pesticide Choice

Tomas Hasing
Former Graduate Research Assistant, Department of Applied Economics and Statistics,
Clemson University, Clemson, SC 29634.

Carlos E. Carpio
Assistant Professor, Department of Applied Economics and Statistics,
Clemson University, Clemson, SC 29634, ccarpio@clemson.edu

David B. Willis
Associate Professor, Department of Applied Economics and Statistics,
Clemson University, Clemson, SC 29634, willis9@clemson.edu

Olha Sydorovych
Researcher, Department of Agricultural and Resource Economics,
North Carolina State University, Raleigh NC, 27695, obsydoro@ncsu.edu

Michele Marra
Professor, Department of Agricultural and Resource Economics,
North Carolina State University, Raleigh NC, 27695, michele_marra@ncsu.edu

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Denver, Colorado, July 25-27, 2010

The Effect of Label Information on Farmers' Pesticide Choice

Abstract

The general objective of this study was to analyze the effect of labeling information on farmers' herbicide choice. Herbicide choices made by farmers were used to estimate their willingness to pay for different herbicide attributes. Estimation results indicate that human health and environmental statements displayed on pesticide labels (which reflect higher level of risk) are important components in herbicide selection. For example, it is estimated that farmers are willing to pay, on average, \$27 per acre to avoid using an herbicide with the word "Warning" and \$38 per acre to avoid using an herbicide with the word "Danger."

Keywords: mixed logit, household production models, non-nested models.

The Effect of Label Information on Farmers' Pesticide Choice

Farmers rely on pesticides to increase agricultural productivity and profits and reduce production risks. As a result, pesticides have become an important agricultural input throughout the world, particularly in the U.S. In 2001, the U.S. agriculture sector used 675 million pounds of active ingredient at a cost of over 7.4 billion dollars which accounts for about 23% of the pesticide world market (Kiely et al., 2004). However, as history has shown, the incorrect use of pesticides can also have some negative effects. For instance, pests can become resistant to pesticides and pesticides can harm and non-target plants and animals (Delaplane, 2000).

Pesticide labeling is one of the measures designed to regulate the use of pesticides and correct some of the externalities that arise from incorrect use. Although the Federal Insecticide, Fungicide and Rodenticide Act (FIFRA) of 1947 established standards for label content, it was not until 1972 that specific methods and standards for control were imposed (Whitford et al., 2004). For example, the use of any pesticide inconsistent with the label was prohibited and violations could result in fines and/or imprisonment. Pesticides were also classified for general or restricted use. Any person (commercial applicators or farmers) applying restricted-use pesticides were required to be certified by the state. Later, as a consequence of the workers "Right to Know" movement in the mid 1970's, the Federal Hazard Communication Standard was promulgated in 1983. This law requires pesticide manufacturers to create material safety data sheets (MSDS) and distribute them to downstream users of their products (Sattler, 2002). Each MSDS includes information regarding the physical properties of the pesticide, toxicity, health effects, first aid, reactivity, storage, disposal, protective equipment, and spill handling procedures.

More generally, product labeling can be seen as policy tool associated with the provision of health and environmental information (Teisl and Roe, 1998) to align individual consumer choices with social objectives (Golan et al., 2000). For this reason, consumers' responses to the information displayed on food product labels have been studied extensively. However, to the best of our knowledge, none or little research has been conducted related to the effect of label information on pesticide choice by farmers.

Previous studies intending to determine the importance of human safety and environmental characteristics on herbicide choice have relied on information displayed on the MSDS and/or in very specialized scientific literature (Higley and Wintersteen, 1992; Lohr et al., 1998; Owens, 1998; Beach and Carlson, 1993; Fernandez-Cornejo and Jans, 1995; Hubbell and Carlson, 1998; Sydorovych and Marra, 2007, 2008; Carpio et al., 2007). In this paper we focus on the importance of human safety and environmental information displayed exclusively on the pesticide label.

The general objective of this study is to estimate the effect of labeling information on farmers' pesticides choice. Specific objectives are: 1) To estimate the relative importance of costs, weed control efficiency, and human safety and environmental attributes displayed on the label on farmers' pesticide choice; 2) To estimate farmers' willingness to pay (*WTP*) for each attribute; and 3) To compare the performance of models based on label information with models based on information available in MSDS's and/or other sources of information.

This study focuses on U.S. farmers' choice of herbicides for soybean production. Herbicides are the most used pesticide in the U.S., accounting for more than two thirds of the market for pesticides in the country. Moreover, soybean producers are one of the most intensive users of herbicides (the sector uses about 50 million pounds per year) (Kiely et al., 2004).

Understanding farmers' response to label information is important for policy makers, such as the Environmental Protection Agency (EPA), who attempt to protect fragile ecosystems and improve human safety though the use of mandatory labeling laws. Golan et al. (2000) argue that an efficient pesticide labeling policy may enhance economic efficiency by helping producers target expenditures toward products they most highly value. In addition, information displayed on labels may reduce externalities that arise from the social consequences of farmer's decisions on the environment, health and productivity. In this context, it is important to determine whether or not current labels information provide farmers with sufficient information to guide their pesticide choices given their risk level.

Pesticides' Labels

In the U.S., the Environmental Protection Agency (EPA) regulates the registration, manufacture, sale, transportation, use and labeling of pesticides under the authority of two federal statutes: the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA) and the Federal Food, Drug, and Cosmetic Act (FFDCA). The EPA establishes standards for location and content of label information corresponding to the following four categories: 1) safety information, 2) environmental information, 3) product information, and 4) use information. Different sections of the label, relevant to this study, are shown on Figure 1 and are briefly described below in the order they appear.

Use classification (A). Pesticides are classified either for "general-use" or "restricted-use". In order to purchase, apply or supervise the application of a restricted-use pesticide, applicators are required to receive proper training and obtain certification.

Signal Word (B). The signal word indicates the approximate toxicity of the pesticide product. It is determined by the most severe toxicity category assigned to five toxicity studies: acute oral toxicity, acute dermal toxicity, acute inhalation toxicity, primary eye irritation and primary skin irritation (Table 1). From the highest to the lowest toxicity level, the signal words and their corresponding associated toxicity categories are: toxicity category I: DANGER, toxicity category II: WARNING, toxicity category III: CAUTION, and toxicity category IV: None Required.

"Skull & Crossbones" symbol and the word "POISON" (C). The word "POISON" and the "skull and crossbones" symbol are required for products classified as toxicity category I for acute oral, acute dermal or acute inhalation toxicity.

Precautionary Statements (D). There are three types of precautionary statements: hazards to humans and domestic animals (D1), environmental hazards (D2), and physical or chemical hazards (D3).

Hazards to Humans and Domestic Animals statements are required when any acute toxicity study results in a product classification of toxicity category I, II, or III. In this case, the proper statement must be shown according to Table 1. Additionally, if a dermal sensitization test is positive for the product, the following statement is displayed: "*Prolonged or frequently repeated skin contact may cause allergic reactions in some individuals*".

The environmental hazard label section provides the precautionary language advising of potential hazards to the environment from transport, use, storage, or spill of the product. Specifically, the following type of label advisories can be included in this part of the label: groundwater statement, surface water statement, bird and mammal hazard statement, fish/aquatic invertebrate statement, honey-bee hazard statements.

Finally, the physical or chemical hazards label section addresses flammability, explosive potential and precautions. The statements: "Extremely flammable", "Flammable", "Combustible" or "Contents under pressure" are displayed according to the criteria set out in the regulations.

Theoretical and Empirical Models

The theoretical framework in this study uses a random utility model (RUM) and the agricultural household model. Within the context of the agricultural household model when farmers select herbicide $h \epsilon \mathcal{H} = \{1, \ldots, H\}$, they face two situations: 1) as consumers, the application of herbicide h might affect their utility by altering human health and/or affecting the environment, and 2) as producers, application of herbicide h affects profits that in turn affect utility through consumption (Singh et al., 1986). In addition, according to the RUM, a farmer i in choice occasion t is assumed to choose the herbicide h^* that provides the greatest utility $U^*_{i,t,h}$ among all herbicide choices. The indirect utility function for herbicide choice can be written as:

$$U^*_{ith}\big(\boldsymbol{x}_{ith}, \boldsymbol{z}_{ith}, c_{ith}(p_{ithh}, \boldsymbol{w}_{ith})\big), \qquad (1)$$

where $c_{ith}(.)$ is a composite commodity whose level is in turn affected by $\boldsymbol{w}_{ith}$, a vector of production attributes of the herbicide, and p_{ith} the cost per acre of the herbicide; $\boldsymbol{x}_{ith}$ is a vector of herbicide characteristics affecting the environment; and $\boldsymbol{z}_{ith}$ is a vector containing human safety characteristics such as acute toxicity levels. The reduced form of the indirect utility function is:

$$U^*_{ith}\big(p_{ith}, \boldsymbol{x}_{ith}, \boldsymbol{z}_{ith}, \boldsymbol{w}_{ithh}\big) = U^*_{ith}(\boldsymbol{\gamma}_{ithh}), \qquad (2)$$

where $\boldsymbol{\gamma}'_{ith} = [p_{ith} \quad \boldsymbol{w}'_{ith} \quad \boldsymbol{x}'_{ith} \quad \boldsymbol{z}'_{ith}]$. Since not all the variables in $U^*_{ith}(.)$ are observed, farmer's utility can be written as $U^*_{ith} = V_{ith} + \varepsilon_{ith}$ where $V_{ith}(\boldsymbol{\gamma}_{ith})$ is the portion of utility that only includes observed attributes and ε_{ith} captures the effect of the factors not included in V_{ith}.

Assuming each ε_{ith} is independently, identically distributed extreme value with cumulative distribution function $F(\varepsilon_{ith}) = e^{-e^{-\varepsilon_{ith}}}$, and that V_{ith} is a linear function of the characteristics ($V_{ith} = \boldsymbol{\beta_i}'\boldsymbol{\gamma}_{ith}$), the probability that farmer i chooses herbicide h in choice occasion *t*, conditional on the coefficient vector $\boldsymbol{\beta_i}$ is (Train, 1998):

$$P_{ith}(\boldsymbol{\beta_i}) = \frac{e^{\beta_i{}'\gamma_{ith}}}{\sum_h e^{\beta_i{}'\gamma_{ith}}}. \tag{3}$$

Since a farmer makes several herbicide applications during the crop growing season, we need the probability of each farmer's sequence of observed choices. Let *h*(*i*,*h*) denote the herbicide that farmer *i* chose in period *t*. Conditional on $\boldsymbol{\beta_i}$, the probability of farmer *i*'s observed sequence of choices is (Revelt and Train, 1998):

$$S_i(\boldsymbol{\beta_i}) = \prod_t P_{ith(i,t)}(\boldsymbol{\beta_i}). \tag{4}$$

The coefficient vector $\boldsymbol{\beta_i}$ is unobserved for each farmer *i* and varies in the population with density $f(\boldsymbol{\beta_i}|\boldsymbol{\theta})$ where $\boldsymbol{\theta}$ are the true parameters of the distribution. Therefore, the unconditional probability of the sequence of choices is:

$$Q_i(\boldsymbol{\theta}) = \int S_i(\boldsymbol{\beta_i}) f(\boldsymbol{\beta_i}|\boldsymbol{\theta}) d\boldsymbol{\beta_i}. \tag{5}$$

The log-likelihood function is $\text{LL}(\boldsymbol{\theta}) = \sum_{\boldsymbol{n}} \boldsymbol{ln}\, Q_i(\boldsymbol{\theta})$. Since the integral in (5) cannot be calculated analytically, estimation can be carried out using simulated maximum likelihood or Bayesian procedures (Train, 1998; Train, 2003; Rigby and Burton, 2006). Notice that in contrast to the conventional logit model, farmers' preferences apply to each choice situation but vary across farmers. Moreover, as shown in Train (2003) this version of the logit model allows for correlation of choices over time. This is important because the data set used for estimation presents farmer's choices of herbicides at different crop growth stages. For example, the pre-emergent herbicide used will likely influence the future weed population, and the subsequent selection of the post-emergent herbicide.

Empirical Model and Data

Herbicide Choice Data

Data on farmers' pesticide use were obtained by a telephone survey of soybean producers conducted by Doane's Market Research in cooperation with North Carolina State University in 2002. Surveys of 610 farmers from 19 states revealed 1,770 herbicide choices for three crop stages: pre-planting, pre-emergence and post-emergence. The surveyed states accounted for 93% of planted U.S. soybean acreage in 2002. States were fairly represented in the sense that the number of respondents from each state was proportional to the state share of the national soybean acreage. The survey also collected information regarding producers' demographics and farm operation characteristics.

Herbicides Characteristics Data and Variables

Empirical implementation of models (2) and (3) required data collection for four sets of herbicides characteristics: herbicide cost, herbicide production, and environmental, and human safety attributes. In this section we present a detailed description of the characteristics included in each set of attributes and the sources of information.

Herbicide costs (p_h). Herbicides contain varying amounts of different active ingredients are applied at different rates; therefore, comparisons between prices per unit (gallon or pound) of commercial formulations or active ingredients do not provide useful information. In the model, the price of each herbicide was adjusted by the recommended application rate for soybeans to obtain standardized per acre prices. Additionally, field application costs of the herbicide were converted to a per acre basis.

Production Attributes ($\boldsymbol{w}_h$). Four variables related to production attributes were included in the model. Two variables measure the efficacy to control grass weeds in pre-emergence applications:

one for grass weeds and another for broadleaf weeds. The other two additional variables measure an herbicide effectiveness to control grass and broadleaf weeds in post emergence applications. All variables are continuous and can take values from 0 to 100. These variables were constructed using information on the ratings of herbicide effectiveness against individual weeds (Zandstra et al., 2004) and the importance of the weeds in each soybean growing regions (Meyer et al., 2006). These measures are average effectiveness measures since the survey did not contain information on the specific weeds the farmers were trying to control.

Human and Environmental Characteristics ($\boldsymbol{x}_h$ and $\boldsymbol{z}_h$). Previous studies analyzing the effect of human and environmental characteristics on farmer herbicide choice have assumed farmers' knowledge of pesticides characteristics beyond the information provided by the label (Figure 1). In these studies farmers were assumed to have access to the information provided in the MSDS and/or other specialized scientific sources. Given our research focus, two models using different sets of human and environmental characteristics were estimated: Model I includes only the information reflected in the labels, and Model II is constructed using variables from the MSDS (see Tables 3 and 4) and other specialized sources.

Human Safety Attributes in Model I ($\boldsymbol{z}_h$). The most distinctive human safety information is related with the "signal word" which reflects the danger level of the herbicide using four toxicological categories. In Model I, dummy variables were used to indicate the presence or not of the words "Danger" and "Warning" (with "Caution" taken as the base).

Human safety information is also presented in the statements from the "Hazards to Humans and Domestic Animals" label section. Hence, dummy variables were used to indicate the presence of any of the following hazards to humans and domestic animal statements: Oral, Dermal, Inhalation, Eye and Skin.

Human Safety Attributes in Model II ($\boldsymbol{z}_h$). If farmers fully understand the information from the MSDS, they would be able to differentiate not only between herbicides that fall in different toxicological categories (Table 1), but also between herbicides in the same category with small differences in toxicity. For example, although the inhalation toxicities for the herbicides halosulfuron and pendimethalin fall in the IV toxicity category, farmers would recognize that for this type of toxicity pendimethalin is safer (LC_{50} = 320) than halosulfuron (LC_{50} = 2.2).[1] Therefore, in this model the indicator variables "oral", "dermal", "inhalation" were replaced by their continuous counterparts. "Oral" was replaced by the variable Oral LD_{50}. Similarly, "dermal" was replaced by dermal LD_{50} and "inhalation" by inhalation LC_{50}**.** Dummy variables indicating the presence of "eye" and "skin" hazards to humans and domestic animal statements were kept in these models since the MSDS does not include more detailed information related to these variables.

Finally, two other human safety characteristics common to Models I and II were the presence of the "restricted use" statement and the presence of the dermal sensitization statement. Dummy variables were created to indicate the presence of these statements.

Environmental attributes in Model I ($\boldsymbol{x}_h$). Even though pesticide labels may display several statements related to their environmental properties, the set of herbicides included in our sample only displayed statements of risk of water contamination at the surface and underground levels, and the level of toxicity to fish and aquatic invertebrates. None of the herbicides in the sample contained statements regarding "bird and mammal" or "honey-bee" hazards. Therefore, dummy variables were used to indicate the presence of statements advising hazards to fish or aquatic invertebrates and groundwater and surface water advisories**.**

[1] LD in LC_{50} stands for "lethal dose" and LC in LC_{50} stands for "lethal concentration." LD_{50} and LC_{50} are standard values for comparing the toxicity of chemicals and correspond to the amount (or concentration) that kills 50% of a group of test animals. Note that the larger these values, the lower the toxicity.

Environmental attributes in Model II ($\boldsymbol{x}_h$). The selection of the variables to include as environmental attributes in model II was complicated by the fact that the mandatory MSDS format from OSHA[2] does not require any environmental or ecological information. Hence, there is much variability regarding the type and detail of pesticides' environmental characteristics available in their MSDS. For example, whereas about 80% of the MSDS of the pesticides included in the study contain the results of toxicological tests on animals (LD50s or LC50s for mammals, fish or bees), only 23% presented parameter values for pesticides' physical and chemical properties related with their potential to contaminate water. Hence, the detail of information to be included in this section depends on how much information the investigator is willing to assume that is available to the producer or how much information she knows.

Regarding pesticides toxicity to animals and consistent with Model I we included toxicity measures for mammals (already included as human safety attributes), fish (acute LC_{50} mg/l), bees (acute LD_{50} µg/bee) and birds (acute LD50 mg/kg). Three specialized variables related to surface water and groundwater contamination were included. These variables were chosen based on published literature, EPA regulations and information availability (Beach and Carlson, 1993; Hubbell and Carlson, 1998; Sydorovych and Marra, 2007, 2008). The first specialized variable is K_{oc} which measures how well chemicals are absorbed by soil particles. Since K_{oc} measures the tendency of chemicals to attach to soil particle surfaces, high values are negatively related to a chemical's ability to get in solution and contaminate surface water via runoff or soil leaching into groundwater (Monaco et al., 2002). The second specialized variable used to measure the potential of a pesticide to impact water is the chemical's soil-life ($t_{1/2}$). The chemical soil life measures the time necessary (in days) for the pesticide to be degraded to 50% of its original

[2] OSHA MSDS format is available online at http://www.osha.gov/dsg/hazcom/msds-osha174/msdsform.html

concentration under given soil conditions. The third and final specialized variable used to describe a pesticide potential to contaminate water sources is water solubility. Water solubility describes the amount of pesticide that will dissolve in a known amount of water (mg/l). The higher the solubility value, the more soluble the pesticide (Vogue et al., 1994; Wauchope, et al., 1992; Augustijn-Beckers, 1994).

Distribution of Random Parameters in the Logit Model

An important element of mixed logit models is the assumption regarding the distribution of the random parameters ($f(\boldsymbol{\beta_i}|\boldsymbol{\theta})$ in equation (5)). The distributions used in this study are based on our expectations regarding individuals' behavior as well a preliminary evaluation of results from different distribution specifications. Expected signs for the marginal effects of the variables in the discrete models can be determined by examining whether attribute variables affect environment and human health, production, or both (tables 2 and 3). In both models, production attributes are expected to have positive impacts and price is expected to have a negative effect since a higher price of the herbicide reduces profits. Moreover, in both models environmental and health precautionary statements are also expected to have negative impacts. In model I, the dummy variables for "danger" and "warning" are expected to have negative impact since their effect is measured relative to "caution." In model II, human or environmental safety attributes measured using LD_{50} or LC_{50} values are expected to have positive effects since the higher their values the lower the toxicity of the herbicide. Finally, for model II, since soil life, solubility and K_{oc} contribute both to the environmental and health impacts (negative effects) and to productive benefits of the herbicides (positive effects), the sign of the net effect is uncertain (Hubbell and Carlson, 1998).

In order to ensure that the *WTP* estimate of each attribute have the expected sign for every decision maker, the initial specification of the mixed logit models used truncated normal distributions for the parameters corresponding to dummy variables (Revelt, 1999) and lognormal distributions for the parameters corresponding to production, health and environmental characteristics that are continuous (Train, 1998), except for the parameters corresponding to K_{oc}, water solubility and soil-life that were assumed to be normal. The price parameter was assumed to be fixed to facilitate the estimation of the distributions of *WTP* (Train, 1998; Train, 2003; Hensher, Shore and Train, 2004). However, in the final specifications of the mixed logit models some of the parameters corresponding to dummy variables were estimated as fixed since we encountered several problems with convergence and/or unreasonably high estimates for the standard deviations of the distributions.

Comparison of Competing Models

Given that the sets of explanatory variables included in models I and II are different, the two models are non-nested. In order to compare the models we used the likelihood ratio test proposed by Vuong (1989). Since a subset of the explanatory variables is common to both models, these models belong to the class of overlapping non-nested models. Vuong's approach considers two conditional models $\boldsymbol{F_\theta} = \{f(y|\boldsymbol{z};\theta);\ \theta\epsilon\Theta\}$ and $\boldsymbol{G_\gamma} = \{g(y|\boldsymbol{z};\gamma);\ \gamma\epsilon\Gamma\}$, where $f(.|.)$ and $g(.|.)$ are conditional distributions, *y* is the dependent variable, ***z*** is a vector of explanatory variables and θ and γ are parameters. Then the test for model selection is based on the likelihood ratio (LR) statistic:

$$LR(\hat{\theta}_n,\hat{\gamma}_n) = \sum_{i=1}^{n} log\,\frac{f(Y_i|Z_i;\hat{\theta}_n)}{g(Y_i|Z_i;\hat{\theta}_n)}\,. \tag{6}$$

For overlapping models Voung proposes a sequential procedure which consists in testing first if $f(.|.;\theta_*)$ = $g(.|.;\gamma_*)$ (θ_* and γ_* are the pseudo-true values corresponding to θ and γ, respectively) and then using the null distribution of $LR(\hat{\theta}_n, \hat{\gamma}_n)$ to construct a model selection test. These two steps can be summarized as follows:

1) Since $f(.|.;\theta_*) = g(.|.;\gamma_*)$ if and only if the variance of $log[f(Y_i|Z_i;\theta_*)/g(Y_i|Z_i;\gamma_*)]$, w_*^2=0, then the test is based on the variance statistic:

$$\widehat{w}_n^2 = \frac{1}{n}\sum_{i=1}^{n}\left[\log\frac{f(Y_i|Z_i;\hat{\theta}_n)}{g(Y_i|Z_i;\hat{\theta}_n)}\right]^2 - \left[\sum_{i=1}^{n}\log\frac{f(Y_i|Z_i;\hat{\theta}_n)}{g(Y_i|Z_i;\hat{\theta}_n)}\right]^2, \qquad (7)$$

and the fact that under the null hypothesis (H_o^w: w_*^2=0), for any $x \geq 0$,

$Pr\ (n\widehat{w}_n^2 \leq x) - M_{p+q}(x;\hat{\lambda}_n^2) \xrightarrow{a.s.} 0$, where $M_{p+q}(.;\hat{\lambda}_n^2)$ is a weighted sum of chi-square distribution with parameters p+q and $\hat{\lambda}_n^2$ (the formulas and the procedure to calculate $\hat{\lambda}_n^2$ is available in Voung (1989)). Hence, the variance test consists in choosing a critical value *x* so that $M_{p+q}(x;\hat{\lambda}_n^2) = 1 - \alpha\%$. If H_o^w: w_*^2=0 is not rejected, conclude that $\boldsymbol{F_\theta}$ and $\boldsymbol{G_\gamma}$ cannot be discriminated given the data. If H_o^w is rejected continue to the second step.

The second step tests the null hypothesis that the two models are equivalent (H_o) against the alternative that $\boldsymbol{F_\theta}$ is better than $\boldsymbol{G_\gamma}$ (H_f) or against the alternative that $\boldsymbol{G_\gamma}$ is better than $\boldsymbol{F_\theta}$ (H_g). Under H_o $n^{-1/2}\ LR(\hat{\theta}_n, \hat{\gamma}_n)/\widehat{w}_n^2 \xrightarrow{D} N(0,1)$. Under H_f and H_g $n^{-1/2}\ LR(\hat{\theta}_n, \hat{\gamma}_n)/\widehat{w}_n^2$ converges asymptotically to +∞ and -∞, respectively. Hence, if the null hypothesis is rejected, positive values of the statistic provide evidence in favor of H_f and negative values provide evidence in favor of H_g. It is important to notice that compared to more traditional model selection approaches using a single measure (e.g., Akaike Information Criteria), Vuong's approach is probabilistic in nature and the distributional results can be used to indicate the strength of evidence in favor of either model.

Results

First we present the results of the test comparing the herbicide choice model based on the label information versus the model using information from the MSDS and other technical sources. The test was conducted under different assumptions regarding the error structure of the model and distributional assumptions for the parameters (see Table 4). In all cases, the tests reject the null hypothesis that Models I and II cannot be discriminated given the data (i.e., Step 1: $H_o^w: w_*^2 = 0$). The test also rejected the null hypothesis that both models are equivalent in favor of the alternative hypothesis that Model I is better than Model II (Step 2). Hence, we will focus our discussion on Model I (results for Model II are presented in the Appendix).

The parameters estimated for the mixed logit specification of Model I are reported in Table 5. The overall model is found to be statistically significant with a Chi-squared statistic of 2,044.56, which is well beyond the critical value of 27.59 ($\chi^2_{17,0.05}$). The fact that the standard deviations of the coefficients enter significantly is an indication that the mixed logit provides a significantly better representation of the choice situations compared to the standard logit, which assumes that the model coefficients are identical for all farmers (Hensher and Green, 2003).

When the parameters are assumed to be normally distributed or fixed, the estimated mean values under "model coefficient" in Table 5 are also the marginal utilities. However, when the estimated parameters are log-normal or truncated normal, the mean and standard deviation shown under this column are not marginal utility effects. In these cases the mean and variance of underlying parameters need to be transformed to generate the marginal effects in the utility function.[3] Marginal utilities associated with all attributes are shown under the "utility

[3] Formally, $V_{ith} = \boldsymbol{\beta_i}'\boldsymbol{\gamma_{ith}}$ from equation (3) becomes $V_{ith} = \boldsymbol{Z}(\boldsymbol{\beta_i})'\boldsymbol{\gamma_{ith}}$ where $\boldsymbol{Z}(\boldsymbol{\beta_i})$ is a vector of transformations depending on $\boldsymbol{\beta_i}$. Lognormal distributions and truncated normal distributions use ln(β) and max(0, β) as the transformations, with $\beta \sim N(\mu, \sigma^2)$. Hence the mean and standard deviations shown in Table 5 under "model coefficients" are estimates of μ and σ.

coefficients" column. For example, even though the mean value of the parameters corresponding to the efficiency measures to control weeds are all negative, the marginal effects in the utility function are all positive.

The estimated utility coefficients can then be used to calculate the amount that respondents are willing to pay, as evidenced through their choices, for a specific herbicide characteristic. The marginal willingness to pay (*WTP*) for a characteristic is the ratio of the marginal utility of a characteristics and the (negative of the) marginal of utility with respect to price. These values are shown in the last column of Table 5. Regarding the production characteristics, it is found that, except for the efficiency to measure control broadleaves during pre-emergent applications whose effect is found to be very small, each additional unit of efficiency to control weeds increases farmers average *WTP* to pay by about 0.13 $/acre.

In general, our results indicate that farmers' choice decisions are significantly affected by a herbicide human and environmental safety characteristics displayed on the label. In regard to the effects of the signal words, the mean *WTP* values shown in Table 5 for "Danger" and "Warning" are relative to the base signal word "Caution" not included in the model. Because these *WTP* values are negative they can be interpreted as the *WTP* to avoid using an herbicide with this signal word relative to "Caution." Thus farmers are willing to pay, on average, $27 to avoid using an herbicide with the word "Warning" and $38 to avoid using an herbicide with the word "Danger." The signal words for the environmental and human safety characteristics have the highest *WTP* values. This was expected since these are the most clearly identified characteristics in a pesticide label.

Since some of the distributions of the parameter estimates corresponding to "Danger" and "Warning" have overlapping confidence intervals, we formally tested the equality of the parameter values (mean and standard deviation estimates). Using a likelihood ratio test we rejected the null hypothesis that the parameters of the distributions corresponding to these variable are equal ($\chi^2(2) = 21.3$; p<0.001). This provides some evidence that farmers are able to differentiate between the toxicity levels for herbicides displaying the words “Danger” versus “Warning.”

The parameter corresponding to the “restriction” variable was not significantly different from zero. This result was consistent across model specifications (see also Appendix 1) but unexpected because a restricted herbicide requires hiring a commercial applicator or obtaining an official certification which results in higher production costs.

Model I suggests that the information displayed in the “hazard to humans and domestic animals” section has a significant effect on the probability of choosing a herbicide. In particular, the warning about possible acute dermal toxicity seems to be the main health concern since its *WTP* value of $24 is the highest among the *WTP* values related to the statements displayed in this section of the label. The average *WTP* to avoid a herbicide with an eye toxicity statement is $9/acre, $6/acre to avoid a herbicide with the skin sensitization (allergy) statement, and $4/acre to avoid the presence of an inhalation toxicity statement. *WTP* values for oral acute toxicity or skin irritation statements are not economically important.

In addition to production characteristics and health risk information, two environmental statements have an economically significant effect on the decision to choose an herbicide: groundwater and surface water advisories. The *WTP* to avoid herbicides with these statements is $15 and $14, respectively. The *WTP* to avoid a herbicide with a statement advising hazards to fish or aquatic invertebrates is only $0.12.

Although the *WTP* estimates seem high relative to the average herbicide price of $10.81, these results are consistent with prior studies evaluating farmers *WTP* to avoid herbicides' environmental and human risk characteristics. For example, in a study examining farmer' *WTP* for herbicide safety characteristics using contingent valuation methods, Owens et al. (1998) found *WTP* values for some characteristics to be 280% higher than the original herbicide price. Their estimates of *WTP* for reductions in risk associated with a non-carcinogenic formulation of an herbicide ranged from $4.92 to $8.47 per acre compared to a baseline price of $3 per acre. For a non-leaching formulation, *WTP* ranged from $4.40 to $7.70 per acre; and for the non-toxic to fish formulation, WTP ranged from $3.94 to $6.81 per acre. In another contingent valuation study, Higley and Winstersteen (1992) found *WTP* values of $12.54, $8.76 and $5.79 to avoid insecticides with high, moderate and low environmental risk characteristics, respectively. Insecticide costs were about $14 per acre. It is important to note that the marginal *WTP* estimates assume that the remaining characteristics do not change which in practice might not be the case. For example, if the level of toxicity is negatively correlated with efficiency, farmers *WTP* for safer herbicides will be lower after compensating for the loss in efficiency.

Summary and Conclusions

The general objective of this study was to analyze the effect of labeling information on farmer herbicide choice. Our theoretical and empirical models of herbicide choice are developed within the context of the agricultural household model and the discrete choice random utility model. Herbicide choices made by farmers were used to estimate their preferences for different herbicide attributes by applying the mixed logit model procedure. The estimation of the theoretical models was based on a sample of U.S. soybean farmers. Characteristics of the herbicides used as explanatory variables included health and environmental characteristics displayed on herbicides' labels and efficiency measures calculated using relevant studies from the agronomic literature. Models estimated using information available on the labels were compared with models estimated with variables obtained from information provided by the MSDS's and other technical sources. This comparison was done to assess the assumption held in previous studies that farmers have a detailed and complete understanding of all the scientific measures used to evaluate the human and environmental risk of pesticide use (e.g., LD_{50} values).

Statistical results suggest that herbicide choice models using environmental and human safety characteristics displayed on the labels are superior to models using more technical measures of these characteristics. In other words, farmers' herbicides choices are better explained by the information displayed on the herbicide label than by published information presented in the MSDS or other technical sources. This result has implications for the specification of models evaluating the effect of pesticides characteristics on pesticide choices as well as models used to estimate individual *WTP* for these characteristics. *WTP* estimates obtained from models that are more consistent with observed choices should be preferred. Moreover, if regulatory agencies want farmers to base their herbicide choice decisions on the information displayed on MSDS, this information should be made more accessible to them. According to Sattler (2002), the average American has a sixth-grade reading level, but the MSDS's are written at a thirteen-grade reading level. In a literature review on the accuracy, comprehensibility, and use of MSDS, Nicol et al. (2008) concluded that that there are serious problems with the use of MSDSs as hazard communication tools. They also report studies in which U.S. workers understand less than 40% of the information on the MSDS's.

Results indicate that human health and environmental statements displayed on pesticide labels (which reflect higher level of risk) are important components in herbicide selection. For example, farmers are willing to pay, on average, $27 per acre to avoid using an herbicide with the word “Warning,” $38 per acre to avoid using an herbicide with the word “Danger,” and $15 per acre to avoid using herbicides with groundwater statements. These results suggest that pesticide companies should emphasize the research and development of new products with safer characteristics.

Understanding farmers’ response to label information is also important to policy makers who are interested in the effectiveness of their mandatory labeling laws. Our findings suggest that some of the information displayed pesticide labels is an important determinant of pesticide selection. However, we also unexpectedly found that labeling a herbicide as “restricted” does not affect its selection. This finding is puzzling, since this suggests that restricting a herbicide does not discourage its use. Additional research is needed to fully explain this result.

In summary, this paper contributes to the empirical valuation literature on pesticide risk exposure. Florax et al. (2005) note that very few studies have estimated farmers’ *WTP* values to avoid human and environmental risk characteristics.

References

Augustijn-Beckers, P.W., A.G. Hornsby, and Wauchope, R.D. 1994. The SCS/ARS/CES Pesticide Properties Database for Environmental Decision-Making. II: Additional Compounds. Reviews of Environmental Contamination and Toxicology 137:1-82.

Beach E. and G. Carlson. 1993. A Hedonic Analysis of Herbicides: Do User Safety and Water Quality Matter? American Journal of Agricultural Economics 75(3): 612-623.

Carpio, C., O. Sydorovych and M. Marra. 2007. Relative Importance of Environmental Attributes Using Logistic Regression. Southern Agricultural Economics Association Annual Meeting, February 4-7, 2007, Mobile, Alabama.

Delaplane, K. 2000. Pesticide Usage in the United States: History, Benefits, Risks, and Trends. University of Georgia Cooperative Extension Service, Bulletin 1121.

Fernandez-Cornejo, J. and S. Jans. 1995. Quality-Adjusted Price and Quantity Indices for Pesticides. American Journal of Agricultural Economics 77(3):645-659.

Florax, R., C. Travisi, and P. Nijkamp. ‘‘A Meta-Analysis of the Willingness to Pay for Reduction in Pesticide Exposure.’’ European Review of Agricultural Economics 32(2005):441–67.

Golan, E., F. Kuchler, and L. Mitchell. 2000. Economics of Food Labeling. Agricultural Economics Report No 793. Economic Research Service, USDA.

Hensher, D., N. Shore, and K. Train. 2005. Households’ Willingness to pay for Water Service Attributes. Environmental and Resource Economics 32(4):509-531.

Hensher, D., and W. Green. 2003. The Mixed Logit Model: The State of Practice. Transportation 30(2):133-176.

Higley, L. and Wintersteen, W. 1992. A Novel Approach to Environmental Risk Assessment of Pesticides as a Basis for Incorporating Environmental Costs into Economic Injury Levels. American Entomologist 38(1):34-39.

Hubbell, B. and Carlson, G. 1998. Effects of Insecticide Attributes on Within-Season Insecticide Product and Rate Choices: The Case of U.S. Apple Growers. American Journal of Agricultural Economics 80(2):382-396.

Lohr, L., T. Park and M. Wetzstein. 1998. Voluntary Economic and Environmental Risk Tradeoffs in Crop Protection Decisions. Agricultural and Resource Economics Review 27(1):108-116.

Keane, M. 1997. Current Issues in Discrete Choice Modeling. Marketing Letters 8(3): 307–322.

Kiely, T., D. Donaldson and A. Grube. 2004. Pesticides Industry Sales and Usage. 2000 and 2001 Market Estimates. U.S. Environmental Protection Agency. Washington, DC.

Meyer, J., M. Horak, E. Rosenbaum, R. Schneider. 2006. Petition for the Determination of Nonregulated Status for Roundup RReady2Yield™ Soybean MON 89788. Available at: http://www.aphis.usda.gov/brs/aphisdocs/06_17801p.pdf

Monaco, T., F. Ashton and S. Weller. 2002. Weed Science: Principles and Practices. John Wiley and Sons. 688 p.

Nicol, A., A. Hurrell, D. Wahyuni, W. McDowall and W. Chu. 2008. Accuracy, Comprehensibility, and Use of Material Safety Data Sheets: A Review. American Journal of Industrial Medicine 51(11):861-876.

Owens, N., S. Swinton, and E. van Ravenswaay. 1998. Farmers Willingness to Pay for Herbicide Safety Characteristics. American Agricultural Economics Association Annual Meeting, August 2-5 1998, Salt Lake City, UT 20942.

Revelt, D. 1999. Three Discrete Choice Random Coefficients Papers and One Policy Crime Study. Ph.D. Thesis, University of California, Berkley.

Revelt, D. and K. Train. 1998. Mixed Logit with Repeated Choices. Review of Economics and Statistics 80:647-657.

Rigby, D. and M. Burton. 2006. Modeling Disinterest and Dislile: A Bounded Bayesian Mixed Logit Model of the UK Market for GM Food. Environmental and Resource Economics 33:485-509.

Roka, F., M. Olexa, K. Smallwood, L. Polopolus, and C. Fountain. 2009. 2009 Handbook of Employment Regulations Affecting Florida Farm Employers and Workers: Occupational Safety and Health Act (OSHA) Hazard Communication Standard. EDIS Document FE409. Department of Food and Resource Economics, Florida Cooperative Extension Service, Institute of Food and Agricultural Sciences, University of Florida, Gainesville, FL. Available online at http://edis.ifas.ufl.edu/fe409, as of January 19, 2010.

Sattler, B. 2002. Finding Information About Chemicals in Our Environment. In Environmental Health and Nursing Practice. Edited by B. Sattler and J. Lipscomb. Springer Publishing Company. 87-98 p.

Singh, I., L. Squire and J. Strauss.1986. Agricultural Household Models: Extensions, Applications, and Policy. The Johns Hopkins University Press. 335 p.

Sydorovych, O and M. Marra. 2007. A Genetically Engineered Crop's Impact on Pesticide Use: A Revealed-Preference Index Approach. Journal of Agricultural and Resource Economics 32(3):476-491.

Sydorovych, O and M. Marra. 2008. Valuing the Changes in Herbicide Risks Resulting from Adoption of Roundup Ready Soybeans by U.S. Farmers: A Revealed-Preference Approach. Journal of Agricultural and Applied Economics 40(3):777-787.

Train, K. 1998. Recreation Demand Models with taste Differences Over People. Land Economics. 74(2):230-239.

Train, K. 2003. Discrete Choice Methods with Simulation. Cambridge University Press. 334 p.

Teisl, M. and B. Roe. 1998. The Economics of Labeling: An Overview of Issues for Health and Environmental Disclosure. Agricultural and Resource Economics Review 27(2):140-150.

Vogue, P., E. Kerle, and J. Jenkins. 1994. Oregon State University Extension Pesticide Properties Database. Oregon State University Extension Service: Corvallis, OR. Available online at http://npic.orst.edu/ppdmove.htm, as of April 14, 2010.

Voung, Q.H. 1989. Likelihood Ratio Tests for Model Selection and Non-Nested Hypothesis. Econometrica 57(2):307-333.

Wauchope, R.D., T.M. Buttler, A.G. Hornsby, P.W. Augustijn-Beckers, and J.P. Burt. 1992. The SCS/ARS/CES Pesticide Properties Database for Environmental Decision-Making. Reviews of Environmental Contamination and Toxicology 123:1-155.

Whitford, F., D. Barber, D. Scott, C. Edwards and J. Caravetta. 2004. Pesticides and the Label. Purdue University Cooperative Extension Service.

Zandstra, B., M. Particka and J. Masabni. 2004. Guide to Tolerance of Crops and Susceptibility of Weeds to Herbicides. Michigan State University - Extension Bulletin E-2833.

Table 1. Typical Label Statements for Each Toxicity Study by Category

Toxicity Category	Toxicity Studies				
	Acute Oral	**Acute Dermal**	**Acute Inhalation**	**Eye irritation**	**Skin Irritation**
I	Fatal if swallowed	Fatal if absorbed through skin	Fatal if inhaled	Corrosive. Causes irreversible eye damage.	Corrosive. Causes skin burns
II	May be fatal if swallowed	May be fatal if absorbed through skin	May be fatal if inhaled	Causes substantial but temporary eye injury	Causes Skin irritation
III	Harmful if swallowed	Harmful if absorbed through skin	Harmful if inhaled	Causes moderate eye irritation	Avoid contact with skin or clothing
IV	None required. Formulators may use category III labeling				

[1]The term "corrosive" is not required if corrosive effects were not observed during the study
Source: Environmental Protection Agency (EPA), 2007

Table 2. Summary Statistics of Herbicide Characteristics Included in Model I (based on information displayed on labels).

Variable (unit)	Expected sign	Mean	Standard Deviation	Min	Max
Price ($/acre)	-	10.80	5.10	0.96	20.40
Production Attributes $(\boldsymbol{w}_h)$					
Efficiency Pre-Grass (%)	+	22.70	24.30	0.00	67.50
Efficiency Post-Grass (%)	+	22.20	28.10	0.00	91.20
Efficiency Pre-Broad (%)	+	28.80	27.50	0.00	72.50
Efficiency Post-Broad (%)	+	33.50	26.10	0.00	86.80
Human Safety Attributes $(\boldsymbol{z}_h)$					
Restricted (Yes=1, No=0)	-	0.05	0.23	0.00	1.00
Signal Word					
Danger (Yes=1, No=0)		0.27	0.45	0.00	1.00
Warning (Yes=1, No=0)	-	0.20	0.40	0.00	1.00
Caution (Yes=1, No=0)	-	0.53	0.50	0.00	1.00
Hazards to Humans Statements					
Oral (Yes=1, No=0)	-	0.65	0.48	0.00	1.00
Dermal (Yes=1, No=0)	-	0.80	0.40	0.00	1.00
Inhalation (Yes=1, No=0)	-	0.47	0.50	0.00	1.00
Eye (Yes=1, No=0)	-	0.95	0.23	0.00	1.00
Skin (Yes=1, No=0)	-	0.20	0.40	0.00	1.00
Sensitization (Yes=1, No=0)	-	0.36	0.49	0.00	1.00
Environmental Safety Attributes $(\boldsymbol{x}_h)$					
Environmental Hazards Statements					
Fish	-	0.49	0.50	0.00	1.00
GWA	-	0.64	0.49	0.00	1.00
SWA	-	0.25	0.44	0.00	1.00

Table 3. Summary Statistics of Herbicide Characteristics Included in Model II (based on information displayed on labels, material safety data sheets and other sources)

Variable (unit)	Expected sign	Mean	Standard Deviation	Min	Max
Price ($/acre)	-	10.80	5.10	0.96	20.40
Production Attributes $(\boldsymbol{w}_h)$					
Efficiency Pre-Grass (%)	+	22.70	24.30	0.00	67.50
Efficiency Post-Grass (%)	+	22.20	28.10	0.00	91.20
Efficiency Pre-Broad (%)	+	28.80	27.50	0.00	72.50
Efficiency Post-Broad (%)	+	33.50	26.10	0.00	86.80
Human Safety Attributes $(\boldsymbol{z}_h)$					
Restricted (Yes=1, No=0)	-	0.05	0.23	0.00	1.00
Toxicity Values					
Oral LD_{50} (mg/Kg)	+	2,503.64	1,815.90	32.00	5,000.00
Dermal LD_{50} (mg/Kg)	+	2,705.95	1,902.88	200.00	13,300.00
Inhalation LC_{50} (mg/Kg)	+	9.46	42.69	0.60	320.00
Hazards to Humans Statements					
Eye (Yes=1, No=0)	-	0.95	0.23	0.00	1.00
Skin (Yes=1, No=0)	-	0.20	0.40	0.00	1.00
Sensitization (Yes=1, No=0)	-	0.36	0.49	0.00	1.00
Chronic (Yes=1, No=0)	-	0.49	0.50	0.00	1.00
Environmental Safety Attributes $(\boldsymbol{x}_h)$					
Toxicity to Animals					
Fish: LC_{50} (mg/l)	+	71.05	146.50	0.09	1,000.00
Bees: LD_{50} (μg/bee)	+	68.22	59.71	0.10	200.00
Birds: LD_{50} (mg/kg)	+	1,960.00	988.63	164.00	5,000.00
Surface and Groundwater Contamination					
K_{oc} coefficient	?	19,623.27	134,702.56	12	1,000,000.00
Water Solubility (mg/l)	?	52,055.92	131,252.05	0.01	626,000.00
Soil-life (days)	?	133.57	411.89	1.20	3,000.00

Table 4. Comparison of Competing Models: Model I ($\boldsymbol{F_\theta}$) based on Information displayed on Labels and Model II ($\boldsymbol{G_\gamma}$) based on Information displayed on Material Safety Data Sheets, Labels and Other Technical Sources

Models	**Hypotheses**	
	Step 1: $H_o^w: w_*^2 = 0$ **The models cannot be discriminated given the data (α=0.05)**	**Step 2: H_o: $F_\theta = G_\gamma$** **The models are equivalent (α=0.05)**
Conventional Logits	Test Statistic=870[a] Critical value = 39.94[b] Conclusion: Reject H_o^w	Test Statistic= 3.07 Critical value = 1.96 Conclusion: Reject H_o in favor of $\boldsymbol{F_\theta}$ being better than $\boldsymbol{G_\gamma}$
Conventional Mixed Logits with Normally Distributed Random Parameters	Test Statistic=1,476 Critical value = 98.83 Conclusion: Reject H_o^w	Test Statistic= 2.20 Critical value = 1.96 Conclusion: Reject H_o in favor of $\boldsymbol{F_\theta}$ being better than $\boldsymbol{G_\gamma}$
Conventional Mixed Logits: Final Model Specifications (see Table 5 and Appendix 1).	Test Statistic=1959.60 Critical value = 735.31 Conclusion: Reject H_o^w	Test Statistic= 6.80 Critical value = 1.96 Conclusion: Reject H_o in favor of $\boldsymbol{F_\theta}$ being better than $\boldsymbol{G_\gamma}$

[a]The test statistic correspond to $\boldsymbol{n\hat{w}^2}$.

[b]The critical value is the value of *x* that makes $\boldsymbol{M_{17+19}(x; \hat{\lambda}_n^2)}$=1-0.05. This value was obtained from the simulated distribution. The weighted sums of Chi-Square Distribution $\boldsymbol{M_{17+19}}(.\,; \boldsymbol{\hat{\lambda}_n^2})$ was generated using 100,000 draws from each of the 36 underlying independent standard normal distributions.

Table 5. Mixed Logit Model of Herbicide Choice based on Human Health and Environmental Information displayed on Labels and Implied Willingness to Pay Values (*WTP*)

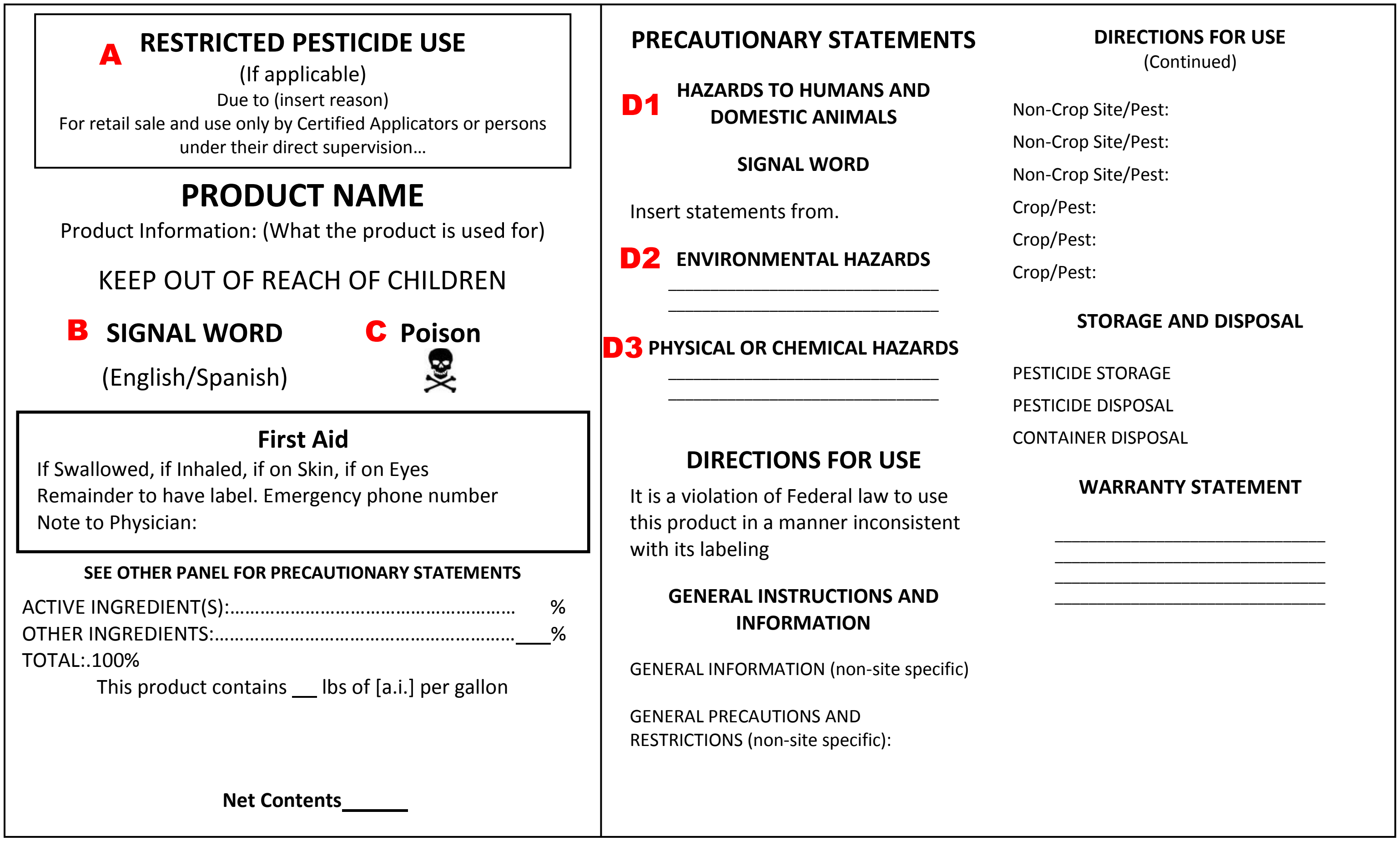
Variable (unit)	**Parameter Distribution**	**Model Coefficients**[a]		**Utility Coefficient**		**Mean *WTP* ($/acre/unit)**
		Mean	**Standard deviation**	**Mean**	**Standard deviation**	
Price ($/acre)	Fixed	-0.051 (0.007)[b]		-0.051		
Efficiency Pre-Broad (%)	Lognormal	-0.902 (0.101)	0.075 (0.052)	0.000	0.000	0.00
Efficiency Post-Broad (%)	Lognormal	-0.293 (0.028)	0.036 (0.020)	0.006	0.004	0.12
Efficiency Pre-Grass (%)	Lognormal	-0.362 (0.052)	0.105 (0.090)	0.006	0.012	0.12
Efficiency Post-Grass (%)	Lognormal	-0.274 (0.014)	0.029 (0.001)	0.008	0.004	0.16
Restricted (Yes=1, No=0)	Fixed	-0.192 (0.178)		-0.192		-3.77
Danger (Yes=1, No=0)	Truncated Normal	-1.813 (0.244)	3.524 (2.099)	-1.967	1.602	-38.34
Warning (Yes=1, No=0)	Truncated Normal	-1.088 (0.185)	3.027 (1.952)	-1.386	1.340	-27.02
Oral (Yes=1, No=0)	Truncated Normal	3.532 (1.067)	1.733 (1.216)	-0.001	0.017	-0.002
Dermal (Yes=1, No=0)	Truncated Normal	-1.224 (0.067)	0.248 (0.074)	-1.227	0.488	-23.92
Inhalation (Yes=1, No=0)	Truncated Normal	1.274 (0.801)	2.793 (1.931)	-0.204	0.535	-3.98
Eye (Yes=1, No=0)	Truncated Normal	-0.176 (0.280)	0.814 (0.400)	-0.481	0.607	-9.38
Skin (Yes=1, No=0)	Truncated Normal	3.341 (1.073)	1.511 (1.511)	-0.0005	0.014	-0.01
Sensitization (Yes=1, No=0)	Fixed	-0.327 (0.077)		-0.327		-6.37
Fish (Yes=1, No=0)	Truncated Normal	2.656 (0.426)	1.482 (1.452)	-0.006	0.059	-0.12
Groundwater (Yes=1, No=0)	Fixed	0.758 (0.068)		-0.758		-14.78
Surface water (Yes=1, No=0)	Fixed	0.610 (0.093)		-0.699		-13.63

Log-likelihood = -6,070.7

Pseudo R^2=0.14

[a] The lognormal and truncated normal parameter distributions are estimated as transformations of a underlying normally distributed parameter β. Hence the mean and standard deviation model coefficients are the estimates of the mean and variance of this underlying parameter.

[b] Standard errors in parenthesis



A RESTRICTED PESTICIDE USE
(If applicable)
Due to (insert reason)
For retail sale and use only by Certified Applicators or persons under their direct supervision…

PRODUCT NAME
Product Information: (What the product is used for)

KEEP OUT OF REACH OF CHILDREN

B SIGNAL WORD
(English/Spanish)

C Poison

First Aid
If Swallowed, if Inhaled, if on Skin, if on Eyes
Remainder to have label. Emergency phone number
Note to Physician:

SEE OTHER PANEL FOR PRECAUTIONARY STATEMENTS

ACTIVE INGREDIENT(S):……………………………………………… %
OTHER INGREDIENTS:…………………………………………………___%
TOTAL:.100%
This product contains __ lbs of [a.i.] per gallon

Net Contents______

PRECAUTIONARY STATEMENTS

D1 HAZARDS TO HUMANS AND DOMESTIC ANIMALS

SIGNAL WORD

Insert statements from.

D2 ENVIRONMENTAL HAZARDS
____
____

D3 PHYSICAL OR CHEMICAL HAZARDS
____
____

DIRECTIONS FOR USE
It is a violation of Federal law to use this product in a manner inconsistent with its labeling

GENERAL INSTRUCTIONS AND INFORMATION

GENERAL INFORMATION (non-site specific)

GENERAL PRECAUTIONS AND RESTRICTIONS (non-site specific):

DIRECTIONS FOR USE
(Continued)

Non-Crop Site/Pest:
Non-Crop Site/Pest:
Non-Crop Site/Pest:
Crop/Pest:
Crop/Pest:
Crop/Pest:

STORAGE AND DISPOSAL

PESTICIDE STORAGE
PESTICIDE DISPOSAL
CONTAINER DISPOSAL

WARRANTY STATEMENT

____
____
____
____

Source: Environmental Protection Agency (EPA), 2007

Figure 1. Pesticide Sample Label Format

Appendix 1. Mixed Logit Model of Herbicide Choice based on Human Health and Environmental Information displayed on Material Safety Data Sheets, Labels and Other Technical Sources and Implied Willingness to Pay Values (*WTP*)

Variable (unit)	**Parameter Distribution**	**Mean Coefficient**		**Utility Coefficient**		**Mean *WTP* ($/acre/unit)**
		Mean	**Standard error**	**Mean**	**Standard error**	
Price ($/acre)	Fixed	-0.142 (0.080)		-0.142		
Efficiency Pre-Grass (%)	Lognormal	-0.190 (0.014)	0.038 (0.015)	0.018	0.012	0.13
Efficiency Post-Grass (%)	Lognormal	-0.194 (0.006)	0.010 (0.003)	0.015	0.005	0.11
Efficiency Pre-Broad (%)	Lognormal	-0.950 (0.068)	0.150 (0.085)	0.000	0.000	0.00
Efficiency Post-Broad (%)	Lognormal	-0.171 (0.011)	0.014 (0.006)	0.020	0.008	0.14
Restricted (Yes=1, No=0)	Fixed	-0.135 (0.257)		-0.135		-0.95
Oral LD_{50} ($1x10^3$ mg/Kg)	Lognormal	-0.009 (0.001)	0.001 (0.007)	0.000	0.000	0.00
Dermal LD50 ($1x10^3$ mg/Kg)	Lognormal	0.127 (0.005)	0.011 (0.003)	0.380	0.130	2.68
Inhalation LC50 ($1x10^1$ mg/Kg)	Lognormal	-1.533 (0.333)	1.320 (0.514)	0.400	0.688	2.82
Eye (Yes=1, No=0)	Truncated Normal	-0.375 (0.191)	0.662 (0.354)	-0.556	0.610	-3.92
Skin (Yes=1, No=0)	Truncated Normal	0.981 (0.328)	0.671 (0.568)	-0.047	0.171	-0.33
Sensitization (Yes=1, No=0)	Fixed	-0.003 (0.073)		-0.003		-0.02
Chronic (Yes=1, No=0)	Truncated Normal	0.1431 (0.2651)	0.578 (0.365)	-0.242	0.403	-1.70
Fish: LC_{50} ($1x10^2$ mg/l)	Lognormal	0.011 (0.010)	0.014 (0.005)	0.120	0.046	0.85
Bees: LD_{50} ($1x10^2$ μg/bee)	Lognormal	-1.090 (0.143)	0.183 (0.054)	0.366	0.162	2.58
Birds: LD_{50} ($1x10^2$ mg/kg)	Lognormal	-0.157 (0.025)	0.051 (0.184)	0.027	0.022	0.19
K_{oc} ($1x10^5$ coefficient)	Normal	0.275 (0.085)	0.060 (0.015)	0.277	0.244	1.95
Water Solubility ($1x10^5$ mg/l)	Normal	-0.314 (0.081)	0.061 (0.013)	-0.305	0.243	-2.15
Soil-life ($1x10^2$ days)	Normal	-0.534 (0.082)	0.243 (0.060)	-0.527	0.483	-3.71

Log-likelihood = -6,391.0
Pseudo R^2=0.10

[a] The lognormal and truncated normal parameter distributions are estimated as transformations of a underlying normally distributed parameter β. Hence, the mean and standard deviation model coefficients are the estimates of the mean and variance of this underlying parameter.
[b] Standard errors in parenthesis.