The Effect of Label Information on U.S. Farmers' Herbicide Choices

Tomas Hasing, Carlos E. Carpio, David B. Willis, Olha Sydorovych, and Michele Marra

This paper analyzes the effect of labeling information on U.S. farmers' herbicide choices. Herbicide choices reported by U.S. soybean farmers are used to estimate farmer preferences for different herbicide attributes using a mixed logit model. Our results indicate that statements displayed on pesticide labels regarding risks to human health and the environment are important components in herbicide selection. We find that farmers are willing to pay an average of $27 per acre to avoid using an herbicide labeled with the word "Warning" and $38 per acre to avoid using an herbicide labeled with the word "Danger."

Key Words: mixed logit model, WTP to avoid human and environmental risk

Farmers rely on pesticides to increase agricultural productivity and profits and to reduce production risks. As a result, pesticides have become an important agricultural input throughout the world and particularly in the United States. In 2001, the U.S. agriculture sector used 675 million pounds of active pesticide ingredients at a cost of more than $7.4 billion, which accounts for about 23 percent of the pesticide market worldwide (Kiely, Donaldson, and Grube 2004). However, history has shown that incorrect use of pesticides can have negative effects. For instance, pests can become resistant to pesticides and pesticides can harm nontargeted plants and animals (Delaplane 2000).

Pesticide labeling is designed to regulate pesticide use and minimize some of the externalities that arise from incorrect use. Although the Federal Insecticide, Fungicide, and Rodenticide Act of 1947 (7 U.S. Code §136 et seq.) established standards for the content of the labels, it was not until an amendment in 1972 that specific methods and standards for control were imposed (Whitford et al. 2004). In the 1972 amendment, pesticide use inconsistent with the label was prohibited and violations could result in fines and/or imprisonment. Pesticides also were classified for general or restricted use. Any person (a commercial applicator or a farmer) who wanted to apply a restricted-use pesticide was required to be certified by the state. Later, as a consequence of the worker's "right to know" movement in the mid-1970s, the Federal Hazard Communication Standard (15 U.S. Code § 1261 et seq.) was promulgated in 1983. This law requires pesticide manufacturers to create material safety data sheets (MSDSs) and distribute them to downstream users of their products (Sattler 2002). Each MSDS includes information regarding the physical properties of the pesticide; its toxicity, reactivity, and health effects; appropriate first aid measures, protective equipment, and spill-handling procedures; and safe storage and disposal.

Most generally, product labeling can be seen as a policy tool associated with the provision of health and environmental information (Teisl and Roe 1998) to align individual consumer choices with social objectives (Golan, Kuchler, and Mitchell 2000). For this reason, consumer responses to information displayed on food product labels have been studied extensively. However, to the best of our knowledge, little or no research has been conducted on pesticide labeling information and how it affects the behavior of farmers. Hence, the general objective of this study is to estimate the effect of labeling information on farmers' pesticide choices. Specific objectives are

Tomas Hasing is a former graduate research assistant in the Department of Applied Economics and Statistics at Clemson University in South Carolina. Carlos E. Carpio is an assistant professor and David Willis is an associate professor in the John E. Walker Department of Economics at Clemson University in South Carolina. Olha Sydorovych is a researcher and Michele Marra is a professor in the Department of Agricultural and Resource Economics at North Carolina State University.

Agricultural and Resource Economics Review 41/2 (August 2012) 200–214

(i) to estimate the relative importance of cost, a product's weed-control efficiency, and the human safety and environmental attributes displayed on product labels to farmers' herbicide choices; (ii) to estimate farmers' willingness to pay (WTP) for each attribute; and (iii) to compare the performance of models based on label information only with models based on information provided by labels plus MSDSs and other more technical sources of information.

Herbicides are the most used pesticide in the United States; they account for more than two-thirds of the pesticide market. This study focuses on U.S. soybean production, which involves intensive use of herbicides; annually, about 50 million pounds of herbicides are applied in soybean production (Kiely, Donaldson, and Grube 2004).

Understanding farmers' responses to label information is important for policymakers such as the Environmental Protection Agency (EPA), which strives to protect fragile ecosystems and improve human safety through mandatory labeling laws. Golan, Kuchler, and Mitchell (2000) argued that an efficient pesticide labeling policy increases economic efficiency by helping producers to target their expenditures on the products they value most. Additionally, the effective use of labels can reduce externalities to the environment, human and animal health, and agricultural productivity. Thus, it is important to determine whether the label information currently provided to farmers is sufficient for them to make informed pesticide choices.

Literature Review

The literature regarding the effect of pesticide attributes on farmers' choices is limited. Two types of studies have evolved: stated-preference methods based on farmer "choices" under hypothetical scenarios and revealed-preference methods based on actual choices made by farmers. Stated-preference studies have relied on contingent valuation (CV) surveys (Higley and Wintersteen 1992, Lohr, Park, and Wetzstein 1998, Owens, Swinton, and van Ravenswaay 1998). Studies under the revealed-preference approach have used hedonic analysis with market prices (Beach and Carlson 1993, Fernandez-Cornejo and Jans 1995) or logit models derived from a random utility framework that utilized survey data (Hubbell and Carlson 1998, Sydorovych and Marra 2007, 2008, Carpio, Sydorovych, and Marra 2007). The human safety and environmental attributes used in both types of studies have consisted of information displayed in MSDSs and specialized scientific publications. This study applies models to revealed-preference data collected from surveys of farmers. However, in contrast to previous studies, our work focuses on how label information that describes human safety and environmental impacts of herbicides affects the products farmers choose. We support this emphasis on label information with statistical tests that compare the performance of models that involve only label information with models that include information from the labels and from other sources. In terms of modeling, this study is unique since it uses a logit model that accounts for the heterogeneous nature of farmer preferences and the panel nature of the data set.

Pesticide Labels

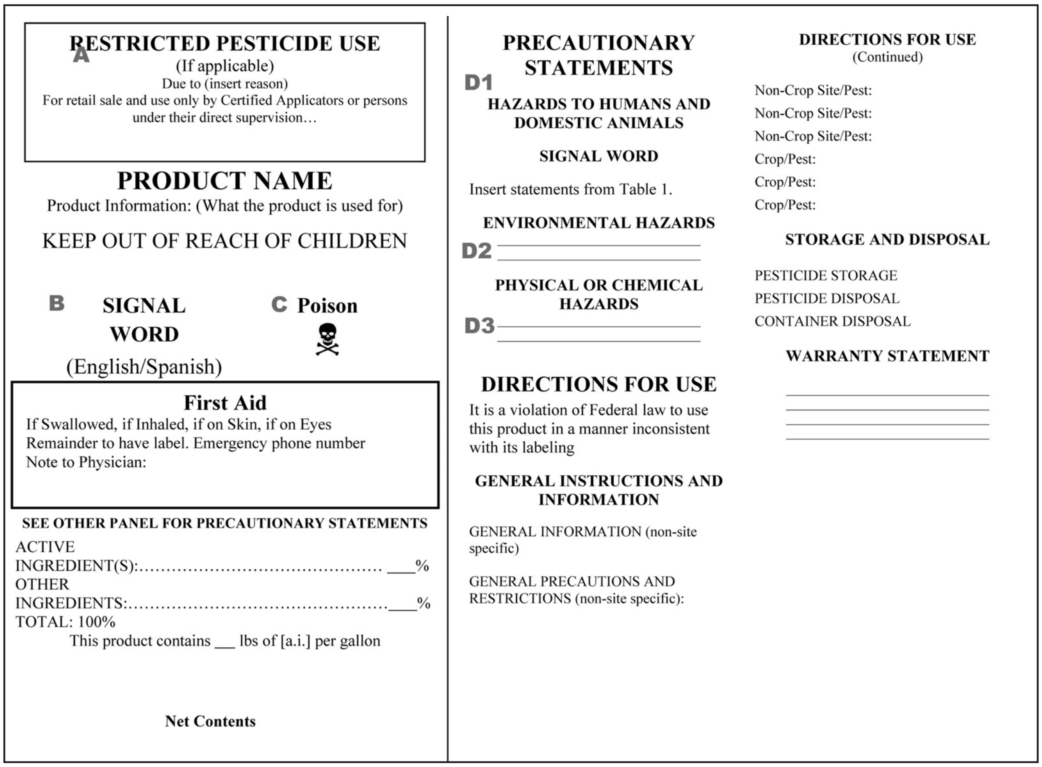
In the United States, EPA regulates the registration, manufacture, sale, transportation, use, and labeling of pesticides under the authority of two federal statutes: the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA) (7 U.S. Code §136 et seq. (1996)) and the Federal Food, Drug, and Cosmetic Act (FFDCA) (21 U.S. Code chapter 9). EPA establishes standards for the location of labels and for their content for four categories: safety, the environment, the product, and its use. In Figure 1, sections of the label that are relevant to this study are marked as A, B, C, and D and are briefly described hereafter.

Use Classification (A)

A pesticide is classified for either "general use" or "restricted use." In order to purchase, apply, and/or supervise application of a restricted pesticide, individuals are required to receive proper training and certification.

Signal Word (B)

The signal word indicates the approximate level of toxicity of the pesticide. As reported in Table 1, each pesticide is subjected to five toxicity studies: acute oral, acute dermal, acute inhalation, eye irritation, and skin irritation. Each study assigns the pesticide to one of four toxicity categories with category I being the most toxic. The signal word


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 Table 1.
ENVIRONMENTAL HAZARDS
D2
PHYSICAL OR CHEMICAL HAZARDS
D3
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

Figure 1. Pesticide Sample Label Format

Source: Environmental Protection Agency (2007).

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.[a] Causes irreversible eye damage.	Corrosive.[a] 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.				

[a] The term "corrosive" is not required if corrosive effects were not observed during the study.
Source: Environmental Protection Agency, 2007.

on the pesticide label is determined by the most severe toxicity level assigned by the studies. The signal words are I – DANGER, II – WARNING, and III – CAUTION. Pesticides assigned to category IV do not require a warning on the label (the area is left blank).

"Skull and 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)

Precautionary statements identify three categories of risk posed by the pesticide: hazards to humans and domestic animals (D1), environmental hazards (D2), and physical or chemical hazards (D3).

Precautions regarding hazards to humans and domestic animals are required when any acute toxicity study results in a product classification of toxicity category I, II, or III. In this case, the appropriate language contained in Table 1 must be printed on the label. Additionally, if a product's dermal sensitization test is positive, the following statement must be displayed: "Prolonged or frequently repeated skin contact may cause allergic reactions in some individuals."

The environmental hazard section advises of potential hazards to the environment from transport, use, storage, and/or spillage of the product. Specifically, label advisories on the following hazards can be included in this section: groundwater, surface water, birds and mammals, fish and aquatic invertebrates, and honeybees.

The physical or chemical hazard section addresses flammability, explosive potential, and other chemical precautions.

Theoretical and Empirical Models

The theoretical framework in this study integrates an agricultural household model with a random utility model. Within the context of the agricultural household model, a farmer who selects an herbicide, $h \in \aleph = \{1, \ldots, H\}$, makes the decision from one of two perspectives: (i) as a consumer, the application of herbicide h could affect the user's utility by altering human health and/or the environment, and (ii) as a producer, application of herbicide h affects net profit, which in turn affects utility through consumption (Singh, Squire, and Strauss 1986). In addition, according to the random utility model, farmer i in choice occasion t is assumed to choose the herbicide h^* that provides the greatest utility, U^*_{ith}, among all herbicide choices. The indirect utility function for herbicide choice can be written as

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

where $\mathbf{x}_{ith}$ is a vector of the herbicides' environmental characteristics, $\mathbf{z}_{ith}$ is a vector of human safety characteristics such as acute toxicity level, and $c_{ith}(\cdot)$ is a composite commodity that is in turn affected by $\mathbf{w}_{ith}$, a vector of production attributes of the herbicide, and p_{ith} herbicide cost per acre. The reduced form of the indirect utility function is

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

where $\boldsymbol{\gamma}'_{ith} = \left[p_{ith} \;\; \mathbf{x}'_{ith} \;\; \mathbf{z}'_{ith} \;\; \mathbf{w}'_{ith}\right]$. Since not all of the variables in $U^*_{ith}(\cdot)$ are observable, a 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 includes only the observed attributes and ε_{ith} captures the effect of the factors not included in V_{ith} (e.g., farmers' habits, brand loyalty, etc.).

Assuming that each ε_{ith} is an independently and 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 characteristic ($V_{ith} = \boldsymbol{\beta}'_i\,\boldsymbol{\gamma}_{ith}$), the probability that farmer i will choose herbicide h in choice occasion t, conditional on coefficient vector $\boldsymbol{\beta}_i$, (Train 1998) is

$$(3) \qquad P_{ith}(\boldsymbol{\beta}_i) = \frac{e^{\boldsymbol{\beta}'_i \boldsymbol{\gamma}_{ith}}}{\sum_h e^{\boldsymbol{\beta}'_i \boldsymbol{\gamma}_{ith}}}.$$

Since a farmer generally makes several herbicide applications during a growing season, we need to determine the probability of each farmer's sequence of observed choices. Let $h(i,t)$ 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 (Revelt and Train 1998) is

$$(4) \qquad S_i(\boldsymbol{\beta}_i) = \prod_t P_{ith(i,t)}(\boldsymbol{\beta}_i).$$

The coefficient vector $\boldsymbol{\beta}_i$ is unobserved for each farmer i and varies in the population with a density $f(\boldsymbol{\beta}_i|\boldsymbol{\theta})$ where $\boldsymbol{\theta}$ represents 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 $LL(\boldsymbol{\theta}) = \sum_n \ln Q_i(\boldsymbol{\theta})$. Because the integral in (5) cannot be calculated analytically, estimation is carried out using simulated maximum likelihood or Bayesian procedures (Train 1998, 2003, Rigby and Burton 2006). Unlike the standard logit model,[1] farmers' preferences apply to each choice situation and vary across farmers. Moreover, as shown in Train (2003), this version of the logit model allows for correlation of choices over time, which is important because our data set consists of farmer herbicide choices at various crop growth stages. For example, the selection of a pre-emergent herbicide is likely to influence the future weed population and, subsequently, selection of the post-emergent herbicide.

Herbicide Choice Data

Data on farmer pesticide use was obtained by a telephone survey of soybean producers conducted by Doane's Market Research in cooperation with North Carolina State University in February 2003. Surveys of 610 farmers from 19 states revealed 1,770 herbicide choices for three crop stages: pre-planting, pre-emergence, and post-emergence. The main objective of the survey was to compare farm management practices for Roundup Ready® (RR) and traditional varieties of soybeans so farmers were asked to list all of the herbicides used in both production systems. Appendix A (available from the authors) contains a sample of the survey questions, which were designed to extract information on herbicide use by farmers. Similar questions were used for herbicides applied to conventional and RR soybeans at different stages of production. The farmers' choice set consisted of 55 herbicides.[2]

The 19 states covered by the survey accounted for 93 percent of planted U.S. soybean acreage in 2002 (Hasing 2009). The number of respondents from each state was proportional to the state's share of national soybean acreage (Hasing 2009). The survey also collected information regarding producer demographics and farm operation characteristics.

Herbicide Characteristic Data and Variables

The three sets of characteristics required for estimation of our empirical model are (i) herbicide cost, (ii) production attributes, and (iii) environmental and human safety attributes. In this section, we present a detailed description of the information used and the sources of the information. Given our objective of measuring the effect of label information on herbicide choices, we estimate two models that use different sets of human and environmental characteristics but provide identical information regarding the cost and efficiency attributes of the individual herbicides. Model I includes only information contained in the pesticide label. Model II is constructed excluding the signal word information contained on the pesticide label and adds information provided by the MSDS (see Tables 3 and 4) and other specialized sources (explained later). The labeling and MSDSs used in the models were available to producers at the time the survey was conducted.

Herbicide Costs (p_h). The active ingredients an herbicide contains and the rate at which it is applied vary, so a comparison of the per-unit cost (gallon or pound) of commercial formulations or of active ingredients is not useful. We adjust the cost of each herbicide in the study by the application rate recommended for soybeans to obtain a standardized per-acre cost. Field application costs for the herbicides also are converted to per-acre values.

Production Attributes ($\mathbf{w}_h$). Four variables related to production attributes are calculated for each herbicide. Two variables measure the efficacy of the herbicide to control weeds in pre-emergence

[1] Other authors refer to a standard logit based on the logit probabilities shown in equation (3) as a conditional logit model or multinomial logit model (Greene 2003).

[2] We assumed the same feasible set for all of the choice occasions. While some herbicides are more likely to be used at a specific stage of production than others (e.g., pre-emergence herbicides are more likely to be used at the initial stages of crop production), every herbicide category can potentially be used at all stages of crop production (Gosset 2006).

applications: one for grass weeds and one for broadleaf weeds. The other two variables measure the herbicide effectiveness at controlling grass and broadleaf weeds in post-emergence applications. The four efficiency variables are continuous and range from a low of 0 to a high of 100. They measure average herbicide effectiveness across each weed category because the survey did not obtain information on specific weeds the farmers were trying to control. The variables are constructed using information on the predominance of individual species of weeds in each of the three soybean-growing regions in the study—Mid-West, Mid-South, and Eastern Coastal—and ratings of how effective the herbicides are against them (Meyer et al. 2006, Zandstra, Particka, and Masabni 2004). Predominant weed species are determined by measuring the number of states in a region that reported the presence of a specific weed weighted by the area's share of U.S. soybean production. The effectiveness ratings came from Zandstra, Particka, and Masabni (2004), which used a scale of 1 for "excellent" control and 2 for "fair" control. The ratings were then applied to the weed species identified as primary targets to generate the effectiveness measures (Hasing 2009).

Human Safety Attributes in Model I ($\mathbf{z}_h$). The most distinctive human safety information contained on the herbicide label is the "signal word," which reflects the degree of danger posed by the herbicide in four toxicological categories. In model I, dummy variables indicate whether the words "Danger" or "Warning" appear on the label with "Caution" taken as the base case. Human safety information also is reported in statements from the Hazards to Humans and Domestic Animals section. Hence, dummy variables indicate

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
Cost (p_h) (dollars per acre)	–	10.80	5.10	0.96	20.40
Production Attributes ($\mathbf{w}_h$)					
Efficiency pre-grass (percent)	+	22.70	24.30	0.00	67.50
Efficiency post-grass (percent)	+	22.20	28.10	0.00	91.20
Efficiency pre-broad (percent)	+	28.80	27.50	0.00	72.50
Efficiency post-broad (percent)	+	33.50	26.10	0.00	86.80
Human Safety Attributes ($\mathbf{z}_h$)					
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 (allergy)(Yes = 1, No = 0)	–	0.36	0.49	0.00	1.00
Environmental Safety Attributes ($\mathbf{x}_h$)					
Environmental Hazards Statements					
Fish (Yes = 1, No = 0)	–	0.49	0.50	0.00	1.00
Groundwater (Yes = 1, No = 0)	–	0.64	0.49	0.00	1.00
Surface water (Yes = 1, No = 0)	–	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
Cost (p_h) (dollars per acre)	–	10.80	5.10	0.96	20.40
Production Attributes ($\mathbf{w}_h$)					
Efficiency pre-grass (percent)	+	22.70	24.30	0.00	67.50
Efficiency post-grass (percent)	+	22.20	28.10	0.00	91.20
Efficiency pre-broad (percent)	+	28.80	27.50	0.00	72.50
Efficiency post-broad (percent)	+	33.50	26.10	0.00	86.80
Human Safety Attributes ($\mathbf{z}_h$)					
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 (allergy) (Yes = 1, No = 0)	–	0.36	0.49	0.00	1.00
Chronic toxicity (Yes = 1, No = 0)	–	0.49	0.50	0.00	1.00
Environmental Safety Attributes ($\mathbf{x}_h$)					
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	12.00	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

Note: LC = lethal concentration; LD = lethal dose.

whether the label discloses any of the following hazards: oral ingestion (*Oral*), dermal absorption (*Dermal*), Inhalation (*Inhalation*), eye irritation (*Eye*), and skin irritation (*Skin*).

Human Safety Attributes in Model II ($\mathbf{z}_h$). If farmers fully understand the information provided in MSDSs, they would be able to differentiate not only between herbicides that fall into different toxicological categories (Table 1) but also between herbicides in the same category that have small toxicity differences. For example, although both halosulfuron and pendimethalin fall in the level IV toxicity category for inhalation, the MSDSs for the two herbicides show that pendimethalin is safer (LC_{50} = 320) than halosulfuron (LC_{50} = 2.2) (LC stands for "lethal concentration;" LD stands for "lethal dose.").[3] Therefore, we replace the indicator variables of *Oral*, *Dermal*, and *Inhalation* with their continuous counterparts. *Oral* is replaced by the variable *Oral* LD_{50}, *Dermal* by *Dermal* LD_{50}, and *Inhalation* by *Inhalation* LC_{50}. Dummy variables that indicate the presence of eye and skin hazards to humans and domestic animals are retained in the models since the MSDSs do

[3] LD_{50} and LC_{50} are standard values for comparing the toxicity of chemicals and correspond to the amount (or concentration) that kills 50 percent of a group of test animals. The greater the lethal concentration and dose levels, the less toxic the chemical is.

Table 4. Comparison of Competing Models: Model I (F_θ) Based on Information Displayed on Labels versus Model II (G_γ) Based on Information Displayed on Material Safety Data Sheets, Labels, and Other Technical Sources

	Hypothesis	
	Step 1: H_o^w: $w_*^2 = 0$	Step 2: H_o: $F_\theta = G_\gamma$
Model	The models cannot be discriminated given the data ($\alpha = 0.05$)	The models are equivalent ($\alpha = 0.05$)
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 $\boldsymbol{G_\gamma}$
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 $\boldsymbol{G_\gamma}$
Mixed logits: final model specifications (see Table 5 and Appendix 2)	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 corresponds to $n\hat{w}_n^2$.
[b] The critical value is the value of x that makes $M_{17+19}(x;\hat{\lambda}_n^2) = 1 - 0.05$. This value was obtained from the simulated distribution. The weighted sum of the chi-square distribution, $M_{17+19}(\cdot;\hat{\lambda}_n^2)$, was generated using 100,000 draws from each of the 36 underlying independent standard normal distributions.

not include more detailed information for those categorical variables. Finally, two other human safety characteristics are common to models I and II: dummy variables that indicate the presence of restricted-use and dermal-sensitization statements.

Environmental Attributes in Model I ($\mathbf{x}_h$). Pesticide labels may display several statements related to the product's environmental properties. In our sample of herbicides, the only environmental statements are for (i) risk of surface water contamination, (ii) risk of groundwater contamination, and (iii) the level of toxicity to fish and aquatic invertebrates. None of the herbicides in the sample contained statements regarding bird and mammal or honeybee hazards. Dummy variables were used to indicate the presence of statements advising hazards to fish or aquatic invertebrates and groundwater and surface water advisories.

Environmental Attributes in Model II ($\mathbf{x}_h$). The selection of variables as environmental attributes in model II was complicated by the fact that the Occupational Safety and Health Administration's (OSHA's) mandatory MSDS format[4] does not require inclusion of any environmental or ecological information. Thus, there is much variability in the type of information provided and the level of detail about each pesticide's environmental characteristics in the MSDSs. For example, whereas about 80 percent of the MSDSs of the pesticides included in the study report the results of toxicological tests on animals (LD_{50} or LC_{50} for mammals, fish, and bees), only 23 percent of the MSDSs provide information on a pesticide's physical and chemical properties related to

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

potential water contamination. Hence, some of the information used in model II was obtained from other sources (Vogue, Kerle, and Jenkins 1994, Wauchope et al. 1992, Augustijn-Beckers, Hornsby, and Wauchope 1994) when not available in the MSDS.

Regarding herbicide toxicity to animals, we include 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 LD_{50} mg/kg). We also include a dummy variable if specialized studies conducted in animals had determined chronic toxicity effects produced by long-term exposure to pesticides. Chronic adverse effects include carcinogenesis, teratogenesis, mutagenesis, blood disorders (hemotoxic effects), endocrine disruption, and reproductive toxicity.

Three specialized environmental variables relate to surface water and groundwater contamination. They were chosen based on the published literature, EPA regulations, and information availability (Beach and Carlson 1993, Hubbell and Carlson 1998, Sydorovych and Marra 2007, 2008). The first specialized variable, K_{oc}, measures how well chemicals are absorbed by soil via their tendency to attach to the surface of a soil particle. High values of K_{oc} are negatively related to a chemical's ability to get in solution and contaminate surface water via runoff or leach into groundwater (Monaco, Ashton, and Weller 2002). The second specialized variable used to measure the potential impact of a pesticide on water is chemical soil life ($t_{1/2}$), the time necessary (in days) for the pesticide to be degraded to 50 percent of its original concentration under given soil conditions. The final specialized variable is water solubility, which describes the amount of pesticide that will dissolve in a known volume of water (mg/l). The higher the water solubility value, the more soluble the pesticide (Vogue, Kerle, and Jenkins 1994, Wauchope et al. 1992, Augustijn-Beckers, Hornsby, and Wauchope 1994).

Distribution of Random Parameters in the Logit Model

The objective of mixed logit modeling is to estimate the entire distribution for the parameter vector $\boldsymbol{\beta}_i$ from equation (5) (i.e., $f(\boldsymbol{\beta}_i|\boldsymbol{\theta})$) that corresponds to the characteristics described in the previous section. Hence, empirical implementation of the econometric procedures requires making some assumptions regarding the distribution. The distributions used in this study are based on our expectations regarding individual behavior (see Tables 2 and 3). In both models, production increasing attributes are expected to have positive impacts while cost is expected to have a negative effect by reducing profit. Moreover, for both models any adverse environmental and health precautionary statement is expected to have a negative impact. In model I, the dummy variables for "Danger" and "Warning" are expected to have negative impacts since their effects are measured relative to the "Caution" benchmark. In model II, human or environmental safety attributes measured using LD_{50} or LC_{50} values are expected to have positive effects since higher values indicate reduced herbicide toxicity. Finally, for model II, the sign of the net effect is uncertain since soil life, solubility, and absorption (K_{oc}) have adverse environmental and health impacts while the effect of herbicide applications on production is expected to be positive (Hubbell and Carlson 1998).

To ensure that the estimates of WTP for each attribute have the expected signs for every decision-maker, the initial specification of the mixed logit models assumed a truncated normal distribution for dummy variable parameters (Revelt 1999) and log-normal distributions for the parameters corresponding to the continuous variables for production, health, and environmental characteristics (Train 1998). The exception is for the parameters corresponding to K_{oc}, water solubility, and soil life, which are assumed to be normal. The cost parameter is assumed to be fixed to facilitate estimation of the distributions of WTP (Train 1998, 2003, Hensher, Shore, and Train 2005). However, in the final specification of the mixed logit models some dummy variable parameters are estimated as fixed since we encountered several problems with convergence and/or unreasonably high estimates for the standard deviations of the distributions.

Estimation Procedures

The conventional and mixed logit models with normally distributed random parameters are estimated using mixed logit procedures. Since mixed logit procedures fail to converge in the case of mixed logit models with normal and non-normal random parameters, those models are estimated using Bayesian procedures. As shown in Train (2003), the posterior distribution of the parameters obtained using Bayesian methods is asymptotically equivalent to that obtained using mixed logit methods. The Bayesian models use 40,000 iterations to obtain 2,000 draws that are used in simulating the estimated distribution of random coefficients: 20,000 for burn-in and 20,000 after convergence with every tenth retained (four-hour run time). The models are estimated using modified versions of Kenneth Train's Matlab programs, which are available online at http://elsa.berkeley.edu/~train/software.html.

Comparison of Competing Models

Because the sets of explanatory variables used in models I and II are different, the models are non-nested. To compare the models, we use the likelihood-ratio test proposed by Vuong (1989). Since a subset of the explanatory variables is common to both models, the models are classed as overlapping non-nested models. Vuong's approach considers two conditional models, $\mathbf{F}_\theta = \{f(y|\mathbf{z};\boldsymbol{\theta}); \boldsymbol{\theta} \in \Theta\}$ and $\mathbf{G}_\gamma = \{g(y|\mathbf{z};\boldsymbol{\gamma}); \boldsymbol{\gamma} \in \Gamma\}$, where $f(\cdot|\cdot)$ and $g(\cdot|\cdot)$ are conditional distributions, y is the dependent variable, $\mathbf{z}$ is a vector of explanatory variables, and $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$ are parameters. The test for model selection is then based on the likelihood-ratio statistic (LR):

$$(6) \qquad LR(\hat{\boldsymbol{\theta}}_n, \hat{\boldsymbol{\gamma}}_n) = \sum_{i=1}^{n} \log \frac{f(y_i|\mathbf{z}_i;\hat{\boldsymbol{\theta}}_n)}{g(y_i|\mathbf{z}_i;\hat{\boldsymbol{\gamma}}_n)}.$$

For overlapping models, Vuong (1989) proposes a sequential two-step procedure that consists of first testing whether $f(\cdot|\cdot;\boldsymbol{\theta}_*) = g(\cdot|\cdot;\boldsymbol{\gamma}_*)$ ($\boldsymbol{\theta}_*$ and $\boldsymbol{\gamma}_*$ are the pseudo-true values corresponding to $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$, respectively) and then using the null distribution of $LR(\hat{\boldsymbol{\theta}}_n, \hat{\boldsymbol{\gamma}}_n)$ to construct a model-selection test. In the first step, since $f(\cdot|\cdot;\boldsymbol{\theta}_*) = g(\cdot|\cdot;\boldsymbol{\gamma}_*)$ if and only if the variance of $\log[f(y_i|\mathbf{z}_i;\boldsymbol{\theta}_*) / g(y_i|\mathbf{z}_i;\boldsymbol{\gamma}_*)]$, $w_*^2 = 0$, the test is based on the statistic

$$(7) \qquad n\hat{w}_n^2 = \sum_{i=1}^{n}\left[\log \frac{f(y_i|\mathbf{z}_i;\hat{\boldsymbol{\theta}}_n)}{g(y_i|\mathbf{z}_i;\hat{\boldsymbol{\gamma}}_n)}\right] - \left[\sum_{i=1}^{n} \log \frac{f(y_i|\mathbf{z}_i;\hat{\boldsymbol{\theta}}_n)}{g(y_i|\mathbf{z}_i;\hat{\boldsymbol{\gamma}}_n)}\right]$$

and a limiting weighted sum of the chi-square distribution, $M_{p+q}(\cdot;\hat{\lambda}_n^2)$, where p and q are the number of parameters in models $\mathbf{F}_\theta$ and $\mathbf{G}_\gamma$, respectively, and $\hat{\lambda}_n^2$ is a parameter that must be estimated (the formulas and procedure to calculate $\hat{\lambda}_n^2$ are found in Vuong (1989)). The variance test consists of 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, we conclude that $\mathbf{F}_\theta$ and $\mathbf{G}_\gamma$ cannot be discriminated given the data. If H_o^w is rejected, we continue to the second step.

Step two tests the null hypothesis that the models are equivalent (H_o) against two alternative hypotheses: (i) $\mathbf{F}_\theta$ is better than $\mathbf{G}_\gamma(H_f)$ and (ii) $\mathbf{G}_\gamma$ is better than $\mathbf{F}_\theta(H_g)$. Under

$$H_o,\ n^{-1/2} LR(\hat{\boldsymbol{\theta}}_n, \hat{\boldsymbol{\gamma}}_n) / \hat{w}_n^2 \to N(0,1).$$

Under H_f and H_g,

$$n^{-1/2} LR(\hat{\boldsymbol{\theta}}_n, \hat{\boldsymbol{\gamma}}_n) / \hat{w}_n^2$$

converges asymptotically to $+\infty$ and $-\infty$, respectively. 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. Compared to more traditional model-selection approaches that use a single measure (e.g., Akaike information criteria as suggested by Davidson and MacKinnon 2004), Vuong's approach is probabilistic and the distributional results are used to indicate the strength of evidence in support of either model.

Results

We first present the results of the test that compares the herbicide choice model based on the label information versus the model using information from the MSDSs and other technical sources. We conduct the test under various assumptions regarding the models' error structures and distribution 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 tests also reject the null hypothesis that the models are equivalent in favor of the alternative hypothesis that model I is better than model II (step 2). Hence, we hereafter focus

Table 5. Mixed Logit Model of Herbicide Choice Based on Human Health and Environmental Information Displayed on Labels and Implied Willingness-to-Pay Values

Variable (unit)	Parameter Distribution	Model Coefficients[a] Mean	Model Coefficients[a] Standard Deviation	Utility Coefficients Mean	Utility Coefficients Standard Deviation	Mean WTP ($/acre/unit)
Cost (p_h) (dollars per acre)	Fixed	–0.051 (0.007)[b]		–0.051		
Efficiency pre-grass (percent)	Log-normal	–0.362 (0.052)	0.105 (0.090)	0.006	0.012	0.12
Efficiency post-grass (percent)	Log-normal	–0.274 (0.014)	0.029 (0.001)	0.008	0.004	0.16
Efficiency pre-broad (percent)	Log-normal	–0.902 (0.101)	0.075 (0.052)	0.000	0.000	0.00
Efficiency post-broad (percent)	Log-normal	–0.293 (0.028)	0.036 (0.020)	0.006	0.004	0.12
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 (allergy) (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-square = 0.14						

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

[b] Standard errors in parenthesis.

the discussion on model I (results for model II are presented in the Appendix).

The estimated parameter values for the mixed logit specification of model I are reported in Table 5. The overall model is 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 statistical significance of the standard deviations of the coefficients indicates that the mixed logit provides a better representation of the choice situations than the standard logit, which assumes identical model coefficients for all farmers (Hensher and Greene 2003).[5]

When the parameters are assumed to be normally distributed or fixed, the estimated mean values under model coefficients in Table 5 can be interpreted as marginal utilities. However, when the estimated parameters have log-normal or truncated normal distributions, the mean and standard deviations shown for model coefficients cannot be interpreted as marginal utility effects. In those cases, the mean and variance of the underlying parameters must be transformed to generate the marginal effects in the utility function.[6] Marginal utilities for all attributes are shown as utility coefficients in Table 5. Even though the mean value of the parameters that correspond to weed control efficiency measures (the model coefficients) are all negative, the marginal effects in the utility function (utility coefficients) are all positive.

The estimated utility coefficients can subsequently be used to estimate the amount respondents are willing to pay, as evidenced through their choices, for a specific herbicide characteristic. Marginal WTP for a specific characteristic is derived as the marginal utility for the characteristic divided by the negative of the marginal utility of cost. The WTP values are reported in the last column of Table 5.

Farmers' WTP for each additional unit of weed control efficiency, with the exception of broadleaf control during pre-emergent applications, is about \$0.13 per acre. In general, farmers' herbicide choices are significantly affected by human and environmental safety characteristics displayed on the product label. In regard to signal words, the mean WTP values shown in Table 5 for "Danger" and "Warning" are relative to the base signal word, "Caution," which is not included in the model. The negative estimated values are interpreted as WTP to avoid using herbicides labeled with those signal words. Thus, 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." The signal words for environmental and human safety characteristics have the highest WTP values. This is not surprising as they are the most clearly identified characteristics on the label.

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

The parameter corresponding to whether the herbicide's use is restricted is not significantly different from zero. This result is consistent across model specifications (see Appendix 2) but unexpected because use of a restricted herbicide requires hiring a commercial applicator or obtaining an official certification, both of which increase production costs.

Model I suggests that information displayed in the Hazard to Humans and Domestic Animals section of an herbicide's label significantly reduces the probability of a farmer choosing the product. In particular, a warning about possible acute dermal toxicity seems to be the main health concern since WTP is \$24 per acre, the highest among the WTP values related to the statements displayed in this section of the label. The average WTP to avoid an herbicide with an eye toxicity statement is \$9 per acre, \$6 per acre to avoid an herbicide with the skin sensitization (allergy) statement, and \$4 per acre to avoid the presence of an inhalation toxicity statement. Values for WTP to avoid acute oral toxicity or skin irritation statements are estimated to be close to zero.

[5] To evaluate the extent of collinearity between the variables, we checked the correlation matrix for *X*. The highest correlation value was 0.69, which falls below the commonly quoted rule that values greater than 0.8 or 0.9 are problematic (Judge et al. 1980).

[6] Formally, $V_{ith} = \boldsymbol{\beta}_i' \boldsymbol{\gamma}_{ith}$ from equation (3) becomes $V_{ith} = \mathbf{Z}(\boldsymbol{\beta}_i)' \boldsymbol{\gamma}_{ith}$ where $\mathbf{Z}(\boldsymbol{\beta}_i)$ is a vector of transformations that depends on $\boldsymbol{\beta}_i$. Log-normal distributions and truncated normal distributions use $\ln(\beta)$ and $\max(0,\beta)$ 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.

In addition to efficiency characteristics and health risk information, two environmental statements have an economically significant effect on herbicide selection: groundwater and surface water advisories. Farmers are willing to pay $15 per acre to avoid a groundwater hazard and $14 per acre to avoid a surface water hazard. The WTP to avoid 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 that evaluated WTP to avoid environmental and human risks posed by herbicides. For example, in a contingent valuation study that examined farmers' WTP for herbicide safety characteristics, Owens, Swinton, and van Ravenswaay (1998) found that WTP values for some characteristics were 280 percent greater than the original herbicide price. Their estimates of WTP for a noncarcinogenic herbicide ranged from $4.92 to $8.47 per acre compared to a baseline price of $3.00 per acre. WTP ranged from $4.40 to $7.70 per acre for a nonleaching formulation and $3.94 to $6.81 per acre for a product that is not toxic to fish. In a contingent valuation study of insecticides, Higley and Wintersteen (1992) found that producers were willing to pay $12.54 per acre to avoid high risk products, $8.76 for products with moderate risk, and $5.79 for products with low risk. The insecticide cost in that study was about $14 per acre.

It is important to note that the estimated marginal WTP values in this study are derived under the assumption that all other characteristics remain constant, which might not be the case. For example, if an herbicide's toxicity level is negatively correlated with its efficiency, farmers' WTP for the safer herbicide will be reduced after compensating for the efficiency loss.

Summary and Conclusions

The primary objective of this study was to analyze the effect of labeling information on farmers' herbicide choices. Florax, Travisi, and Nijkamp (2005) noted that very few studies had estimated farmers' WTP to avoid human and environmental risk characteristics of pesticides. Our theoretical and empirical models were developed within the context of an agricultural household model and a discrete-choice random-utility model. Herbicide choices reported by farmers were used to estimate farmers' preferences for various herbicide attributes using a mixed-logit model procedure. The theoretical models were then applied to a sample of U.S. soybean farmers. The herbicide characteristics used as explanatory variables included health and environmental effects displayed on product labels and efficiency measures calculated from relevant agronomic studies. We compared a model involving only label information with one that included information from labels and from MSDSs and other technical sources. This comparison assessed the validity of an assumption in previous studies that farmers have a detailed and complete understanding of all of the scientific measures used to evaluate the human and environmental risks posed by pesticides (e.g., LD_{50} values that are shown in MSDSs).

The statistical findings suggest that the model that used only label information is superior to the one that provided more technically complete measures of the risks associated with an herbicide. That is, farmers' choices are better explained by the information displayed on the herbicide label than by the published information presented in the MSDSs and technical sources. This finding has implications not only for appropriate specification of models designed to evaluate the effect of pesticide characteristics on users' choices but also on the type of model used to estimate individual's WTP for the characteristics. WTP estimates obtained from models that are more consistent with observed choices are preferable. Moreover, if regulatory agencies want farmers to base herbicide choices on the information displayed in MSDSs, that information must be easy for farmers to understand. According to Sattler (2002), the average American reads at a sixth-grade level while MSDSs are written at a thirteenth-grade level. In a literature review on the accuracy, comprehensibility, and use of MSDSs, Nicol et al. (2008) concluded that there are serious problems with the use of MSDSs as hazard communication tools; they report U.S. studies that suggest that farm workers understand less than 40 percent of the information.

Our results indicate that the human health and environmental statements displayed on pesticide labels that indicate elevated risk are important components in herbicide selection. For example, farmers are willing, on average, to pay $27 per acre to avoid using an herbicide labeled with "Warning," $38 per acre to avoid using an herbicide labeled with "Danger," and $15 per acre to avoid using herbicides with a warning about groundwater contamination. This suggests that pesticide companies can benefit by developing new products that are safer to use.

Understanding farmers' responses to label information is important for policymakers who are interested in the effectiveness of mandatory labeling laws. Our findings suggest that some of the information displayed on pesticide labels is an important determinant of pesticide selection. However, we also unexpectedly found that labeling an herbicide as restricted does not discourage its use. Additional research is needed to fully explain this result.

Several caveats regarding the results of the study are important. Since survey responses can depend on the survey mode used, research is needed to compare the results of this study, which used responses to a telephone survey, with results generated by other survey formats. As suggested by a reviewer, farmers may understate their use of higher-risk pesticides to avoid social stigma. Recall bias could also be present in this analysis since the survey asked farmers to report herbicide choices made during a prior production period. Finally, even though this study provides a comparison of two sets of variables corresponding to different "assumed" sources of information, additional research is needed to better evaluate the overall pesticide decision-making process, including the types and sources of information used to make such choices. Future surveys on the effect that label information has on herbicide choice could, for example, include questions regarding the farmers' level of understanding and/or familiarity with pesticide labels and MSDSs and the information they provide.

References

Augustijn-Beckers, P.W., A.G. Hornsby, and R.D. Wauchope. 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." Paper presented at the 2007 Southern Agricultural Economics Association Annual Meeting, Mobile, AL.

Davidson, R. and J.G. 2004. MacKinnon. Econometric Theory and Methods. New York, NY: Oxford University Press, Inc.

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

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. 2005. "A Meta-Analysis of the Willingness to Pay for Reduction in Pesticide Exposure." *European Review of Agricultural Economics* 32(4): 441–467.

Golan, E., F. Kuchler, and L. Mitchell. 2000. "Economics of Food Labeling." Agricultural Economic Report 793, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Gossett, B.J. 2006. Weed Scientist, Department of Entomology, Soils, and Plant Sciences, Clemson University, Clemson, SC. Personal communication. (October).

Greene, W.H. 2003. *Econometric Analysis*. Upper Saddle River, NJ: Pearson Education, Inc.

Hasing, T. 2009. "The Effect of Label Information on Farmers' Pesticide Choice." Unpublished M.S. thesis. Department of Applied Economics and Statistics, Clemson University.

Hensher, D., and W. Greene. 2003. "The Mixed Logit Model: The State of Practice." *Transportation* 30(2): 133–176.

Hensher, D., N. Shore, and K. Train. 2005. "Households' Willingness to Pay for Water Service Attributes." *Environmental and Resource Economics* 32(4): 509–531.

Higley, L., and W. Wintersteen. 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 G. Carlson. 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.

Judge, G.G., W.E. Griffiths, R.C. Hill, and T.C. Lee. 1980. *The Theory and Practice of Econometrics*. New York, NY: John Wiley and Sons.

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

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.

Meyer, J., M. Horak, E. Rosenbaum, and R. Schneider. 2006. "Petition for the Determination of Nonregulated Status for Roundup Ready2Yield^{TM} Soybean MON 89788." Available at http://www.aphis.usda.gov/brs/aphisdocs/06_17801p.pdf (accessed January 19, 2010).

Monaco, T., F. Ashton, and S. Weller. 2002. *Weed Science: Principles and Practices*. New York, NY: John Wiley and Sons.

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." Paper presented at the 1998 American Agricultural Economics Association Annual Meeting, Salt Lake City, UT.

Revelt, D. 1999. "Three Discrete Choice Random Coefficient Papers and One Policy Crime Study." Unpublished Ph.D. dissertation, Department of Economics, University of California, Berkley, CA.

Revelt, D., and K. Train. 1998. "Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level." *Review of Economics and Statistics* 80(4): 647–657.

Rigby, D., and M. Burton. 2006. "Modeling Disinterest and Dislike: A Bounded Bayesian Mixed Logit Model of the UK Market for GM Food." *Environmental and Resource Economics* 33(4): 485–509.

Sattler, B. 2002. "Finding Information about Chemicals in Our Environment." In B. Sattler and J. Lipscomb, eds., *Environmental Health and Nursing Practice*. New York, NY: Springer Publishing Company.

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

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.

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.

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*. New York, NY: Cambridge University Press.

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

Vuong, 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." PPP-24, Purdue University Cooperative Extension Service, West Lafayette, IN.

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