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Preference-Directed Regulation When Ethical Environmental Policy  
Choices Are Formed With Limited Information

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## Abstract

Preference-directed regulation (PDR) can supplement traditional environmental policies through frequent regulatory revision (Livermore, 2007). Stakeholders can use PDR to garner popular support for a specific policy. By providing individuals with information that augments their opinions about the effectiveness of a policy at driving environmental outcomes, stakeholders can induce preference switching in favor of or in detriment to a specific policy. This paper documents the extent to which this is true using cross-sectional data from an original national survey where individuals were asked to choose one of three policies aimed at reducing the number of products manufactured in environmentally damaging ways. Proxies for policy-specific opinions about the effectiveness of each policy are extracted from the data and form the central focus of inducing preference switching. PDR is operationalized by exogenously augmenting individual opinions via counterfactual simulations within a limited information discrete choice model. The results demonstrate that the extent of preference switching depends not only on the relative change in opinion for a specific policy, but that different forms of PDR may be more effective at inducing preference switching. The substitution patterns arising from the counterfactual simulations are further explained by analytically demonstrating the mitigation of the Independence of Irrelevant Alternatives property endemic to traditional multinomial choice models (i.e., full information). Additional empirical results are documented by comparing the results to a full information model, including downward bias in mean utility levels and individual-level preference switching across the limited and full information conditional choice utilities.

## 1 Introduction

Environmental policies aim to mitigate the harmful effects of environmental degradation or pollution. Based on an efficiency or cost-effectiveness criterion, the optimal policy is often derived within a political economy model where political feasibility and the distribution of benefits and costs across different sociodemographic groups are important concerns (Keohane, Revesz, & Stavins, 1998; Oates & Portney, 2003; Goulder & Parry, 2008). Livermore (2007) notes that traditional environmental regulations can be supplemented with preference-directed regulation. By strengthening or creating social norms (Sunstein, 1995, 1996) or through government information provisions (Sartzetakis, Xepapadeas, & Petrakis, 2009), preference-directed regulation overcomes stagnant political regimes and policies by “allowing for more frequent regulatory revision (Livermore, 2007, p. 314).” Individual preferences for different environmental policies are thus discovered by or altered through preference-directed regulation, and one way to evaluate these preferences is with contingent valuation methods and stated preference data (Loomis & Allen, 2008).

Calfee, Winston, and Stempiski (2001) note that stated preference data are useful for analyzing preferences because choices can be ranked against alternatives, providing a complete ranking. Empirical analyses of stated preference data often use logit and probit models to examine individual behavior. These traditional discrete choice models were developed under the assumption that the underlying choices are fully and equally salient to the individual. This is a questionable assumption in the context of choosing an environmental policy instrument to mitigate the number of products manufactured in environmentally damaging ways. Not only are the direct implications of a Pigouvian tax versus a product ban drastically different, the secondary and tertiary effects of these policies on individuals and the economy are not directly obvious, especially when the choice involves an ethical dimension.

Products which are manufactured in environmentally damaging ways impose not only negative externalities via pollution, for example, but also invoke normative concerns for the

environment. Previous research has documented the sociodemographic characteristics that drive individuals to stop purchasing products for broader environmental concerns (Scruggs et al., 2011), or to start purchasing ethically manufactured products (Starr, 2009). These are actions consumers take to affect environmental and social outcomes and are best described as ethical consumption behaviors. Governments can increase the prevalence of ethical consumption through environmental policies and the regulation of production processes, in other words, by facilitating ethical production. Consumers certainly take their own actions, such as boycotting products based on a company’s pollution record or purchasing only locally grown foods and organic produce, but consumers may want some government assistance to “green the marketplace.”

To examine the extent to which this is true, this paper uses individual response data from an original national survey to empirically investigate and rank three environmental policy instruments. The empirical analysis employs a relatively new limited information discrete choice framework developed in the applied industrial organization and marketing literature by Goeree (2008), and extended by Cohen and Rabinowitz (2011) and Draganska and Klapper (2011). The full information assumption is relaxed by modeling the probability the individual is informed of his or her inside choice options through an information technology, which is specified as a binary logit probability. The choice probability is thus a multiplicative function of the information technology and a multinomial choice probability conditioned on information. The aggregate demand models used in the papers cited above incorporate advertising data into the information technology and demonstrate the effects of limited information on product choice for computers, breakfast cereal, and coffee, respectively. In the present context, the information technology is primarily a function of proxies for individual opinions about the effectiveness of each policy at doing its stated job, which is to reduce the number of products manufactured in environmentally damaging ways.

Individuals can have limited information about the effectiveness of policies directed at this goal. Governments and firms can use preference-directed regulation to augment indi-

vidual opinions to possibly gain popular support for a specific policy. Politicians seeking to enact a particular environmental policy, for example, can provide individuals with information about policy effectiveness through various media outlets. This information could possibly augment an individual's opinion about a policy. Political action committees influence political decision-making through advertising campaigns and financial donations. Traditionally, firms use advertising to influence individual preferences, but now they have an additional avenue. In 2010, the United States Supreme Court ruled that the government cannot regulate the political speech of firms. Corporations are now free to spend money in the political marketplace during candidate elections. For firms manufacturing products in environmentally damaging ways, certain environmental policies are likely to have varying effects on profit margins. A firm facing certain environmental regulations can now use its political clout to implement preference-directed regulation in favor of other policies. All of these factors provide various outlets to implement preference-directed regulation, but the extent to which it actually works is currently unknown. This paper provides a first step in this direction.

The empirical results show that the strength of agreement about the effectiveness of the environmental policies is positively related to an individual's environmental policy choice. This is interesting because simple cross-tabulations and correlations between policy choice and policy-specific opinion demonstrate that the two are not always positively related. Counterfactual simulations provide additional results that would not be revealed in a traditional multinomial choice model. Policy-specific opinions are exogenously changed and the effects on predicted policy choice are illustrated and discussed. For example, by strengthening individual opinions about the effectiveness of a tax, while holding fixed or weakening opinions about the two other policies, the simulations demonstrate the extent to which individuals exhibit preference switching among policies. Though in a different context, these results are similar to those found by Chetty, Looney, and Kroft (2009), who show that the salience of a tax impacts the extent to which the behavioral responses of consumers are affected. In total, there are 18 different counterfactual simulations which demonstrate that increasingly polar-

ized opinions are positively related to policy choice and, more importantly, they demonstrate the magnitude of the behavioral response via preference switching. Furthermore, depending on the policy, different forms of preference-directed regulation will lead to varying degrees of preference switching. In other words, simply attempting to positively augment the opinion of one policy may be a less effective way to induce preference switching to that policy. Instead, it may be necessary to augment the relative opinion of one policy by diminishing the opinions about the alternative policies, or by positively increasing the opinion of one policy while diminishing the opinions of the alternatives. These results are specifically relevant for policy-makers that wish to garner popular support for a particular class of environmental policies (List & Sturm, 2006), and firms that wish to do the same.

The results are compared to those from a traditional multinomial logit model to document analytical and empirical similarities and differences. The main analytical finding is that the limited information model mitigates the Independence of Irrelevant Alternatives (IIA) property at the individual level. This has serious implications for the degree of preference switching. The remaining findings are empirical in nature. First, including additional sociodemographic characteristics within both models leads to a switch in mean preference rankings that holds across model specifications. This is important information for a policy-maker basing legislation decisions on the characteristics of his or her constituency. Second, despite a relatively few individuals choosing the outside option, the limited information model predicts that some individuals would make this choice while the traditional model fails to do so. Third, the results empirically document downward bias in mean utility levels resulting from assuming full versus limited information, similar to the findings of Dragan-ska and Klapper (2011). Fourth, in certain specifications there is individual-level preference switching across the full and limited information models. This finding supports the role of information heterogeneity in the choice process. If it were an insignificant aspect then preference switching would not occur across models.

This paper proceeds in the following way. First, the data and variables used in the

empirical analysis are described in detail. This is followed by a section describing the relationship between policy choice and policy-specific opinion. The policy choice models are then developed inclusive of a section about identification and a potential endogeneity issue. Then the IIA property of the limited information model is derived and compared to that of the full information model. This is followed by an overview of the empirically challenging estimation procedure. Next the estimation results are presented and followed by the counterfactual simulations and conclusion.

## **2 Data**

The data are from a nationally representative telephone survey conducted by the University of Connecticut Center for Survey Research and Analysis in 2009. The main purpose of the survey was to descriptively assess individual ethical consumption behavior as well as an individual's (i.e., respondent's) general understanding of aspects of ethical consumption. Individuals were asked various questions about past and present social, economic, and environmental issues. Each individual was also asked a battery of demographic questions which were then used to calculate survey weights in an effort to make the data nationally representative. This paper uses a subset of the questions from this survey to conduct the empirical analysis.

### **2.1 Demographic Characteristics**

Columns one to five of Table 1 summarize the unweighted demographic characteristics of each individual in the sample. Each individual had the option of refusing to answer a question or responding "don't know." Column five lists the count for each variable, reflecting only those who responded to the question. For example, 852 individuals answered the income question and roughly 63% stated an income of greater than or equal to \$50,000.

For estimation purposes, individuals that refused or did not know an answer to the



sociodemographic questions were excluded. Also excluded were individuals that refused or responded “don’t know” to the questions whose answers are included in the information technology. The demographic characteristics of the 302 dropped individuals are listed in Table 2. Columns six to ten of Table 1 reflect the demographic characteristics of the 704 individuals with no missing data. Empirical estimations were conducted using various sample sizes between 704 and 1006, including dummy variables for missing observations and grouping missing observations into the mean or modal values. In most cases, multicollinearity was an estimation problem or, in the case of grouping, national representativeness of the sample was diminished. For ease of comparison, the sample size used in the empirical analyses is 704 individuals. A major concern after dropping nearly a third of the sample is the degree to which the demographic characteristics are similar to the full sample. In Table 1, comparing the sample of 1006 (columns one to five) to the sample of 704 (columns six to ten) reveals very little difference in terms of demographic characteristics between the full sample and the subsample.

The core demographic characteristics are age, income, race, gender, employment status, education level, and marital status. The average age of each individual is 50.74 and roughly 65% have an income of greater than or equal to \$50,000. Close to 80% are white, 52% are female, and 60% are employed either full or part-time. 48% have a four year college degree or higher and 39% are single (i.e., single, separated, divorced, and widowed). The additional demographic control variables included in the empirical analysis are home ownership status, number of years having lived in the current community, number of kids living at home under the age of 17, political party (i.e., Republican, Democrat, or Independent), and census region (i.e., Midwest, Northeast, South, and West). 82% claimed to own their home (compared to renting), and the average number of years in the community is 22.86. On average, individuals had 0.7 kids under the age of 17 living at home. 28% self reported Republican, 35.7% Democrat, and 36% Independent. 23.7% were from the Midwest, 19.3% from the Northeast, 34.2% from the South, and 22.9% from the West.

## 2.2 General Knowledge and Opinion

The accuracy of an individuals' answers to five general knowledge questions are also included in the information technology. According to the survey design, these questions aim to gauge the amount of factual knowledge people obtain from television, newspapers, magazines, and other news media sources. The role of these general knowledge questions is to control for cognitive understanding that is broader than policy-specific opinion (discussed below) and fundamentally different from education level. The questions and answers are listed in Appendix One and the distribution of responses is displayed in Table 4. The correct answer is coded as one, zero otherwise.

The survey design notes that the answers to these questions are correct at the national level. It is plausible that there are different yet correct answers to G1 and G4 at a regional level. For example, the most common cause of pollution in Washington could be very different from that in Florida, just as the primary cause of animal extinction in Maine could be different from that in Idaho. That said, the analysis assumes, as did the structure of the survey, that the answers are focused on the national level, though the empirical specifications include region fixed effects to capture regional heterogeneity not explicitly accounted for through individual demographic characteristics.

One may question the relevance including question G5 in the analysis. Clearly G1-G4 are directly related to the environment, while I5 is indirectly related to the environment by way of supplying the individual with an incorrect answer about the primary function of the World Trade Organization (i.e., to promote environmentally sustainable development). To the extent that individuals believed this was the correct answer, the coding will capture this flaw. Furthermore, and perhaps more importantly, the general knowledge questions are solely control variables for factual knowledge.

In addition to the general knowledge questions, a general opinion question called *necessary evil* is also included. This variable reflects the strength of agreement or disagreement

with the need for businesses to emit more greenhouse gases to enable lower consumer prices. The specific question wording is listed in Appendix One and the distribution of responses are listed in the first two rows of Table 5. Most individuals tended to have some level of disagreement with this statement. The answers to this question are coded from one to four and have been scaled to the unit interval for estimation purposes, as have all variables used in the empirical analyses.

### 2.3 Environmental Policy Choice

Each individual in the survey had the option of choosing one of three national policies directed at reducing the number of products produced in environmentally damaging ways.<sup>1</sup> The three policy choices are summarized as: (1) ban; (2) tax; and (3) label.<sup>2</sup> Individuals also had the choice of an outside option (don't know or refused). The specific question that generated the choice outcome is listed in Appendix One and the responses are noted in Table 3. Each individual that did not choose an inside option was coded as choosing the outside option. Based solely on the distribution of responses, for  $n \in \{302, 704, 1006\}$ , individuals had the following rankings on average: ban  $\succ$  label  $\succ$  tax  $\succ$  outside option. Choosing the outside option can indicate any number of reasons for not choosing one of the three policies. If opinion is a driving factor in the choice process, then the empirical analysis will provide evidence of this and the counterfactual simulations will offer additional support.

### 2.4 Policy Specific Opinion

As noted in Goeree (2008), the ideal variable to include in the information technology is one that is specifically related to the choice outcome. For example, with respect to some policy  $j$ , an ideal opinion generating statement would read: A  $j$  will discourage consumers from purchasing products manufactured in environmentally damaging ways. The answers could follow the same opinion range as those discussed above. Instead, given the nature of the data, proxies for individual opinions about the effectiveness of each of the policies are

included in the information technology and act as the primary driver of informedness. The specific questions are listed in Appendix One and the last six rows of Table 5 illustrate the distribution of responses by opinion level. For ban and label opinion, the coding is identical to that of the necessary evil question. The coding for tax, however, is different due to the wording of the question.

While the question for ban opinion is rather longwinded, the intuition behind including it in the information technology is straightforward: It is possible for the case of a tax or a label that some minimal threshold of environmental protection is still violated. Thus to ensure minimal environmental standards, a ban would be most effective (although this is not explicitly stated in the question). It is assumed that an individual that agrees with this statement is more likely to choose ban over tax or label. Ideally, the proxy for ban would at least indicate the nature of a ban. The proxy for tax requires different coding due to the inclusion of the word seldom in the question, as noted in row six of Table 5.<sup>3</sup> It is assumed that disagreement with this statement would lead an individual to choose tax over ban or label. The proxy for label is coded like that for ban. An individual is assumed to be more likely to choose label the stronger he or she agrees with this statement.

For  $n = 704$ , 72.4% of individuals strongly agree with the ban question, while 20.31% somewhat agree, 3.41% somewhat disagree, and 3.84% strongly disagree. For the tax question, the majority of individuals somewhat disagree (31.68%) and strongly disagree (31.39%), while the minority strongly agree (17.19%) and somewhat agree (19.74%). For label, 44.6% strongly agree and another 23.58% somewhat agree. The remaining 31.82% somewhat disagree (15.2%) and strongly disagree (16.62%).

## 2.5 Sampling Weights

Going forward each individual is weighted using sampling weights,  $w_i$ , which denote the inverse of the probability that the observation is included due to sampling design. The functional form for the choice outcome is thus  $y_{ij}w_i$ , for  $y_{ij}$  the unweighted choice outcome.

According to the survey design, the weights were created based on the sampling distribution of four demographic characteristics: region, age, education, and gender. The weights therefore allow for a direct connection between the data and national representativeness.

### **3 Policy Choice and Policy-Specific Opinion**

From a utility maximizing perspective, an individual chooses a policy that maximizes his or her utility subject to an income or budget constraint. Opinions, on the other hand, do not arise from this type of behavior. Instead, individuals are free to have as many varied opinions as they wish subject to a cognitive constraint or, in other words, subject to brain capacity. Consider a simple case, outside of the present context, where an individual is faced with purchasing one of two generic medicines which cure the symptoms of a single ailment. In the absence of opinions about the effectiveness of either medicine, which are considered a driver of the individual's information set, the individual will simply purchase the one that gives her the highest consumption utility. Assuming she has the funds, if one is cheaper than the other, she will purchase the cheaper of the two. Suppose instead that each medicine claims to be 100% effective and call the cheaper medicine, A and the relatively expensive medicine, B. Now, assume that she has one of three opinions about the effectiveness of either A or B at curing her ailment: (1) definitely will; (2) most likely will; and (3) definitely will not. Given her past experience, or perhaps she forms an opinion in the aisle, she is free to have any combination of opinions about both A and B. If she believes B will definitely cure her ailment while A most likely will, then which will she choose given A is relatively cheaper than B? Though product effectiveness is a characteristic of the product, it is immediately clear that her opinion is not a characteristic of the product but rather a belief about the effectiveness of the product at curing her ailment. If her belief about B is relatively strong, it may be enough to drive her to purchase B over A, despite A being cheaper. If, however, she receives higher utility from the price difference between A and B relative to the opinion

difference between A and B, then she might purchase A even though she feels it is a less effective option than B. Suppose now that A and B are the same price but her opinions of both are that neither will help cure her ailment. Even if she can afford either medicine, there is no reason she has to purchase either one. In this case, her weak opinions about both have driven her to the no-purchase option.

These examples illustrate the fundamental distinction between opinions about a product and the choice of a product conditional on information. There are many cases in which, given prices, opinions will drive the choice of a product, just as there are cases when the effect of price differentials will dominate the role of opinion in a choice process. If this is true, then there is no reason to a priori assume that increasingly polarized opinions about the effectiveness of a product are always positively related to the choice of that product, especially when there are other opinions and products in the mix. For certain substitution patterns, it is plausible that no relationship exists between increasingly favorable opinions about a product and the choice of that product. A negative relationship, however, will likely never arise. If this outcome were realized, it is likely stemming from some other change that is not captured by the variation in the data. For example, perhaps positive opinion about a product becomes stronger with concurrent increases in price. The price change could be significant enough to force the consumer to purchase a different product thereby resulting in an odd relationship between choice and opinion.

This reasoning also applies to the present context, though it is subtly different given the lack of price data for each environmental policy.<sup>4</sup> A policy imposed on a product will have a direct price effect and an effect on relative prices. The policy, in other words, acts to differentiate the product through its policy-inclusive price. Depending on whether or not the individual purchases the products which are manufactured in environmentally damaging ways, her opinions about the effectiveness of each policy can play varying roles. She might have a very high opinion about the effectiveness of a ban, but still choose tax or label because she purchases the products that would be banned. If she believes a label will yield a smaller

price effect than a tax but has a high opinion about the effects of a tax on environmental outcomes, she might opt for label because it will be cheaper. Though intuitively it stands to reason that increasingly positive opinions about the effectiveness of a policy should be related to the choice of that policy, the data show policy choice and policy-specific opinion (in the aggregate) are not always positively related.

Tables 6 and 7 offer basic statistical support of the distinction between policy choice and policy-specific opinion. In Table 6, policy-specific opinion is cross-tabulated, column-wise and row-wise, with policy choice for the entire sample. To read the column sum, for example, 17.61% of individuals that chose tax strongly disagree that a tax seldom discourages consumers from purchasing environmentally harmful products. However, out of those that strongly disagree with this statement, 41.18% chose ban, 39.37% chose label, and only 14.03% chose tax. The remaining 5.43% chose the outside option. For ban, it is clear that more individuals chose ban the higher their agreement with the ban-specific opinion question. But this is also true for the relationship between choosing tax or label, and ban-specific opinion. Cross-tabulations, however, only tell part of the story.

Table 7 displays two simple correlation matrices between policy choice and policy-specific opinion. The first matrix represents the Pearson Correlation Coefficients (PCC) and the second represents Spearman's Rank Correlation Coefficients (SRCC). PCC measures the degree of linear association between opinion and choice. For example, the correlation between the choice of ban and increasing agreement about the effectiveness of a ban is 0.2404 and is significant at the 1% level. However, for tax, the correlation coefficient is -0.1593 and is also significant at the 1% level. There is also a negative and statistically significant correlation between label-specific opinion and the choice of label. These relationships are interesting because they suggest that, on average, increasingly polarized opinions - in the direction that would suggest an individual would chose either policy - are in fact negatively related to policy choice. SRCC is used to examine the extent to which opinion and choice are monotonically related, rather than through a simple linear relationship. The interpretation

of the coefficients is identical, but the value is equal to 1 (-1) if opinion and choice are positively (negatively) and perfectly monotonically related. The results are almost identical except for tax, where the sign on the correlation coefficients with ban-specific opinion and label-specific opinion are now negative. Since the results from calculating PCC and SRCC are almost identical, the data are most likely elliptically distributed.

## 4 Policy Choice Models

### 4.1 Utility

Individual  $i$ , for  $i = 1, \dots, n$ , chooses a policy  $j \in J$  for  $J = \{1, 2, 3, 4\}$ . Each element of  $J$  is respectively defined by the following set: {Outside, Label, Tax, Ban}. There are no specific attributes of the policy or the underlying products associated with the policy choices, therefore policy specific attributes are captured by policy constants. Individual demographics are also included, and thus the indirect utility individual  $i$  derives from  $j$  is,

$$u_{ij} = \delta_j + \mu_{ij} + \epsilon_{ij}, \quad (1)$$

where  $\delta_j = x'_j \beta$  captures the mean utility that the sample of individuals obtain from  $j$ . The variable  $x_j$ , also known as the design matrix, takes a different form depending on the information setting. Individual specific deviation from  $\delta_j$  is captured by  $\mu_{ij} = x'_j \Omega D_i$  for  $D_i$  the demographic characteristics of individual  $i$ .  $\epsilon_{ij}$  is an independently and identically distributed type I extreme value model error.



## 4.2 Multinomial Choice Model

The nature of the policy choice question lends itself well to a multinomial choice process where the probability that  $i$  chooses policy  $j$  is defined as,

$$p_{ij}^F = \frac{\exp\{\delta_j + \mu_{ij}\}}{\sum_{r=1}^4 \exp\{\delta_r + \mu_{ir}\}}, \text{ for } j = 1, \dots, 4. \quad (2)$$

Equation 2 is obtained by taking the integral of  $u_{ij} \mid \epsilon_{ij}$  over all values of  $\epsilon_{ij}$  weighted by the probability density function of  $\epsilon_{ij}$  (Train, 2003, p. 36-37). Individual  $i$  is assumed to choose policy  $j$  when  $p_{ij}^F \geq p_{i-j}^F \forall j$ . In this case, the individual is assumed to be fully informed of the effects of all policy choices on environmental outcomes. The design matrix in the full information setting is defined as follows:

$$x_j^F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \text{ for } j = \begin{bmatrix} \text{Ban} \\ \text{Tax} \\ \text{Label} \\ \text{Outside} \end{bmatrix}. \quad (3)$$

Each of the four rows corresponds to a placeholder for the three inside policy choices and the outside option. This truncated identity matrix is repeated  $\forall i$  and used to capture parameter estimates for each inside policy relative to the outside option. The design matrix normalizes the base category to the outside option (i.e.,  $u_{i1} = \epsilon_{i1}$ ) and thus the probability that  $i$  chooses  $j = 1$  is given by,

$$p_{i1}^F = \frac{1}{1 + \sum_{r=2}^4 \exp\{\delta_r + \mu_{ir}\}}. \quad (4)$$

### 4.3 Limited Information Choice Model

The major difference between the full and limited information models is the structure of the choice probability,  $p_{ij}$ . This has been shown to be considerably important in estimating and conducting inference with discrete choice models (Goeree, 2008; Cohen & Rabinowitz, 2011; Draganska & Klapper, 2011). Following the form of the choice models outlined in Goeree (2008) and Cohen and Rabinowitz (2011), the conditional probability that individual  $i$  chooses policy  $j$  is defined as,

$$p_{ij}^L = \sum_{S \in C_j} \underbrace{\prod_{l \in S} \phi_{il} \prod_{k \notin S} (1 - \phi_{kl})}_{T_j} \underbrace{\frac{\exp\{\delta_j + \mu_{ij}\}}{1 + \sum_{r \in S} \exp\{\delta_r + \mu_{ij}\}}}_{P(j|I)}, \text{ for } j = 2, 3, 4, \quad (5)$$

where  $C_j$  is the set of all choice sets that include policy  $j$ .  $\phi_{il}$  denotes the information technology, and the outside sum is over all choice sets that include policy  $j$ .  $T_j$  is the information probability for policy  $j$ , and  $P(j|I)$  is the probability of choosing policy  $j$  conditional on information ( $I$ ). The probability that the individual chooses the outside option is  $p_{i1} = 1 - \sum_{j=2}^4 p_{ij}^L$ . Individual  $i$  chooses policy  $j$  when  $p_{ij}^L \geq p_{i-j}^L \forall j$ . Since it is virtually impossible for a researcher to capture opinions about a potentially infinite range of underlying outside options, the individual is assumed to be fully informed, in whatever subjective sense, of the implications of his or her outside option choice. This is the assumption also employed by Goeree (2008). The implication of this assumption is that it is conceptually impossible and structurally inconsistent to incorporate opinions into the traditional multinomial choice model.

The design matrix in the limited information setting is defined as follows:

$$x_j^L = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \text{ for } j = \begin{bmatrix} \text{Ban} \\ \text{Tax} \\ \text{Label} \end{bmatrix}. \quad (6)$$

Given the full information assumption for the outside option and method of calculating the probability of choosing the outside option, this identity matrix facilitates the limited information estimation procedure.

$\phi_{ij}$  is constructed using the responses to other survey questions, and the information sets are thus formed using this data. Answers to the general knowledge and opinion based survey questions enter the binary logit information technology in the following way:

$$\phi_{ij} = \frac{\exp\{\tau_i + \gamma_{ij}\}}{1 + \exp\{\tau_i + \gamma_{ij}\}}, \quad (7)$$

where  $\tau_i$  incorporates  $i$  specific answers to the five general knowledge questions and the necessary evil variable, while  $\gamma_{ij}$  captures policy-specific opinion. The policy-specific opinion variables stacked in  $\gamma_{ij}$  drive an individual's level of opinion, and ultimately his or her information sets, of the implications or effects of a ban, tax, or label on mitigating the number of products manufactured in environmentally damaging ways.

The specific functional forms for  $\tau_i$  and  $\gamma_{ij}$  are as follows:

$$\tau_i = G_i' \rho + W_i \pi, \quad (8)$$

and,

$$\gamma_{ij} = Z_{ij} \alpha + Z_{ij}' \lambda D_i. \quad (9)$$

$G_i$  represents the five general knowledge questions and  $\rho$  is the coefficient estimate on each.  $\pi$  is the coefficient estimate on the necessary evil variable,  $W_i$ .  $Z_{ij} \alpha$  captures the mean level of information utility each individual obtains from the policy-specific opinion variables.  $\lambda$  translates demographic characteristics into policy-specific information utility.

## 5 Identification

There are three main identification issues surrounding the use of the limited information model in this context. These are: (1) disentangling limited information about policy effectiveness from pure distaste for a policy; (2) the inability to incorporate policy-specific opinions into a basic multinomial choice model; and (3) endogeneity between the choice outcome and policy-specific opinion. While it is straightforward to account for issues (1) and (2), endogeneity is considerably more difficult to control for and, due to data limitations, not pursued here. The following subsections demonstrate how to control for issues (1) and (2), and offers a method to account for endogeneity given a more complete data set.

### 5.1 Limited Information Response Function

Modeling the information technology as described above warrants a discussion on identifying limited information from policy distaste. For an information probability that does not vary across  $j$ , the estimation yields only a single point on the logit response function for each  $j$ . For example, consider the same choice process but with an information technology of the following form:

$$\phi_i = \frac{\exp\{\tau_i\}}{1 + \exp\{\tau_i\}},$$

which is solely a function of  $i$ 's general knowledge and opinion. In this case, each choice probability is scaled down by the same factor, leading to a preservation of the ranking of the conditional choice probabilities. In other words, if the ranking is such that ban is preferred to all other choices, then ban will continue to be the preferred choice in this setting. The rankings across policies would also not change. Specifying the information technology to include  $\tau_i$  and  $\gamma_{ij}$  provides the necessary variation to trace out the information technology response function independent of the conditional choice utility response function. In fact,

$\gamma_{ij}$  alone would be sufficient, but controlling for general levels of knowledge and opinion that do not vary across  $j$  but rather across  $i$  is important for identifying the relationship between opinions and policy choice.

This difference also helps distinguish between distaste and choosing the outside option. In the traditional multinomial model, if an individual simply does not like tax, for example, and chooses something else, the outcome is treated the same as if the individual did not understand the implications of a tax for consumer behavior. In other words, it is impossible to distinguish between disliking a policy and not understanding a policy (or being informed of the effects of a policy). However, in the limited information model it is possible to disentangle preference from information. An individual could rank tax the lowest (conditional on information) but be most informed about the effects of a tax compared to the other policies. The full choice probability for,  $p_{itax}^L$ , could still be the highest compared to the remaining  $J - 1$  choices. The reverse could also be true if the individual prefers tax (conditional on information) but really does not understand the implications of a tax.

## 5.2 The Inability to Incorporate Opinion into the Basic Framework

Since the outside option is latent, policy-specific opinions cannot be included in the traditional multinomial logit model. Not only is it impossible to feasibly identify an opinion level over the effectiveness of the outside option as an environmental policy instrument, there is no guarantee that the individual had some other policy in mind when choosing the outside option. Thus attempting to include such an opinion leads to dubious and arbitrary coding and, most likely, results. It is still important, however, for a policy-maker or researcher to understand why an individual chose the outside option. Individuals could simply be misinformed of the effects of the three policies rather than dislike them, or vice versa.<sup>5</sup>

Recall that the individual is assumed to be fully informed of the outside option in both the full and limited information models. Furthermore, normalization in equation 4 leads to the calculation of the probability of choosing the outside option in the full information

setting. Thus, if it were possible to include policy-specific opinion as a covariate in the full information setting, the variable could have the following form for  $i$  across  $j$  (for example):

$$Z_{ij} = \begin{bmatrix} 0.75 \\ 0.50 \\ 0.25 \\ \diamond \end{bmatrix}. \quad (10)$$

But how would  $\diamond$  be coded? There is no variable in the survey that captures individual opinion about the effectiveness of the outside option (whatever it may be), thus any coding for  $\diamond$  is dubious. In other words, it is impossible to determine the coding for  $\diamond$ , especially because it denotes some possibly infinite range of outside options. Calculating the choice probability of the outside option in the way it is done in the limited information model also does not provide a way to incorporate policy-specific opinion into the full information model. The relationship between information and policy choice would no longer be probabilistic and structural in nature. Instead, while capturing some effect of policy-specific opinion through the consumption utility, the individual would be fully informed of each policy. The general inability to incorporate policy-specific opinion into the basic framework for the case when an outside option is latent is a major shortcoming, not only of this data but also for any choice model with a latent outside option. The limited information setting can easily incorporate these facets of the choice process.

### 5.3 Endogeneity

The policy-specific opinion variables could suffer from an endogeneity problem. The same is true for the general knowledge and necessary evil variables. Despite controlling for choice and information heterogeneity across individuals, there could still be some underlying psychological factor or idiosyncratic characteristic driving an individual's policy choice and opinion lev-

els. For example, an underlying pro-environmental attitude or history of pro-environmental behavioral choices (Martínez-Espíñeira & Lyssenko, 2011). While not pursued here due limited data availability (i.e., a lack of instruments), this form of endogeneity can be controlled for by way of a two-step estimation process. In the first step, an ordered logit model predicts policy-specific opinion levels based on a set of included and excluded instruments. In the second stage, equation 5 is estimated using the predicted opinion levels instead of the reported opinion levels. This approach is similar to that of Petrin and Train (2010). To the extent that endogeneity is a problem, there is no meaningful way to account for it here given the available data. This suggests the need for a more carefully designed survey, especially when the empirical application intends to use the limited information framework.

## 6 Independence of Irrelevant Alternatives

At the individual level, or the unit-of-observation level in general, the limited information model mitigates the IIA property endemic to traditional multinomial choice models, thereby allowing for a behaviorally robust interpretation of policy choice. IIA is a restrictive property in this context, essentially reducing the choice of the  $J$  alternatives to a series of pairwise comparisons that are unaffected by the characteristics of other alternatives. These comparisons are also unaffected by the information probabilities,  $T_j \forall j$ . For example, the conditional probability of choosing ban given the choice of ban and label is assumed to be independent of the choice of tax. In reality, however, if individuals have limited information about the effects of a ban or label, the introduction of tax could affect the choice of ban or label. This is especially true if the individual has a stronger (or weaker) opinion about the effects of a tax relative to ban or label. The full information model does not allow for this type of substitution behavior.

The IIA properties of the limited information model are derived in Appendix Two for a simple model where  $\delta = x'_j\beta$ , and all else as discussed above. The information set

probabilities are of the size  $2^{J-1}$  for  $J$  total choices and, for  $J = 4$ ,  $2^3 = 8$ . Adding, as is typically the case with the discussion of IIA, another inside option to the mix leads to exponential growth in the information sets by  $2^{\hat{J}-2}$  for  $\hat{J}$  the *new* number of inside choices. For example, suppose  $\hat{J} = 5$ , then  $2^4 = 16$  and the information sets increased by a factor of  $2^3$  (i.e., 16–8). So, the addition of another choice option directly impacts  $T_j \forall j$  and does not lead to a preservation of the odds ratio between two pre-existing choices.

The derivative of the log odds ratio with respect to a parameter in the consumption utility yields a result that depends on: (1) the full choice probabilities,  $p_j$  and  $p_b$ ; (2) the probabilities of choosing a policy conditional on information,  $P(j|I)$  and  $P(b|I)$ ; and (3) the information probabilities,  $T_j$  and  $T_b$ . So, for example, a change in the information probability leads to a change in the log odds ratio, unlike the basic multinomial logit model where the derivative of the log odds ratio is fixed and does not depend (in any way) on any of the other choices not under consideration. Similar results hold with respect to an inside option and the outside option. The derivative of the log odds ratio depends on: (1)  $p_j^L$  and  $p_1^L$ ; (2)  $P(j|I)$ ; and (3)  $T_j$ . As explained in Appendix Two, these derivatives reduce to the full information results when full information is assumed. Thus, the limited information model leads to mitigation of the IIA property between policy choices as well as between a policy choice and the outside option, and it does so without using a nesting structure or random parameters.

## 7 Estimation Procedure

The models presented above are each specified as a maximum likelihood estimation problem. Each is coded with matrix language on the MATLAB platform and apply state-of-the-art optimization tools using KNITRO via the TOMLAB optimization environment.

To estimate the basic model, the objective function, score function, and Hessian of the multinomial choice process are included in the coding. The same is true for the objective and



score functions of the limited information model, however the Hessian is approximated using a finite differences approach, which is the recommended approach when the exact gradient, or score function, is provided (Holmström, Göran, & Edvall, 2009). The estimation procedure is terminated when the optimality error tolerance is  $\leq 1e^{-10}$ . Appendix Three summarizes the log-likelihood and score functions for both models, and the Hessian for the multinomial choice model.

## 8 Estimation Results

Tables 8 and 9 illustrate the parameter estimates for the full information specifications. Table 9 presents the final specification of the full information mixed multinomial logit model. Out of the four specifications, this is the best fit based on five of the six model statistics reported in Table 12. The Bayesian Information Criterion (BIC) penalizes more for degrees of freedom and thus it is not surprising given the relative proximity of the log-likelihoods across each specification that BIC is higher under specification four with 48 parameters to estimate compared to the next lowest at 33, followed by six, and three. Tables 10 and 11 illustrate the results for the limited information specification. Each specification is the logical extension of the full information counterpart. Table 11 presents the final specification of the limited information model.

Comparing specifications three and four within the full and limited information settings yields a switch in mean utility rankings from  $\text{ban} \succ \text{label} \succ \text{tax} \succ \text{outside}$  (consistent with the data) to  $\text{tax} \succ \text{ban} \succ \text{label} \succ \text{outside}$ . This results from including additional sociodemographic variables. From a policy perspective, this is important because an environmental policy based on the outcome of a simpler specification (i.e., one or two) could lead to different welfare implications for the underlying individuals compared to specifications three or four. Controlling for additional heterogeneity is non-trivial, especially if doing so results in preference switching

Another primary result is the nature of the bias in mean utility levels across the full and limited information models. Given the estimation process and the cross-sectional data, policy-specific opinion does not vary across  $t$ . For constant policy informedness, the basic model leads to downward biased mean utility levels compared to the limited information model, similar to the results of Draganska and Klapper (2011). The bias is seen by comparing  $\delta_j$  in specifications one to four of the full information models to specifications one to four of the limited information model. Accounting for limited information clearly leads to absolutely and relatively larger mean utility levels for each policy.<sup>6</sup>

The full and limited information models are compared in Table 12. While it would be useful to conduct a likelihood-ratio test to select the best fitting model, the nature of model nesting across the full and limited information models is complicated. In terms of number of parameters, each successive specification within each setting nests the previous specification(s) but, for example, specification four of the limited information setting may not necessarily nest specification four of the full information setting. The number of parameters estimated within the conditional choice utility is the same across both specifications, and it is intuitively appealing to note that the limited information model includes 22 more parameters and therefore nests the full information model. Yet the probability of being fully informed of any one policy is degenerate and equal to one under the full information specification while it is between zero and one for the limited information setting. These two properties complicate the ability of performing a traditional likelihood-ratio test.<sup>7</sup>

Table 11 illustrates the positive and statistically significant relationship between policy-specific opinion (PO) and policy choice. As opinion approaches strong agreement for the ban and label questions and strong disagreement for the tax question, an individual is more likely to choose any one policy. To a certain extent, this empirical relationship confirms the nonnegative relationship between opinions and choice, despite the findings of the descriptive quantitative analysis. Also, some of the policy heterogeneity parameters are statistically significant indicating that policy-specific opinion varies across certain sociodemographic groups.

Some of the general knowledge variables as well as the necessary evil variable are also statistically significant: G1 and G2 are negatively related to the choice outcome while G5 and the necessary evil variable are positively related. Clearly general knowledge has a varied relationship with policy choice. That the necessary evil variable is positively related to the choice outcome is perhaps a surprising finding. More emissions could lead to environmental damage and thus the need for some sort of private or public intervention to mitigate the harm. In exchange for lower prices via more greenhouse gas emissions, the policy outcome would instead lead to higher prices. A product ban leads to arguably infinite costs for procuring the good (excluding a black market); a tax is a relative increase in the price of the good; and a label leads to a one-time learning cost and possibly higher packaging prices passed on to consumers.

## 8.1 Individual-Level Preference Switching

Across the full and limited information models, there is individual-level preference switching that is masked by the overall mean utility rankings. The conditional choice probabilities are used to compare preference rankings across the fourth specifications of the full and limited information models. That is, to determine the extent of preference switching at the individual level, the following analysis compares  $p_{ij}^F$  to  $P(j|I)$ , where the former is the full information choice probability and also the conditional choice probability.

There are 395 latent classes based solely on the various combinations of dummy variables included in Tables 9 and 11. A latent class is, for example, some sociodemographic clustering for which there are estimated parameters associated with each characteristic, including the mean utility level for policy  $j$  common to the  $n$  individuals. The inclusion of age, years in the community, and number of kids under 17 living at home, however, yields 704 unique latent classes or, in other words, individuals.

Tables 13 and 14 illustrate the concept of latent classes by dummy variable specification inclusive of the distribution of the continuous variables across each latent class. These latent

classes make up 26.84% of the total latent classes and are, coincidentally, the 15 latent classes for which there are more than five of each in the data. The first latent class is comprised of 10 individuals who are an average age of 48.30 years. These individuals have lived in their respective communities for an average of 4.74 years and have an average of 2.53 kids under 17 living at home. The minimum age, number of years lived in the community, and kids under 17 living at home are, respectively, 30, five, and zero. The maximum values are 63, 53, and four, respectively.

The column entitled “Preference Switching” denotes the cases where preference switching either has (i.e., yes) or has not (i.e., no) occurred for each of the individuals within the latent class. For the first latent class, there are four instances where the preference ranking was preserved across the full and limited information and six where it was not. This means, for example, that the ranking could have been  $\text{tax} \succ \text{ban} \succ \text{label}$  under full information, but  $\text{label} \succ \text{ban} \succ \text{tax}$  under limited information. Ban is still ranked in the middle, but now label is ranked first and tax is ranked last.<sup>8</sup> Out of the 704 individuals, there are 456 cases where preference switching occurs and 248 cases where preferences are preserved. This is an important finding stemming from the limited information model. If controlling for information heterogeneity across individuals was unimportant, there would be 704 cases of preference preservation (i.e.,  $p_{ij}^F = P(j|I)$  for  $i$  across  $j$ ). Instead, the results indicate that there are only 248 individuals for which, given the included sociodemographic controls, the full information assumption is innocuous. This is not the case for the 456 individuals for which preference switching occurred. The implications of this result are important for policy-makers and firms. Simply assuming that all individuals have full information about the effects of each policy, thereby ignoring the role of policy-specific opinions and general knowledge and opinion in the choice process, would not capture the 456 cases of preference switching. If individual votes matter, then individual-level preference switching via limited information cannot be ignored.

## 9 Counterfactual Simulations

Governments, political action committees, and firms can use preference-directed regulation to augment environmental policy preferences, thereby inducing preference switching.<sup>9</sup> For example, a government information campaign directed at providing individuals with concise data about the function of taxes in shaping purchasing behavior could augment opinions about the role of taxes in affecting environmental outcomes, for better or worse. The change in opinions would filter through an individual's information sets, which are fundamentally different from information the government provides, and possibly affect his or her preferred policy choice. Such an information campaign could be fine-tuned to provide information to only those people with a limited formal education, for example. Andina-Díaz (2007) points out that ideological media outlets can influence viewers by “reinforcing agents in their already existing opinions and modifying the opinion itself (p. 70).” Social media outlets, in addition to traditional media sources, marketing campaigns, and television advertising, are also other avenues for attempting to augment opinions. The counterfactual simulations demonstrate how political actors in general can use preference-directed regulation to shape individual opinions about the effects of the three policies. Furthermore, and more importantly, the results yield the magnitude of preference switching, which is relevant data for policy-makers looking to capture votes. The present context shows how this process might work in an actual voting scenario.<sup>10</sup>

At the individual level, preference-directed regulation is operationalized by exogenously changing policy-specific opinion levels (i.e., ranging from strongly disagree to strongly agree) in various combinations. In order to perform the 18 counterfactual simulations discussed below, equation 5 is estimated using the parameter values from Table 11 and the new opinion levels resulting from the exogenous changes to opinion. If the range of opinions were broader and included levels both higher than strongly agree and lower than strongly disagree, then the assumed relationship between the strength of an opinion and the likelihood of choosing

a specific policy would likely be magnified. In other words, strongly agree and strongly disagree are not necessarily the peaks, or troughs, of polarized opinion.

For all individuals, there are three exogenous changes to opinion. In the first, called CF1, the opinion for policy  $j \forall i$  is increased by one level, keeping the maximum level fixed. In CF2, the opinions for policies  $-j \forall i$  are decreased by one level, keeping the minimum level fixed. This is fundamentally different from directly augmenting opinion about the policy of focus. Though the relative strength of the opinion for policy  $j$  is increased, this occurs because the nominal opinions of policies  $-j$  are diminished. In CF3, the opinion for policy  $j \forall i$  is increased by one level, while the opinions for policies  $-j \forall i$  are decreased by one level. This is essentially the combination of CF1 and CF2. The same counterfactual simulations are performed for only those with some college education or less (i.e., the 364 individuals with college=0), denoted by CF4, CF5, and CF6 respectively. This is to illustrate the fact that preference-directed regulation can be specifically aimed at different sociodemographic clusters of the population. Table 15 illustrates an example of the changes in opinion for ban ( $j=4$ ) for two hypothetical individuals, one with college=0 and the other with college=1.

Table 16 presents the numerical results for each counterfactual simulation, while Figures 1 through 6 graphically demonstrate the results for ban (Figures 1 and 2), tax (Figures 3 and 4), and label (Figures 5 and 6).<sup>11</sup> The first three columns of each Figure, for each policy choice, represent the response distribution from the data followed by the full and limited information model predictions using the fourth specification of each model. The last three columns represent the results of the counterfactual simulations labeled as such.

Increasing the opinion for ban by one level, while holding the opinions for tax and label fixed, leads to an increase in the number of individuals choosing ban compared to the data and the full and limited information predictions. The largest increase is under CF2, where the relative opinion of ban is increased by diminishing the nominal opinions of tax and label. Similar results hold for the sample of individuals with some college education or less.

Relative to the predicted outcomes of the full and limited information models, CF1,

CF2, and CF3 lead to an increase in the number of individuals choosing tax. The largest increase is under CF3, where, based on Table 16, 18.32% of individuals choose tax, which is 5.32% than the limited information prediction and 10.08% more than the full information prediction. The results are similar for those with some college education or less, where CF6 leads to the largest increase. Stronger disagreement with this statement is consistent with the predictions of economic theory. In general, taxes on products do negatively affect purchasing behavior, the extent to which depends on the salience of the tax (Chetty et al., 2009).

Compared to the data and the predicted outcome from the limited information setting, CF1, CF2, and CF3 lead to an increase in the number of individuals choosing label, with the largest increase occurring under CF3. For those with some college education or less, CF4 and CF5 lead to no change compared to the full information prediction and an increase compared to the limited information prediction. CF6 leads to an increase in those choosing label compared to both the full and limited information predictions.

Aside from the simulations, an empirical result for the outside option choice is shown in each figure. The data include individuals that chose the outside option yet the full information model fails to predict that any individuals will choose this option. The limited information model, however, is able to predict that individuals will choose the outside option. This is an important result because both models assume full information over the outside option, yet the limited information model, by virtue of assuming limited information over the inside options, is able to capture this segment of the data generating process in the predicted choice probabilities.

## 10 Conclusion

This paper not only advances the limited information choice model, it is the first to apply it to individual response data. Furthermore, by abstracting away from the context in which

the model was initially developed, this paper demonstrates a richer level of applicability for the model and introduces it for the sake of studies that estimate choice models in general. The results of this paper cannot be derived without using the limited information model, yielding broad implications for discrete choice models and survey data analysis when the role of information is an important consideration. While the results of this paper are interesting for environmental policy in general, the application of the limited information model is of equal or greater importance. The model itself has various implications for other areas of research.

Various results have been documented, illustrating the superior performance of the limited information model compared to the traditional multinomial logit model. Controlling for preference heterogeneity, as well as for general knowledge and opinion, the empirical results showed that an individual's opinion of policy effectiveness is positively related to his or her policy choice. Counterfactual simulations demonstrated how to operationalize preference-directed regulation to supplement environmental policy choices. The simulation results empirically demonstrated that strengthening respondent opinions about the effectiveness of each policy leads to an increase in the count of positive responses for the targeted policy and, in most cases, a decrease in the count of positive responses for the other policies. Furthermore, depending on the policy, different forms of preference-directed regulation may induce a greater magnitude of preference switching. What works for positively augmenting the opinions about label may be fundamentally different from that of ban.

The results also empirically documented downward estimation bias in mean utility levels within the full information model, as well as the mitigation of the IIA property (at the respondent level) under limited information. Relaxing the IIA property is especially important in this context. As the three environmental policies are quite broad, a more fruitful survey could include additional broad policies but, perhaps more importantly, specific environmental instruments in the choice set. As more policies are added to the choice set, the information sets also grow and the respondent is faced with an increasingly complex



choice problem. Unlike the limited information model, the full information model masks this complexity via IIA.

## 11 Appendix One

### 11.1 General Knowledge Questions

The survey design provides the following as the correct answers for the general knowledge questions: (1) G1-b; (2) G2-d; (3) G3-d; (4) G4-b; and (5) G5-a. The respective sources for each question are as follows: (1-3) the Environmental Protection Agency; (4) Nature (2000); and (5) the World Trade Organization.

1. G1: What is the most common cause of pollution of streams, rivers, and oceans? Is it...
  - (a) Dumping of garbage by cities
  - (b) Surface water running off yards, city streets, paved lots, and farm fields
  - (c) Trash washed into the ocean from beaches
  - (d) Waste dumped by factories
  - (e) Don't know
  - (f) Refused
2. G2: Ozone forms a protective layer in the earth's upper atmosphere. What does ozone protect us from? Is it Is it...
  - (a) Acid rain
  - (b) Global warming
  - (c) Sudden changes in temperature
  - (d) Harmful, cancer-causing sunlight
  - (e) Don't know
  - (f) Refused

3. G3: Where does most of the garbage in the U.S. end up? Is it in...
- (a) Oceans
  - (b) Incinerators
  - (c) Recycling centers
  - (d) Landfills
  - (e) Don't know
  - (f) Refused
4. G4: What is the most common reason that an animal species becomes extinct? Is it because...
- (a) Pesticides are killing them
  - (b) Their habitats are being destroyed by humans
  - (c) There is too much hunting
  - (d) There are climate changes that affect them
  - (e) Don't know
  - (f) Refused
5. G5: What is the primary function of the World Trade Organization? Is it to...
- (a) Promote free trade
  - (b) Promote safe working conditions
  - (c) Promote environmentally sustainable development
  - (d) Promote fair wages for workers
  - (e) Don't know
  - (f) Refused

## 11.2 Necessary Evil Question

The answers to the following question are: strongly disagree, somewhat disagree, somewhat agree, strongly agree, don't know, and refused.

1. Sometimes businesses need to emit more greenhouse gases to enable consumers to pay lower prices.

## 11.3 Environmental Policy Question

1. Which of the following approaches would you like the government to pursue to reduce the number of products that are made in ways that damage the environment, would it be to...
  - (a) Ban products that are made in ways that damage the environment to prevent consumers from buying them
  - (b) Tax products that are made in ways that damage the environment to discourage consumers from buying them
  - (c) Label products that are made in ways that damage the environment to inform consumers before buying them
  - (d) Don't know
  - (e) Refused

## 11.4 Policy-Specific Opinion Questions

The answers to following questions are: strongly disagree, somewhat disagree, somewhat agree, strongly agree, don't know, and refused.

1. Ban: Now I am going to read you a few standards that could be included in international trade agreements. For each one I read, please tell me whether you agree

or disagree with including this standard in trade agreements with foreign countries. First, all countries involved would have to ensure minimal environmental protection standards.

2. Tax: Increasing taxes on products harmful to the environment seldom discourages consumers from buying them.
3. Label: The government should require every product to have a label describing how a product was made.

## 12 Appendix Two

The following drops the  $i$  subscript and  $L$  superscript for convenience. For the simplest case where  $\delta_j = x'_j\beta$ , the derivative of the logs odd ratio with respect to  $x_j$  in the traditional multinomial logit setting is equal to  $\beta$ . For  $\delta_j = x'_j\beta$ , define the log odds ratio between  $p_j$  and  $p_b$  (for both inside goods) as:

$$\ln\left[\frac{p_j}{p_b}\right] = \ln p_j - \ln p_b, \quad (11)$$

for  $p_j$  defined in equation 5. Then, the derivative of the log odds ratio with respect to  $x_j$  is:

$$\frac{\partial \ln\left[\frac{p_j}{p_b}\right]}{\partial x_j} = \frac{1}{p_j} \frac{\partial p_j}{\partial x_j} - \frac{1}{p_b} \frac{\partial p_b}{\partial x_j}. \quad (12)$$

After some simplification and rearranging, the derivative can be rewritten as:

$$\frac{\partial \ln\left[\frac{p_j}{p_b}\right]}{\partial x_j} = \beta \underbrace{\left[ \frac{1}{p_j} \sum_{s \in C_j} T_j [P(j|I) - P(j|I)^2] + \frac{1}{p_b} \sum_{s \in C_b} T_b P(j|I) P(b|I) \right]}_{\Re}, \quad (13)$$

which is equal to  $\beta$  if  $\Re = 1$ , which is true under the full information assumption. In other words, under the assumption of full information within the limited information setting,  $p_j = P(j|I)$ , for  $P(j|I)$  defined in equation 5.

Similarly, with respect to the outside option,  $p_1 = 1 - \sum_{j=2}^4 p_j$  write the derivative as:

$$\frac{\partial \ln\left[\frac{p_j}{p_1}\right]}{\partial x_j} = \frac{1}{p_j} \frac{\partial p_j}{\partial x_j} - \frac{1}{p_1} \frac{\partial p_1}{\partial x_j}, \quad (14)$$

which after some simplification and rearranging can be rewritten as:

$$\frac{\partial \ln\left[\frac{p_j}{p_1}\right]}{\partial x_j} = \beta \underbrace{\left[ \frac{1}{p_j} \sum_{s \in C_j} T_j [P(j|I) - P(j|I)^2] + \frac{1}{p_1} \sum_j \sum_{s \in C_j} T_j [P(j|I) - P(j|I)^2] \right]}_{\Re}. \quad (15)$$

This expression is only equal to  $\beta$  if  $\aleph = 1$  which is the case under full information. That is,

$$p_j = \frac{\exp\{\delta_j + \mu_i\}}{1 + \sum_{r=2}^4 \exp\{\delta_r + \mu_i\}} \text{ and } p_1 = 1 - \sum_{j=2}^4 p_j, \text{ where } p_1 = \frac{1}{1 + \sum_{r=2}^4 \exp\{\delta_r + \mu_i\}}.$$

## 13 Appendix Three

The following briefly outlines the log-likelihood and score functions for both the multinomial choice model and the limited information multinomial choice model, and the Hessian for the multinomial choice model.

### 13.1 Multinomial Choice Model

Define  $Y_{ij} = y_{ij}w_i$  as the weighted choice outcome of policy  $j$  for individual  $i$ . Then, the log-likelihood function is written as:

$$\ell^F = \sum_{i=1}^n \sum_{j=1}^J Y_{ij} \ln(p_{ij}^F). \quad (16)$$

Let  $\theta^F = \{\beta, \Omega\}$  represent the parameters to be estimated and write the gradient of  $\ell^F$ , also known as the score function, as:

$$\frac{\partial \ell^F}{\partial \theta^F} = \sum_{i=1}^n \sum_{j=1}^J Y_{ij} \left[ \frac{\partial p_{ij}^F}{\partial \theta^F} - \sum_{r=1}^4 p_{ir}^F \frac{\partial p_{ir}^F}{\partial \theta^F} \right]. \quad (17)$$

The Hessian of  $\ell^F$  is calculated by taking the derivative of the score function. The result is a matrix whose size is determined by the number of parameters in  $\theta^F$ . Dropping the  $F$  superscript from  $\theta^F$ , the Hessian for  $m$  parameters is written as:

$$H^L = \begin{bmatrix} \frac{\partial^2 \ell^F}{\partial \theta_1^2} & \frac{\partial^2 \ell^F}{\partial \theta_1 \partial \theta_2} & \cdots & \frac{\partial^2 \ell^F}{\partial \theta_1 \partial \theta_m} \\ \frac{\partial^2 \ell^F}{\partial \theta_2 \partial \theta_1} & \frac{\partial^2 \ell^F}{\partial \theta_2^2} & \cdots & \frac{\partial^2 \ell^F}{\partial \theta_2 \partial \theta_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 \ell^F}{\partial \theta_m \partial \theta_1} & \frac{\partial^2 \ell^F}{\partial \theta_m \partial \theta_2} & \cdots & \frac{\partial^2 \ell^F}{\partial \theta_m^2} \end{bmatrix}. \quad (18)$$



### 13.2 Limited Information Choice Model

Using similar notation as above, write the log-likelihood function for the limited information choice model as:

$$\ell^L = \sum_{i=1}^n \sum_{j=1}^J Y_{ij} \ln(p_{ij}^L) \quad (19)$$

Let  $\theta^{P(j|I)} = \{\beta, \Omega\}$  represent the parameters to be estimated in  $P(j|I)$ , and  $\theta^{T_j} = \{\rho, \pi, \alpha, \lambda\}$  represent the parameters to be estimated in the  $T_j$ . The score function is thus a vector split into two segments. The first corresponds to the gradient of  $\ell^L$  with respect to  $\theta^{P(j|I)}$ , and the second corresponds to the gradient of  $\ell^L$  with respect to  $\theta^{T_j}$ . Write the first segment, including the outside option, as:

$$\frac{\partial \ell^L}{\partial \theta^{P(j|I)}} = \sum_{i=1}^n \sum_{j=1}^J \frac{Y_{ij}}{p_{ij}^L} \sum_{S \in C_j} T_j P(j|I) \bullet \begin{bmatrix} (\frac{\partial \delta_j}{\partial \beta} - \sum_{r \in S} P(r|I) \frac{\partial \delta_j}{\partial \beta}) \\ (\frac{\partial \mu_{ij}}{\partial \Omega} - \sum_{r \in S} P(r|I) \frac{\partial \mu_{ij}}{\partial \Omega}) \\ -(\sum_{r \in S} \frac{\partial p_{ij}^L}{\partial \theta^{P(j|I)}}) \end{bmatrix}. \quad (20)$$

Write the second segment, including the outside option, as:

$$\frac{\partial \ell^L}{\partial \theta^{T_j}} = \sum_{i=1}^n \sum_{j=1}^J \frac{Y_{ij}}{p_{ij}^L} \bullet \begin{bmatrix} \frac{\partial T_j}{\partial \theta^{T_j}} P(j|I) \\ -\sum_{r \in S} \frac{\partial T_j}{\partial \theta^{T_j}} P(j|I) \end{bmatrix}. \quad (21)$$

The gradient of  $\ell^L$ ,  $\nabla \ell^L$ , is thus:

$$\nabla \ell^L = \begin{bmatrix} \frac{\partial \ell^L}{\partial \theta^{P(j|I)}} \\ \frac{\partial \ell^L}{\partial \theta^{T_j}} \end{bmatrix}. \quad (22)$$

## Notes

<sup>1</sup>Konisky (2011) notes that the public generally prefers the national government to handle broader environmental issues, especially those on a national or global scale. The phrasing of the question, however, could refer to any level of government, seriously complicating statistical inference. This is a primary example of the importance of question wording in survey design. As there is no way to discern exactly which level of government the individuals were considering when answering the question, the empirical models assume that the level of government was at least the same across individuals.

<sup>2</sup>Negative labels include Type III Environmental Declarations (International Organization for Standardization) and carbon footprint labels (Schenck, 2009), for example. For more on negative labels, see Grankvist, Dahlstrand, and Biel (2004).

<sup>3</sup>This coding issue demonstrates the importance for a researcher planning on using a limited information model on individual response data to carefully design the questions aimed at capturing opinions about the underlying choice outcome.

<sup>4</sup>The lack of price data does not imply the relationship between opinions and choices as described above does not exist, but rather that it is harder to identify. Furthermore, absent an experimental setting, the nature of the price data is not immediately clear.

<sup>5</sup>For more on the distinction between limited information and dislike see Draganska and Klapper (2011).

<sup>6</sup>The standard errors of  $\delta_j$ , relative to the parameter estimates, also increased across each specification suggesting a more uniform distribution of mean utility when accounting for heterogeneity in policy choice, and/or a potential endogeneity problem.

<sup>7</sup>Other tests for model selection, such as the Vuong Test (1989), which are indifferent to the nature of nesting, could be used to determine the statistically best fitting model. However, the statistically best fitting model is not necessarily the most relevant from an economics perspective. The Vuong Test might yield similar results as BIC, or the opposite

might be true. The fact that it is impossible to incorporate policy-specific opinions into the full information model, along with the logically intuitive arguments for using the limited information model, provide a reasonable economic argument for using the limited information model.

<sup>8</sup>For ease of exposition this is counted as a single instance of preference switching as opposed to two.

<sup>9</sup>Of course preferences are also influenced by strangers, family, and friends.

<sup>10</sup>For more on the relationship between information and voting behavior, see Houser, Morton, and Stratmann (2011), Lupia (1994) and Nordin (2010).

<sup>11</sup>Four additional counterfactual simulations were conducted but are excluded from the figures and tables. First, individual opinions for each policy were simultaneously increased by one level and the general result was that more individuals chose an inside policy and fewer chose the outside option. The opposite is true when the opinions for all policies were diminished. The same two counterfactual simulations were conducted on those with college=0 with similar results.

Table 1: Demographic Characteristics of n=1006 and n=704

Variable	n=1006				n=704				Count (10)	
	Mean (1)	Std. Dev. (2)	Max. (3)	Min. (4)	Count (5)	Mean (6)	Std. Dev. (7)	Max. (8)		Min. (9)
Age (as of 2009); 18–97 years; 18–92 years	0.541	(0.173)	1	0.19	983	0.551	(0.178)	1	0.20	704
Income ≥ \$50k	0.627	(0.484)	1	0	852	0.646	(0.478)	1	0	704
White	0.801	(0.399)	1	0	961	0.794	(0.404)	1	0	704
Female	0.543	(0.498)	1	0	1,006	0.521	(0.500)	1	0	704
Employed, Full– or Part–time	0.553	(0.497)	1	0	986	0.598	(0.490)	1	0	704
College Education Plus	0.479	(0.500)	1	0	993	0.483	(0.500)	1	0	704
Single	0.416	(0.493)	1	0	988	0.393	(0.489)	1	0	704
Own Home	0.827	(0.378)	1	0	948	0.820	(0.385)	1	0	704
Years in Community (as of 2009); 6m–87 years; 6m–85 years	0.265	(0.212)	1	0.01	965	0.269	(0.212)	1	0.01	704
Number of Kids Under 17; 0–7 kids	0.090	(0.162)	1	0	984	0.098	(0.164)	1	0	704
Political Party										
Republican	0.261	(0.440)	1	0	263	0.281	(0.450)	1	0	198
Democrat	0.395	(0.489)	1	0	346	0.357	(0.479)	1	0	251
Independent	0.344	(0.475)	1	0	346	0.362	(0.481)	1	0	255
Total					955					704
Census Regions										
Midwest	0.237	(0.425)	1	0	238	0.237	(0.425)	1	0	167
Northeast	0.193	(0.395)	1	0	194	0.193	(0.395)	1	0	136
South	0.342	(0.475)	1	0	344	0.342	(0.475)	1	0	241
West	0.229	(0.420)	1	0	230	0.229	(0.420)	1	0	161
Total					1,006					704

Source: Author's calculations

Note: 302 respondents were dropped due to missing observations.

Table 2: Demographic Characteristics of the Dropped Respondents, n=302

Variable	Mean (1)	Std. Dev. (2)	Max. (3)	Min. (4)	Count (5)
Age (as of 2009); 18–97 years	0.587	(0.177)	1	0.19	279
Income $\geq$ \$50k	0.534	(0.501)	1	0	148
White	0.821	(0.384)	1	0	257
Female	0.593	(0.492)	1	0	302
Employed, Full– or Part–time	0.440	(0.497)	1	0	282
College Education Plus	0.471	(0.500)	1	0	289
Single	0.472	(0.500)	1	0	284
Own Home	0.832	(0.374)	1	0	302
Years in Community (as of 2009); 6m–87 years	0.271	(0.223)	1	0.01	277
Number of Kids Under 17; 0–7 kids	0.532	(1.110)	7	0	280
Political Party					
Republican	0.259	(0.439)	1	0	65
Democrat	0.378	(0.486)	1	0	95
Independent	0.363	(0.482)	1	0	91
Total					251
Census Regions					
Midwest	0.248	(0.433)	1	0	75
Northeast	0.205	(0.405)	1	0	62
South	0.338	(0.474)	1	0	102
West	0.209	(0.407)	1	0	63
Total					302

Source: Author's calculations

Note: These are the demographic characteristics of the dropped respondents.

Table 3: Summary Statistics for Environmental Policy Question

Policy	Code	n=1006	n=704	n=302
Ban to prevent purchase	4	35.98%	35.80%	36.42%
Tax to discourage purchase	3	23.06%	25.00%	18.54%
Label to inform purchase	2	34.99%	35.09%	34.77%
Outside option (Don't know and refused)	1	5.96%	4.12%	10.26%
		100%	100%	100%
<b>Summary Statistics</b>				
Mean		1.89	1.92	1.81
Std. Dev.		0.97	0.93	1.04
Max.		3.00	3.00	3.00
Min.		0	0	0

Source: Author's calculations

Table 4: General Knowledge Questions, n=704

Answer	Code	1	2	3	4	5
Correct Answer	1	27.41%	54.40%	86.08%	70.74%	55.11%
Otherwise	0	72.59%	45.60%	13.92%	29.26%	44.89%
<b>Combined Correct Answers</b>	<b>Percentage</b>					
0	1.56%					
1	9.80%					
2	22.87%					
3	33.95%					
4	22.73%					
5	9.09%					

Source: Author's calculations

Table 5: Necessary Evil and Policy-Specific Opinions, n=704

Variable / Code	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree
<b>Necessary Evil</b>	11.22%	23.15%	22.87%	42.76%
Code	4	3	2	1
<b>Opinion of Ban</b>	72.44%	20.31%	3.41%	3.84%
Code	4	3	2	1
<b>Opinion of Tax</b>	17.19%	19.74%	31.68%	31.39%
Code	1	2	3	4
<b>Opinion of Label</b>	44.60%	23.58%	15.20%	16.62%
Code	4	3	2	1

Source: Author's calculations

Note: Opinion coding is scaled to the unit interval. The coding for tax is different due to the inclusion of the word "seldom" in the question wording.

Table 6: Cross-Tabulations of Policy Choice and Policy-Specific Opinion

Opinion Level	Ban	Column Sum		Outside	Ban	Tax	Row Sum		Outside	N
		Tax	Label				Label	Outside		
Cross-Tabulations with Ban-Specific Opinion										
Strongly Disagree	0.40%	3.41%	5.67%	20.69%	3.70%	22.22%	51.85%	22.22%	27	
Somewhat Disagree	1.98%	2.27%	5.67%	3.45%	20.83%	16.67%	58.33%	4.17%	24	
Somewhat Agree	9.92%	23.30%	28.34%	24.14%	17.48%	28.67%	48.95%	4.90%	143	
Strongly Agree	87.70%	71.02%	60.32%	51.72%	43.33%	24.51%	29.22%	2.94%	510	
Cross-Tabulations with Tax-Specific Opinion										
Strongly Disagree	36.11%	17.61%	35.22%	41.38%	41.18%	14.03%	39.37%	5.43%	221	
Somewhat Disagree	29.37%	32.95%	33.60%	27.59%	33.18%	26.01%	37.22%	3.59%	223	
Somewhat Agree	17.06%	28.98%	15.79%	20.69%	30.94%	36.69%	28.06%	4.32%	139	
Strongly Agree	17.46%	20.45%	15.38%	10.34%	36.36%	29.75%	31.40%	2.48%	121	
Cross-Tabulations with Label-Specific Opinion										
Strongly Disagree	9.92%	11.93%	24.29%	37.93%	21.37%	17.95%	51.28%	9.40%	117	
Somewhat Disagree	9.52%	17.61%	18.62%	20.69%	22.43%	28.97%	42.99%	5.61%	107	
Somewhat Agree	17.86%	30.11%	25.51%	17.24%	27.11%	31.93%	37.95%	3.01%	166	
Strongly Agree	62.70%	40.34%	31.58%	24.14%	50.32%	22.61%	24.84%	2.23%	314	

Source: Author's calculations

Note: For the column sum, the number of observations for ban, tax, label, and outside are 252, 176, 247, and 29, respectively. Recall the wording for tax-specific opinion slightly complicates the interpretation.

Table 7: Correlations of Policy Choice and Policy-Specific Opinion

Policy-Specific Opinion	Ban	Policy Tax	Choice Label	Outside
Pearson Correlation Coefficients				
Ban-Specific Opinion	0.2404***	0.0045	-0.1813***	-0.1543***
Tax-Specific Opinion	0.0478	-0.1593***	0.0782**	0.044
Label-Specific Opinion	0.2471***	0.0139	-0.2081***	-0.1266***
Spearman's Rank Correlation Coefficients				
Ban-Specific Opinion	0.2573***	-0.0117	-0.2010***	-0.1122**
Tax-Specific Opinion	0.0553	-0.1698***	0.0800**	0.0443
Label-Specific Opinion	0.2641***	-0.0056	-0.2109***	-0.1185**

Source: Author's calculations

Note: \* Significant at the 10% level; \*\*, 5%; and \*\*\*, 1%.

Table 8: Full Information MNL and Mixed-MNL Models of Policy Choice, 1 of 2

	MNL (1)	Mixed-MNL (2)		Mixed-MNL (3)							
	$\delta_j$	$\delta_j$	Inc.	$\delta_j$	Inc.	Age	White	Female	Emp.	Edu.	Single
Ban	2.334*** (0.205)	2.310*** (0.326)	0.044 (0.421)	2.812** (1.097)	0.201 (0.476)	0.983 (1.206)	-1.179* (0.686)	0.213 (0.407)	0.456 (0.451)	-0.750* (0.430)	-0.078 (0.438)
Tax	1.867*** (0.210)	1.586*** (0.342)	0.483 (0.435)	3.531*** (1.128)	0.357 (0.495)	-1.530 (1.259)	-1.273* (0.698)	0.476 (0.420)	0.468 (0.466)	-0.347 (0.444)	-0.733 (0.460)
Label	2.210*** (0.206)	2.097*** (0.330)	0.206 (0.424)	2.581** (1.099)	0.207 (0.477)	-0.170 (1.206)	-1.001 (0.687)	0.381 (0.407)	0.407 (0.451)	-0.173 (0.430)	-0.075 (0.439)
Stats.											
Obs.	2816	2816									
RFE	No	No									
LL	-849.06	-846.50									
-2LL	1698.13	1693.01									
AIC	1704.13	1705.01									
BIC	1721.96	1740.67									
% PC	0.3580	0.3580									
											2816 Yes -819.17 1638.34 1704.34 1900.46 0.3920

Source: Author's calculations

Note: Standard errors in parentheses. Obs. is number of observations. RFE is region fixed effects (base region is South).

LL is log-likelihood. -2LL is the Deviance Criterion. AIC is Akaike Information Criterion. BIC is Bayesian Information Criterion.

% PC is percent predicted correctly. \* Significant at the 10% level; \*\* 5%; and \*\*\* 1%.



Table 9: Full Information MNL and Mixed-MNL Models of Policy Choice, 2 of 2

Mixed-MNL (4)													
	$\delta_j$	Inc.	Age	White	Female	Emp.	Edu.	Single	Own	Years	Kids	Rep.	Dem.
Ban	2.564** (1.256)	0.484 (0.491)	0.565 (1.372)	-0.975 (0.726)	0.266 (0.441)	0.516 (0.469)	-0.912* (0.490)	-0.005 (0.490)	0.515 (0.538)	1.122 (1.397)	0.103 (1.520)	-1.808*** (0.531)	0.463 (0.683)
Tax	2.814** (1.290)	0.590 (0.506)	-2.094 (1.444)	-1.009 (0.737)	0.517 (0.451)	0.503 (0.481)	-0.440 (0.498)	-0.599 (0.509)	0.608 (0.555)	1.756 (1.441)	1.135 (1.523)	-1.402** (0.545)	0.602 (0.697)
Label	2.157* (1.255)	0.374 (0.488)	-0.709 (1.371)	-0.978 (0.724)	0.437 (0.440)	0.414 (0.466)	-0.213 (0.483)	0.123 (0.489)	0.620 (0.536)	1.769 (1.402)	1.312 (1.490)	-1.281** (0.526)	-0.008 (0.689)
Stats.													
Obs.	2816												
RFE	Yes												
LL	-797.71												
-2LL	1595.43												
AIC	1691.43												
BIC	1976.70												
% PC	0.4574												

Source: Author's calculations

Note: Standard errors in parentheses. Obs. is number of observations. RFE is region fixed effects (base region is South).

LL is log-likelihood. -2LL is the Deviance Criterion. AIC is Akaike Information Criterion. BIC is Bayesian Information Criterion.

% PC is percent predicted correctly. \* Significant at the 10% level; \*\*, 5%; and \*\*\*, 1%.

Table 10: Limited Information MNL and Mixed-MNL Models of Policy Choice, 1 of 2

	LIMNL (1)	Mixed-LIMNL (2)	Mixed-LIMNL (3)								
	$\delta_j$	$\delta_j$	Inc.	$\delta_j$	Inc.	Age	White	Female	Emp.	Edu.	Single
Ban	3.724*** (0.585)	4.018*** (0.852)	-0.994 (1.090)	4.927*** (1.832)	1.051 (0.730)	-2.358 (2.290)	-0.135 (0.883)	0.928 (0.715)	-1.289 (0.874)	-1.952*** (0.683)	2.911* (1.701)
Tax	3.323*** (0.582)	3.350*** (0.844)	-0.507 (1.090)	5.908*** (1.823)	1.189 (0.741)	-5.266** (2.282)	-0.097 (0.885)	1.144 (0.720)	-1.309 (0.883)	-1.488** (0.692)	2.193 (1.654)
Label	3.563*** (0.572)	3.744*** (0.838)	-0.758 (1.068)	4.807*** (1.819)	1.075 (0.742)	-3.685 (2.257)	0.002 (0.881)	1.102 (0.713)	-1.378 (0.879)	-1.342* (0.685)	2.842* (1.695)
Info. Params.											
PO	1.925*** (0.588)	1.783** (0.808)	1.442 (1.854)	9.226*** (2.785)	-0.464 (1.149)	-3.604* (1.968)	-0.585 (1.310)	1.080 (1.088)	1.853 (1.729)	2.191 (2.792)	-4.868*** (1.635)
G1	-1.006** (0.401)	-1.365* (0.774)		-2.693** (1.089)							
G2	-1.442** (0.597)	-1.487** (0.736)		-1.134 (1.024)							
G3	0.232 (0.490)	0.264 (0.601)		-1.398 (0.856)							
G4	0.389 (0.335)	0.296 (0.427)		1.032 (1.060)							
G5	1.145** (0.552)	1.255** (0.542)		1.482 (1.614)							
NE	0.757 (0.670)	0.962 (0.933)		2.022 (1.560)							
Stats.											
Obs.	2816	2816									2816
RFE	No	No									Yes
LL	-825.24	-822.13									-774.92
-2LL	1650.47	1644.27									1549.84
AIC	1670.47	1672.26									1649.84
BIC	1729.90	1755.47									1946.99
% PC	0.3665	0.3636									0.3949

Source: Author's calculations

Note: Standard errors in parentheses. Obs. is number of observations. RFE is region fixed effects (base region is South).

LL is log-likelihood. -2LL is the Deviance Criterion. AIC is Akaike Information Criterion. BIC is Bayesian Information Criterion.

% PC is percent predicted correctly. \* Significant at the 10% level; \*\*, 5%; and \*\*\*, 1%.

Table 11: Limited Information MNL and Mixed-MNL Models of Policy Choice, 2 of 2

Mixed-LIMNL (4)													
	$\delta_j$	Inc.	Age	White	Female	Emp.	Edu.	Single	Own	Years	Kids	Rep.	Dem.
Ban	4.348** (2.322)	0.788 (0.909)	-2.142 (3.048)	0.518 (0.970)	0.703 (0.734)	-1.788 (1.114)	-2.653*** (0.882)	3.022** (1.533)	1.567 (0.971)	-0.400 (2.196)	0.243 (2.286)	-0.573 (0.765)	1.496 (1.054)
Tax	4.832** (2.328)	0.833 (0.913)	-5.200* (3.070)	0.564 (0.975)	0.911 (0.739)	-1.832 (1.119)	-2.120** (0.888)	2.396 (1.536)	1.762* (0.977)	0.415 (2.219)	1.521 (2.283)	-0.233 (0.772)	1.581 (1.060)
Label	4.242* (2.314)	0.738 (0.907)	-3.938 (3.049)	0.294 (0.969)	0.919 (0.732)	-1.960* (1.111)	-1.909** (0.879)	3.087** (1.531)	1.742* (0.968)	0.499 (2.190)	1.534 (2.263)	-0.023 (0.761)	0.834 (1.054)
Info. Params.													
PO	9.147** (3.834)	0.636 (1.321)	-7.461*** (2.517)	-0.825 (1.845)	3.138*** (1.103)	0.511 (1.062)	3.583 (2.885)	-2.788** (1.210)	-0.850 (1.481)	7.445** (3.649)	1.179 (3.776)	-1.880 (1.600)	-1.582 (1.242)
G1	-2.548*** (0.845)												
G2	-1.894*** (0.663)												
G3	-0.937 (0.955)												
G4	0.426 (0.749)												
G5	1.846** (0.885)												
NE	2.147** (1.087)												
Stats.													
Obs.													2816
RFE													Yes
LL													-752.53
-2LL													1505.06
AIC													1645.06
BIC													2061.07
% PC													0.4545

Source: Author's calculations

Note: Standard errors in parentheses. Obs. is number of observations. RFE is region fixed effects (base region is South). LL is log-likelihood. -2LL is the Deviance Criterion. AIC is Akaike Information Criterion. BIC is Bayesian Information Criterion. % PC is percent predicted correctly. \* Significant at the 10% level; \*\*, 5%; and \*\*\*, 1%.

Table 12: Model Selection Criteria

Model	Respondents	Observations	Parameters	RFE	LL	-2LL	AIC	BIC	% PC
Full Information									
1	704	2816	3	No	-849.063	1698.127	1704.127	1721.956	0.3580
2			6	No	-846.504	1693.009	1705.009	1740.667	0.3580
3			33	Yes	-819.170	1638.339	1704.339	1900.461	0.3920
4			48	Yes	-797.715	1595.429	1691.429	1976.697	0.4574
Limited Information									
1	704	2816	10	No	-825.236	1650.472	1670.472	1729.903	0.3665
2			14	No	-822.132	1644.265	1672.265	1755.468	0.3636
3			50	Yes	-774.918	1549.837	1649.837	1946.990	0.3949
4			70	Yes	-752.530	1505.059	1645.059	2061.074	0.4545

Source: Author's calculations

Table 13: Latent Class Preference Switching, 1 of 2

Latent Class by Dummy Variable Specification									
	Age	Average Years	Kids	Standard Deviation Age	Years	Kids	Count	Preference No	Switching Yes
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Republican, Midwest	48.30	4.74	2.53	11.96	14.47	1.42	10	4	6
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, South	49.00	3.33	3.01	12.11	13.84	1.01	9	0	9
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Republican, South	44.88	2.43	4.94	6.94	7.88	1.25	8	0	8
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, Northeast	49.63	2.40	4.17	10.16	6.67	1.11	8	2	6
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, Midwest	50.57	2.71	1.11	10.69	15.26	0.75	7	1	6
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, South	53.14	3.10	2.90	10.53	19.34	1.31	7	4	3
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, Northeast	51.14	3.13	1.92	8.68	11.27	1.01	7	3	4
White, Female, Income $\geq$ \$50k, Unemployed, No College, Married, Own Home, Republican, South	65.29	2.31	0.86	15.28	20.08	0.72	7	0	7
White, Female, Income $\geq$ \$50k, Employed, No College, Married, Own Home, Independent, Northeast	49.86	2.97	1.68	7.56	8.40	1.19	7	1	6
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, South	47.67	1.70	4.12	10.93	5.72	1.50	6	0	6
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, West	50.50	2.22	2.71	9.31	8.94	0.84	6	2	4
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, West	50.83	2.40	2.92	10.38	15.24	0.92	6	5	1
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, Midwest	52.50	3.20	0.31	3.93	17.79	0.38	6	0	6
White, Male, Income $\geq$ \$50k, Employed, No College, Married, Own Home, Independent, Midwest	40.17	3.54	1.70	8.22	17.73	1.03	6	1	5
Non-White, Female, Income $\geq$ \$50k, Employed, No College, Single, Own Home, Democrat, South	40.33	4.83	0.62	18.76	16.18	0.79	6	2	4
<b>Subtotal Top 15 Latent Classes</b>							<b>106</b>	<b>25</b>	<b>81</b>
<b>Total Latent Classes</b>							<b>395</b>	<b>248</b>	<b>456</b>
<b>Percent of Total</b>							<b>26.84%</b>	<b>10.08%</b>	<b>17.76%</b>

Source: Author's calculations

Table 14: Latent Class Preference Switching, 2 of 2

Latent Class by Dummy Variable Specification										Preference Switching	
		Age	Minimum Years	Kids	Maximum Years	Kids	Count	No	Yes		
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Republican, Midwest		30.00	5.00	-	63.00	4	10	4	6		
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, South		32.00	5.00	-	75.00	3	9	0	9		
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Republican, South		31.00	2.00	-	54.00	3	8	0	8		
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, Northeast		33.00	3.00	-	63.00	3	8	2	6		
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, Midwest		38.00	3.00	-	70.00	2	7	1	6		
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, South		38.00	8.00	-	66.00	4	7	4	3		
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, Northeast		41.00	11.00	-	66.00	2	7	3	4		
White, Female, Income $\geq$ \$50k, Unemployed, No College, Married, Own Home, Republican, South		44.00	4.00	-	92.00	2	7	0	7		
White, Female, Income $\geq$ \$50k, Employed, No College, Married, Own Home, Independent, Northeast		40.00	7.00	-	60.00	3	7	1	6		
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, South		27.00	3.00	-	62.00	4	6	0	6		
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, West		38.00	3.00	-	67.00	2	6	2	4		
White, Male, Income $\geq$ \$50k, Employed, College, Married, Own Home, Democrat, West		40.00	3.00	-	64.00	2	6	5	1		
White, Female, Income $\geq$ \$50k, Employed, College, Married, Own Home, Independent, Midwest		47.00	1.00	-	59.00	1	6	0	6		
White, Male, Income $\geq$ \$50k, Employed, No College, Married, Own Home, Independent, Midwest		30.00	3.00	-	50.00	2	6	1	5		
Non-White, Female, Income $\geq$ \$50k, Employed, No College, Single, Own Home, Democrat, South		19.00	18.00	-	63.00	2	6	2	4		
<b>Subtotal Top 15 Latent Classes</b>							<b>106</b>	<b>25</b>	<b>81</b>		
<b>Total Latent Classes</b>							<b>395</b>	<b>248</b>	<b>456</b>		
<b>Percent of Total</b>							<b>26.84%</b>	<b>10.08%</b>	<b>17.76%</b>		

Source: Author's calculations

Table 15: Counterfactual Coding Example for Ban (j= 4)

Resp. ID	Policy ID	Edu.	PO	CF1	CF2	CF3	CF4	CF5	CF6
1	Ban	0	0.75	1.00	0.75	1.00	1.00	0.75	1.00
1	Tax	0	0.50	0.50	0.25	0.25	0.50	0.25	0.25
1	Label	0	0.25	0.25	0.25	0.25	0.25	0.25	0.25
2	Ban	1	0.50	0.75	0.50	0.75	0.50	0.50	0.50
2	Tax	1	0.25	0.25	0.25	0.25	0.25	0.25	0.25
2	Label	1	0.75	0.75	0.50	0.50	0.75	0.75	0.75

Source: Author's calculations

Table 16: Counterfactual Results

Model/Simulations	Percent of All Respondents			Percent of Respondents with College=0		
	Ban	Tax	Label	Ban	Tax	Label
<b>Ban</b>						
Data	35.80%	25.00%	35.09%	21.59%	12.22%	16.34%
Full Information	48.58%	8.24%	43.18%	34.80%	3.13%	13.78%
Limited Information	50.00%	13.07%	34.66%	34.23%	4.55%	11.51%
CF1	51.70%	12.93%	33.81%	35.51%	4.40%	10.65%
CF2	55.11%	11.36%	30.97%	36.93%	3.41%	9.80%
CF3	53.55%	13.64%	30.26%	35.80%	4.69%	9.66%
<b>Tax</b>						
Data	35.80%	25.00%	35.09%	21.59%	12.22%	16.34%
Full Information	48.58%	8.24%	43.18%	34.80%	3.13%	13.78%
Limited Information	50.00%	13.07%	34.66%	34.23%	4.55%	11.51%
CF1	48.01%	16.34%	33.66%	32.95%	6.25%	11.22%
CF2	51.14%	14.77%	31.25%	33.95%	5.54%	10.51%
CF3	49.01%	18.32%	30.40%	32.81%	7.39%	10.23%
<b>Label</b>						
Data	35.80%	25.00%	35.09%	21.59%	12.22%	16.34%
Full Information	48.58%	8.24%	43.18%	34.80%	3.13%	13.78%
Limited Information	50.00%	13.07%	34.66%	34.23%	4.55%	11.51%
CF1	46.73%	12.07%	39.35%	32.24%	4.40%	13.78%
CF2	48.01%	10.65%	38.49%	32.81%	3.27%	13.78%
CF3	44.18%	10.23%	43.32%	30.68%	3.13%	16.34%

Source: Author's calculations

Note: For College=0, the percentage results use a base of N=704.



Figure 1: Ban Counterfactual Results for All Respondents

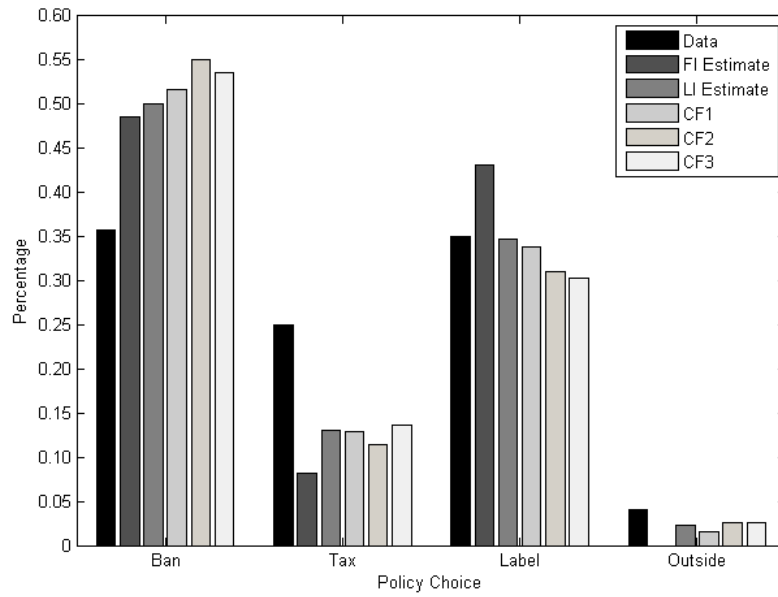


Figure 2: Ban Counterfactual Results for Respondents with College=0

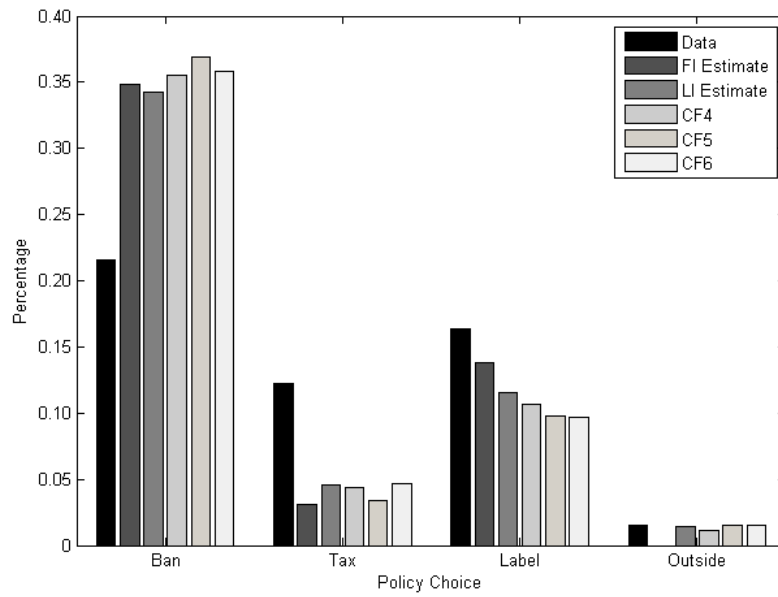


Figure 3: Tax Counterfactual Results for All Respondents

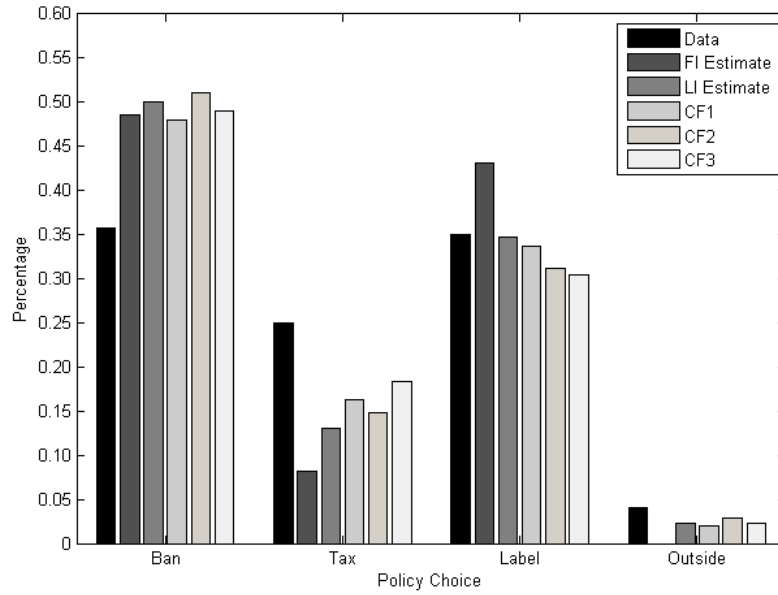


Figure 4: Tax Counterfactual Results for Respondents with College=0

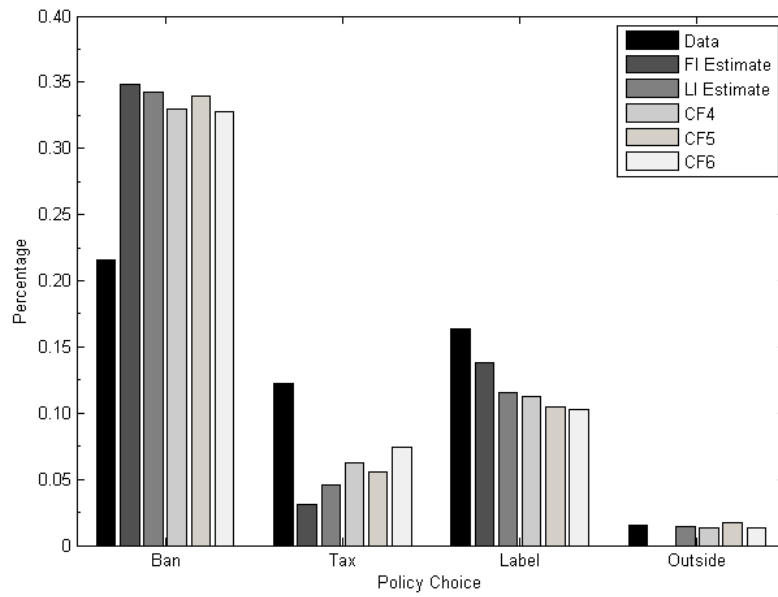


Figure 5: Label Counterfactual Results for All Respondents

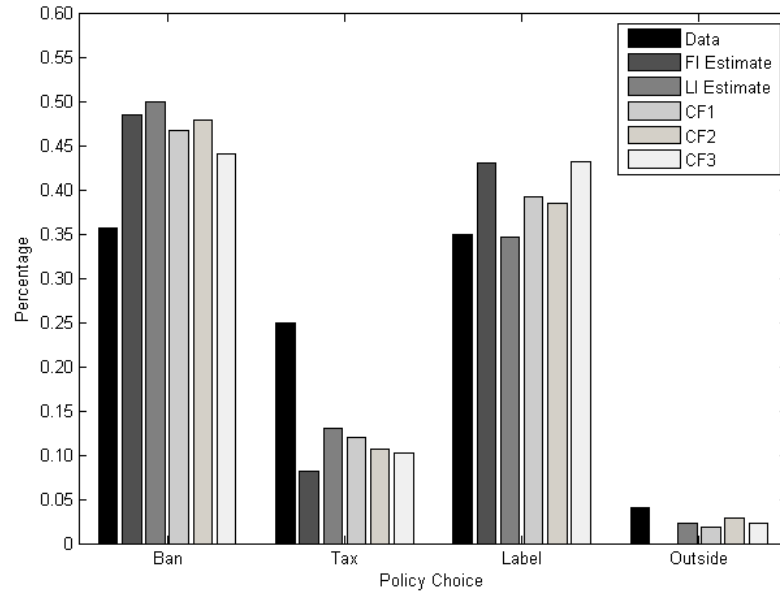
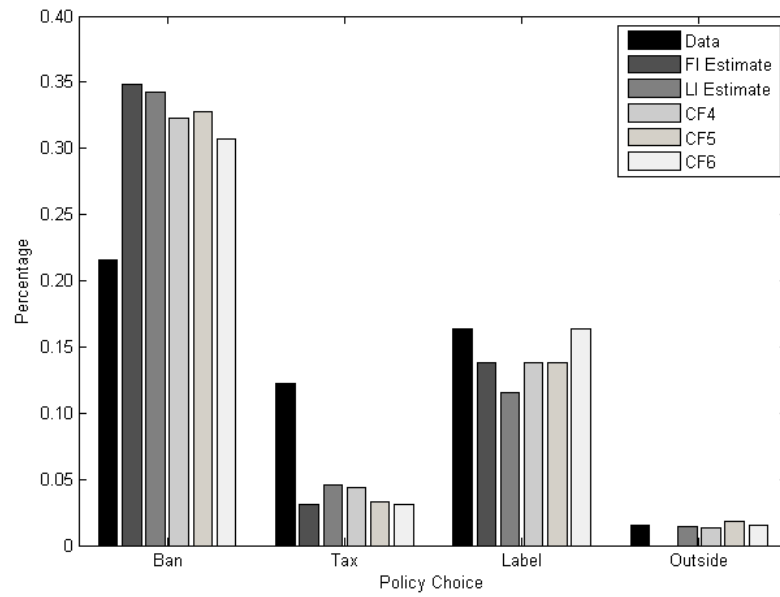


Figure 6: Label Counterfactual Results for Respondents with College=0



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