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Attribute Based Modeling of Recycling Preferences at
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ATTRIBUTE BASED MODELING OF RECYCLING PREFERENCES AT MICHIGAN STATE UNIVERSITY

By

David J Gebben

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ABSTRACT

ATTRUBUTE BASED MODELING OF RECYCYCLING PREFERENCES AT MICHIGAN STATE UNIVERSITY

By

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Environmental, economic, and political pressures increasingly make recycling programs important parts of both public and private solid waste management strategies. Recycling programs differ across communities, businesses, and public institutions yet share common attributes such as the materials to be recycled, and the material separation required of recyclers. Effective recycling programs should benefit from an understanding of the recycling behaviors, attitudes, and preferences of the people the program intends to serve.

This thesis examines recycling preferences though a stated preference choice experiment performed at Michigan State University. We perform a trade-off analysis to provide policy makers information about the trade-offs campus members are willing to make between program attributes and costs. The first essay examines the preferences and trade-offs for the campus populations: students, faculty, and staff. The second essay compares two econometric methods for identifying segments of the population that have distinct preferences. All else equal, we find that campus members want a recycling program in which they can recycle more materials, in some sort of container, in locations close to their dorm rooms or offices, with lower costs. In terms of the trade-offs between program costs and the program attributes, all groups were willing to incur additional costs to have recycling locations that are near their dorm rooms or offices.

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Chapter 1 - Introduction

Environmental, economic, and political pressures increasingly make recycling programs important parts of both public and private solid waste management strategies. Recycling programs differ across communities, businesses, and public institutions yet most recycling programs often share common attributes such as the materials to be recycled, the location of collection sites, and the material separation required of recyclers. Each of these attributes can affect program costs and revenues as well as the participation and satisfaction of the recyclers to be served by the program. Designing effective recycling programs should benefit from an understanding of the recycling behaviors, attitudes, and preferences of the people the program intends to serve.

Although several studies on the behaviors and preferences of recyclers have been conducted for households and cities, there are few studies focused on large institutions such as college campuses. This thesis addresses this gap by conducting a trade-off analysis of attributes of a potential university recycling program. The data are from a stated preference survey of university students, faculty and staff. The two main goals of this thesis are:

1. To estimate campus members' preferences for recycling program attributes and their marginal rates of substitution between program attributes and program costs;
2. To compare and contrast the performance of two econometric tools, interaction effects and latent class models, for explaining consumer heterogeneity and segmentation regarding recycling preferences.

To accomplish these objectives this thesis presents two essays analyzing stakeholder recycling preferences. Essay 1 addresses the first objective and presents estimated recycling program preferences for three campus groups: students, faculty, and staff. The recycling program attributes are materials to be recycled, the location of recycling receptacles, the degree of source separation required by users, the type of recycling containers provided to users, and the cost of the program to the institution. The data are from a web-based stated preference survey conducted from November to December 2007. Random effects probit models are used to estimate the preferences, and marginal rates of substitution (MRS) are derived for the individual user groups and for the campus as a whole. The MRS are useful for comparing preferences across user groups and represent the trade-offs stakeholders are willing to make between additional program costs and the different possible attributes of the recycling program.

Essay 2 compares and contrasts two approaches for examining consumer heterogeneity. The first approach relies on interaction terms to distinguish unique segments of users with distinct underlying preference structures. With this approach the researcher's choice of the interaction terms, perhaps based on prior understanding of the population, determines the possible market segments. The second approach uses latent class models (LCM) to let the data reveal different underlying market segments. Numerous variants of the LCM models are reported. The preferences and marginal rates of substitution that are revealed by the LCM and interaction effects models are compared to those of the interaction effects models, and the relative merits of the approaches are discussed.

Chapter 2 – Essay 1

1. Introduction

Environmental, economic, and political pressures increasingly make recycling programs important parts of both public and private solid waste management strategies. While recycling programs differ across communities, businesses, and public institutions, most recycling programs share some common attributes. These attributes include such things as: the materials to be recycled, the location of collection sites, the design and type of recycling receptacles, as well as the procedures and processes for material separation. Designing effective recycling programs should benefit from an understanding of the recycling behaviors, attitudes, and preferences of the people the program intends to serve. Although several studies of these features focus on households and cities, there are not many studies focused on large institutions. Solid waste management decisions facing large institutions like universities, businesses and industries in many ways parallel those of communities and cities. The design of such programs impacts the size and distribution of such factors as collection costs, separation costs, operational costs, as well as potential revenue streams from recycled materials. This paper focuses on developing an understanding of the recycling behaviors, attitudes, and preferences of the various constituencies of a new recycling program at a large, institution-- Michigan State University (MSU), a Big Ten university.

MSU occupies a 5,200-acre campus with 2,100 acres in existing or planned development. It is comprised of approximately 579 buildings, 46,000 students, 4800 faculty, and 6100 staff. The university generates more than 12,000 tons of solid waste per year (Selke et al. 2006). As is typical for a major public university, MSU has several characteristics that complicate the recycling planner's tasks--buildings spread out over a large area; building ages that may be more than 100 years old and others that may be new; and a wide range of types of wastes, from radioactive materials to food stuffs to office paper. Furthermore, planning for a new recycling facility and program requires decisions about what materials to recycle; whether and where materials are to be separated; how to collect such materials, as well as what facilities to build and staff. The reported research is part of an effort to plan, develop and implement an integrated, campus-wide recycling program that is cost effective and responsive to the desires and preferences of the in situ stakeholders of a large institution—the students, faculty and staff of a tier-one, research-intensive university.

Public participation in the design and implementation of recycling programs has been associated with improved recycling program performance (e.g., Folz 1991, Folz and Hazlett 1991, Nyamwage 1996). Our study was designed to elicit university community members' preferences for recycling program attributes as part of the university's efforts to build new recycling facilities and develop a new recycling program. To do so, we implemented a university-wide preference survey (also called a trade-off analysis or choice experiment) that asked respondents to evaluate alternative recycling program configurations. The Attribute Based Method (ABM) was used to identify the relative importance that different program attributes have on people's preferences for alternative recycling programs. Using ABM allowed us to estimate the preferences people have for alternative programs (combinations of program attributes) that the university could implement. We included a cost constraint to facilitate examining individuals' willingness to make trade-offs between various program attributes and costs.

1.1 *Previous Literature*

There is an extensive literature on municipal and regional recycling programs, both on participation rates and the economics of recycling. Previous research suggests that recycling rates of university campuses and cities may be increased by increasing community recycling options, raising community members' knowledge of recycling, and by improving the convenience of recycling (Folz 1991). It has been observed that "cities with higher rates of [recycling] participation and waste stream diversion place more importance on citizen involvement in the policy initiation and program design decisions" (Folz and Hazlett 1991). Others have pointed out that increased participation in community recycling seems to have resulted from community input regarding changes to the recycling containers and location of collection points (Nyamwage 1996). One such study found that "democratizing" the recycling program was associated with an increase in the recycling program participation rates (Folz 1991). Others have examined the economics of household recycling resulting in the development of a model where information about recycling policies can be examined (Choe and Fraser 1999).

Narrowing the focus to valuation studies of recycling programs, previous research has examined drop-off recycling programs (Tiller, Jakus, and Park 1997) as well as curbside recycling programs (Caplan, Grijalva, Jakus 2002; Aadland, Capland 2003). This previous valuation literature focuses mainly on the waste stream that is created by households with survey research examining household or municipal managers' responses.

While household waste streams are significant, large institutions and companies also have significant waste stream management concerns. This paper begins to address and assess recycling program preferences of community members (i.e., stakeholders) of an institution that shares characteristics of a small community, a corporation, and a public entity.

Examining recycling program preferences at an institutional level has advantages over looking at such data from the household level. Large institutions by their very nature produce more waste than a single household, yet they are, in some important ways, a single decision-making entity. In the context of institutional decision making, planners may be able to identify and organize groupings of individuals, waste-stream producers, or reduction opportunities to a greater degree than a municipal entity might be able to manage. Furthermore, large institutions such as universities and large businesses often manage their own waste streams, have centralized planning, and may be able to fashion their own systems with greater ability to effect change than a typical city with numerous autonomous households. As has been shown, institutions can implement resource recovery and waste recycling with relative ease resulting in reduced pressure on solid waste disposal sites (Mbuligwe 2002).

Universities are unique institutions for undertaking waste reduction and recycling program efforts. University constituencies are inherently more educated than the general population, and therefore may be better able to understand complex and integrative problems as well as large-scale problems such as environmental pollution and climate change (Hines 1987). In addition, the university setting provides a social and psychological location for the development of environmental values and concerns in community members (Ewert and Baker 2001). Studies of university students' recycling choices and motivations have found that university students' pro-environmental attitudes predicted their pro-environment behaviors and that increased environmental knowledge added to the pro-environmental impact of attitudes on behaviors (Mienhold and Malkus, 2005). Jennings (2004) found the most important determinants of recycling behavior in a university setting to be both attitudinal (i.e., requires greater education to create change) and logistical (e.g., can be altered, a new recycling center can be constructed, etc.). Our study will address preferences over some of these logistical factors associated with a campus recycling program.

To date, the numbers of campus recycling studies are few relative to studies of recycling of the population at large or of residential populations. Almost all previous college campus recycling studies have looked at respondents' recycling attitudes, knowledge, and behaviors. This paper differs from those studies in that we examine specific recycling program attributes and analyze the trade-offs that respondents make between recycling program characteristics when they choose among possible recycling programs for the university. In the next section we discuss the methods for quantifying attribute preferences and trade-offs.

2. Methods

2.1 *Theory and background*

In a choice experiment, the researcher asks each respondent to make a choice between two bundles of attributes with an associated price. The choice problem mimics actual market behavior, where consumers choose between different types of cars or shoes with different attributes and prices (Holmes & Adamowicz 2003). The estimates and preferences are then derived from the respondents' choices based on the underlying utility that the different bundles provide the individuals.

Attribute based methods of analysis seek to understand consumer choices in terms of the attributes (or characteristics) of the alternatives that are chosen by individuals. That is, goods or programs are seen as consisting of bundles of attributes that combine to produce consumers' utility (Louviere et al. 2000). The Attribute Based Method estimates economic values for a technically divisible set of attributes, and the inclusion of price as an attribute in the choice sets provides a constraint to the choice. Eliciting and quantifying these trade-offs is one way our study differs from what other campus recycling literature offers where the examinations tend to address behavioral and attitudinal research.

Building on the attribute based model, this study uses Random Utility Theory to understand and evaluate individuals' choices among alternative recycling programs (Adomowicz and Boxall 2001). Under the assumptions of Random Utility Theory (RUT), the general model of choice starts with the indirect utility, U, a consumer is able to obtain which is a function of income I, a vector of attribute levels, $\mathbf{x}$, and individual preferences, e.

$$U = u(\mathrm{I}, \mathbf{x}, e) \qquad (1)$$

In our choice experiment, respondents were asked to choose between two bundles of attributes, each with a price. Therefore, the indirect utility for an amount p paid for an attribute would be:

$$U_1 = u(I - p_1, x_1, e_1). \qquad (2)$$

where, utility U_1 is a function of x_1 a vector of attributes provided to the consumer at prices p_1. In our choice experiments, the participants were presented with two recycling program choices, and were asked to choose the program that they preferred. Therefore, the indirect utility associated with the second recycling option can be expressed as:

$$U_2 = u(I - p_2, x_2, e_2). \tag{3}$$

Following RUT, an individual would select (be willing to pay p_1) for the bundle of goods x_1 if the utility is greater than the utility from x_2 at p_2 (i.e., $U_1 > U_2$). So the probability that a respondent would say *Yes* when asked if x_1 is preferred to x_2, may be expressed as:

$$\begin{aligned} \Pr(yes) &= \mathbf{Pr}[u_1(x_1, I - p_1, e_1) \geq u_2(x_2, I - p_2, e_2)] \\ \Pr(yes) &= \Pr[\Delta u > 0]. \end{aligned} \tag{4}$$

Using the basic approach embodied in (4), we can parameterize the utility functions to quantify preferences. Let utility be given by the sum of observable and unobservable components:

$$u_{ij} = v_{ij} + e_{ij}. \tag{5}$$

where v_{ij} represents the observable portion of utility; e_{ij} represents the unobservable portion of utility; *j* represents alternatives, and *i* represents people. With that, we can then modify (4) so that:

$$\Pr(yes) = \Pr[v_{ij} + e_{ij} > v_{ik} + e_{ik}] \tag{6}$$

The observable portion of utility is made up of the following characteristics:

$$v_{ij} = \alpha x_j + \beta(I_i - p_j), \tag{7}$$

where x_j is a vector attributes associated with alternative *j*, α is a vector of estimable parameters, β is an estimable parameter, I_i is income of respondent *i*, and p_j is the price of alternative *j*.

Substituting (7) into (6) we can write the probability of a *yes* answer to a preference question comparing *j* versus *k* (where a respondent prefers program *j* to program *k*) as follows:

$$\begin{aligned}
\Pr(yes) &= \Pr[\alpha x_j + \beta(I_i - p_j) + e_{ij} > \alpha x_k + \beta(I_i - p_k) + e_{ik}] \\
\Pr(yes) &= \Pr[(\alpha x_j - \alpha x_k) - (\beta p_j - \beta p_k) > e_{ik} - e_{ij}] \\
\Pr(yes) &= \Pr[\alpha(\Delta x\ \ ) - \beta(\Delta p\ \ ) > e_{ik} - e_{ij}].
\end{aligned} \qquad (8)$$

It is typically assumed that the marginal utility of income does not change from one choice to another. Since the utility of income does not change from one state to another, we can then drop the ΔI_i terms as in the second line of (8). This is because the income (and other individual-specific variables) does not vary for the individual as he or she makes choices. We can next make the assumption that the difference in the error terms is normally distributed allowing for a model that gives the probability of an individual choosing alternative *j* over alternative k:

$$\Pr(yes) = \Pr[\alpha(\Delta x) - \beta(\Delta p) > e] = \Phi[\alpha(\Delta x) - \beta(\Delta p)], \qquad (9)$$

where Φ is the cumulative distribution function (cdf) of the standard normal distribution, assuming that $\sigma = 1$. Equation (9) can be estimated using the maximum likelihood estimation procedure for a probit model. Due to the discrete nature of the choices, σ cannot be identified in a probit, so one can take it as if $\sigma = 1$ or simply recognize that all parameters are identified up to the unknown variance term. As such, model comparisons that involve parameter ratios are fully identified since the unknown variance term will cancel. We report such calculations below.

The Marginal Rate of Substitution (MRS) allows the comparison of magnitudes for the preference of one attribute over another. Of particular relevance is the MRS between an attribute and money. The calculation of the MRS was α / β, where α is the coefficient on the attribute variable and β is the negative of the cost coefficient from the regression output. This MRS measurement provides a ratio that expresses in common units people's willingness to make monetary trade-offs for changes in an attribute. The MRS expressions can be compared across the populations and from one attribute to another.

2.2 *Choice Experiment Survey Design*

As mentioned, a choice experiment survey was conducted that elicited preferences over possible recycling programs. The survey contained several sections including background information and questions about the university's plans to develop a new recycling program. In the survey, each respondent was presented with three sets of two possible recycling programs and respondents were asked to select their preferred program among each pair. The recycling programs were described by several attributes and each program had a cost associated with it. Adequately describing the program and the attributes was crucial to ensure that when each respondent made their choices, each respondent has in mind the same good. It is well-known that stated choice surveys should be as realistic as possible so that the respondents are able to provide accurate, realistic answers (Carson et al. 2001). Therefore, we now review the efforts that went into the attribute selection and the way that attributes were conveyed to respondents.

The survey instrument was developed in three phases that centered on focus group studies, survey design, and pretesting/revision of the survey (Kaplowitz et al. 2004). A series of key informant interviews were conducted with university administrators, consulting engineers, faculty active in university environmental affairs, as well as student activists. These were conducted so that the survey targeted appropriate recycling program attributes and levels as well as to design an instrument that adequately informed respondents about the various recycling program attributes and the possible levels for each attribute. The focus groups were qualitative studies conducted to gauge the recycling knowledge, behaviors, and attitudes of MSU. The focus group results then guided subsequent interviews and the design and implementation of the survey itself (Hansen et al. 2007).

The result of our focus groups and interview efforts with university administrators, consulting engineers, and university community members was the identification of five program attributes with various possible levels for each attribute. The program attributes consisted of the materials to be recycled (paper, cardboard, non-deposit containers, and deposit containers[1]), the type of recycling container individuals would be provided, the location where recyclables would be taken, the amount of waste stream separation required by individuals, and the amount the program would cost the institution. (See Table 2.1 and discussion below).

[1] Michigan has a deposit on certain types of beverage containers.

Table 2.1: Recycling Program Attributes and Attribute Levels

Attribute	Attribute Level
Materials	Paper, Cardboard, Non-deposit containers, Deposit containers
	Paper, Non-deposit containers, Deposit containers
	Paper, Deposit containers, Cardboard
	Paper, Non-deposit containers
	Paper, Non-deposit containers, Cardboard
	Paper, Deposit containers
	Paper, Cardboard
Location	Floor/Classroom
	Building
	Drop-Off
	Central
Containers	No bin
	Multiple small bins
	One large bin
	A single hanging bag
Separation	One stream
	Multiple streams
	Complete separation
Cost	\$50
	\$150
	\$300
	\$500

In the survey, respondents were told that MSU was designing a recycling program and that their feedback was needed on the type of program to be implemented. To introduce survey respondents to the attributes included in the recycling program, respondents were first presented with a description and sometimes a photograph of the each program attribute and the possible attribute levels. We then provided a Likert scale question about the attribute for the respondent to answer. Asking a question about the attribute immediately after providing information about the attribute and its levels was done to get respondents to read the information rather than just skip over the text. After informing the respondents about all of the possible program attributes and their levels, we then presented the three pair-wise program choice experiment questions (see figure 1 for an example of one of the choice pairs).

Note that there are many possible combinations of all the attributes, yet each respondent only saw three of the many possible pairs. The attributes pairs were then varied across respondents following an experimental design. The experimental design consisted of a mix of pairs from a main-effects design for these attribute levels and random pairing of the attribute levels. By varying the attribute pairs across respondents, the statistical techniques outlined above can be used to identify the effect that each attribute level has on the probability that an alternative is preferred.

The survey allowed for the collection of data in a simulated market setting by asking respondents to indicate choices from realistic sets of alternatives that included costs (McFadden 1986). Since the respondents were asked to make choices under a constraint, cost, it was crucial that we explain how program costs would be paid. The program costs were costs to the institution, and the construction costs would be paid for through a capital bond mechanism, as was explained to the respondents. Further, respondents were told that when the costs of the program were incurred, it would leave less money for the institution to use in other areas. In the choice questions, the cost to the institution was expressed in per-person terms. Hence, the cost associated with the program is not a direct cost to the respondent, rather it is an opportunity cost to the campus – as more money is spent on the recycling program, less money is available to spend on other campus items. That is, implementation of a more expensive project would translate into a higher per person expenditure (cost) and less money would be available to spend on campus elsewhere.

2.3 Survey Administration

Most stated preference surveys have been done in person, or through a mail survey. Both methods have their advantages and disadvantages. Both methods are relatively expensive to implement. In person surveys offer greater control of information because the survey interviewer may provide immediate feedback, while mail surveys have the advantage of being able to reach a much larger number of potential respondents than a team of interviewers would be able to contact. As in other fields of survey research, web surveys are increasingly being used for stated preference studies including choice experiments and other ABMs. Given that the study population (university students, faculty, and staff) all had access to and use e-mail and the web for everyday university business, the survey was designed for, and implemented as a web based instrument. Doing so allowed for a low cost and a highly sophisticated study design. The method also allowed each respondent, depending on their status as student, staff, or faculty, to receive only those questions relevant to them and it allowed the researchers to monitor and control the information viewed. The web-based method also allows the researcher to randomize the pairs for the respondent. In this way, the web-based survey design utilized some of the pros of both in person surveys and mail surveys. (A copy of the web survey is available at http://recycle-survey.msu.edu/Default.aspx?uid=961085352397 .)

The sample list for the study was drawn from the university's official lists of faculty, staff and student. The registrar provided a random list of the email and mailing addresses of about 30% of each group – students, faculty, and staff. Those on the list received either a postcard or an email inviting them to participate in the survey. We were then able to track the participation rates and responses of each group. This degree of control and information is unique relative to other web based surveys since we could track who responded and we knew characteristics of the entire population. An initial invitation was sent to all members of the sample in November 2007 informing them of the study and providing them with a link to the survey. Up to two additional invitations to participate were sent to potential respondents during November and December 2007. That is, those members of our sample that did not participate in the survey after the first invitation were asked or reminded to participate a second time, and finally, nonrespondents were contacted a third time and reminded/asked to participate. The overall response rate for this study was 25% with students responding at a lower rate than faculty or staff. Table 2.2 presents the differences across the three strata of university community members.

Table 2.2: Web-Survey Response Rates

	All campus	Faculty	Staff	Students
Percent responding	25%	38%	42%	20%
Number responding	3896	563	883	2450

In our choice experiment, each individual is asked to respond to more than one stated preference question making it likely that there are unobserved characteristics specific to individuals that induce correlation across individuals' responses. Therefore, we estimate the model using a random effects probit model (Wooldridge 2002). In random effects models, the error term is treated as two separate components. One component is the unobservable portion that is unique to the individual respondent. The second component is the random component across all individuals and their responses (Boxall et al. 2003). This utility model can be written as:

$$\Delta u_{ij} = \alpha(\Delta x_j) - \beta(\Delta p_j) + \mu_i + e_{ij}, \tag{10}$$

where μ_i is the unique individual error term, and e_{ij} is the random error term across the whole population sample.

Coding the survey responses followed typical conventions. We estimated a random effects probit regression using the standard statistical software package STATA ®. The probability of an individual choosing the first bundle of attributes (Program A) as opposed to the second bundle of attributes (Program B) was treated as a "yes" and coded as a "1." Because the recycling program attribute levels, with the exception of costs, are all dummy variables, not all levels can be identified. For each attribute, one level is set as the baseline and is omitted from the estimation. The coefficients on the remaining attribute levels then require an interpretation in relation to the base level. Thus, a negative coefficient implies that that the attribute level is less preferred than the baseline level for that attribute, while a positive value implies that attribute level is more preferred than the baseline.

3. RESULTS

3.1 *Preferences*

The respondents were informed that university recycling programs could focus on the following materials: paper, cardboard, deposit containers, and non-deposit containers. The results, presented in Table 2.3, not surprisingly, indicated that people prefer recycling programs with more materials for recycling rather than recycling programs with fewer materials. Also not surprisingly, deposit containers are a less preferred program recycling material for respondents than the other recycling program materials. We speculate that this is due to the residual value that a deposit bottle or can retains in Michigan because of the state bottle bill requiring refundable deposits on carbonated beverage bottles and cans.

Table 2.3 Estimated Coefficients from the Random Effect Probit Model for Recycling Program Attribute Preferences

	Students*		Faculty**		Staff***	
	Coef.	p-value	Coef.	p-value	Coef.	P>z
Materials						
Paper, NDC, DC, CB (baseline)						
Paper, NDC, DC	-0.33	0.000	-0.40	0.000	-0.33	0.002
Paper, NDC, CB	-0.16	0.003	-0.22	0.014	-0.31	0.006
Paper, NDC	-0.45	0.000	-0.45	0.000	-0.56	0.000
Paper, DC, CB	-0.36	0.000	-0.46	0.000	-0.37	0.001
Paper, DC	-0.57	0.000	-0.66	0.000	-0.69	0.000
Paper, CB	-0.72	0.000	-0.63	0.000	-0.67	0.000
Location						
Floor/Classroom (baseline)						
Building	-0.12	0.009	-0.14	0.062	0.05	0.595
Drop-off	-0.68	0.000	-0.91	0.000	-0.95	0.000
Central	-0.80	0.000	-0.86	0.000	-0.94	0.000
Containers						
No Bin (baseline)						
One	0.50	0.000	0.52	0.000	0.41	0.000
Bag	0.43	0.000	0.32	0.000	0.26	0.002
Multiple	0.49	0.000	0.49	0.000	0.38	0.000
Separation						
Separate all (baseline)						
Multiple streams	0.06	0.121	-0.01	0.858	-0.07	0.388
No separation	-0.07	0.113	-0.17	0.013	-0.25	0.007
Cost (by 1000s)	-2.20	0.000	-1.80	0.000	-1.70	0.000
Sigma U	0.20	0.000	0.22	0.000	0.23	0.000
Rho	0.03	0.000	0.44	0.000	0.05	0.023
Log Likelihood	-2746.66		-1088.11		-622.75	

DC = Deposit Containers NDC= Non-Deposit Containers CB = Cardboard

* Number of Students: 2450 **Number of Faculty : 883 *** Number of Staff : 563

Respondents also learned that the university recycling program was considering alternative material collection locations. The possible collection stations included floor or classroom, building, drop-off points on campus, and a central location. The results for respondents' location preference indicate that respondents would like the more decentralized options (on floor or classroom; in building). Students seemed to prefer being able to recycle on their dorm building floor while faculty preferred a floor or office level collection of materials. Interestingly, university staff seemed to prefer a single drop point per building for recycling materials. Never the less, there was a clear preference in all groups for recycling options that were closer to offices or dorms when compared to the less convenient options of drop-off locations or a central location.

In recycling programs, recyclable materials may be source separated into multiple streams, one comingled stream, or could be completely separated. Students did not show significant preferences one way or another regarding separation of material. Faculty and staff however did show a significant preference towards complete separation of recyclables at the source compared to no separation. This result was not expected as it was thought that complete separation at the source is less convenient for recyclers than one comingled stream.

Survey respondents were also informed that the university recycling program had an array of options for either providing or not providing individual collection bins to campus community members. These options included a set of small bins, one large bin, a bag that hangs on a door handle, or no university-provided recycling container. As the results in Table 2.3 show, there was a strong preference by all groups for some sort of university provided collection bin over the baseline comparison of no bin. The results also show that for all groups the bag was the least preferred collection bin.

All groups showed a significant and negative sensitivity to the program costs, That is, programs that cost the university more money were less likely to be preferred. Because the discrete nature of the dependent variable in the probit estimation makes it impossible to identify the underlying variance within each model, one cannot easily compare the strength of the preferences across user groups. However, by taking parameter ratios, as we do in the next section, one can make such comparisons. The lower rows of table 2.3 provide the estimated panel error terms which indicate that in each case the panel error structure was significant and has a statistically better fit than a model that ignored the panel nature of the data.

3.2 *Marginal Rate of Substitution*

The Marginal Rate of Substitution (MRS) between an attribute and the per-person program cost informs us of the rate that a person is willing to trade off that attribute for additional program costs. The MRS are useful because unlike the individual parameter estimates, the MRS can be used to compare preferences (willingness to make trade-offs) across attributes and across user groups. Table 2.4 illustrates the per-person MRS for the attributes for each of the three user groups. The final column also shows the population-level MRS (labeled "All campus"). These latter values provide a measure of the rate at which the total campus community would be willing to substitute program costs for attribute levels. The costs associated with these bundles represent the opportunity costs that the campus would be willing to incur to get a particular attribute level relative to the baseline level for that attribute. These total campus values were computed by scaling up from the per-person. Specifically, for each group the per-person MRS were multiplied by population size and summing all these for students, staff, and faculty. In all cases, the baseline MRS value is left blank as that is the level that the other values are either moving away or towards.

Table 2.4 Per-Person MRS for Each Campus Group and Aggregate MRS for Campus

	Per-person MRS			All Campus MRS
	Students	**Faculty**	**Staff**	
Materials				
Paper, NDC DC, CB, (baseline)				
Paper, NDC, DC	-148	-215	-187	-9000
Paper, NDC, CB	-71	-122	-180	-5000
Paper, NDC	-201	-244	-322	-12000
Paper, DC, CB	-161	-250	-213	-9900
Paper, DC	-259	-361	-397	-16000
Paper, CB	-326	-343	-383	-19000
Location				
Floor/Classroom (baseline)				
Building	-52	-76	28	-2600
Drop-off	-305	-498	-545	-20000
Central	-361	-469	-542	-22000
Containers				
No Bin (baseline)				
One	224	280	232	13000
Bag	194	173	148	10600
Multiple	221	267	216	12700
Separation				
Separate all (baseline)				
Multiple streams	28	-7	-42	1000
No separation	-30	-95	-142	-2600

DC = Deposit Containers, NDC = Non Deposit Containers, CB = Cardboard
Numbers for the all campus MRS are rounded and reported in 1000s.

One of the most striking results from the MRS is that people are very willing to incur additional program costs in order to have a recycling collection location closer to them. The MRS indicates that location is the program attribute that when compared to any of the other attributes, stakeholders are willing trade off the most for -- especially for faculty or staff. The MRS values for waste separation also indicate that the preferences of faculty and staff lean more towards source separation than single stream separation.

4. CONCLUSIONS

Across all three of the institution's subpopulations, we found a strong preference for recycling programs that include more recyclable materials as compared to those with fewer materials. The results show that if a recycling program had to be limited to only three of the four possible materials, the first material to be given up by respondents would be deposit containers. This makes sense given the state's deposit bill. If the campus recycling program had to be limited to two materials for recycling, the MRS based on the model results show that the stakeholders preferred choice for recycling materials would be paper and non-deposit containers. Of course, if cost were not a factor, the overall results show support for including as many recyclable materials in the program.

The study's results support recycling program designs that reduce the inconvenience of recycling and those that place recycling collection containers in close proximity to respondents work/study/living areas. These findings are in line with previous studies on recycling behavior (Kelly et al. 2006). These authors reported significant difference in respondents' occupation (staff or student) and their on-campus recycling behavior which "appeared to be predominantly a contrast between undergraduate students recycling sometimes on campus against general staff and postgraduate students (and to a lesser extent, academic staff) recycling on campus frequently" (Kelly et al. 2006). While our study found that students, faculty and staff cannot be treated as the same groups since each population has preferences that are significantly different statistically, we did find that the preference orderings were similar across groups.

Program cost was highly significant and negative across all groups, as was expected. Cost was explained as an opportunity cost, the coefficient on price and significance therefore indicates the sensitivity to the opportunity cost of a new program for the various programs. Our results indicate that students are more sensitive to the opportunity cost of campus spending on recycling programs than either staff or faculty. Put differently, the faculty and staff are more willing to spend MSU's money on recycling programs than students are.

A waste stream management plan that focuses only on source reduction ignoring the subsequent user behaviors is not a comprehensive plan. A comprehensive plan needs to consider full examination of the waste stream. Policies aimed at reducing the waste generated can inadvertently redirect the consumer to purchasing alternative products that do not meet as stringent requirements (Choe & Fraser 1999). While our study looked only at the end user options portion of the stream, hopefully it will assist policy makers in devising strategies that in the end will be more comprehensive.

Source separation can increase revenue, but collection can increase cost. We found that people were willing do source separation, or showed no preference regarding how source separation was done. However, we also found that people showed a strong preference towards recycling closer to their dorms or offices. The design implication of these findings suggests the collection of materials in multiple separate streams in multiple locations within each campus building, rather than investing in specialized, central separation facilities.

Students showed no preference regarding the form of source separation. The faculty and staff showed waste stream separation preference, and so along with that, the logical choice of recycling containers would be multiple small bins. This would allow for one bin for paper, one bin for cardboard, and one bin for plastic bottles and containers. All of the groups preferred having some sort of bin to collect the materials to no bin. Either a bag to or multiple small bins for collection would be greatly preferred to no bin by a great deal.

Areas for future research include incorporating socioeconomic features into the model or comparing the colleges to each other for preference differences. This would fall in line with other campus recycling research and potentially help target information campaigns on campus. Our survey also had a number of Likert scale questions in the data set that were used to help explain the various attributes. For this paper we concentrated only on the choice experiment questions, however, there is the potential to examine if respondents who ranked items as "highly important" also show a strong correlation towards recycling attribute choices in the choice experiment. Another potential area for research would be to examine if department major has any significant effect on responses to the choice experiment.

References

Aadland, Capland. 2003. Willingness to Pay for Curbside Recycling with Detection and Mitigation of Hypothetical Bias. *American Journal Agricultural Economics*, Vol 85 No (2) pp. 492-502.

Adamowicz, V., and P. Boxall. 2001. Future directions of stated choice methods for environment valuation. *Paper read at Choice Experiments: A New Approach to Environmental Valuation, April 10, 2001, at London, England.*

Caplan R.J., Grijalva, T.C., Jakus, P.M. 2002. Waste not or want not? A Contingent ranking analysis of curbside waste disposal options. *Ecological Economics*.Vol 43, No. 2-3 pp. 185-197.

Carson, R.T., N.E. Flores and N.F. Meade. 2001. Contingent valuation: Controversies and Evidence. *Environmental and Resource Economics*. Vol **19. No 2. pp.**173-210.

Choe, C. and Fraser, Iain. 1999. An Economic Analysis of Household Waste Management. *Journal of Environmental Economics and Management*.Vol 38. No 2. pp 234-246.

Cropper, M. I., Deck, L., Kishor, N., and McConnel, K.E. 1993.Valuing Product Attributes Using Single Market Data: A Comparison of Hedonic and Discrete Choice Approaches. *The Review of Economics and Statistics*. Vol. 75, No 2. pp. 225-232.

Ewert, A. and D. Baker. 2001. Standing for Where You Sit: An Exploratory Analysis of the Relationship between Academic Major and Environment Beliefs. *Environment and Behavior* Vol. 33. No. 5. pp. 687-707.

Folz, D.H. (1991). Recycling Program Design, Management, and Participation: A National Survey of Municipal Experience. *Public Administration Review*. Vol 53. No. 3. pp. 222-231.

Folz, D.H., Hazlett, J.M. 1991. Public Participation and Recycling Performance: Explaining Program Success. *Public Administration Review*. Vol 51. No.6. pp 526-533.

Hansen, L.T. McMellen, C. Olson, L. 2007.Recycling Attitudes andBehaviors on a College Campus: Use of Qualitative Methodology in a Mixed-Methods Study. *Working Paper*. MSU.

Holmes, T.P., and Adomowicz, W.L. 2003. Attribute-Based Methods. In: Champ, P.A., Boyle,K.J., Brown, T.C., (eds.) A Primer on Nonmarket Valuation. Kluwer Academic Publishers: Dordrect/Boston/London pp. 171-220.

Hines, J. M., Hungerford, H. R. and Tomera, A. N. 1986. Analysis and Synthesis of Research on Responsible Environmental Behavior: A Meta-Analysis. *The Journal of Environmental Education*. Vol.**18** **No.** 2 pp.1-8.

Jennings, M. E. (2004). An Instrument to Measure the Recycling Attitudes and Beliefs of Undergraduate Students at a Large Northeastern University. Online Submission, *Education Resources Information Center*: 22.

Kaplowitz, M.D., Hadlock, T.D., Levine, R. 2004. *A Comparison of Web and Mail Survey Response Rates*. Public Opinion Quarterly. Vol. 68 No.1 pp. 94-101.

Kelly, T. C., I. G. Mason, M. W. Leiss and S. Ganesh. 2006.University community responses to on-campus resource recycling. *Resources, Conservation and Recycling*. Vol. **47**. No. 1. pp. 42-55.

Louviere, J.J., D.A. Hensher, and J.D. Swait. 2000. Stated Choice Methods: Analysis and Application. Cambridge: Cambridge University Press..

McFadden, D. 1986. The Choice Theory Approach to Market Research. *Marketing Science*. Vol. 5, No. 4 pp. 275-297.

Mbuligwe, S. E. 2002. Institutional solid waste management practices in developing countries: a case study of three academic institutions in Tanzania. *Resources, Conservation and Recycling*. Vol. **35. No.** 3. pp. 131-146.

Nyamwage, M. 1996. Public Perception of Strategies for Increasing Participation in Recycling Programs. *The Journal of Environmental Education.* Vol. 27 pp. 19-22.

Resource Book, 2008. http://www.recycle.msu.edu/downloads/educational_resource_4-4-08.pdf

Selke, S.E., Joshi, S., Sidique, S., Dabholkar, G. (2006). *Michigan State University White Paper on Solid Waste*. http://www.ecofoot.msu.edu/documents/solid.waste.wp.pdf.

Sidique, S. 2008*Analyses of Recycling Behavior, Recycling Demand, and Effectiveness of Policies Promoting recycling.* Ph.D diss., Michigan State University.

Tiller, K.M, Jakus, P.M., and Park, W.M. 1997. Household Willingness to for Drop-off Recycling. *Journal of Agricultural and Resource Economics*. Vol 22. No. 2. pp. 310-320.

Wooldridge, J.M. 2002. Econometric Analysis of Cross Section and Panel Data. Cambridge, MA: MIT Press.

Fig. 2.1. Example page of choice experiment a respondent might have seen.

WHICH OF THESE TWO PROGRAMS IS BETTER?

Compare the characteristics of Program A and Program B and choose the program that you prefer for recycling at MSU.

Michigan State University Recycling Program Characteristics

Characteristics (Click hyperlink for more information)	**Program**	
	A	**B**
Recyclable Materials accepted by the MSU program	**Paper, Non-deposit containers**	**Paper, Non-deposit containers**
Material Separation at collection site	**All non-paper materials mixed together in one container**	**Group similar materials together in collection containers**
Collection Locations you bring materials to	**Remote collection**	**Central collection**
Containers for your room/office	**Single large basket**	**Multiple smaller baskets**
MSU Cost (per person) (to build facility, collect and process materials, and operate program)	**$150**	**$150**

32. **Which of the above programs do you think is better?** (Pick One Response)
    - Program A
    - Program B

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Chapter 3 - Essay 2

3.1 Introduction

Environmental economists use many varieties of survey methods and modeling tools for the estimation of non-market values. "Despite differences in format, all survey-based nonmarket valuation methods attempt to measure trade -offs between money and environment," thus allowing for estimates of a Marginal Rate of Substitution (MRS) for the environmental quality (Siikamaki and Layton 2007). While average trade-offs for a population are often of interest, in many cases it would be useful to identify segments of the population that may hold different preferences, and hence, have different MRS. Recent econometric methods offer new tools for accounting for such preference heterogeneity. Utilizing the same choice experiment data set, we will compare and contrast two approaches for identifying preference heterogeneity within a population.

The first method, interaction effects models, requires the researcher to have an *a priori* idea about the nature of the heterogeneity in the population. The approach uses demographic variables or other knowledge about the individuals to segment the population into distinct groups with different preference structures. The assumptions about the segments can then be tested. The second method, latent class models, uses the information inherent in the data to segment the population into different classes. The latent class models can also use demographic information about the respondents to help estimate the segments. As such, both models can incorporate individual-specific socio-demographic variables into the preference structures that would otherwise not be identified in the standard variant of the choice experiment. While there are random parameters models and heteroskedastic error structures that can also incorporate heterogeneity, those approaches are beyond the scope of our current research.

3.2 Motivation and Literature

The use of latent class models for explaining consumer heterogeneity arose out of marketing research. Marketers were addressing problems of "identifying segments of households in a population, determining their associated sensitivity to market variables, and investigating the possible bases of segmentation" (Gupta and Chintagunta 1994). Marketers developed techniques for taking aggregate demographic variables in combination with revealed preferences, and determining the latent class membership probabilities (Gupta and Chintagunta 1994).

The idea underlying LCM proposes that individual behavior "depends on observable attributes and on latent heterogeneity that varies with factors that are unobserved by the analyst" (Greene and Hensher 2003). Therefore, individuals are implicitly sorted into some number of classes or segments, the individual may or may not know which class she or he falls into, and the analyst does not know which class the particular person falls into. Since the LCM does not require an assumption about which class any one person falls into, the analyst avoids making "possibly strong or unwarranted distributional assumptions about individual heterogeneity" (Green and Hensher 2003). This is a useful characteristic for situations when the analyst has no reasonable *a priori* way to distinguish the exact segments of the population. In contrast to the interaction effects model where the researcher must make that *a priori* assumption.

Kamakura and Russell (1989) developed a model for preference segmentation that rested on the "assumption that consumers can be placed into a small number of segments each characterized by a vector of mean preferences and a single price sensitivity parameter" (Kamakura and Russell 1989). They developed a model that both estimated the segment level parameters and determined the likely segment membership for the individual. The Kamakura and Russell (1989) method made possible model building that then led to homogenous segments rather than deconstructing it from aggregate numbers as previous LCM work had done.

The use of latent class modeling is becoming more common in environmental and resource economics. Often LCM has been used in eliciting recreation site preferences or choices (Boxall and Adamowicz 2002, Scarpa and Thiene 2005). The use of attitudinal data from preference scales has also been incorporated into modeling the environmental quality preferences of anglers (Morey et al. 2006).

"Latent class modeling can be viewed as a means of modeling heterogeneity across individuals in a random parameters framework" (Greene 2003). This characteristic is useful as it allows estimation of unbiased models and "forecasting demand by including individual characteristics. The goal is that through understanding heterogeneity the researcher "will provide information on the distributional effects of resource use decisions or policy impacts" (Boxall and Adamowicz 2002).

Work has been done by a number of researchers examining the performance of the latent class model in comparison to other models. Greene and Hensher (2003) contrasted latent class and mixed logit choice analysis using a travel choice data set. Other research has been done to examine various forecasting capabilities of differing models. For example, Provencher and Bishop (2004) examined the forecasting efficiencies of the random parameters logit versus the latent class logit model for predicting the recreational fishing decisions of anglers. On a more theoretical level, Provencher and Moore (2006) derived the likelihood functions of the latent class models of Boxall and Adomawicz (2002) and Morey et al. (2006), where Boxall and Adamowicz used a latent class model and Morey et al. a latent class model that included attitudinal data, and determined that the two are "structurally similar." Each of these papers that contrast modeling methods used data sets related to some sort of site choice, be it recreational or travel choice. Compared to these examples using revealed preference data, our research is unique in that we use stated preference data and methods, and our application is aimed at estimating recycling program preferences.

Some research has been done investigating the relationship between recycling attitudes and actual recycling behaviors as a method of explaining recycling preference heterogeneity outside the realm of environmental economics. Looking just at recycling preferences, some research has suggested that attitudinal questions do a better job of explaining general behaviors rather than specific actions, while other research has suggested values can only be interpreted in the context of tradeoffs and possible tradeoffs (Ewert and Baker 2001). Studies including a gender constraint have also had mixed results. Ewert and Baker (2001) state that the results can be generalized to say that higher income, higher educated, younger, less conservative people tend to show greater concern for the environment. Lack of knowledge about environmental issues has been shown to be an important factor determining environmental attitudes and behaviors (Gamba and Oskamp 1994, Oskamp et al. 1991). The results of these research studies are not uniformly consistent. Jennings (2004) found the most important determinants of recycling behavior to be both logistical and attitudinal. Much of the above mentioned work has been done in the areas of psychology and sociology.

Within recycling literature, there is an extensive body of work on municipal and regional recycling programs, both on participation rates and the economics of recycling at the household level. Though little work has been done examining why some people choose to recycle, and some choose not to recycle. Some research has been done polling various municipal leaders exploring what is effective at increasing participation rates, but none to our knowledge that examines the consumer heterogeneity. One such study found that "democratizing" the program can increase the participation rates (Folz and Hazlett 1991). Others examined the economics of household recycling; they derived a model whereby information about what policies should be implemented can be examined (Choe and Fraser 1999). Narrowing the discussion further to looking at valuation studies of recycling program attributes, there is research on drop-off recycling programs (Tiller, Jakus, and Park 1997), and curbside attributes (Caplan, Grijalva, Jakus 2002; Aadland, Capland 2003).

Using methods similar to these latter studies, in this research the Attribute Based Method (ABM) was used to identify the relative importance that different attributes have on people's preferences for alternative recycling programs. Using ABM allowed us to estimate the preferences people have for alternative programs (combinations of program attributes) that the university could implement. We included a cost constraint to allow for a Marginal Rate of Substitution analysis, which will be discussed further later in the paper.

Attribute based methods of analysis seek to understand consumer choices in terms of the attributes (or characteristics) of the alternatives that are chosen by individuals. That is, goods or programs are seen as consisting of bundles of attributes that combine to produce consumers' utility (Louviere et al. 2000). The Attribute Based Method estimates economic values for a technically divisible set of attributes, and the inclusion of price as an attribute in the choice sets provides a constraint to the choice. Eliciting and quantifying these trade-offs is one way our study differs from what other campus recycling literature offers where the examinations tend to address behavioral and attitudinal research.

3.3 Theory

Most stated preference studies and ABM's fall under the broader umbrella of Random Utility Models (RUM). Starting with a theory that builds on utility theory, "with utility a function of product attributes" (Cropper et al. 1993), we can begin building a model of preferences. The goods, or in our case bundles, are of use either individually or in combinations that combine to produce the consumer's utility (Lourviere et al. 2000). The basic formulation of a RUM is: $U_{in} = V_{in} + \varepsilon_{in}$ where U_{in} is the utility that person *n* associates with option *i*; V_{in} is the explainable portion of utility that is estimated from observable behavior and choices. While ε_{in} is the random and unobservable portion of utility.

In our choice experiment individual *n* faced a choice of bundle A or bundle B. Each respondent faced three experiments, resulting in 3 binary choices. The probability (π) that the individual will choose alternative *i* over alternative *k* is equal or greater than the probability that the utility gained is greater than the alternative. Hence, the probability of choosing i is:

$$\pi_n(i) = \Pr ob_i\{V_{ni} + \varepsilon_{ni} \geq V_{nk} + \varepsilon_{nk}; i \neq k, \forall k \in C\}. \tag{1}$$

If the random terms are assumed to be independently distributed Type-I extreme value variates; then we can estimate these probabilities with the conditional logit model. When we then substitute the attributes associated with our deterministic component of utility (V), and following Boxall and Adamowicz (2002), select a linear functional form allowing the choice probabilities to take the form:

$$\pi_n(i) = \frac{\exp(\mu\beta X_i)}{\sum_{k\in C}\exp(\mu\beta X_k)} \tag{2}$$

where μ is a scale parameter assumed to be 1, and β is a vector of parameters. In this model, β is common for all individuals (Boxall and Adamowicz 2002).

With a logit or probit model the individual's characteristics cannot be measured since they do not vary across the choices the individual makes. "However, individual specific variables can interact with alternative-specific attributes to provide some identification of attribute parameter differences in response to changes in individual factors" (Holmes and Adamowicz 2003). This requires the researcher to make a possibly strong assumption about segment membership, and have the means to control for that. In our study we examined the effect that being a student, faculty, or staff member of the campus community has on choice preferences, since we have information about each respondent's status on campus. This is modeled in equations 3.

$$\pi_n(i) = \frac{\exp(\mu\beta_1 X_i)}{\sum_{k\in C}\exp(\mu\beta_1 X_k)}, \tag{3.1}$$

$$\pi_n(i) = \frac{\exp(\mu\beta_2 X_i)}{\sum_{k\in C}\exp(\mu\beta_2 X_k)}, \tag{3.2}$$

$$\pi_n(i) = \frac{\exp(\mu\beta_3 X_i)}{\sum_{k\in C}\exp(\mu\beta_3 X_k)}, \tag{3.3}$$

$$\pi_n(i) = \frac{\exp(\mu\beta_1 d_1 X_i + \mu\beta_2 d_2 X_i + \mu\beta_3 d_3 X_i)}{\sum_{k\in C}\exp(\mu\beta_1 d_1 X_k + \mu\beta_2 d_2 X_k + \mu\beta_3 d_3 X_k)}, \tag{3.4}$$

The above equations with $\beta_1, \beta_2, \beta_3$ representing students (3.1), faculty (3.2), and staff (3.2) respectively, are the models that will be used in our regression analysis. Equation 3.4 represents the interaction effects where d_1, d_2, d_3 are dummy variables for the respondent's status on campus, coded in the standard way as a one if they are the respective status, zero otherwise. This allows us to explicitly segment the campus population using the status on campus as the controlling variable. This is possible since we have a strong *a priori* assumption about what the segmentation of the campus is, and because we can easily determine which status each respondent had in answering the survey.

The above equations allows the researcher to segment the population, one could say this is an example of manually segmenting population. There are times however where that might not be feasible, or the researcher may not wish to be quite so heavy handed in his or her approach to segmenting the population. In such cases the latent class model can be of more use as it allows the researcher to take a more hands-off approach to population segmentation.

With that in mind, we turn to the latent class models where we assume that there exists within our population a certain number of S (s=1...S) segments. Further, individual n belongs to segment s. This allows us to express the utility function as $V_{ni|s} = \beta_s X_{ni} + \varepsilon_{ni|s}$. With this, we can then make the utility parameters segment specific, and rewrite equation (2)

$$\pi_{n|s}(i) = \frac{\exp(\mu_s \beta_s X_i)}{\sum_{k \in C} \exp(\mu_s \beta_s X_k)} \tag{4}$$

with β_s segment specific and μ_s a scale parameter (Boxall and Adomwicz 2002).

Following Boxall and Adomwicz (2002), we consider an unobservable or latent membership function M* classifying individuals into one of the S segments For any one individual n, this function can be described by the following set of equations:

$$\begin{aligned} M_{ns}^* &= \Gamma_{ps} P_n^* + \Gamma_s S_n + \xi_{ns} \\ P_n^* &= \beta_p Pn + \xi_{np} \end{aligned} \tag{5}$$

where M* is the membership likelihood function for n and segment s. P_n^* is a vector of latent psychometric constructs held by n. S_n is a vector of observed sociodemographic characteristics of individual n. P_n is a vector of observed indicators of latent psychometric constructs held by n. Γ and β_p represent parameter vectors to be estimated. ξ representing the error for both equations. Following the Boxall and Adamowicz (2002) methodology, we can then relate this function to the classical latent variables approach where observed variables are related to the latent variable, M* is then represented at the individual level as:

$$M^*_{ns} = \lambda_s Z_n + \xi_{ns}, \quad s = 1, \ldots, S \tag{6}$$

where Z_n is a vector of both the psychometric constructs (P_n) and the sociodemographic characteristics (S_n), and λ_s a vector of parameters.

Swait (1994), points out that these membership functions are random and one must specify the distribution of their error terms in order to use them in practice. Given that we followed Kamakura and Russel (1989), Gupta and Chintagunta (1993), Swait (1994), and Boxall and Adamowicz (2002), all point out that the error terms are assumed to be independently distributed across individuals and segments with Type I extreme value distribution and scale factor α. Incorporating these assumptions allows the probability of membership in segment s to be characterized by equation:

$$\pi_{ns} = \frac{\exp(\alpha\lambda_s Z_n)}{\sum_{s=1}^{S} \exp(\alpha\lambda_s Z_n)}, \tag{7}$$

Schmidt and Strauss (1975) developed a multinomial logit model in which probabilities are explained by individual-specific characteristics rather than attributes of choices. This is important since in our latent class modeling the β_j changes, while the X_i does not change across the respondents. There are other functional forms that could be used, but regardless of form chosen, $\sum_{s=1}^{S} \pi_{ns}$ must equal 1, and $0 \le \pi_{ns} \le 1$. Defining the probability $\pi_{ns}(i)$ as the joint probability that individual n belongs to segment s and chooses alternative i, this can then be expressed as the product of the probabilities defined in equations (3) and (6): $\pi_{ns}(i) = \pi_{ns}\pi_{n|s}(i)$. Thus, the probability that a randomly chosen individual n chooses alternative i is given by:

$$\pi_n(i) = \sum_{s=1}^{S} \pi_{ns}\pi_{n|s}(i) \tag{8}$$

and substituting the equations for the choice equation (4) and class membership equation (7) probabilities provides the expression:

$$\pi_n(i) = \sum_{s=1}^{S} \left[\frac{\exp(\alpha\lambda_s Z_n)}{\sum_{s=1}^{S} \exp(\alpha\lambda_s Z_n)} \right] \left[\frac{\exp(\mu_s \beta_s X_i)}{\sum_{k \in C} \exp(\mu_s \beta_s X_k)} \right] \quad (9).$$

This model, "allows choice attribute data and individual consumer characteristics to simultaneously explain choice behavior" (Boxall and Adamowicz 2002).

As discussed in the next section, in our survey data, each individual responds to more than one stated preference question. Since it is likely that there are unobserved characteristics specific to that individual that induce correlation across his or her responses, estimation uses the random effects logit model (Wooldridge 2002). In random effects models, the error term is treated as two separate components. One component is the unobservable portion that is unique to the individual. The second component is the random shocks across all individuals and all responses (Boxall et al. 2003). This utility model can be written as:

$$\Delta u_{ij} = \beta_s \Delta X_j + v_i + e_{ij}, \tag{10}$$

where v_i is the individual specific error term, e_{ij} is the random disturbance term across all individuals and observations, and β_s is the parameter vector for market segment s, and ΔX_j represents the change in the program attributes that a respondent sees. For our first model, the interaction effects model, the random effects specification was used, but our second method, the latent class models, did not use random effects.

3.4 Data Collection

As mentioned, a choice experiment survey was conducted that elicited preferences over possible recycling programs. The survey contained several sections including background information and questions about MSU's plans to develop a new recycling program. In the survey, each respondent was presented with two possible recycling programs and asked to select their preferred program. The recycling programs were described by several attributes and each program had a cost associated with it. Adequately describing the program and the attributes was crucial to ensure that when each respondent made their choices, each person has in mind the same type of item. It is well-known in the literature that stated choice surveys should be as realistic as possible so that the respondents are able to provide accurate, realistic answers (Carson et al. 2001). As such, this section reviews the efforts that went into the attribute selection and the way that attributes were conveyed to respondents.

The survey instrument was developed in three phases that centered on focus group studies, survey design, and pretesting/revision of the survey (Kaplowitz et al. 2004). A series of key informant interviews were conducted with university administrators, consulting engineers, faculty active in university environmental affairs, as well as student activists. These were conducted so that the survey targeted appropriate recycling program attributes and levels as well as to design an instrument that adequately informed respondents about the various recycling program attributes and the possible levels for each attribute. The focus groups were qualitative studies conducted to gauge the recycling knowledge, behaviors, and attitudes of MSU. The focus group results then guided subsequent interviews and the design and implementation of the survey itself (Hansen et al. 2007).

The result of our focus groups and interview efforts was the identification of five program attributes with various possible levels for each attribute. The program attributes consisted of the materials to be recycled (paper, cardboard, non-deposit containers, and deposit containers[2]), the type of recycling container individuals would be provided, the location where recyclables would be taken, the amount of waste stream separation required by individuals, and the amount the program would cost the institution. (See Table 3.1 and discussion below).

[2] Michigan has a deposit on certain types of beverage containers.

Table 3.1 Recycling Program Attributes

Attributes	Attribute Levels
Materials	Paper, Non Deposit Containers, Deposit Containers, Cardboard, (Baseline)
	Paper, Non Deposit Containers, Deposit Containers
	Paper, Cardboard, Non Deposit Containers
	Paper, Non Deposit Containers
	Paper, Deposit Containers, Cardboard
	Paper, Deposit Containers
	Paper, Cardboard
Location	Floor/Classroom (Baseline)
	Building
	Drop-off
	Central
Containers	No Bin (Baseline)
	One large bin
	Bag
	Multiple small bins
Preparation	One stream (Baseline)
	Multiple streams
	Complete separation
Cost	\$50
	\$150
	\$300
	\$500

In the survey, respondents were told that MSU was designing a recycling program and that their feedback was needed on the type of program to be implemented. After informing the respondents about all of the possible program attributes and their levels, we then presented the three pair-wise program choice experiment questions (see figure 3.1 for an example of one of the choice pairs).

Note that there are many possible combinations of all the attributes, yet each respondent only saw three of the many possible pairs. The attributes pairs were then varied across respondents following an experimental design. The experimental design consisted of a mix of pairs from a main-effects design for these attribute levels and random pairing of the attribute levels. By varying the attribute pairs across respondents, the statistical techniques outlined above can be used to identify the effect that each attribute level has on the probability that an alternative is preferred.

Since the respondents were asked to make choices under a constraint, cost, it was crucial that we explain how program costs would be paid. The program costs were costs to the institution, and the construction costs would be paid for through a capital bond mechanism, as was explained to the respondents. Further, respondents were told that when the costs of the program were incurred, it would leave less money for the institution to use in other areas. In the choice questions, the cost to the institution was expressed in per-person terms. Hence, the cost associated with the program is not a direct cost to the respondent, rather it is an opportunity cost to the campus – as more money is spent on the recycling program, less money is available to spend on other campus items.

Fig 3.1 Example of a choice experiment question a respondent may have seen

WHICH OF THESE TWO PROGRAMS IS BETTER?

Compare the characteristics of Program A and Program B and choose the program that you prefer for recycling at MSU.

Michigan State University Recycling Program Characteristics

Characteristics (Click hyperlink for more information)	**Program**	
	A	**B**
Recyclable Materials accepted by the MSU program	**Paper, Non-deposit containers**	**Paper, Non-deposit containers**
Material Separation at collection site	**All non-paper materials mixed together in one container**	**Group similar materials together in collection containers**
Collection Locations you bring materials to	**Remote collection**	**Central collection**
Containers for your room/office	**Single large basket**	**Multiple smaller baskets**
MSU Cost (per person) (to build facility, collect and process materials, and operate program)	**$150**	**$150**

32. **Which of the above programs do you think is better?** (Pick One Response)

○ Program A ○ Program B

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3.4 Interaction Effects Model

We tested whether we can pool data from the three populations. In examining the pooled model with a simple random effects logit, we determined that three types of person on campus: students, faculty, and staff have different utility functions. Performing the log likelihood ratio tests allowed us to reject the pooled sample versus the restricted samples. We tested this with a log likelihood ratio test which is: $-2(LL_j - \sum LL_i)$ which follows a χ^2 distribution with K(M-1) degrees of freedom (Wooldridge 2002). LL_j is the unrestricted pooled sample log likelihood value, and LL_i are the log likelihood values for the separate student, faculty and staff models. K is the number of restrictions in the model, while M is the number of model treatments. For this test, we had 16 restrictions on the models, with 3 models being tested, resulting in 32 degrees of freedom for the pooled sample. We also tested each of the possible combinations of faculty, staff and students against each other to see if we could pool together data for any of these subsamples.

Table 3.2 also shows that we can with confidence reject the hypothesis that the pooled sample is equal to the sub-samples. However, for the combined sub samples, we can only say with 99% confidence that the students are different than staff or faculty. For staff and faculty we cannot only reject the hypothesis that they are the same at the 90% confidence level. In the results that follow, we report on the pooled model, and the interaction effects model that separates students from the combined group of faculty and staff.

Table 3.2 Tests on the Interaction Effects Models

	LL	Degrees of Freedom	LR Test Value	Significance Level
Pooled (LL_j)	-4479.52			
Student (LL_i)	-2726.36			
Staff (LL_i)	-616.57			
Faculty (LL_i)	-1100.30	32	72.58	0.00005
Faculty+Staff (LL_j)	-1724.10			
Faculty (LL_i)	-1100.30			
Staff (LL_i)	-616.57	16	14.46	0.56449
Faculty+Student (LL_j)	-3846.39			
Faculty (LL_i)	-1100.30			
Student (LL_i)	-2726.36	16	39.46	0.000093
Student+Staff (LL_j)	-3364.76			
Student (LL_i)	-2726.36			
Staff (LL_i)	-616.57	16	43.66	0.000022

LL=Log Likelihood, LR= Likelihood Ratio

Looking at the interaction effects coefficients in table 3.3, we find that almost all of the attributes are significant except for the waste-stream separation variables for students. For faculty and staff all the variables except for multiple stream separation were significant. While at the combined, unrestricted population level, the coefficient and p-value are so weak that preferences between the baseline of total separation and multiple stream separation were not significantly distinguishable. The coefficients sign and size also provide information about the ordinal ranking of the different attributes compared to the baseline attribute comparison. Negative signs indicate that that attribute level is less preferred, while a positive sign indicates that that level is more preferred to the baseline level. The coefficients indicate that people want to recycle more materials, and that they would like more decentralization of location, and some type of bin for recycling. However, since we cannot compare coefficients across logit models, we need to determine a marginal rate of substitution in order to gauge the magnitude of for one attribute over another as revealed by the various models. This will be discussed in a latter section of the paper.

Table 3.3 Parameter Estimates from the Interaction Effects Models

	Pooled Model		Students		Faculty and Staff	
	Coef.	P-Value	Coef.	P-value	Coef.	P-Value
Materials						
Paper, NDC, DC, Cardboard (Baseline)						
Paper, NDC, DC	-0.55	0.000	-0.46	0.000	-0.70	0.000
Paper, NDC, Cardboard	-0.29	0.000	-0.21	0.046	-0.43	0.002
Paper, NDC	-0.77	0.000	-0.72	0.000	-0.89	0.000
Paper, DC, Cardboard	-0.65	0.000	-0.57	0.000	-0.78	0.000
Paper, DC	-0.99	0.000	-0.93	0.000	-1.13	0.000
Paper, cardboard	-1.09	0.000	-1.08	0.000	-1.17	0.000
Location						
Floor/classroom (Baseline)						
Building	-0.14	0.038	-0.18	0.043	-0.09	0.444
Drop-off	-1.28	0.000	-1.15	0.000	-1.55	0.000
Central	-1.39	0.000	-1.40	0.000	-1.46	0.000
Containers						
No bin (Baseline)						
One	0.78	0.000	0.82	0.000	0.78	0.000
Bag	0.61	0.000	0.71	0.000	0.47	0.000
Multiple	0.80	0.000	0.87	0.000	0.76	0.000
Preparation						
Separate all (Baseline)						
Multiple streams	0.00	0.947	0.10	0.227	-0.15	0.137
No separation	-0.27	0.000	-0.18	0.032	-0.43	0.000
Cost (in 1000s)	-3.00	0.000	-4.00	0.000	-3.00	0.000
Sigma U	0.28	0.003	0.00	0.480	0.49	0.000
Rho	0.02	0.084	0.00	0.492	0.07	0.017

DC = Deposit Containers, NDC = Non - Deposit Containers

3.5 Latent Class Model

Given previous research regarding what influences choices regarding recycling, both in the general population and on a college campus, a set of questions were developed for the survey to gauge the attitudes and knowledge regarding recycling and the environment on campus. These included questions related to attitudes about recycling, the time involved with recycling, and general recycling knowledge information. We then used responses to the questions to test for their effect in segmenting the population.

Using the LIMDEP 9.0 software regression package, we constructed a latent class model using 5 of the additional questions from the survey. The variable questions we tested are in table 3.3. These questions were chosen since it was felt that they would provide good indicators of how people feel regarding recycling and the amount of time or effort required.

Table 3.4 The Three Sets of Variables Tested in the Latent Class Models

Model Name	Variables	Description of Variables Used to Determine Influence on Segment Membership
No Variables	None	This formulation of the LCM did not include any variables for class membership
Demographic Questions	Time	"In general, it takes a lot of time and effort to recycle at MSU" (yes=1, no=0)
	Benefits	"I would like to learn more about the benefits of recycling" (yes=1, no=0)
	Donate	"I would give part of my income if I was certain the money would be used to prevent environmental pollution" (yes=1, no=0)
	Gender	Gender (Female = 0, Male = 1)
	Knowledge	"How knowledgeable are you about the range of paper products that may be recycled at MSU?" (Coded as a 1 to 5 likert scale, low to high)
Staff and Faculty Dummies	Staff	Dummy variable for Staff (Staff member=1, 0 otherwise)
	Faculty	Dummy variable for Faculty (Faculty member =1, 0 otherwise)

Using the LIMDEP 9.0 software, we were able to arrive at the results in Table 3.5 examining the latent class tests. There is no set test for determining the exact number of segments. Using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) as guides provides some help, however "conventional rules for this purpose do not exist and judgment and simplicity play a role in the final selection of the size of S" (Boxall and Adamowicz 2002). So following the suggestion that choosing the segment where we balance a decrease in the AIC begins with an incease in the BIC, we suspect that the optimum number of segments that the campus can be divided into is 2. This concurs with what our log likelihood ratio tests suggested when testing the interaction effects. Though it could be that there are a different number of segments, for our study we are going to examine more closely only the two segment case.

Table 3.10 in the appendix examines what effect being a faculty or staff member has on segment membership for the two segment population for the LCM with Faculty and Staff as the class membership variables. In the table, the First constant is the baseline measurement, so everything is measured against that level. Hence, the average person is less likely to fall into that category than the person into the second. This probability can also be seen at the bottom of Table 3.5. From this we can learn the probability of membership in the first instead of the second segment of the population is 0.21 for faculty members, 0.11 for staff members and a 0.32 for students.

Table 3.5 AIC and BIC Results for Each of the LCM Models that Converged

LCM Segments	Latent Class Explanatory Variables	Number of Parameters	AIC	BIC
1	No Variables	15	1.028	1.038
1	Demographic Questions	15	1.028	1.038
1	Staff and Faculty Dummies	15	1.028	1.038
2	No Variables	31	1.016	1.035
2	Staff and Faculty Dummies	33	1.013	1.034
3	No Variables	47	1.005	1.035
3	Demographic Questions	65	1.006	1.046
4	Demographic Questions	87	0.998	1.052

Only those models that created a Hessian - Positive Definite solution are reported.

Table 3.6. MRS for Two-Segment Latent Class Models for the "Faculty and Staff Dummies" Version and the "No Variables" Version

	First Segment				Second Segment			
	Staff & Faculty Dummies		No Variables		Staff & Faculty Dummies		No Variables	
	MRS	Rank	MRS	Rank	MRS	Rank	MRS	Rank
Materials								
Paper, NDC, DC, Cardboard (Baseline)		1		1		1		1
Paper, NDC, DC	-52.75	6	-51.16	6	-332.11	3	-321.72	3
Paper, NDC, Cardboard	-32.39	3	-33.39	3	-188.93	2	-175.53	2
Paper, NDC	-46.06	5	-47.25	5	-544.91	5	-513.69	5
Paper, DC, Cardboard	-19.13	2	-11.15	2	-480.46	4	-478.32	4
Paper, DC	-43.74	4	-40.48	4	-805.29	6	-769.48	6
Paper, cardboard	-68.29	7	-60.72	7	-820.72	7	-801.54	7
Location								
Floor/classroom (Baseline)		1		1		1		1
Building	-22.44	2	-15.45	2	-110.02	2	-119.25	2
Drop-off	-47.36	3	-44.01	3	-1063.67	3	-1013.97	3
Central	-80.79	4	-71.55	4	-1094.99	4	-1060.56	4
Containers								
No bin (Baseline)		4		4		4		4
One	43.86	1	39.48	1	570.10	2	561.15	2
Bag	22.11	3	13.19	3	477.47	3	483.00	3
Multiple	30.11	2	25.54	2	602.80	1	589.20	1
Preparation								
Separate all (Baseline)		2		2		1		1
Multiple streams	39.68	1	32.22	1	-56.99	2	-35.06	2
No separation	-0.31	3	-7.04	3	-164.94	3	-138.30	3
Prob. of Segment Membership	0.25		0.26		0.75		0.74	

DC = Deposit Containers, NDC = Non – Deposit Containers

Table 3.7 Marginal Rates of Substitution and Attribute Ranks from the Interaction Effects Models

	Pooled		Staff and Faculty		Students	
	MRS	Rank	MRS	Rank	MRS	Rank
Materials						
Paper, NDC,DC CB (Baseline)		1		1		1
Paper, NDC, DC	-164.44	3	-238.18	3	-123.84	3
Paper, NDC, CB	-86.14	2	-147.13	2	-55.29	2
Paper, NDC	-230.93	5	-302.25	5	-194.01	5
Paper, DC, CB	-196.88	4	-266.85	4	-154.23	4
Paper, DC	-297.11	6	-386.73	6	-249.07	6
Paper, CB	-327.83	7	-398.59	7	-289.83	7
Location						
Floor/Classroom (Baseline)		1		1		1
Building	-41.97	2	-29.2	2	-47.39	2
Drop-off	-384.20	3	-528.99	4	-310.11	3
Central	-418.31	4	-497.27	3	-375.6	4
Containers						
No Bin (Baseline)		4		4		4
One	234.95	1	264.65	1	219.05	2
Bag	184.35	3	161.97	3	191.44	3
Multiple	242.04	2	258.19	2	233.34	1
Preparation						
Separate all (Baseline)		1		1		2
Multiple streams	-1.23	2	-52.74	2	25.83	1
No separation	-81.33	3	-147.43	3	-47.86	3

DC = Deposit Containers, NDC = Non - Deposit Containers, CB = Cardboard

Table 3.8. Marginal Rates of Substitution Averaged Across Segments

	LCM Dummy		LCM No Variables		Interaction Effects	
	Average MRS	Rank	Average MRS	Rank	Average MRS	Rank
Materials						
Paper, NDC,DC Cardboard (Baseline)		1		1		1
Paper, NDC, DC	-262.27	3	-251.37	3	-181.43	2
Paper, NDC, cardboard	-149.80	2	-138.57	2	-105.52	3
Paper, NDC	-420.20	5	-392.42	5	-241.61	5
Paper, DC, cardboard	-365.13	4	-356.86	4	-208.05	4
Paper, DC	-614.90	6	-579.94	6	-309.40	6
Paper, cardboard	-632.61	7	-608.93	7	-329.11	7
Location						
Floor/Classroom (Baseline)		1		1		1
Building	-88.13	2	-92.26	2	-32.19	2
Drop-off	-809.60	3	-761.78	3	-413.77	3
Central	-841.44	4	-803.42	4	-414.92	4
Containers						
No Bin (Baseline)		4		4		4
One	438.54	1	425.52	1	226.74	1
Bag	363.63	3	360.83	2	156.48	3
Multiple	459.63	2	442.65	3	227.26	2
Preparation						
Separate all (Baseline)		1		1		1
Multiple streams	-32.82	2	-17.58	2	-23.73	2
No separation	-123.78	3	-104.17	3	-103.41	3

DC = Deposit Containers, NDC = Non – Deposit Containers

For each population segment, the individual Marginal Rates of Substitutions (MRS) of an attribute level for program costs were calculated by dividing the coefficient on the attribute level by the negative of the cost coefficient $(\alpha / -\beta)$. The averaged MRS measures were calculated by multiplying the probability of being in class i by that attributes individual marginal rate of substitution plus the other segments probability and marginal rate of substitution, i.e., $Average\ MRS = \sum(\Pr Class\_i * induvidual\_i\,MRS)$.

Tables 3.6 and 3.7 show the ordinal ranks of the various attributes and the individual MRS measures controlling for staff and faculty through dummy variables. What we can see in table 3.5 is that there is a segment of the campus that is very price sensitive, and a segment that is not. The first segment is highly sensitive to the opportunity cost to the campus of this new program. While the second segment of the campus is more willing to spend the universities money. The magnitude of the values helps to provide an idea of how much each segment prefers one attribute compared to another level. The MRS values help us to get a sense of how much more an attribute is preferred. For instance, we can see with location that not only do campus members prefer having a decentralized location, but that they would prefer a building location at more than three times the amount compared to a drop-off location option.

In addition, the Marginal Rates of Substitution (MRS) measures for the Interaction Effects Models for Students, and the Faculty plus Staff were closer together than with the two segments identified by the LCM estimates. Since the modeling approaches all use the same choice data, we might expect that the MRS measures be somewhat similar, or at least not as dissimilar those provided in the LCM estimates. This occurred for both the model with faculty and staff dummy variable covariates, and for the model with no covariates. After combining the model estimates (Table 3.7) we see that the preference rankings again are consistent, but the LCM again provides higher estimates of MRS than the interaction effects model provides.

3.5 Discussion

An implication of this research is that there is strong support for the campus population having at least two preference segments. This is made clear from the Log Likelihood tests and from the results of the LCM. The interaction effects model suggests that the two segments are students and a combination of faculty and staff. The latent class model also suggests at least two segments, one segment that is highly price sensitive and one that is less price sensitive.

The interaction effects and latent class models both provided identical preference orderings when averaged across the segments. Both predicted that people largely want to be able to recycle more things, at more decentralized places. A bag or bin is preferred to none. Cost was always negative and highly significant. People consider deposit containers the first item to be given up from the materials accepted, which makes intuitive sense as they retain value after use.

We had a strong *a priori* idea of how the segments would break down. Interaction effects also allowed for a Log Likelihood test of our hypothesis of different preferences between students, faculty and staff, which confirmed out *a priori* assumptions. While the LCM did provide some useful information regarding population segmentation, there is yet to be developed a test of what is the correct number of classes as determined by the LCM which is a weakness.

The also found that in our case use of the attitudinal and other demographic data did little to advance what we already knew regarding recycling preferences and MRS. If anything, attitudinal questions performed worse than controlling for the segment membership directly through faculty and staff dummy variables

3.6 Conclusion

This paper was motivated by the desire to examine the relative performance capabilities of the latent class model and the interaction model. The advantage of the LCM is that when the researcher does not have strong *a priori* knowledge of preference heterogeneity, the model does impose potentially unwarranted assumptions onto the data. However, when the researcher does have a good understanding of probable sources of heterogeneity, then it may be worthwhile for the researcher to use that information and use the simpler interaction effects model.

Other research using the LCM has shown that it does have strong potential for understanding of preference segments. Our results were less clear cut. All the models we examined provided the same averaged rankings of the attributes being studies, though the rankings did differ within some subpopulations. It may be that LCM is of more use in cases where the preferences are more heterogeneous whereas the findings from this study indicated strong uniformity in rankings. Even though in our case both methods would provide the policy maker with same ordinal preferences, the magnitude of the MRS differed, and perhaps that is the cautionary tale of the two methods.

Future research could examine the out of sample predictive qualities that the two models provide as our sample size is large enough to examine that question. Another area would be to further explore what the three and four segment models look like and could imply. Another area of furthering the research would be to rework the models so that the latent class model is also a random effects model, allowing a closer comparison of the two models. Finally, the possibility of examining a random parameters regression on the data set might also provide insights.

Appendix A.

Table 3.9 Coefficient Estimates for the Two-Segment Latent Class Models

	Staff and Faculty Dummies LCM				No Variables LCM			
	Segment 1		Segment 2		Segment 1		Segment 2	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-Value
Materials								
Paper, NDC, DC, Cardboard (Baseline)								
Paper, NDC, DC	-1.24	0.000	-0.48	0.000	-1.32	0.000	-0.48	0.000
Paper, NDC, Cardboard	-0.76	0.026	-0.27	0.008	-0.86	0.022	-0.26	0.010
Paper, NDC	-1.08	0.000	-0.78	0.000	-1.22	0.000	-0.76	0.000
Paper, DC, Cardboard	-0.45	0.236	-0.69	0.000	-0.29	0.503	-0.71	0.000
Paper, DC	-1.02	0.002	-1.15	0.000	-1.04	0.004	-1.14	0.000
Paper, Cardboard	-1.60	0.000	-1.17	0.000	-1.56	0.000	-1.19	0.000
Location								
Floor/classroom (Baseline)								
Building	-0.53	0.101	-0.16	0.052	-0.40	0.253	-0.18	0.029
Drop-off	-1.11	0.003	-1.52	0.000	-1.13	0.019	-1.50	0.000
Central	-1.89	0.000	-1.57	0.000	-1.84	0.000	-1.57	0.000
Containers								
No bin (Baseline)								
One	1.03	0.000	0.82	0.000	1.02	0.000	0.83	0.000
Bag	0.52	0.028	0.68	0.000	0.34	0.188	0.72	0.000
Multiple	0.71	0.000	0.86	0.000	0.66	0.001	0.87	0.000
Preparation								
Separate all (Baseline)								
Multiple streams	0.93	0.007	-0.08	0.283	0.83	0.024	-0.05	0.487
No separation	-0.01	0.983	-0.24	0.003	-0.18	0.652	-0.21	0.011
Cost (in 1000s)	-23.41	0.000	-1.00	0.000	-26.00	0.000	-1.00	0.000

DC = Deposit Containers, NDC = Non - Deposit Containers.

Table 3.10 Coefficients on Probability of Membership in Segment One from the Two Segment Staff and Faculty Dummies LCM

	Coefficient	P-Value
Constant	-0.76	0.000
Faculty_Dummy	-0.58	0.000
Staff_Dummy	-1.34	0.000

References

Aadland, Capland. 2003. Willingness to Pay for Curbside Recycling with Detection and Mitigation of Hypothetical Bias. *American Journal Agricultural Economics,* Vol 85 No (2) pp. 492-502.

Adamowicz, W.L., and Boxall, P.C., 2001. *Future directions of stated choice methods for environment valuation.* Paper read at Choice Experiments: A New Approach to Environmental Valuation, April 10, 2001, at London, England.

Boxall, P.C., and Adamowicz, W.L., 2002. *Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach.* Environmental and Resource Economics. Vol.23. pp. 421-446.

Boxall, P.C., Englin, J., & Adamowiczc, W.L. 2003. *Valuing aboriginal artifacts: a Combined revealed-stated preference approach.* Journal of Environmental Economics and Management. Vol. 45, pp. 213-230.

Caplan R.J., Grijalva, T.C., Jakus, P.M. 2002. Waste not or want not? A Contingent ranking analysis of curbside waste disposal options. *Ecological Economics.*Vol 43, No. 2-3 pp. 185-197.

Carson, R.T., N.E. Flores and N.F. Meade. 2001. *Contingent valuation: Controversies and Evidence.* Environmental and Resource Economics. vol. 19 pp.173-210.

Choe, C. and Fraser, Iain. 1999. An Economic Analysis of Household Waste Management.*Journal of Environmental Economics and Management.*Vol 38. No 2. pp 234-246.

Cropper, M. I., Deck, L., Kishor, N., and McConnel, K.E., 1993.*Valuing Product Attributes Using Single Market Data: A Comparison of Hedonic and Discrete Choice Approaches.* The Review of Economics and Statistics, Vol. 75, No 2. pp. 225-232.

Ewert, A. and D. Baker. 2001. *Standing for Where You Sit: An Exploratory Analysis of the Relationship between Academic Major and Environment Beliefs.* Environment and Behavior. Vol. **33. No.**5.pp. 687-707.

Folz, D.H., Hazlett, J.M. 1991. Public Participation and Recycling Performance: Explaining Program Success. *Public Administration Review.* Vol 51. No.6. pp 526-533.

Gamba, R., & Oskamp, S. 1994. *Factors influencing community residents' participation In Commingled curbside recycling programs.* Environment and Behavior. Vol. 6. Pp. 587- 612.

Greene, W.H. 2003. Econometric Analysis Fifth Edition. Upper Saddle River, New Jersey. Pretince Hall.

Greene, W.H., & Hensher D.A. 2003. *A latent class model for discrete choice analysis: Contrasts with mixed logit.* Transportation Research Part B 37, 681-698.

Gupta, S., & Chintagunta, P.K. 1994. *On Using Demographic Variables to Determine Segment Membership in Logit Mixture Models.* Journal of Marketing Research. Vol.31. No.1 pp. 128-136.

Hansen, L.T. McMellen, C. Olson, L. 2007.*Recycling Attitudes andBehaviors on a college campus: Use of Qualitative Methodology in a Mixed-Methods Study.* Working Paper, MSU.

Holmes, T.P., and Adomowicz, W.L. 2003. *Attribute-Based Methods.* In: Champ, P.A., Boyle,K.J., Brown, T.C., (eds.) A Primer on Nonmarket Valuation. Kluwer Academic Publishers: Dordrect/Boston/London pp. 171-220.

Jennings, M. E. 2004. *An Instrument to Measure the Recycling Attitudes and Beliefs of Undergraduate Students at a Large Northeastern University. Online Submission*, Education Resources Information Center: 22.

Kamakura, W.A., & Russell, G.J. 1989. *A Probabilistic Choice Model for Market Segmentation and Elasticity Structure.* Journal of Marketing Research. Vol.26 No.4. pp. 379-390.

Kaplowitz, M.D., Hadlock, T.D., Levine, R. 2004. *A Comparision of Web and Mail Survey Response Rates.* Public Opinion Quarterly. Vol. 68 No.1 pp. 94-101..

Kelly, T. C., I. G. Mason, M. W. Leiss and S. Ganesh. 2006.University community responses to on-campus resource recycling. *Resources, Conservation and Recycling*. Vol. 47. No. 1. pp. 42-55.

Louviere, J.J., D.A. Hensher, and J.D. Swait. 2000. *Stated Choice Methods: Analysis and Application.* Cambridge: Cambridge University Press.

Louviere, J., Street, D., Carson, R., Ainslie, A., Deshazo, J.R., Cameron, T., Henseher, D., Kohn, R., & Marley, T. 2002. *Dissecting the Random Component of Utility.* Marketing Letters. Vol.13 No.3. pp. 177-193.

Morey, E., Thacher, J., & Breffle, W. 2006. *Using Angler Characteristics and Attitudinal Data to Identify Environmental Preference Classes: A Latent-Class Model.* Environmental & Resource Economics. Vol.34. pp. 91-115.

Oskamp, S., Harrington, M., Edwards, J., Sherwood, D., Okuda, S., & Swanson, D. 1991. *Factors influencing household recycling behavior.* Environment and Behavior, Vol. 23, pp. 494-519.

Provencher, B., and Bishop, R.C. 2004. *Does accounting for preference heterogeneity improvethe forecasting of a random utility model? A case study.* Journal of Environmental Economics and Management. Vol. 48. pp. 793-810.

Provencher, B. and Moore, M. 2006. *A Discussion of "Using Angler Characteristics and Attitudinal Data to Identify Environmental Preference Classes: A Latent-Class Model."* Environmental & Resource Economics. Vol. 34. pp. 117-124.

Schmidt, P. and R. Strauss 1975. *The Predictions of Occupation Using Multinomial Logit Models* International Economic Review **Vol.16**, pp 471–486.

Scarpa, R., & Thiene, M., 2005. *Destination Choice Models for Rock Climbing in the NortheasternAlps: A Latent-Class Approach Based on Intensity of Preferences.* Land Economics. Vol.81. No. 3. pp. 426-444.

Siikamäki, J., & Layton, D. 2007. *Discrete choice survey experiments: A comparison using flexible methods.* Journal of Environmental Economics and Management. Vol. 53. No. 1. pp. 123-139.

Swait, J. R. 1994. *A Structural Equation Model of Latent Segmentation and Product Choice For Cross-Sectional Revealed Preference Choice Data*, Journal of Retailing and Consumer Services. vol.**1**, pp. 77–89.

Tiller, K.M, Jakus, P.M., and Park, W.M. 1997. Household Willingness to for Drop-off Recycling. *Journal of Agricultural and Resource Economics.* Vol 22. No. 2. pp. 310-320.

Wooldridge, J.M. 2002. Econometric Analysis of Cross Section and Panel Data. Cambridge, MA: MIT Press.