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Understanding Preferences for Recycling Electronic Waste in California

The Influence of Environmental Attitudes and Beliefs on Willingness to Pay

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Increasing stockpiles of electronic waste (e-waste) combined with low recycling rates are threatening human and environmental health because of the hazardous materials in electronic products. To date, however, little is known about household preferences for e-waste recycling alternatives. This study starts filling this gap. Our 2004 mail survey indicates that California households prefer "drop-off recycling at regional centers," with "curbside recycling" a close second. A contingent ranking (CR) analysis shows that households are willing to pay approximately $0.13 per equivalent mile per

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month to increase e-waste recycling convenience. Our results show that ignoring environmental attitudes and beliefs leads to biased estimates of the trade-offs households are making between cost and recycling convenience. A good understanding of these trade-offs is necessary for a successful recycling program. Finally, this article illustrates some of the strengths and weaknesses of CR, an underused technique for analyzing preference rankings.

Keywords: *electronic waste; recycling; environmental attitudes and beliefs; contingent ranking; stated preferences; rank-ordered logit*

Introduction

Increasing demand for consumer electronics combined with the trend to replace, rather than upgrade, older electronics has led to a new environmental challenge: electronic waste (e-waste). E-waste is a concern for public policy because it contains a variety of materials potentially toxic to human and environmental health. In addition to organic chemicals like brominated flame retardants, consumer electronic devices (CEDs) contain heavy metals such as arsenic, cadmium, chromium, lead, and mercury (Townsend & Musson, 2006). Lead in televisions and computer monitors is of particular concern as cathode ray tubes (CRTs) contain 4 to 8 lbs of lead.

The Environmental Protection Agency (EPA, 2003) estimates that approximately 2.2 million tons of e-waste are generated annually in the United States, yet only 9% are recovered or recycled. One explanation for this low percentage is that consumers who want to recycle their e-waste often face relatively high fees and limited recycling options (General Accounting Office [GAO], 2005). In fact, the General Accounting Office cites inconvenience as a major factor discouraging proper end-of-life management of used consumer electronic devices.

To deal with e-waste recycling, different programs have been developed around the Unites States, including permanent collection facilities (often colocated with municipal hazardous waste collection programs), drop-off special events (one- or multiple-day events held at temporary sites), retail collection programs, curbside recycling, and nonprofit or thrift retail collection (see California Integrated Waste Management Board [CIWMB], 2004, for an overview of the pros and cons of each model).

Since 2001, when the California Department of Toxic Substances Control designated cathode ray tubes as universal waste, local governments have taken the primary role in diverting these items from landfills not only because of concerns about the environmental consequences of illegal dumping (California Integrated Waste Management Board, 2004) but also because of pressure from the Basel Action Network (BAN) and other nongovernmental organizations to stop e-waste exports to developing countries.[1] Given their financial situation, however, many municipalities are reluctant to finance the management of e-waste.

To date, however, there does not appear to be any research that explores the preferences of households for various e-waste recycling programs, which is unfortunate because the cost to set up and operate these programs is not trivial. This article starts addressing this gap by conducting a contingent ranking (CR) study of Californian households' preferences for different recycling programs. More specifically, we ask our respondents to rank five hypothetical e-waste recycling alternatives: (1) "Pay As You Throw"; (2) "Drop-Off Recycling at Regional Collection Centers"; (3) "Curbside Recycling"; (4) "Drop-Off Recycling at Retail Locations"; and (5) "Deposit-Refund Program at Retail Locations." For option 1, households return used e-waste to a manufacturer for a set recycling fee; the other options are self-explanatory. We estimate trade-offs between convenience and cost for e-waste recycling, and we examine how these trade-offs are influenced by environmental attitudes and beliefs (EABs). Although a number of studies have shown that EABs are important predictors of willingness to pay (WTP) for environmentally friendly products such as organic food or "green" electricity (see, e.g., Laroche, Bergeron, & Barbaro-Forleo, 2001, and Diamantopoulos, Schlegelmilch, Sinkovics, & Bohlen, 2003), we are unaware of any study that focuses on e-waste recycling.

This article is organized as follows. First, some key articles from the behavioral psychology and economics literatures on household recycling and the impact of EAB on WTP are reviewed; a brief overview of the CR literature to justify our methodological choices is also presented. Then our survey data are summarized. This is followed by a presentation of our methodology and a discussion of our results. Finally, the article is concluded by discussing some policy recommendations.

Literature Review

Excellent reviews of household recycling literature, which is quite extensive, can be found in Hornik, Cherian, Madansky, and Narayana (1995), Oskamp (1995), and Schultz, Oskamp, and Mainieri (1995); Saphores, Nixon, Ogunseitan, and Shapiro (2006) discuss a number of articles published after 1990. We focus here on articles directly relevant to our study.

Mannetti, Pierro, and Livi (2004) provide a convenient starting point. They discuss two primary theoretical approaches associated with individual motivation to recycle. In the first approach, individuals are primarily utility-maximizers and their behavior can be modified through incentives. An alternate approach suggests instead that internal values, attitudes, and beliefs are the primary motivating factors. Many studies in the field of psychology adopt this second approach (see, e.g., Boldero, 1995, or Chu & Chiu, 2003), whereas the economics literature typically emphasizes external variables such as price or socioeconomic characteristics (see, e.g., Jenkins, Martinez, Palmer, & Podolsky, 2003). A few articles, however, have attempted to combine these two approaches for a holistic understanding of the variables that influence proenvironmental behavior including recycling (see, e.g., Clark, Kotchen, & Moore, 2003, and Guagnano, Stern, & Dietz, 1995). This is the approach we adopted.

A primary goal for our research is to quantify the trade-off individuals make between the cost and the convenience of recycling e-waste. Several articles on household recycling including Jenkins et al. (2003), Sterner and Bartelings (1999), and Jakus, Tiller, and Park (1996, 1997) emphasize the importance of convenience. As expected, recycling convenience often depends on the level of development of the recycling infrastructure.

To understand the role that EABs play in the trade-offs people make between the cost and the convenience of recycling e-waste, it is useful to review articles from the environmental psychology literature that analyze how EABs influence the purchase of environmentally friendly ("green") products. Laroche et al. (2001) offer a useful overview of the literature on WTP for "green" products. They find that environmental attitudes, knowledge, and values are often more important predictors of WTP than demographic and socioeconomic characteristics even though most studies, especially in economics, tend to focus on the latter. Loureiro and Hine (2004), Harris and Burress (2000), Krystallis and Chryssohoidis (2005), and Lockie, Lyons, Lawrence, and Grice (2004) all find that environmental attitudes and values are key predictors of individual preferences for "green" products.

Furthermore, the literature suggests that different proenvironmental actions such as recycling, purchasing "green" products, or taking public transit reflect an individual's "general conservation stance" (Thogersen & Olander, 2006). Thus, we expect a priori that EAB will play an important role in our analysis.

Although the importance of accounting for environmental values has been noted in empirical studies, a balanced model that incorporates demographic and socioeconomic characteristics as well as values and beliefs is likely to produce better results. This point is highlighted by Poortinga, Steg, and Vlek (2004), who study household energy use: Adding demographic data to attitudinal variables significantly improves the explanatory power of their model.

In economics, many studies rely on contingent valuation (CV) to estimate WTP for environmental goods, such as protecting an endangered species or improving air quality. With CV, survey respondents are asked to directly state their WTP for a change in environmental quality. This method has become very popular because of its relative simplicity. Some excellent references on CV include Carson, 1997; Carson, Flores, & Hanemann, 1998; and Hanemann, 1994, 1996.

However, because it is typically difficult for someone to state a reliable WTP in an unfamiliar context, CR has been proposed as an alternative. Instead of probing for a monetary amount associated with an environmental change, CR asks respondents to rank their preferences for different alternatives, which encourages them to explore their preferences. It requires, however, assuming the functional form of our respondents' utility function (i.e., the function used to represent their preferences).

Surprisingly, only a handful of CR studies have been published so far, even though CR avoids some of the potential problems associated with CV (see, e.g., Garrod & Willis, 1998; or Foster & Mourato, 2000; Lareau & Rae, 1989). The limited number of CR studies may be because of a lack of familiarity with this approach or to the need to rely on more sophisticated statistical techniques (Mitchell & Carson, 1989). In fact, Alwin and Krosnick (1985) also observe that advanced statistical techniques for analyzing ranked responses are seen as a barrier in the social-psychology literature.

CR was first proposed to estimate the demand for electric cars at a time when they were not available on the market (Beggs, Cardell, & Hausman, 1981). Since then, its applications to environmental issues include water quality (Bateman, Cole, Georgiou, & Hadley, 2006; Machado & Mourato, 2002; Smith & Desvouges, 1986), diesel odor exposure (Lareau & Rae, 1989), forest biodiversity (Garrod & Willis, 1997), the visual impact of power lines and pipelines along recreational canals (Garrod & Willis, 1998), or the recreational values of national parks (Isangkura, 1998). CR has also been used to estimate health and biodiversity affects associated with pesticide application (Foster & Mourato, 2000; Mourato, Ozdemiroglu, & Foster, 2000) and to value various curbside waste disposal options (Caplan, Grijalva, & Jakus, 2002). We found no published study on households' WTP for recycling e-waste.

Survey Data

In 2004, we conducted a mail survey of 3,000 randomly chosen California households, stratified by county to capture the state's diverse population. A pilot test of our survey on 30 prospective respondents helped us refine our survey instrument. All sample households received a survey package that included a cover letter detailing the purpose of the study and a postage-paid return envelope. Approximately 2 weeks later, all respondents were sent a reminder postcard. Finally, after another 2 weeks, a second complete survey package was sent to all nonresponding households with valid addresses. A total of 229 surveys were received from the first mailing; they were followed by an additional 128 surveys from the second mailing.

Our survey (available on request) consisted of four sections: (1) general questions about environmental attitudes, beliefs, and behaviors, as well as household recycling; (2) questions regarding e-waste recycling, knowledge of e-waste regulations, and quantity of e-waste stored at home; (3) standard demographic and socioeconomic questions; and (4) the CR exercise where respondents were asked to rank five hypothetical e-waste recycling alternatives. Many questions in our survey were adapted from similar surveys on recycling preferences (see, e.g., Caplan et al., 2002).

The overall response rate was 12.4% (357 returned answers out of 2,848 valid addresses), which is at the low end of similar general population mail surveys (Alreck & Settle, 1995);[2] this is disappointing but not unexpected. To explore the impact of environmental beliefs on e-waste recycling preferences, we asked a wide range of questions, 12 of which are summarized in factors PC1, PC2, and PC3 (see Table 1). As a result, our questionnaire was lengthy (12 pages), which may have been too demanding for many respondents. However, as two of these factors turned out to be statistically significant in our analyses, we feel partly vindicated.

Our contingency table analysis revealed that, in general, our respondents are older and more educated than the California population; they also have higher incomes, and they are less ethnically diverse. Therefore, care is warranted when generalizing our results to a more diverse population. Table 2 presents a summary of our respondents' characteristics compared to 2000 Census data. A more extensive discussion can be found in Saphores et al. (2006).

In our CR exercise, we first provided some background information on e-waste describing current California laws, the quantity of discarded e-waste, and information about the potential public health and environmental concerns associated with e-waste. We then asked respondents to rank five e-waste recycling options that differed based on cost and level of convenience. Each recycling alternative was described in detail, and a recycling cost

Table 1
Principal Components Analysis (PCA) of Environmental Attitudes and Behaviors

Survey Items and Principal Components	Scoring Coefficients	% Variance Explained v; Cronbach's alpha; KMO; Bartlett
PC1—money matters and the environment		$v = 40.08\%$
1. "Environmental protection should be a priority, even if it slows economic growth and causes some job losses."	.341	$\alpha = 0.811$ KMO = 0.763 Bartlett: $p < .001$
2. "I would agree to a tax increase if the extra money was used to prevent environmental damage."	.577	
3. "I would buy things at higher than usual prices to protect the environment."	.571	
4. "Do you think we're spending too much money, too little money, or about the right amount on environmental protection?"	.428	
PC2—environmental quality attitudes		$v = 15.44\%$
1. "The word environment is used to describe the world around us—land, sea, air, rivers, lakes, climate, and so on. Do you feel that the environment has become better or worse in the past 10 years?"	.393	$\alpha = 0.736$ KMO = 0.716 Bartlett: $p < .001$
2. Environmental quality in the United States (very good, good, fair, or poor)	.420	
3. Environmental quality in California (very good, good, fair, or poor)	.597	
4. Local environmental quality (very good, good, fair, or poor)	.484	
PC3—Environmental activism		$v = 9.93\%$
1. "During the last 12 months, have you attended a meeting or signed a letter or petition aimed at protecting the environment?"	.462	$\alpha = 0.742$ KMO = 0.681 Bartlett: $p < .001$
2. "During the last 12 months, have you contributed to an environmental organization?"	.597	
3. "During the past 12 months, have you participated in any local environmental activities such as Earth Day, Beach Clean-Up, and so on?"	.598	

Note: KMO = Kaiser-Meyer-Olkin. A higher value of PC1 indicates more support for the environment and a greater willingness to pay (WTP) more to protect the environment. A higher value of PC2 indicates less concern for the environment and a belief that environmental quality has improved recently. A higher value of PC3 indicates more involvement with environmental activities and organizations. Cronbach's alpha indicates how well a set of variables measures a single underlying construct; it is high when interitem correlations are high. KMO measures sampling adequacy and tests whether partial correlations between variables are small; it should be >.5 for a satisfactory factor model. Bartlett's test of sphericity checks whether the correlation matrix of the variables differs significantly from the identity matrix; if not, the factor model is inappropriate.

Table 2
Selected Demographic Characteristics of Respondents Versus 2000 Census

Characteristic	Respondents	2000 Census
Age	18-24: 2.2%; 50-64: 30.2% 25-34: 10.0%; ≥65: 20.9% 35-49: 36.8%;	18-24: 13.5%; 50-64: 18.7% 25-34: 21.4%; ≥65: 14.2% 35-49: 32.1%
Marital status	Married: 68.7%; Divorced: 13.5% Widowed: 6.3%; Never married: 10.3% Separated: 1.3%	Married: 53.6%; Divorced: 9.7% Widowed: 5.4%; Never married: 29.0% Separated: 2.2%
Ethnicity	White: 79.9%; Hispanic: 9.1% Black: 1.6%; Asian: 6.5% Other: 3.0%	White: 55.2%; Hispanic: 23.3% Black: 5.6%; Asian: 10.7% Other: 5.2%
Education	High school or less: 10.6% Some college: 37.2% Bachelor's degree: 29.4% Graduate or professional degree: 22.8%	High school or less: 38.3% Some college: 31.3% Bachelor's degree: 19.5% Graduate or professional degree: 10.9%
Household income	<$20K: 4.6%; $60K-$74K: 20.5% $20K-$39K: 15.9%; $75K-$99K: 10.9% $40K-$59K: 15.6%; >$99K: 32.5%	<$20K: 16.2%; $60K-$74K: 11.3% $20K-$39K: 21.2%; $75K-$99K: 12.8% $40K-$59K: 18.5%; >$99K: 20.0%
Home ownership	Own: 87.5%; Rent: 12.5%	Own: 59.2%; Rent: 40.8%
Type of dwelling	Single-family home: 83.5% Duplex: 6.9%; Mobile home: 2.8% Apartment: 6.5%; Other: 0.3%	Single-family home: 54.9% Duplex: 9.6%; Mobile home: 3.4% Apartment: 32.0%; Other: 0.1%
Household size	1: 17.1%; 2: 38.8%; 3: 16.5% 4: 18.0%; >4: 9.6%	1: 23.1%; 2: 30.8%; 3: 16.4% 4: 15.0%; >4: 14.7%
Number of children under 18 per household	0: 65.1%; 1 or more: 34.9%	0: 60.5%; 1 or more: 39.5%
Vehicle availability	99.1% of respondents have a vehicle available for their use.	92.2% of households have a vehicle available for their use.

Note: Census data is for the six California counties surveyed (Alameda, Contra Costa, Kern, Mono, Orange, and San Diego). Some values do not total 100% because of rounding.

schedule for various types of consumer electronics (TVs, computers, etc.) was provided. After the description of all five recycling options, respondents were instructed to rank them from most preferred to the least one; they were

Table 3
Contingent Ranking Scenarios

Option	Description
1. Pay as you throw	Consumers contact a manufacturer or an authorized collector directly and pay a fixed recycling fee. This was widely available at the time of the survey and is considered our status quo option.
2. Drop-off recycling at regional collection centers	An environmental handling charge (EHC) is collected on all new retail consumer electronic sales. Funds are used to finance recycling programs at regional centers.[a]
3. Curbside recycling	Monthly curbside pick-up of e-waste for a flat fee. All households pay regardless of use.
4. Drop-off recycling at retail locations	An EHC is collected on all new retail consumer electronic sales. Funds are used to finance recycling programs at retail stores.[b]
5. Deposit-refund Program at retail locations	Consumers pay a deposit when purchasing new electronics. On return to a retail location for recycling, consumers receive a refund. A small fee is subtracted from the deposit to finance this program.

a. Recycling centers would be located not more than 25 miles from residence.
b. For our CR calculations, we used the actual distance a respondent lived from the nearest electronics retailer such as Best Buy.

also reminded that there was no "correct" way to come up with a ranking. We limited our respondents' choices because typically people have difficulties ranking more than six alternatives or excessively complex scenarios (see, e.g., Smith & Desvouges, 1986, or Foster & Mourato, 2002). The five options are: (1) "Pay As You Throw"; (2) "Drop-Off Recycling at Regional Collection Centers"; (3) "Curbside Recycling"; (4) "Drop-Off Recycling at Retail Locations"; and (5) "Deposit-Refund Program at Retail Locations." Table 3 provides additional details of each option considered.

A common problem in CR studies is the presence of inconsistent rankings.[3] From our 357 respondents, 324 provided usable responses.[4] However, only 164 respondents provided consistent rankings resulting in a total of 145 respondents with both consistent rankings and complete responses to all of our socioeconomic, demographic, and environmental belief variables of interest.

The number of inconsistent rankings is clearly disappointing, but it is not unusual in CR studies: In their excellent study of trade-offs between pesticide use, bird deaths, and bread price, Foster and Mourato (2002) find that approximately half of their respondents did not provide fully consistent rankings, which is similar to our results. A thorough analysis reveals that many of the ranking inconsistencies in our study are because of Option 4,

Table 4
Descriptive Statistics for Key Variables

Variable	*M*	*SD*	Minimum	Maximum
Option-specific attributes				
Convenience of recycling option (in "equivalent miles"[a])	10.73	17.78	0	93
Cost of recycling option (in dollars)	1.99	0.94	0.29	3
Individual characteristics				
PC1[b] "Money and the Environment"	0.60	0.22	0	1
PC2[b] "Environmental Quality Attitudes"	0.51	0.22	0	1
Age between 18 and 35 years (*yes* = 1)	0.11	0.31	0	1
Age > 65 years (*yes* = 1)	0.21	0.41	0	1
Ethnicity (*White* = 1)	0.81	0.40	0	1
Role of business in protecting the environment (*major* = 1)	0.78	0.41	0	1
Role of individuals in protecting the environment (*major* = 1)	0.72	0.45	0	1
Gender (*female* = 1)	0.35	0.48	0	1

a. "equivalent miles" refers to an estimate of convenience based on the distance a respondent lives from the relevant recycling option (e.g., nearest electronics retailer). For the "Pay As You Throw" and "Deposit-Refund Program at Retail Locations" options, five additional miles are added to the distance calculation to account for the added inconvenience of contacting the manufacturer for e-waste recycling information and packaging the item for mailing, in addition to wait times at their local post office (for the former option) or electronics retailer (to obtain their refund for the latter option).
b. PC1 and PC2 are both treated as continuous indexes. They are normalized to be between 0 and 1. All other independent variables are binary (0 or 1) indicator variables. These are based on the 145 observations used to estimate our best model.

"Drop-Off Recycling at Retail Locations." We conjecture that many respondents picked this option ahead of other seemingly more convenient ones because they did not plan to make a special trip to an electronics retailer to return obsolete electronics. This highlights the difficulty of designing CR studies with realistic options (which is desirable for exploring policy options), as opposed to more abstract alternatives as in, for example, Lareau and Rae (1989) or Foster and Mourato (2002).

Although our sample of 145 complete and consistent rankings is not large, we want to emphasize that it is comparable with published CR studies, for which the number of valid responses ranges from 115 for Slothuus, Larsen, and Junker (2002) to 932 for Garrod and Willis (1998). Fortunately, a comparison of our consistent sample with all our respondents shows that they have very similar socioeconomic characteristics.

Our models to estimate WTP for e-waste recycling rely on 10 key variables including cost and convenience of recycling, factors reflecting EABs, demographic characteristics, and attitudes about the role of businesses and individuals in protecting the environment. Basic statistics for these variables are presented in Table 4. Additional variables considered, but not statistically significant in our best model, include education, income, quantity of e-waste stored in the household, stated willingness to recycle at drop-off facilities as a proxy for willingness to recycle e-waste, and a third factor reflecting environmental activism.

Modeling Preferences for E-Waste Recycling

Principal Components Analysis (PCA) Methodology and Results

To condense 11 survey questions on EABs, we performed a PCA with varimax rotation to facilitate the interpretation of the resulting factors (Kline, 1994). To assess the adequacy of these factors, we first checked for appropriate intercorrelation between our variables using Bartlett's test for sphericity. Intercorrelations need to be high enough to limit the number of factors but not too high to avoid multicollinearity; we relied on the Kaiser-Meyer-Olkin (KMO) statistic to detect this problem. For PCA to work well, the Bartlett's test should reject the hypothesis that the correlation matrix is the identity matrix, and the KMO should be greater than 0.6 (KMO ranges between 0 and 1). We also used Cronbach's alpha to measure the reliability of our factors; Cronbach's alpha generally increases with the correlations between the underlying questions. Its maximum value is 1 and a value of at least 0.6 is desirable. We also normalized our factors to be between 0 and 1.

We developed three factors, normalized between 0 and 1, to reflect respondents' attitudes and beliefs about the environment (see Table 1). Overall, our three factors account for 65.45% of the variance between the individual variables. These factors reflect a wide array of environmental attitudes, ranging from the manner in which individuals prioritize environmental protection and economic growth to the respondent's level of environmental activism. Our first factor (PC1) reflects support for the environment and WTP higher prices and taxes to protect the environment. Another four questions were designed to elicit individual attitudes about environmental quality; they are summarized by the second factor (PC2). The third factor (PC3) synthesizes information on participation in environmental activities and organizations collected in three survey questions. Questions underlying each factor are detailed in Table 1.

CR Methodology

The basis for modeling preferences using CR is an extension of McFadden's (1974) random utility model developed by Beggs et al. (1981) to take advantage of complete preference rankings. The random utility model assumes that individuals select the alternative that maximizes their utility subject to a budget constraint, but it generalizes the standard microeconomics framework by assuming that utility is not fully known. Instead, the utility U_{ij} of individual i when she selects alternative j is expressed as the sum of a deterministic term V_{ij}, which is observable, and a random term ε_{ij} that captures all nonmeasured factors. In that context, individual i will select alternative k in a set of J alternatives if $U_{ik} = V_{ik} + \varepsilon_{ik} > U_{ij} = V_{ij} + \varepsilon_{ij}$ for all $j \in \{1, \ldots, J\}$ such that $j \neq k$. For this study, we further assume that $V_{ij} \equiv V(q_{ij}, c_{ij}, s_i)$ where q_{ij} is the convenience associated with recycling option j; c_{ij} is the corresponding recycling cost; and s_i is a vector of socioeconomic and demographic characteristics, as well as information about environmental attitudes and behavior.

Following Caplan et al. (2002), Garrod and Willis (1997), and Lareau and Rae (1989), we assume that V_{ij}, the observable component of utility of individual $i = 1, \ldots, I$ when she chooses recycling alternative $j = 1, \ldots, J$, is a linear function of unknown parameters. We write it as follows:

$$V_{ij} \equiv V(q_{ij}, c_{ij}, s_i) \equiv \beta_0 q_{ij} + \gamma_0 c_{ij} + q_{ij} \sum_{m=1}^{M} \beta_m s_{im} + c_{ij} \sum_{n=1}^{N} \gamma_n s_{in}, \tag{1}$$

where q_{ij} are c_{ij} are again the convenience and the cost of recycling option j, respectively; s_{im} and s_{in} are either socioeconomic and demographic characteristics, or information about environmental attitudes and behavior; and ε_{ij} is an error term. The two summation terms above represent, respectively, interaction terms between respondent i's characteristics (s_{im} or s_{in}) and the convenience q_{ij} of recycling option j, or its associated costs, c_{ij}. Finally, the coefficients β_j ($j = 0, \ldots, M$) and γ_k ($k = 0, \ldots, N$) are unknown parameters that need to be estimated from the data.

To obtain an explicit expression of the probability of a preference ordering, the error terms (the ε_{ij}s) are assumed to have independent and identically distributed (i.i.d.) extreme value (Weibull) distributions (for details, see Caplan et al., 2002, or Beggs et al., 1981). The method of maximum likelihood can then be used to find the coefficients β_j ($j = 0, \ldots, M$) and γ_k ($k = 0, \ldots, N$) that maximize the probability of observing the survey rankings.

In our analysis, WTP is the "payment" that makes an individual indifferent between two recycling options. For simplicity, suppose that the convenience of individual i's e-waste recycling alternatives increases with their numbering so that $q_{i1} < q_{i2} < \ldots < q_{iJ}$ and that her costs are ranked so that

$c_{i1} < c_{i2} < \ldots < c_{iJ}$; if costs were ranked differently, for example if $c_{i1} > c_{i2}$, then alternative 2 would dominate alternative 1 (it would be cheaper and more convenient), so alternative 1 would not need to be considered further. In that context, individual i's WTP for option j is the amount denoted by wtp_{ij} that equalizes her utility, that is, $V(q_{ij}, wtp_{ij}, s_i) + \varepsilon_{ij} = V(q_{i1}, c_{i1}, s_i) + \varepsilon_{i1}$ (see Caplan et al., 2002). Combining this definition with the expression of $V(q_{ij}, c_{ij}, s_i)$ given in Equation (1) leads to the expected marginal rate of substitution between cost and convenience (i.e., the expected change in WTP for a change in e-waste recycling convenience):

$$E\left(\frac{dwtp_{ij}}{dq_{ij}}\right) = -\frac{\beta_o + \Sigma_m \beta_m s_{im}}{\gamma_o + \Sigma_n \gamma_n s_{in}}. \qquad (2)$$

For this approach to be valid, however, the independence of irrelevant alternatives (IIA) criterion needs to hold. The IIA states that the probability of any one alternative being chosen over the other is not affected by any other alternatives (Smith & Desvouges, 1986). If there are close substitutes in the choice set, failure of this assumption can lead to inconsistent estimates of the coefficients.

To test the IIA assumption, we calculate the Hausman-McFadden (HM) test and the Small-Hsiao (SH) test, which are two of the most common IIA tests (Long & Freese, 2006). The HM test has poor size properties, whereas the SH test works reasonably well on smaller samples (Cheng & Long, 2007). As noted by McFadden (1974), problems can arise unless respondents view the alternatives considered as independent of one another. To clearly differentiate our alternatives, respondents were provided with detailed descriptions of each recycling option.

Results

Recycling Preferences

Table 5 summarizes our respondents' preferences for different recycling options. Among our sample with consistent rankings and complete demographic data, we find that Option 2 ("Drop-Off Recycling at Regional Collection Centers") was ranked first or second by nearly two thirds of our respondents (64%). In addition, this option was least likely to be ranked last (only 2%). Option 3 ("Curbside Recycling") was the second most popular option (34%). Very few people (only 6%) ranked Option 4 ("Drop-Off Recycling at Retail Locations") first, but the least preferred option was

Table 5
Summary of Rankings of Recycling Alternatives (Consistent Rankings Only)

Recycling Alternative	First Choice (%)	Second Choice (%)	Third Choice (%)	Fourth Choice (%)	Fifth Choice (%)
Option 1: Pay as you throw	15.0	20.0	15.7	17.9	31.4
Option 2: Drop-off at regional recycling centers	33.6	30.1	19.6	14.7	2.1
Option 3: Curbside recycling	29.1	19.1	19.9	15.6	16.3
Option 4: Drop-off at retail locations	6.4	30.0	25.0	30.7	7.9
Option 5: Deposit-refund program at retail locations	26.1	21.8	10.6	13.4	25.2

Notes: Totals may not sum to 100 because of rounding.

Option 1 ("Pay As You Throw"), which was ranked last by 31% of respondents. Interestingly, almost the same number of respondents ranked Option 5 ("Deposit-Refund Program at Retail Locations") first and last (26% and 25%, respectively), so preferences for this alternative are highly polarized.

CR

We used Stata (StataCorp LP, College Station, TX) to estimate our rank-ordered logit model. Table 6 presents results for four of the specifications we analyzed. Model A includes only option-specific variables (convenience and cost of recycling) with no interactions. The coefficient for the convenience variable is statistically significant at 5% (but not the coefficient for cost) and the signs of both estimated coefficients match a priori expectations: our respondents negatively value increases in the equivalent distance to recycling facilities and in recycling costs.

In Model B, we estimate a rank-ordered logit model with interactions between the option-specific variables (cost and convenience) and our respondents' characteristics (demographic, socioeconomic, as well as EABs). These characteristics were selected after our literature review as variables that are likely to influence proenvironmental behavior.

Our preferred specification is Model C. Several published CR studies retain all variables regardless of statistical significance to calculate WTP levels (see, e.g., Caplan et al., 2002, or Lareau & Rae, 1989, among others). Our findings indicate that including statistically insignificant variables in

Table 6
Estimation Results for Different Models

	Specification			
Variable	Model A	Model B	Model C	Model D
Option-specific attributes				
Convenience of recycling option (in "equivalent miles"[a])	–0.0075**	–0.1461***	β_0 = –0.1126***	–0.0764***
	[0.003]	[0.046]	[0.026]	[0.023]
Cost of recycling option	–0.0404	–0.6236	γ_0 = –0.5183***	–0.1986***
	[0.049]	[0.393]	[0.173]	[0.105]
Interactions between option-specific attributes and individual characteristics				
Convenience * PC1 "Money and the Environment"		0.0531***	β_1 = 0.0536***	
		[0.019]	[0.012]	
Convenience * PC2 "Environmental Quality Attitudes"		0.0144	β_2 = 0.0391***	
		[0.027]	[0.012]	
Convenience * PC3 "Environmental Activism"		–0.0238		
		[0.015]		
Convenience * Gender (*female* = 1)		0.0025		
		[0.010]		
Convenience * age 18-35 years (*yes* = 1)		–0.1056**	β_3 = –0.1076*	–0.1190**
		[0.054]	[0.057]	[0.057]
Convenience * age >65 years (*yes* = 1)		–0.0061	β_4 = –0.0157**	
		[0.009]	[0.007]	
Convenience * White (*yes* = 1)		0.0975**	β_5 = 0.0776***	0.0551***
		[0.044]	[0.024]	[0.021]
Convenience * Hispanic (*yes* = 1)		–0.0122		
		[0.064]		
Convenience * college education (*yes* = 1)		0.0132**		0.0127*
		[0.006]		[0.008]
Convenience * income <$40K (*yes* = 1)		0.0059		0.0171**
		[0.009]		[0.008]
Convenience * income >$80K (*yes* = 1)		–0.0026		
		[0.008]		

(continued)

Table 6 (continued)

Variable	Specification Model A	Model B	Model C	Model D
Convenience * role of individual in protecting the environment (*major* = 1)		–0.0011		–0.0154
		[0.021]		[0.010]
Convenience * role of business in environment (*major* = 1)		–0.0164	β_6 = –0.0251***	
		[0.021]	[0.008]	
Convenience * role of government in protecting the environment (*major* = 1)		0.0252		0.0221*
		[0.016]		[0.012]
Convenience * knowledge of toxics in e-waste		0.0037		
		[0.008]		
Convenience * knowledge of CA's cathode ray tub e law (*yes* = 1)		0.0082		
		[0.007]		
Cost * PC1 "Money and the Environment"		–0.2853		
		[0.370]		
Cost * PC2 "Environmental Quality Attitudes"		0.5296	γ_2 = 0.5332**	
		[0.334]		[0.251]
Cost * PC3 "Environmental Activism"		–0.1812		
		[0.235]		
Cost * gender (*female* = 1)		0.3729**	γ_1 = 0.2653**	0.2349**
		[0.144]	[0.109]	[0.117]
Cost * age 18-35 years (*yes* = 1)		–0.4603**	γ_3 = –0.4918**	–0.4018*
		[0.216]	[0.219]	[0.232]
Cost * Age >65 years (*yes* = 1)		0.0541		
		[0.159]		
Cost * White (*yes* = 1)		0.0655		
		[0.233]		
Cost * Hispanic (*yes* = 1)		–0.1434		
		[0.291]		
Cost * college education (*yes* = 1)		0.1191		
		[0.136]		
Cost * income <$40K (*yes* = 1)		–0.0321		
		[0.181]		
Cost * income >$80K (yes = 1)		–0.1025		
		[0.146]		

(continued)

Table 6 (continued)

	Specification			
Variable	Model A	Model B	Model C	Model D
Cost * role of individual in protecting (*major* = 1)		0.2423 [0.171]	$\gamma_4 = 0.1418$ [0.113]	
Cost * role of business in protecting the environment (*major* = 1)		–0.2911* [0.174]		
Cost * role of government in protecting the environment (*major* = 1)		0.2059 [0.171]		
Cost * knowledge of toxics in e-waste		0.1529 [0.158]		0.1573 [0.113]
Cost * knowledge of CA's cathode ray tube law (*yes* = 1)		0.1361 [0.139]		
Unrestricted log likelihood	–765.675	–614.226	–679.68	–689.26
Restricted log likelihood	–763.004	–579.721	–652.06	–666.05
Pseudo R^{2b}	0.004	0.056	0.041	0.034
Wald chi-square	5.06 $df = 2$ $p = .0795$	110.19 $df = 34$ $p < .0001$	50.05 $df = 12$ $p < .0001$	33.63 $df = 11$ $p = .0004$
Marginal rate of substitution (MRS)[c]	$0.185/ eq. mile	$0.095/ eq. mile	$0.131/ eq. mile	$0.171/ eq. mile
Standard error of MRS	NA	$0.03/eq. mile	$0.04/eq. mile	$0.04/eq. mile
Number of observations	820	650	725	735
Number of groups	164	130	145	147

Note: *, **, *** identify coefficients significant at the 10%, 5%, and 1% levels, respectively.
Robust standard errors are shown in brackets.

a. "Equivalent miles" measure recycling convenience based on the distance between a respondent's home and the recycling option considered (e.g., nearest electronics retailer). For "Pay As You Throw" and "Deposit-Refund Program at Retail Locations" options, five equivalent miles were added to physical distances to account for the added inconvenience of getting e-waste recycling information and packaging the item for mailing, in addition to wait times at their local post office (for the former) or electronics retailer (to obtain a refund for the latter). Doubling these five equivalent miles did not significantly change our results.

b. Pseudo R^2 is an alternate goodness-of-fit measure for probabilistic choice models (McFadden, 1974). It is calculated as 1—(restricted log likelihood/unrestricted log likelihood).

c. For MRS calculations, 3, 5, and 4 outliers, respectively, were excluded for Models B, C, and D, respectively. They correspond to very large (in absolute value) and unrealistic MRS values, which were more than 3 standard errors away from the estimated MRS.

WTP calculations inflates estimated standard errors (see below). In Model D, we examine the impact of excluding factors summarizing EABs; we discuss it in more detail below.

A key underlying assumption of CR is the IIA. Surprisingly, only a handful of published CR studies report testing this assumption (exceptions include Foster & Mourato, 2000; Lareau & Rae, 1989; and Caplan et al., 2002). For both the HM and the SH tests, we fail to reject the null hypothesis that underlies the IIA (at 10%), so our rank-ordered logit models do not seem to be misspecified.

To calculate WTP for increased e-waste recycling convenience (i.e., the marginal rate of substitution between e-waste recycling cost and convenience), we insert estimated rank-ordered logit coefficients (see Table 6) into Equation (2) to generate results for each of the four models. For our best model (Model C), we find that respondents are willing to pay \$0.13 per month per equivalent mile to increase recycling convenience.

To illustrate this result, recall that "Curbside Recycling" and "Drop-Off at Regional Centers" are two of the most preferred recycling alternatives. The latter has a lower recycling cost, but curbside recycling is likely to be more convenient. On average, our respondents live 8.2 miles from the nearest regional recycling facility. Based on this information, our results suggest that our respondents would be willing to pay approximately \$13 annually for curbside e-waste recycling as opposed to drop-off at a regional center (8.2 miles × \$0.13 per month × 12).

This compares to \$0.19 per equivalent mile for the naïve model with only cost and convenience (Model A), and \$0.10 per equivalent mile for Model B, where our WTP calculations include many nonsignificant variables. The discrepancy between Models A and C (our "best" model) may be explained by omitted variable bias, because a number of variables missing from Model A are correlated with cost and convenience through interaction terms. This is clearly not a problem with Model B: A cursory look at Table 6 shows that Model C parameter estimates are within two standard errors of their Model B values.

To examine how EABs influence WTP, we compare our preferred model (Table 6, Model C) to a model that excludes environmental factors (Table 6, Model D). Although there are strong similarities between these two models, there are also some interesting differences worth exploring.

First, the WTP for these two models is noticeably different: It is \$0.17 for Model D (no factors) compared to \$0.13 for Model C. This suggests that EABs play an important role, and excluding this information can lead to overestimates of WTP. This means, as expected, that people with proenvironmental attitudes need a smaller decrease in recycling cost to compensate for increased recycling inconvenience.

Another difference is the statistical significance of education when EABs are not included. As expected, all else equal, college-educated individuals accept higher levels of recycling inconvenience for a unit recycling cost increase. Previous research suggests that more education is related to increased proenvironmental behaviors such as recycling (Owens, Dickerson, & Macintosh, 2000; Vining & Ebreo, 1990).

Interestingly, Model D results suggest that lower income households (those earning less than $40,000 per year) require less compensation on recycling cost for increased recycling inconvenience. One possible explanation for this result comes from contingency table analyses (not shown): We find that lower income households are more likely to rate their local environmental quality as poor or fair, so their WTP for e-waste recycling may reflect a desire to prevent additional degradation of their local environment.

Finally, we conducted detailed analyses of the impact of socioeconomic and demographic characteristics on WTP, but it is omitted here to save space.

Policy Considerations and Conclusions

End-of-life management of used electronics is a growing concern, particularly for municipal governments with limited budgets. The number of recyclers and recycling programs has increased substantially in the past few years, yet there is still much room for improvement (IAER, 2006). Our study sheds light not only on the amount of money consumers are willing to pay to increase recycling convenience, which we estimate to be approximately $0.13 per month per equivalent mile annually, but also on their preferences for different types of e-waste recycling program. Nearly two thirds of respondents ranked “Drop-Off at Regional Centers” first or second, and only 2% ranked this alternative last. The status quo alternative, “Pay As You Throw,” was least preferred: It was ranked last by nearly one third of our sample.

Our article also contributes to the literature by showing that people’s environmental beliefs are statistically significant and play a role in their WTP for recycling convenience. In fact, excluding this information can lead to biased estimates of the trade-offs people are making between cost and convenience for recycling e-waste. This is important information for municipalities seeking to implement an e-waste recycling program.

More generally, the main tool we rely on for estimating trade-offs between cost and convenience, CR, should be of interest to environmental psychology researchers concerned with analyzing discrete choices. Statistical sophistication should not be an obstacle because a wide range of discrete choice models are now available in popular statistical software such as Stata or Limdep. One downside, however, of estimating a CR model with extensive socioeconomic, demographic, and behavioral variables is the need for extensive information, which may be challenging to collect. A mail survey is likely not the best vehicle for that purpose as illustrated by our response rate (we were limited by a small budget).

For policy makers, it appears that developing e-waste recycling programs using regional collection centers may be the best alternative. Indeed, drop-off recycling programs tend to be less expensive than curbside recycling (respondents' second most preferred alternative). In our CR survey scenarios, financing for the "Drop-Off Recycling at Regional Collection Centers" option would be provided through an environmental handling charge imposed on new retail sales of consumer electronics. This would reduce the burden on municipalities, and it would decrease the likelihood of illegal dumping compared to end-of-life fees.

It may also be desirable to organize occasional curbside e-waste pickups, given the popularity of these programs. Such events could be implemented in higher density communities with a relatively high number of residents aged more than 65 years or between the ages of 18 and 35 years because people in these age groups seem to be willing to pay higher prices for increased convenience.

Finally, because our results are based on a small sample that imperfectly reflects characteristics of California's population, additional research is needed to confirm our findings.

Notes

1. See the Basel Action Network at http://www.ban.org/.

2. Unfortunately, most environmental CR studies referenced herein do not report a response rate.

3. Inconsistent rankings occur when a respondent prefers an alternative with a higher recycling cost to a lower cost alternative even when the inconvenience (based on driving distance to the recycling alternative) is greater. For example, a respondent who lives 5 miles from the nearest regional recycling center and 10 miles from the nearest electronics retailer but prefers "Drop-Off at Retail Locations" to "Drop-Off at Regional Collection Centers" would generate in an inconsistent ranking because the recycling cost at the retail location is higher than at the regional center.

4. Four respondents provided no information regarding distance to nearest recycling center and 29 did not complete the CR exercise.

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