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Estimating the demand for drop-off recycling sites: A random utility travel cost approach

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ABSTRACT

Drop-off recycling is one of the most widely adopted recycling programs in the United States. Despite its wide implementation, relatively little literature addresses the demand for drop-off recycling. This study examines the demand for drop-off recycling sites as a function of travel costs and various site characteristics using the random utility model (RUM). The findings of this study indicate that increased travel costs significantly reduce the frequency of visits to drop-off sites implying that the usage pattern of a site is influenced by its location relative to where people live. This study also demonstrates that site specific characteristics such as hours of operation, the number of recyclables accepted, acceptance of commingled recyclables, and acceptance of yard-waste affect the frequency of visits to drop-off sites.

1. Introduction

The four primary methods to collect recyclables in the United States are curbside programs, drop-off centers, buy-back centers, and deposit or refund programs (USEPA, 2010). Drop-off recycling is a recycling program where designated sites are established to collect a range of recyclables and usually the recyclers themselves are required to deposit the sorted recyclables in specially marked containers. Drop-off recycling is also one of the most widely adopted recycling programs by local governments in this country. As of 1998, there were 12,000 recyclable drop-off sites and 9000 curbside programs established in the United States (USEPA, 2000).

Drop-off recycling centers are less costly to operate compared to curbside programs, and they are also faster to implement than take-back programs or other similar programs involving manufacturers (Saphores et al., 2006). Drop-off program operators are able to save on labor and transportation costs because these costs are transferred on the recyclers. Drop-off operations typically do not impose any charges to recyclers utilizing drop-off sites. Drop-off recycling is also considered to be the most financially viable recycling option in areas with low population density such as in rural areas (Tiller et al., 1997).

Despite its wide implementation, relatively little published literature analyzes the demand for drop-off recycling. Curbside recycling as a waste management policy tool is the more popular in the field of recycling and waste management research. Fullerton and Kinnaman (1996), Hong and Adams (1999), Van Houtven and Morris (1999), Kinnaman and Fullerton (2000), Jenkins et al. (2003) analyze the effect of curbside recycling, together with other policy tools such as variable garbage pricing, on the amount of waste generation and recycling. Other curbside recycling research investigates the value consumers place on curbside recycling by computing their willingness to pay for the service (Lake et al., 1996; Aadland and Caplan, 1999, 2003; Blaine et al., 2005; Karaousakis and Birol, 2008).

Some of the few examples exceptions of recycling research that is related to drop-off recycling include Sidique et al. (2010a), Sidique et al. (2010b), and Tiller et al (1997). Using a panel of recycling rates of Minnesota counties, Sidique et al. (2010b) find that variable pricing of waste and that the availability of both curbside and drop-off recycling significantly increase a county's rate of recycling. Sidique et al. (2010a) find that utilization of drop-off recycling sites increases with familiarity with recycling, perceived convenience of recycling, and the perceived amount of social pressure to recycle.

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Tiller et al (1997) is the stated preference study of a drop-off program conducted by Tiller, Jakus and Park in 1997. Their study analyzed the economic feasibility of establishing a drop-off recycling program in a rural and a suburban area of Tennessee by utilizing the contingent valuation method to calculate household willingness to pay (WTP) for the program. The estimated WTP for the three different types of households controlled for respondents' income, education level, age and attitudes toward the importance of recycling. They find that suburban recyclers, which consist of households with curbside recycling services, are willing to pay the most for drop-off recycling, with a mean WTP point estimate of \$11.74 per month. Rural recyclers have a mean WTP of \$7.07, and rural non-recyclers have the lowest mean household WTP of \$4.05.

Chang and Wei (1999) examined the strategic planning aspects of drop-off recycling centers in Kaohsiung, Taiwan. Their study analyzed the trade-off between the number and size of drop-off centers, walking distances to the drop-off centers, population covered in a service area and the driving distance of collection vehicles. The analysis was conducted by formulating a multi-objective mixed-integer linear programming model which balanced the following objectives: to maximize the population served by recycling centers, to minimize walking distance and to minimize total routing distance of collection vehicles subject to several physical constraints such as limit on drop-off centers in an area, service efficiency, capacity limitations, scheduling limitation and service area.

There are also a few other studies that have indirectly looked into drop-off recycling. Folz and Hazlett (1991) in a study examining the success of recycling programs reported that solid waste management experience of recycling coordinators is a very important factor in maximizing participation in drop-off programs. It was argued that experienced coordinators make better decisions in choosing the best strategic locations for drop-off centers. Folz also reported that advertising and promotion of recycling results in higher waste diversion to drop-off programs. In a descriptive study, Speirs and Tucker (2001) examined the profile of recyclers utilizing drop-off recycling sites in Glasgow and around Ayrshire in south–west Scotland. They reported on the recyclers' travel distances, the weights and types of recyclables and demographic characteristics. They also found that people whose trips were solely for the purpose of recycling tend to be a shorter distance from the sites compared to people who combine their recycling trips with other activities. In a more recent publication, Saphores et al. (2006) studied willingness to recycle electronic waste at drop-off centers by conducting a mail survey of households in California. The results from their multivariate analysis indicated that familiarity and convenience were very important factors in influencing willingness to recycle. People who are familiar or accustomed with glass, metal, paper or plastic recycling are more willing to recycle electronic waste. The study also found that people who lived more than 5 miles away from the nearest drop-off recycling center were less likely to recycle.

In comparison to the broader literature on recycling, and specifically the attention paid to curbside recycling, there are relatively few studies that analyze drop-off recycling. We address this gap by studying the demand for drop-off recycling sites in an urban area with several substitute sites using the random utility model (RUM). The main objective of this study is to use an economic demand model to examine the impact of location and different drop-off recycling site characteristics on drop-off recycling visits. We hypothesize that the travel costs incurred by recyclers to drop-off sites reduce site visits. We also hypothesize that site specific characteristics such as operating hours, number of recyclables accepted, acceptance of commingled recyclables and acceptance of yard-waste affect recycling visits. This study employs the RUM model to predict the changes in drop-off recycling patterns given the changes in site characteristics. This study improves our understanding to drop-off site attributes that may influence visitation demand. The study findings can be used by local governments and recycling and waste management companies to design and establish recycling drop-off centers that will increase site visitation and collection of recyclables.

Our study utilizes the revealed preference approach which is different from the study conducted by Tiller et al. (1997) that uses the stated preference approach. Unlike stated preference studies that rely on a respondent's survey answers on monetary amounts, choices, ratings or other preference indications to establish a measure of value on non-market goods or services (Brown, 2003), a revealed preference study collects information on respondents' actual behavior, such as number of visits and cost of traveling to particular sites, to establish the demand and value of these non-market goods or services. The RUM model which originates from the transportation field has been widely used in environmental economics to analyze the demand for recreational sites (e.g., Knoche and Lupi, 2007; Kotchen et al, 2006). However, we believe that our application of the RUM travel-cost method specifically to estimate the demand for drop-off recycling sites is a novel contribution to extant drop-off recycling research.

2. Theoretical framework

The RUM model is widely used to analyze discrete choices in the face of many substitutes. In our case, the RUM is appropriate because it is able to consider a household's selection of a drop-off recycling site, chosen from a set of many alternative drop-off sites, on an occasion in which they have chosen to visit a particular drop-off site. While the decision to utilize a drop-off site has many elements of a cost minimizing decision, we posit that households also have preferences (and hence derive utility) from the convenience attributes and other attributes of recycling sites. Thus, when selecting a particular site, the household is assumed to take into account the trip cost to arrive to the site as well as the site characteristics. The trip cost would mainly be the driving cost and time cost to travel to and from the site. Site characteristics are the features of each drop-off site such as operating hours and types of recyclables accepted. Hence, each recycling site will give households different utility levels and, after factoring in the travel costs, households are assumed to visit sites that yield them the highest utility.

Specifically, to model the drop-off site selection process, we assume that households derive utility from the quality or characteristics of a particular drop-off site. Each household has a choice set of S number of sites that they could visit denoted by $j = 1,2,\ldots S$. Let x_{ij} represent trips household i takes to site j with a vector of M site characteristics $[q_{j1}, q_{j2}, \ldots q_{jM}]$. In evaluating the utility household i derives from a trip to site j, we assume that $q_k = 0$ for all $k \neq j$. The utility function for household i is defined as follows

$$U\left\{z_i, x_{ij}\left(q_{j1}, q_{j2}, \ldots q_{jM}\right)\right\} \tag{1}$$

where z_i is a composite consumer good and the utility function is assumed to be increasing and strictly quasi-concave in all its arguments. Households maximize utility subject to a budget constraint (2) and time constraint (3)

$$\sum_{j=1}^{n} x_{ij} c_{ij} + z_i \leq y_i \tag{2}$$

$$\sum_{j=1}^{n} x_{ij} t_{ij} + h_i + l_i \leq T \tag{3}$$

where c_{ij} is the round-trip driving cost to site j, $z_i$is purchased at a normalized price equal to 1, $y_i$is the household income which is further defined in Equation (4), t_{ij} is the time taken for each round-trip to site j, h_i is the hours spent working, l_i is the time spent for leisure and T is the total time available. Income is given by

$$y_i = y_i^0 + w_i h_i \tag{4}$$

where y_i^0 is fixed income and w_i is the wage rate. Solving the time constraint using Equation (4) for h and substituting it into the budget constraint yields

$$\sum_{j=1}^{n} x_{ij}(c_{ij} + w_i t_{ij}) + z_i \leq y_i'. \tag{5}$$

By solving the utility maximization problem, we derive the Marshallian demand function for x_{ij} and substituting the demand function in the utility function results in the indirect utility function that is expressed as follows:

$$v_{ij} = v\left(y_i' - (c_{ij} + w_i t_{ij}), q_j\right). \tag{6}$$

The indirect utility function can be represented in a linear form where βs are the parameters to be estimated and e_{ij} is the random error term

$$v_{ij} = \beta(y_i' - (c_{ij} + w_i t_{ij})) + \beta_q q_j + e_{ij}. \tag{7}$$

The cost of visiting site j that consists of round-trip driving and time costs, $c_{ij} + w_i t_{ij}$, is essentially the travel cost which will be simplified as tc_{ij}. We also note that y_i' will drop from the equation as it does not vary across sites. Thus, the indirect utility function can rewritten as follows

$$v_{ij} = \beta_{tc} tc_{ij} + \beta_q q_j + e_{ij}. \tag{8}$$

On a given a choice occasion, a household decides to recycle at the site that yields the highest utility. A recycling site k is chosen by household i if:

$$\beta_{tc} tc_{ik} + \beta_q q_k + e_{ik} \geq \beta_{tc} tc_{ij} + \beta_q q_j + e_{ij} \quad \text{for all } j \in S. \tag{9}$$

We express the choice to visit a recycling site in a probabilistic framework, where the probability of a household visiting site k is:

$$\Pr\left(\beta_{tc} tc_{ik} + \beta_q q_k + e_{ik} \geq \beta_{tc} tc_{ij} + \beta_q q_j + e_{ij} \quad \text{for all } j \in S\right). \tag{10}$$

The choice probability of household i visiting site k is expressed using the conditional logit form, where:

$$\Pr(ik) = \frac{\exp(\beta_{tc} tc_{ik} + \beta_q q_k)}{\sum_{j=1}^{S} \exp\left(\beta_{tc} tc_{ij} + \beta_q q_j\right)} \tag{11}$$

The model estimators can be derived by maximizing the following log-likelihood function constructed from Equation (11)

$$\log L_n(y, \beta) = \sum_{n=1}^{N} \log P\left(\frac{\exp(\beta_{tc} tc_{ik} + \beta_q q_k)}{\sum_{j=1}^{S} \exp\left(\beta_{tc} tc_{ij} + \beta_q q_j\right)}\right) \tag{12}$$

The equation in (12) provides the likelihood function for a random sample of drop-off recyclers. However, if our data is collected using a choice-based, i.e. an on-site, sampling method, then we would need to correct for the potential endogenous stratification in the data. With on-site sample data, if we know the population proportions of recyclers visiting the S sites, we can to use the Weighted Exogenous Sampling Maximum Likelihood (WESML) method to derive consistent estimates of the model parameters (Manski and Lerman, 1977). The WESML estimator is obtained by weighting the population proportions by the sample proportion and incorporating these weights in the likelihood function. From Equation (12), the weighted exogeneous likelihood function is presented as follows

$$\log W_n(y, \beta) = \sum_{n=1}^{N} \frac{Q_j}{H_j} \log P\left(\frac{\exp(\beta_{tc} tc_{ik} + \beta_q q_k)}{\sum_{j=1}^{S} \exp\left(\beta_{tc} tc_{ij} + \beta_q q_j\right)}\right) \tag{13}$$

where Q_j is the proportion of the population selecting site j and H_j is the analogous proportion for our choice based sample. To use the demand model to forecast changes, we use the WESML estimates for the parameters to predict the probability for the households across our sample.

3. Survey methods

3.1. Questionnaire design

The questionnaire used in this study consisted of questions pertaining to the respondents' recycling activities. We included questions on the frequency of visits to drop-off sites in the past three months and one year to calculate site visits. Questions on the respondent's income and home address were also included in the questionnaire to compute the travel costs. These questions were asked at the end of the interview because we felt respondents would be more comfortable sharing personal information after going through a set of more general questions. On the home address question, we asked the nearest street intersection to the respondent's home whenever they were reluctant to reveal their address.

The questionnaire also consisted of questions eliciting general demographic information of the respondent such as gender, education, employment status and marital status. The questionnaire was pre-tested and further improved before conducting the actual survey. The questionnaire pretest was conducted by interviewing several randomly selected recyclers at one of the drop-off sites. The pretest resulted in some wording refinements and changes to the arrangement of questions in the instrument.

3.2. Data collection

We define our population to consist of recyclers utilizing eight drop-off recycling sites in and around Lansing, Michigan (Fig. 1). Most of the recyclers are from the cities of Lansing and East Lansing. Lansing is the capital city of Michigan, with a population of 114,297 and East Lansing is a college town with a population of 48,579 (US Census, 2010). The median household income for East Lansing is \$27,898 as compared to \$37,678 for Lansing. The median household incomes for both cities are lower than the median income for United States which is \$48,700. Being a college town, the education level in East Lansing is relatively high with approximately 68% of its population with bachelor's degree or higher. The education level in Lansing is similar to the education level in the United States where approximately 24% of its population has a bachelor's degree or higher.

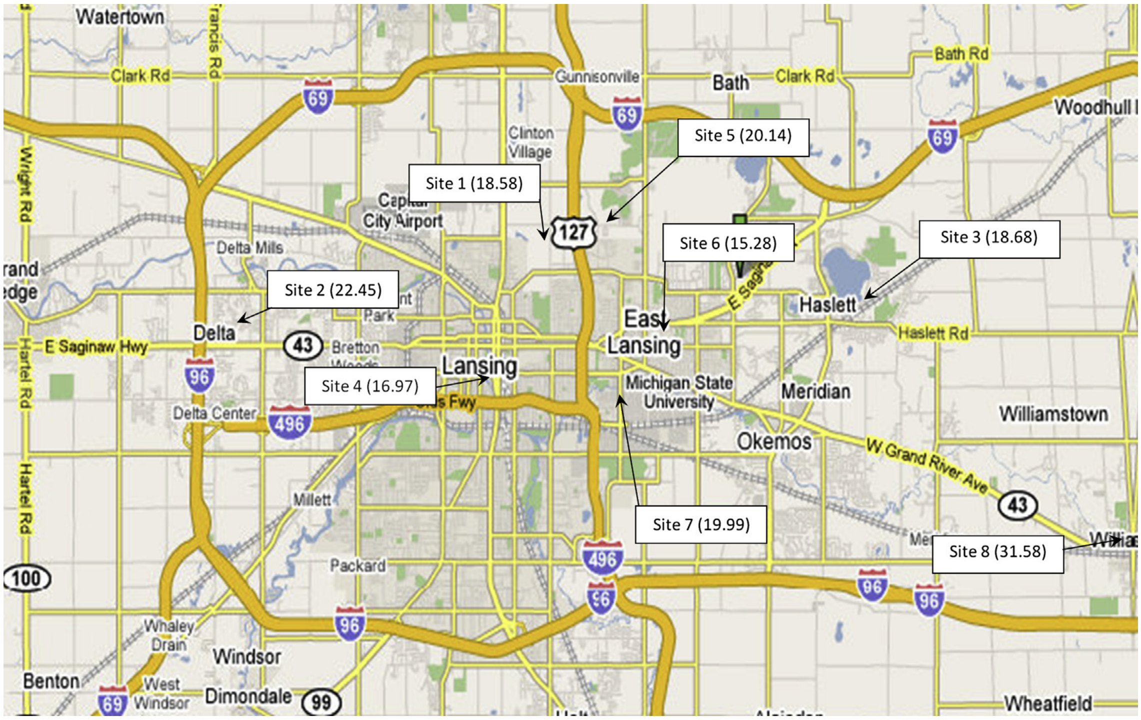

Fig. 1. Locations and mean distance (miles) for drop-off recycling sites.

We used on-site interviews to collect our survey data. This on-site survey method is chosen over a random population survey because we expected the percentage of population that recycles at drop-off sites to be low and we would require a large sample size to obtain sufficient number of drop-off recyclers in such a sample. Furthermore, with low proportions for the target population, the costs involved in conducting a detailed survey with such large sample size are also high. Manski and Lerman (1977) suggest that choice based survey can achieve the economies of scale not available with a population survey in circumstances where the respondents are physically clustered according to the alternative they select. Similarly, Haab and McConnell (2002) note that on-site sample surveys are a more cost effective approach for data collection for multiple site models when the proportion of the population participating in the activity is quite low.

However, there is a problem associated with on-site sample surveys – the sampling scheme is often independent of the population proportions visiting the survey sites. The problem arises as model parameter estimates depend on the sampling proportions. If the sampling proportions differ from the population proportions, the model will suffer from inconsistent parameter estimates. In other words, sampling proportions that differ from population proportion will result in the parameter estimates capturing effects of both the sampling plan and recycler's behaviors, rather than behavior alone. Nevertheless, the on-site sampling endogeneity problem can be addressed using the WESML method if the population shares are known (Manski and Lerman, 1977).

There were two separate processes involved in obtaining our survey data: the first part was to measure recycling effort at each drop-off site and the second part was to conduct on-site interviews of recyclers. The measures of recycling effort at each site are used to estimate the population proportions of the eight drop-off sites to construct the WESML weights to correct for possible choice-based sampling bias. To measure recycling effort, we counted the vehicles visiting each of the drop-off sites. The counting exercise was conducted simultaneously at seven of the eight drop off sites during busiest recycling period on a weekend. The exercise was carried out on a separate day at Site 8 due to the site's operating hour restriction, which was reported to be its busiest day.

Table 1 provides the distribution of number of cars visiting various drop-off sites during our simultaneous effort sampling period, which we use as estimates of population proportions. While this is not a perfect measure of population proportions, according to the city officials, the busy day accounted for most of the visits and hence likely provides the best estimates of population proportions.

For the second part, on-site survey interviews were conducted for four weeks starting from the last week of October 2006 to the last week of November 2006. Each site was randomly visited 4 times, on a 3-h interval each time throughout the survey period. For each visitation time, we randomly selected the sites. A site that was not open on a particular visitation time was excluded to ensure a zero probability of selection for that time. With the exception of Site 2 and Site 8, we excluded sites that had been selected on the same visitation time in the previous weeks. For example, if Site 1 had been selected for Week 1, Sunday 3–6 pm, the site was excluded in the drawing for that time period for Week 2 at the same time. We made an exception for Site 2 and Site 8 because both sites have limited operating hours and if we were to impose a duplicate time restriction on these sites, the sites would have been visited

Table 1
Distribution of cars by sites from the effort survey.

Site name	Cars	Percentage
Site 1	146	25.44%
Site 2	202	35.19%
Site 3	113	19.69%
Site 4	29	5.05%
Site 5	50	8.71%
Site 6	26	4.53%
Site 7	3	0.52%
Site 8	5	0.87%

Table 2
Distribution of respondents by sites from the on-site survey.

Site name	Respondents	Percentage
Site 1	94	26.4%
Site 2	73	20.51%
Site 3	81	22.75%
Site 4	19	5.34%
Site 5	44	12.36%
Site 6	30	8.43%
Site 7	4	1.12%
Site 8	11	3.09%

less than 4 times. A site was excluded from the draw once it had been selected 4 times. At the end of the survey duration, we approached 527 recyclers. Out of the total approaches made, 356 recyclers agreed to participate in the survey giving us a response rate of approximately 68%. The distribution of respondents according to recycling sites is given in Table 2.

Table 3 presents the demographic profile of the recyclers in our sample. We had more males (55.62%) than female respondents (44.38%) in the survey. With regards to age, the majority of the respondents are 40 years or older, and the highest age group was between 50 and 59 years old (28.16%). The lowest age group was between 30 and 39 years old which accounts to only 10.92% of the respondents. As for household composition, about 71% of the respondents are either married or living with a partner. Approximately 80% of the respondents lived in a household comprised of 2 or more people. The respondents were mostly college-educated as approximately 70% of the sample have a bachelor's degree or higher. The majority of the respondents were also employed full time (64.27%). In terms of household income, roughly 60% of the respondents reported a household income of $45,000 or more.

Table 3
Demographic characteristics of drop-off recyclers.

Variable	Frequency	Percentage
Gender		
Male	154	44.38
Female	193	55.62
Age		
18–30 years old	56	16.09
30–39 years old	38	10.92
40–49 years old	86	24.71
50–59 years old	98	28.16
60 years old or more	70	20.11
Education		
Some high school	3	0.86
High school or GED	54	15.56
Vocational or trade school	5	1.44
Two year degree	36	10.37
Four year degree	133	38.33
Graduate school	116	33.43
Employment status		
Employed full time	223	64.27
Employed part time	29	8.36
Unemployed	3	0.86
Retired	63	18.16
At home parent	8	2.31
Student	21	6.05
Income		
Less than $25,000	43	12.36
$25,000 to $44,999	75	21.55
$45,000 to $74,999	78	22.41
$75,000 to $99,999	77	22.13
$100,000 or more	75	21.55
Marital status		
Single	69	19.94
Married/Living with partner	245	70.81
Divorced/Widowed/Separated	32	9.25
Household size		
1	65	18.79
2	149	43.06
3	53	15.32
4	57	16.47
5	13	3.76
More than 5	9	2.60

4. Model estimation and results

Our model uses the WESML estimation method specified as follows:

$$v_{ij} = \beta_1 TRAVELCOST_{ij} + \beta_2 HOURS_{ij} + \beta_3 NUMREC_{ij} + \beta_4 COMMING_{ij} + \beta_5 YARDWASTE_{ij} + e_{ij} \tag{14}$$

where v_{ij} is the indirect utility individual i gets from visiting site j, and each j has the same independent, Type 1 extreme value distribution,

$$F_e(e_{ij}) = \exp(-\exp(-e_{ij})) \tag{15}$$

which, under maximization, yields the conditional logit model for the choice probabilities as in (11). We also examine an extension of the basic model by incorporating interactions between demographic variables and the site attributes. The extended model is specified as follows:

$$\begin{aligned} v_{ij} = {} & \beta_1 TRAVELCOST_{ij} + \beta_2 HOURS_{ij} + \beta_3 NUMREC_{ij} \\ & + \beta_4 COMMING_{ij} + \beta_5 YARDWASTE_{ij} + \beta_6 EHOURS_{ij} \\ & + \beta_7 ENUMREC_{ij} + \beta_8 ECOMMING_{ij} + \beta_9 EYARDWASTE_{ij} \\ & + \beta_{10} HHOURS_{ij} + \beta_{11} HNUMREC_{ij} + \beta_{12} HCOMMING_{ij} \\ & + \beta_{13} HYARDWASTE_{ij} + \beta_{14} ITRAVELCOST_{ij} + e_{ij} \end{aligned} \tag{16}$$

Table 4 provides a list of variables and their definition. For each site and for each respondent, the travel cost variable was calculated by adding up the roundtrip driving cost and the time cost to travel from the recycler's home to drop-off site. The distance from home to the recycling site was obtained with Mapquest using the shortest distance option. The driving cost was assessed at 35 cents per mile (AAA, 2006). Driving cost consists of per mile vehicle operating cost plus depreciation per mile. Time cost was the opportunity cost incurred by the recycler during the drop-off recycling activity calculated using the recycler's income. The trip time is computed assuming that a recycler travels at 35 miles per hour on average.

Table 4
Definition of variables.

Variable	Definition
TRAVELCOST	Roundtrip travel and time cost from home to site *j*
HOURS	Total operating hours per week
NUMREC	Number of recyclables accepted
COMMING	Number of types of commingled recyclables accepted
YARDWASTE	1 if site accepts yard-waste (0 otherwise)
EHOURS	Interaction between full employment dummy (1 = fully employed, 0 = otherwise) and *HOURS*
ENUMREC	Interaction between full employment dummy and *NUMREC*
ECOMMING	Interaction between full employment dummy and *COMMING*
EYARDWASTE	Interaction between full employment dummy and *YARDWASTE*
HHOURS	Interaction between household size (= the number of household members) and *HOURS*
HNUMREC	Interaction between household size and *NUMREC*
HCOMMING	Interaction between household size and *COMING*
HYARDWASTE	Interaction between household size and *YARDWASTE*
ITRAVELCOST	Interaction between *TRAVELCOST* and high income dummy

The recreation literature has generally accepted 1/3 of an individual's wage as a lower bound and an individual's full wage as an upper bound for the hourly value of time spent driving (Parsons, 2003). We use 1/3 of the recycler's wage in our time cost calculation, and the wage is computed by dividing annual income by 2000 h of work time (50 weeks at 40 h per week).

The site characteristics data used in our model were obtained from the information given at the site and through our own observations. The operating hours for the recycling sites varied from as low as only 15 h per week to 24 h a day. We expect operating hours per week to increase site visitation because it increases flexibility and convenience for recyclers. The number of recyclables accepted also varies from site to site. There are sites accepting as few as 5 types of recyclables to a 17 different types of recyclables. We expect sites accepting a wider range of recyclables to receive higher visitation rates when compared to sites accepting a limited range of recyclables. There are sites that accept commingled plastic or papers and recyclers visiting these sites are not required to separate the different types of recyclable plastics or papers. This attribute is expected to increase site visits as it makes recycling easier and more convenient. We also included a dummy variable to represent sites that accept yard-waste. The sites that accept yard-waste are Site 1, Site 2, Site 3 and Site 8 and they charge fees ranging from $5 to $10 per cubic yard of yard-waste recycled. However, as Site 2 only accepts yard-waste from its township residents, the yard-waste dummy variable for Site 2 will only take a value of 1 if the respondent lives in the township where Site 2 is located.

EHOURS, *ENUMREC*, *ECOMMING*, *EYARDWASTE* are the interactions between the dummy variable for full employment and the attribute variables: operating hours, number of recyclables accepted, acceptance of commingled recyclables and acceptance of yard-waste. These variables are included to ascertain the degree of influence of the site attributes on drop-off site visits for persons with a full-time employment. We also interact household size (the number of people in the household) with the same four attribute variables to form HHOURS, *HNUMREC*, *HCOMMING*, *HYARDWASTE* to determine if households with different sizes place a different weight on the site attributes. We interact a dummy for high income (respondents earning $45,000 per annum or more) with *TRAVELCOST* to determine if household income affects the decision to travel to a drop-off site. We expect that respondents with higher income will be less affected by the cost of driving to a drop-off site compared to respondents with lower income.

A concern with estimation procedures employed here is the potential endogeneity of the travel cost to drop-off sites. If households choose where they live to reduce their travel costs to a drop-off site, the estimated coefficients of travel costs may be biased. However, we are not aware of any literature on housing choices that suggest this would be the case. We conducted conversations with local officials that suggest locations of drop off sites are governed mostly by exogenous factors such as availability of public land of sufficient size (for storage, parking and vehicle access), and neighborhood concerns about traffic, nuisance and odor. Moreover, recycling site locations are almost always ex-post decisions after the neighborhoods are already well developed, rather than ex-ante optimally planned locations. Hence we feel that such endogeneity is not likely to be significant problem in our estimation. Another caveat is that these results are contingent upon the population of individuals who have already decided to be drop-off recyclers, and not the population as a whole.

The estimation results are presented in Table 5. Model 1 is the basic model, and Model 2 is the extended model that includes interaction variables between demographics and site attributes and also the interaction between high income and travel cost. All the parameters in Models 1 are statistically significant, and all the parameters in Model 2 are statistically significant except for *NUMREC*. The travel cost variable is negative and highly significant as expected in both the models. In other words, the parameter indicates that by holding all other variables constant, it is expected that the probability of visiting a recycling site will decrease as the cost of traveling to the site increases. The parameter estimate for the travel cost variable in Model 2 is higher than Model 1 because of the inclusion of the interaction variable between high income and travel cost. The positive estimate for the interaction variable suggests that high income respondents are less affected by the costs of traveling to a drop-off site. The estimates for *YARDWASTE* indicate that yard-waste acceptance has a large impact on increasing the probability of site visits. The parameter estimates for *HOURS* indicate that increasing site operating hours per week will increase site visits. However, this interpretation is only applicable to non 24 h sites.

Table 5
Random utility model results.

(Dependent variable = Number of visits in the past year)	Model 1		Model 2	
	Estimate	Std. error	Estimate	Std. error
TRAVELCOST	−0.304	0.008**	−0.473	0.013**
HOURS	0.010	0.001**	0.002	0.001
NUMREC	0.193	0.011**	−0.022	0.023
COMING	0.531	0.035**	0.864	0.086**
YARDWASTE	2.339	0.081**	1.348	0.163**
EHOURS			0.010	0.001**
ENUMREC			0.054	0.022*
ECOMMING			0.137	0.077*
EYARDWASTE			0.682	0.156**
HHOURS			0.001	0.000**
HNUMREC			0.081	0.011**
HCOMMING			−0.158	0.029**
HYARDWASTE			0.334	0.072**
ITRAVELCOST			0.211	0.016**
Observations	343		342	
Adj-R_2	0.498		0.528	
Log-likelihood	−6283		−5825.678	

**$\alpha < 0.01$, *$\alpha < 0.10$.

The results in Model 1 also imply that increasing the number of recyclables accepted at a drop-off site will increase the probability of site visits. The parameter estimates for *COMMING* in Model 1 indicate that allowing for an additional type of commingled recyclables will increase the probability recyclers visit that drop-off site. *NUMREC* is no longer significant in Model 2 although its interaction with the fully employed, and household size variables are both significant. The positive parameter estimates for *EHOURS*, *ENUMREC*, *ECOMMING* and *EYARDWASTE* in Model 2 suggests that site attributes such as operating hours, the number of recyclables, acceptance of commingled and acceptance of yard-waste have more impact in increasing site visits for recyclers that are working full-time. This result is intuitive as one would expect a fully employed person to be more occupied and might place a higher value on convenience-related site attributes when compared to recyclers who are not employed. The positive estimates for *HHOURS*, *HNUMREC* and *HYARDWASTE* indicate that site operating hours, the number of recyclables and acceptance of yard-waste have more impact in increasing site visits for larger households. Perhaps not intuitive, the negative parameter estimate for *HCOMMING* suggests that the acceptance of commingled recyclables would reduce recycling visits of larger households.

In interpreting the results for the site attribute variables, it is important to note that with only eight sites in the model, there are limitations on the independent variation in the site attributes. Indeed, with the exception of travel costs, we found some evidence

Table 6
Marginal implicit prices (MIP) for changes in site characteristics.

Variable	Baseline MIP (Model 1)	High Income MIP (Model 2)	Low Income MIP (Model 2)
HOURS	$0.07	$0.09	$0.02
NUMREC	$1.36	$1.91	$0.52
COMING	$3.48	$ 4.10	$1.85
YARDWASTE	$15.69	$20.99	$6.76

of multicollinearity between the site attributes. Further, with only eight sites in our model, we can include a maximum of eight site attribute variables before our model is over identified. Thus, we found that due to multicollinearity between the site attributes, the parameter estimates are sensitive to the combination of attributes included in our model. Nevertheless, the travel cost parameter estimate was stable and consistent regardless of the site attributes included in our model. To further aid the interpretation of the results, we construct Table 6 that provides the marginal implicit prices for changes in site characteristics. We compute three sets of marginal implicit prices, the baseline, high income and low income marginal implicit prices. The baseline marginal implicit prices are calculated using the estimates from our basic model (Model 1). The high and low income marginal implicit prices are calculated using the estimates from Model 2. The marginal implicit price of a variable is calculated as a ratio of the variable's parameter estimate to the travel cost parameter estimate and represents the marginal rate of substitution between a site attribute and travel costs. Marginal implicit prices can be used to compare the relative importance of different site characteristics to travel costs.

The marginal implicit price of $15.69 for *YARDWASTE* in the baseline model indicates that yard-waste acceptance has the highest impact on recycling visits compared to a one unit change in the other site attributes. *HOURS* has the lowest marginal implicit price per unit. The results suggest that a 20 h increase in operating hours per week for a non 24 h site has almost the same impact as accepting an additional type of recyclable. Similarly a change from the lowest site operating hours, 15, to 24 h operation would have about the same effect as accepting an additional eight kinds of recyclables (a change in *NUMREC* of eight).

The results also suggest that a change from zero to two types of commingled recyclables accepted has approximately the same impact as accepting 5 additional types of recyclables or having an additional 100 operating hours. While *YARDWASTE* has the largest effect for a one unit change in the variable, since it is a dummy variable the one unit change is akin to a change from its lowest value to its highest value. Considering the effect of a change from the lowest to highest value of *NUMREC*, a change of 17, when multiplied by its marginal implicit price, reveals that it has the largest overall effect of any of the site attributes over their respective ranges. The marginal implicit prices for *HOURS*, *NUMREC*, *COMING* and *YARDWASTE* are also consistently higher in the high income model than the low income model. The results indicate that these site attributes impact the visits of high income recyclers more than lower income recyclers.

4.1. Scenario analysis and policy implications

In this section, we use the basic model to impute the probability of site visitation to the respective eight sites. The probability of visitation for each site is calculated by substituting the parameter estimates derived from our weighted model into the household weighted site choice probability function (Equation (11)) and summing it up across all respondents. Table 7 presents the probability of visitation, in descending order, to each drop-off site.

Table 7
Probability of site visitation.

Site name	Predicted probability of trip
Site 3	0.270
Site 1	0.212
Site 2	0.208
Site 6	0.105
Site 5	0.094
Site7	0.053
Site 8	0.044
Site 4	0.014

The model predicts that most recycling trips are taken to the Site 3 drop-off recycling site. The recycling site with the lowest probability of site visitation is Site 4. The difference between the site with the highest and lowest probability of visitation is also very large. Given that a recycler makes a trip to a drop-off site, the probability of the recycler choosing to visit Site 3 is approximately 19 times larger than the probability of the recycler choosing Site 4.

Using the model we predict changes in visitation rates when a recycling site is closed. Table 8 displays the probability of site visits to remaining sites when one particular site is closed. The closed site in the table is indicated by a zero probability of visitation. A site closure will result in recyclers resorting to alternative sites, and they will substitute the closed site with its next best alternative. The next best alternative site might be a site that is closest in distance to the recycler or a site with similar attributes to the site that has been closed. Since we cannot know which site is each person's next best alternative, we report the predicted probability of site choice after the change. The best substitute for a closed site, on average, will experience the highest increase in probability of site visitation. The simulation results indicate that if we close Site 1, the site that experiences the highest increase in visitation probability is Site 5. This is probably because of the proximity between Site 5 and Site 1 although Site 5 lacks some of the attributes Site 1 has, such as the acceptance of yard-waste. Another site that receives an equally high increase in probability of visits when Site 1 is closed is Site 2. An explanation for this is the similarity in features between the two sites such as the acceptance of a wide variety of recyclables although the distance between the two sites is quite far.

We also use the model to predict the changes in visits when we change the attributes of a recycling site. We create a hypothetical combination of good attributes for a recycling site: 24 h of operating time, accepts 10 different types of recyclables, accepts two types of commingled recyclables and accepts yard-waste. One possible scenario is to improve the features of Site 6 to the hypothetical site attributes. Site 6 is a smaller and a less comprehensive site as compared to the popular sites such Site 1, Site 2 and Site 3. However, Site 6 is strategically located in the middle of all the eight

Table 8
Probability of site visitation due to site closure.

Site name	Predicted probability of trip when a site is closed							
	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6	Policy 7	Policy 8
	Close	Close	Close	Close	Close	Close	Close	Close
	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 8
Site 1	–	0.349	0.280	0.216	0.248	0.241	0.225	0.215
Site 2	0.260	–	0.217	0.211	0.216	0.215	0.213	0.209
Site 3	0.309	0.291	–	0.271	0.292	0.303	0.283	0.299
Site 4	0.020	0.022	0.016	–	0.016	0.016	0.016	0.014
Site 5	0.150	0.111	0.148	0.096	–	0.112	0.102	0.097
Site 6	0.144	0.118	0.189	0.107	0.122	–	0.117	0.110
Site 7	0.071	0.063	0.081	0.055	0.061	0.066	–	0.056
Site 8	0.046	0.045	0.068	0.045	0.046	0.047	0.045	–

Table 9
Probability of site visitation after changes in site attributes.

Site name	Predicted probability of a trip if the attributes of site 6 are improved	Predicted probability of a trip if the attributes of site 8 are improved
Site 1	0.119	0.206
Site 2	0.179	0.207
Site 3	0.155	0.243
Site 4	0.007	0.013
Site 5	0.043	0.090
Site 6	0.441	0.099
Site 7	0.022	0.050
Site 8	0.034	0.092

sites, and it has the lowest mean distances for all respondents (see Fig. 1). This simulation will indicate what happens to visitation patterns when we improve the attributes of Site 6. Alternatively, another possible scenario is to change the features of Site 8 to the hypothetical site attributes described above. Site 8 is one of the least popular sites mainly because of its location but also due to its attributes such as a low level of recyclables accepted and limited operating hours. Table 9 outlines the probability of site visitation to all eight sites under these two scenarios: changing the attributes of site 6, and changing the attributes of site 8.

By improving the attributes of Site 6, the probability of visits to the recycling site has substantially increased from 0.11 to 0.44. On the contrary, the probability of a visit to all other substitute sites has decreased with Site 1 having the greatest reduction from 0.21 to 0.12. This is anticipated as we have enhanced a substitute for Site 1 at a more convenient location. It is also interesting to note that Site 2 experiences a smaller decrease in probability of visits when compared to Site 3. This suggests that most of the recyclers using Site 2 are from the Site 2 township itself, and it would not be convenient, distance wise, to switch to Site 6. Furthermore, for a Site 2 township resident, the site offers similar attributes to the 'new' Site 6 such as the acceptance of yard-waste and wide variety of recycling materials.

Subsequently, improving the site attributes of Site 8 also results in an increase in the probability of visit to the site. However, the increase is only from 0.04 to 0.09 which is not as large compared to our first scenario when we change the attributes of Site 6. Changing the attributes of Site 8 also did not result in large decreases in the probability of visits to other remaining sites. This implies that attributes alone are not enough to substantially increase visitation rates and a recycling site needs to be both conveniently located and equipped with comprehensive attributes to attract a large share of users.

5. Conclusions

There are only a few studies on drop-off recycling despite the wide implementation of drop-off programs across this country. This study addresses this gap by using the RUM method to assess the demand for drop-off recycling sites. The use of a RUM model, which has been traditionally employed in transportation and recreation economics, is an appropriate and theoretically consistent way to analyze the demand for drop-off recycling sites in an urban setting with several substitute sites. The findings demonstrate that higher travel costs significantly reduce the probability of visiting a drop-off recycling site. This implies that the location of a site relative to where people live clearly affects site visitation. The findings also indicate that site-specific convenience-related attributes such as site operating hours, the number recyclables accepted, acceptance of commingled recyclables, and acceptance of yard-waste significantly affect which drop-off recycling sites get visited. However, some caution is warranted when interpreting the specific effects of individual site attributes (other than travel costs) due to our finding of potential multicollinearity between these attributes. Nevertheless, taken as a group, the site attributes were always highly significant in explaining site choices.

Given the significance of all these factors, policy makers should consider the influence of site location and site attributes when planning and designing facilities in order to maximize the use of drop-off recycling sites. Drop-off sites should be located in areas that are relatively near and accessible to a majority of the population. The results from the scenario simulation demonstrate that a site that is conveniently located will attract a high usage if equipped with convenience-related attributes such as accepting a wide variety of recyclables and yard-waste. Our scenario simulation results also demonstrate that improving convenience-related attributes alone will not be sufficient to significantly increase site visits if the site is not strategically located.

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