Title
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Journal
Environment and Behavior, 38(2)

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Publication Date
2006

Peer reviewed

HOUSEHOLD WILLINGNESS TO RECYCLE ELECTRONIC WASTE
An Application to California

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Abstract

Electronic waste (e-waste) has become the main contributor of lead (Pb) to landfills in the U.S. (EPA 2000). Households also store large volumes of e-waste, yet little is known about their willingness to recycle e-waste. This paper starts filling this gap based on a 2004 mail survey of California households. Using multivariate models, we find that gender, education, convenience, and environmental beliefs, but not income or political affiliation, are key factors explaining the willingness to drop-off e-waste at recycling centers. A comparison of an ordered probit with a semi-nonparametric extended ordered probit model of the survey responses shows that the latter better predicts less frequent answers. Our results suggest targeting public education programs about recycling at teenagers or younger adults, and making recycling more convenient for older adults; moreover, e-waste drop-off centers should first be created in communities that already offer curbside collection programs for conventional recyclable products.

Keywords: recycling behavior; electronic waste; principal components analysis; semi-nonparametric extended ordered probit.

The growing stockpile of used and obsolete consumer electronic devices (CEDs) has been called the "largest toxic waste problem of the 21st century" (Schmidt, 2002, p. A188). Two trends compound this problem. First, more consumers around the globe are using an increasing number of CEDs. Second, with technological advances, the average life span of the typical CED has dropped significantly in the past several years. For example, since 1995, the useful life of a cellular phone in the U.S. has decreased by 50% (it is currently approximately 18 months), while the number of subscribers has increased from 33.8 million to 140.8 million (Fishbein, 2002; Most, 2003). As a result, e-waste is one of the fastest growing components of the municipal waste stream: according to the EPA (2002), at least 2 million tons of consumer e-waste is generated annually in the U.S., and approximately 90% is discarded.

Anecdotal reports suggest that a large percentage of discarded e-waste is exported to Asia, where processing is very cheap; unfortunately e-waste is often handled improperly there, which results in severe human exposure and environmental pollution (Basel Action Network & Silicon Valley Toxics Coalition, 2002). Indeed, e-waste contains many toxic materials such as lead (Pb), cadmium (Cd), mercury (Hg), barium (Ba), beryllium (Be), hexavalent chromium, and brominated flame-retardants.

When it is not exported, discarded e-waste is often landfilled. It has become the largest contributor of Pb to the solid waste stream in the U.S. since the creation of battery recycling programs (U.S. EPA, 2000). In addition, large volumes of e-waste are stored. In California alone, for example, an estimated 6 million obsolete computers and televisions are stockpiled in homes ("Electronic Waste Recycling Act of 2003 (SB 20)," 2003).

To address this problem, the California Electronic Waste Recycling Act of 2003 (SB 20) authorizes the collection of e-waste recycling fees at the point of sale and mandates a reduction in the use of hazardous substances in electronic products sold in California in accordance with regulations recently passed in Europe (see Schoenung et al., 2004). In addition, California recently classified cathode ray tubes (CRTs) as Universal Waste so they can no longer be landfilled. A recent study of e-waste diversion in California indicates, however, that the current recycling infrastructure is inadequate to handle the projected increase in volume of materials between now and 2006 (CIWMB, 2001).

In order to implement effective policies to tackle the increasing stockpile of e-waste and to upgrade the existing recycling infrastructure, an understanding of households' willingness to recycle e-waste is necessary. Although the household recycling literature is extensive, there does not appear to be any study in the behavioral analysis literature that focuses on e-waste.

In this context, this paper makes two contributions. First, it analyzes the behavioral determinants of households for recycling e-waste at drop-off locations using data we gathered during a mail survey of 3,000 randomly selected California residents. Drop-off facilities are typically less expensive to operate than curbside collection programs and they are faster to implement than take-back or other programs involving manufacturers. Second, our paper contributes methodologically to the recycling literature by combining principal components analysis (PCA) with a semi-nonparametric extension of the ordered probit model (Stewart, 2004) to better understand the willingness of California households to recycle e-waste at drop-off centers and to reveal opportunities for enhancing recycling behavior.

Our approach offers two advantages: first, it provides more flexibility than standard models based either on bivariate correlation or on logistic regression, by allowing for more than two alternatives. Second, our approach relaxes the distributional assumptions behind the logit and probit models. It is well known that if these assumptions fail, then estimated parameters of qualitative response models are inconsistent and hypothesis testing is invalid (Greene, 2003). In spite of recent papers by Glewwe (1997) and Weiss (1997), such tests are not reported in recent recycling papers that rely on logit or probit models.

We find that important predictors of the willingness to recycle e-waste include age, gender, a college education, the availability of curbside collection programs for conventional recyclables, the distance to the nearest drop-off recycling centers for e-waste, living in a rural community, and three environmental factors generated by principal components analysis. These factors summarize willingness to pay for various environmental issues, beliefs regarding the state of the environment, and environmental activism. Contrary to what contingency table analyses may suggest, however, willingness to recycle is best explained by variables other than political affiliation, and education is an important predictor.

Our findings suggest that: 1) public education recycling programs should target teenagers or younger adults; 2) recycling should be made more convenient for older adults; 3) proximity to recycling centers is important; and 4) if public funds are limited, recycling centers should first be established in communities that offer curbside collection of conventional household recyclables.

This paper is organized as follows. In the next section, we briefly review some of the main findings of the relevant recycling literature. We then present an overview of our survey results, before summarizing our modeling and testing of Californians' willingness to drop-off e-waste at recycling centers. After discussing our results, we present our conclusions and suggestions for future research.

Literature Review

Several theoretical orientations can be identified in the applied behavioral analysis literature dealing with recycling (Mannetti, Pierro, & Livi, 2004). One strand of the literature is grounded in the belief that people are primarily utility maximizers motivated by costs and benefits (see Porter, Leeming, & Dwyer, 1995). Alternatively, many authors adopt an "attitude approach" that tries to account for beliefs and attitudes in explaining behavior. This has led to different models, including Schwartz's altruism model (1970), the theory of reasoned actions, and the theory of planned behavior (see Mannetti, Pierro, & Livi, 2004 for references). More generally, a large strand of the literature focuses on the impact of general environmental attitudes (e.g., Schultz & Oskamp, 1996), specific attitudes towards recycling (e.g., Ebreo, Hershey, & Vining, 1999), or demographic variables (e.g., Berger, 1997).

Our purpose here is to summarize key findings of the behavioral literature on household recyclables (glass, metals, paper, and plastics) to justify our modeling approach and to place our results in context. A cursory review of this literature suggests that recycling behavior depends on a variety of factors (Barr, Gilg, & Ford, 2001). Because of the size of this body of literature, we focus on papers published after 1993. Surveys by Hornik et al. (1995), Oskamp (1995), as well as Schultz, Oskamp, and Mainieri (1995) summarize important contributions of earlier papers.

Many studies in the social-psychology literature focus on the link between pro-environmental beliefs and behavior. Evidence is mixed and attitudes may have shifted over time. Schultz, Oskamp, and

Mainieri (1995) report that studies conducted prior to the 1980s consistently find statistically significant relationships between beliefs and behavior, but not studies from the early 1990s. They hypothesize that motivations underlying recycling have become more complex with the growing popularity of recycling programs (see also Bamberg 2003). However, Oskamp et al. (1998) and Guerin, Crete, and Mercier (2001) find small but significant statistical relationships between environmental concerns and recycling.

Several researchers also investigate the impact on behavior or intentions of specific attitudes towards recycling; in general, they conclude that these matter. Recent contributors to this line of research include Guagnano, Stern, and Dietz (1995), Oskamp (1995), Taylor and Todd (1995), Corral-Verdugo (1997), Werner and Makela (1998), Cheung, Chan and Wong (1999), and McCarty and Shrum (2001).

Economic arguments suggest that convenience, and more generally costs, may significantly impact recycling behavior (Jenkins et al., 2003). This includes the proximity of recycling containers (Ludwig, Gray, & Rowell, 1998; Margai, 1997), available storage space and the difficulty of recycling some materials (Sterner & Bartelings 1999), and providing curbside collection. Residential density is thus a key factor for the viability of recycling programs, as it is often impractical for low-density communities to provide curbside recycling. For rural households, Jakus, Tiller, and Park (1997) highlight the importance of perceived time commitment in recycling participation.

Many studies also explore links between demographic, socioeconomic characteristics, and recycling, with mixed results. The most commonly examined variables are age, education, gender, and income, but dwelling type, ethnicity, family size, and political beliefs have also been considered.

Schultz, Oskamp, and Mainieri (1995) report that women appear more likely to recycle, but Gamba and Oskamp (1994) and Werner and Makela (1998) detect no relationship between gender and recycling. Some authors find a positive association between income and recycling (Gamba & Oskamp, 1994; Oskamp, 1995), but others disagree (Scott, 1999). Likewise, the effect of education is ambiguous: some suggest that more education contributes to recycling (Owens, Dickerson, & Macintosh, 2000), but not others (Corral-Verdugo, 1997; Gamba & Oskamp, 1994; Werner & Makela, 1998). The same conclusion holds for age: some studies conclude that age is significant (Gamba & Oskamp, 1994; Margai, 1997; Scott, 1999), but not others (Corral-Verdugo, 1997; Werner & Makela, 1998).

Schultz and Stone (1994) suggest that political ideology is an important indicator of environmental concern, but this relationship has not been widely studied. The relationship between household size and recycling behavior is not well examined either. Scott (1999) does not detect such a relationship, but McQuaid and Murdoch (1996) find some weak evidence that household size is positively associated with recycling behavior in lower income, multi-family dwellings. Some research also suggests a positive association between residence type (single family vs. multi-family) and recycling. Finally, the link between ethnicity and recycling has not been widely examined, although Johnson, Bowker, and Cordell (2004) conclude that Blacks and foreign-born Latinos are less likely to recycle than Whites.

The mixed evidence presented above suggests that we should consider general attitudes towards the environment, environmental activism, convenience, as well as a broad array of socio-economic variables in trying to assess what factors influence the willingness to recycle e-waste. In addition to evolving attitudes towards recycling, multivariate models may help explain some of the apparent discrepancies highlighted by this overview of the literature.

Survey and Results

Survey instrument and administration

Data for this research was collected using a mail survey of 3,000 California households stratified by county, conducted between January and April 2004. To capture the diversity of the California population, we randomly selected three counties in Northern California (two urban counties: Alameda and Contra Costa; one rural: Mono) and three counties in Southern California (two urban counties: Orange and San Diego; one rural: Kern). We then asked Fox's Data Services (Oakland, California) to randomly select 500 household addresses in each county from their most recent (end of 2003) database.

Conducting a survey via mail offers a number of advantages (Fowler Jr., 1988). Mail surveys enable the researcher to access a more dispersed sample, at a lower cost, than other survey methods. They also allow presenting more detailed questions and scenarios with visual aids, which is impossible during a telephone interview. Moreover, interviewer bias is eliminated. Finally, mail surveys give respondents more time to come up with thoughtful answers.

However, mail surveys also suffer from several disadvantages. Careful questionnaire design is essential to convey information in a clear and easily understood manner. To that end, our questionnaire was pre-tested on a small sample of potential respondents. Mail surveys also tend to have a lower response rate that could indicate a non-response bias. Low response rates are not uncommon with mail surveys although persistent follow-up can boost response rates (Alreck & Settle, 1995; Fowler Jr., 1988). Additionally, answering a mail survey requires relatively strong literacy skills.

Our survey package included a letter of explanation, a questionnaire with a stamped return envelope, and a card for requesting a summary of our survey results. Two weeks after mailing the survey package, we sent a reminder card to our entire sample; it was followed by another complete survey package to non-respondents shortly thereafter.

Our survey questionnaire has four main sections. The first one collects information about general environmental attitudes and behaviors. Its purpose is to gauge how respondents feel toward the environment and how likely they are to engage in pro-environmental behavior. The last question in this section asks respondents how willing they would be to drop-off e-waste at a recycling center.

The second section assesses the respondents' knowledge of e-waste and asks them to tabulate eight different categories of obsolete electronic items. We use this information elsewhere to extrapolate how much e-waste is stored by California households as there is still little reliable data on stored e-waste.

The last two sections gather demographic and socioeconomic data and ask about preferred e-waste recycling options for a contingent ranking exercise. The socioeconomic data are necessary for modeling purposes and for comparing characteristics of our respondents with data from the 2000 Census.

Overview of Survey Results

From our original sample of 3,000 households, 132 addresses were invalid. We received a total of 357 valid responses, which represents a 12.4% response rate; this is comparable with response rates for general population mail surveys (Alreck & Settle, 1995). Only 265 of the respondents, however, provided information for all the socio-economic variables of interest.

< Insert Table 1 approximately here>

Selected respondent characteristics are presented in Table 1 and compared to data from the 2000 Census for the six counties surveyed using contingency table analyses (details not shown). Among our respondents, we have noticeably fewer young adults (less than 35) and more mature ones (age 65+) than expected, so people who were never married are under-represented. Likewise, Asians, Blacks and Hispanics are under-represented. Our respondents are also more likely to have at least some college education, so their income distribution is shifted towards higher income categories compared to census data. Consequently, they are more likely to live in single-family homes, to be homeowners (rather than renters), and to have access to a vehicle (which makes recycling more convenient). Finally, our respondents are less likely to have children, but if they do, they are more likely to have two children and less likely to have only one child or a large family with more than four kids. These results are not unexpected. Our survey was lengthy (12 pages), it was administered only in English because of our limited budget, and it covered a topic the recycling literature suggests is of more interest to certain segments of society. Caution is therefore required when extrapolating our results to the whole state.

Before undertaking a multivariate analysis, it is instructive to briefly summarize results of contingency table analyses linking demographic and socioeconomic characteristics on one hand, and the propensity to engage in e-waste recycling on the other hand. First, age appears to be important: middle-aged adults (36 to 65 years) seem more willing to take e-waste to drop-off recycling centers, even though they typically have full-time jobs and families. Gender is also important. Based on twenty of the thirty-one variables examined, women engage more readily in pro-environment behaviors; in particular, they are much more willing to take e-waste to drop-off recycling centers. Likewise, Democrats exhibit a stronger willingness to recycle e-waste. Surprisingly, however, we detect no correlation between income (or education) and the willingness to take e-waste to drop-off recycling centers.

Modeling people's willingness to drop-off e-waste at recycling centers

Methodology

Our survey asks respondents about their willingness to recycle e-waste at drop-off centers by selecting one of four categories: 1) "Not willing at all;" 2) "Not very willing;" 3) "Willing;" and 4) "Very willing." Since only a handful of respondents chose the first category, we combine it with "Not very willing." To model responses to the last three categories, we proceed in two stages.

First, we perform a Principal Components Analysis (PCA) with varimax rotation in order to condense our fifteen survey questions on environmental attitudes and behavior into a small set of factors (Hair et al., 1995). For PCA to work well, the intercorrelations between variables should be significant but not excessive. If intercorrelations are too small, too many factors are necessary, which is inconvenient. To detect this problem, we rely on the Bartlett test for sphericity, which assesses whether the correlation matrix of the variables considered is significantly different from the identity matrix (Bartlett 1947). Its null hypothesis is that the variables are not intercorrelated, so it should be rejected for PCA to be acceptable. On the other hand, excessive intercorrelations indicate a multicollinearity problem. To guard against it, we compute Kaiser-Meyer Olkin (KMO) statistics. The overall KMO statistic should be at least 0.6 to proceed with PCA (KMO statistics range between 0 and 1). We also use Cronbach's alpha to measure the reliability of the components developed through the PCA (Cronbach, 1951). Finally, to select the number of factors to consider, we adopt the Kaiser criterion.

In the second step, we use these factors along with socio-economic and demographic variables in an ordered response model. Many papers in the behavioral recycling literature rely on correlation or contingency table analyses, but these approaches cannot disentangle the joint impact of several explanatory variables. Some researchers instead estimate an easy-to-interpret linear regression model, but this typically introduces an unacceptable bias with ordered dependent variables (Long, 1997). A few investigators (Boldero, 1995; Daneshvary et al., 1998; or do Valle et al. 2004) rely instead on ordered logit (OL) or ordered probit (OP) models. The latter is used as our starting point; it is useful to briefly describe it to better understand the semi-nonparametric approach proposed by Stewart (2004). For convenience, let us introduce an unobserved latent dependent variable y^* such that, for i=1,…,N,

$$y_i^* = x_i^{'}\beta + \varepsilon_i, \quad (1)$$

where the x_i s are vectors of explanatory variables; β is vector of unknown parameters; and the ε_is are standard normal, independently distributed error terms whose cumulative distribution function is denoted by F. For model identification, we suppose that Equation (1) has no intercept (Long, 1997). Our observed dependent variable y, which here takes 3 different integer values, is related to y^* as follows:

$$y_i = \begin{cases} 1 = \text{not very willing}, & \text{if } \tau_0 \equiv -\infty < y_i^* < \tau_1, \\ 2 = \text{somewhat willing}, & \text{if } \tau_1 \le y_i^* < \tau_2, \\ 3 = \text{very willing}, & \text{if } \tau_2 \le y_i^* < \tau_3 \equiv +\infty. \end{cases} \quad (2)$$

τ_1 and $\tau_2 > \tau_1$ are unknown thresholds that may be estimated jointly with β by maximum likelihood. The variable y_i thus indicates in what interval y falls into, so the probability of outcome $j \in \{1,2,3\}$ is

$$\Pr(y_i = j) = F(\tau_j - x_i^{'}\beta) - F(\tau_{j-1} - x_i^{'}\beta), \quad (3)$$

with $F(\tau_0 - x_i^{'}\beta) = 0$ and $F(\tau_2 - x_i^{'}\beta) = 1$.

The consistency of the estimates of β, however, depends crucially on the assumed distribution of the ε_is. To circumvent this distributional assumption, we rely in this study on SNEOP, an extension of the ordered probit model (Stewart, 2004). SNEOP offers several advantages over OP (and OL). First, it relaxes the distributional assumption required by OP or OL; instead, $F(.)$ is estimated by maximum likelihood from a semi-nonparametric family of cumulative distributions whose density is the product of the square of an unknown polynomial multiplied by the normal density (Gallant & Nychka, 1987), so that

$$F_K(z) = \int_{-\infty}^{z} \left(\sum_{k=0}^{K} \gamma_k u^k \right)^2 \phi(u)du \left(\int_{-\infty}^{+\infty} \left(\sum_{k=0}^{K} \gamma_k u^k \right)^2 \phi(u)du \right)^{-1}. \quad (4)$$

In Equation (4), K is the order of the unknown polynomial and $\phi(z)$ is the standard normal density at z.

After choosing K based on simple likelihood-ratio tests (Stewart, 2004) and setting τ_1 to its ordered probit value for identification, the coefficients γ_k are estimated jointly with τ_2 and β by maximum likelihood. This versatile approach can accommodate any distribution provided it is smooth enough and its tails are not too fat. Second, SNEOP nests the OP model, which corresponds to both K=1 and K=2. Third, SNEOP was programmed in Stata by Stewart (2004), which greatly simplifies its use.

Prior to estimating our models, we check our independent variables for multicollinearity: we regress each independent variable on the others and check that the corresponding R^2 is not too close to unity. After estimating a standard OP model, we test the underlying distributional assumption two ways: first, we compute Weiss' (1997) Lagrange Multiplier (LM) test, and second, we perform likelihood ratio tests on the value of K in SNEOP, as in Stewart (2004). We then conduct a battery of tests to detect misspecification. They include testing for the exclusion of relevant variables, for incorrect functional form, and for including irrelevant variables. Second and third order polynomial contrasts of our continuous variables (the PCA factors) are also added to the model and tested for statistical significance using Likelihood Ratio (LR) tests. Likewise, interaction terms are added to the model and their statistical significance is examined. Finally, we assess goodness of fit by comparing the model's prediction for each category to observed values, and by calculating the Adjusted Count R^2, which gives the proportion of correct predictions beyond what would have been guessed by simply choosing the largest marginal category (Long, 1997).

Principal Components Analysis Results

Using PCA, we develop three factors to summarize fifteen survey questions on environmental attitudes and behaviors. These factors are normalized to be between 0 and 1. Table 2 summarizes these results.

<Insert Table 2 approximately here>

The first factor reflects attitudes with regard to financial matters related to the environment. It is based on five questions that include willingness to pay for environmentally friendly products or for e-waste recycling, as well as support for a tax increase for environmental protection. It accounts for 71 percent of the variance in the original variables. Cronbach's alpha is 0.879, which suggests fairly high intercorrelations (KMO = 0.801, Bartlett test $p < 0.001$). The second factor captures general environmental attitudes from seven questions dealing with environmental quality and how to prioritize economic growth versus environmental protection. This factor explains 18 percent of the variance in the analysis (Cronbach's alpha=0.808, KMO = 0.813, Bartlett test $p < 0.001$). The third factor synthesizes information on individual environmental activism; it explains approximately 14 percent of the variance (Cronbach's alpha=0.746, KMO = 0.684, Bartlett test $p < 0.001$).

Comparisons of OP with SNEOP

The three factors described above are then used, along with demographic and socio-economic variables, to explain people's willingness to drop-off e-waste at recycling centers. Descriptive statistics for key independent variables found to be statistically significant for our best models are shown in Table 3.

<Insert Tables 3 and 4 approximately here>

We first estimate an ordered probit (OP) model using Stata. A series of diagnostic tests detect no problems with the selected functional form. Moreover, likelihood ratio tests indicate that only the nine variables described in Table 4 are significant at the 10% level; other variables considered but not retained include household income, ethnicity, as well as more detailed age and community density categories.

The validity of these results, however, is contingent on the normality of the error term in Equation (1), which is rejected by Weiss' (1997) LM test (p-value < 0.01). Using Stata, we then evaluate SNEOP with the nine explanatory variables of our best OP model and find that the appropriate value for K is 4. A likelihood ratio test comparing SNEOP with K=4 and OP confirms the rejection of the OP model (p-value

<0.0001). In addition, diagnostic tests similar to those for OP indicate that only the nine variables of Table 4 should be included in our model, without power or interaction terms.

Estimated SNEOP parameters and their robust standard errors are displayed in Table 4. In agreement with contingency table analysis, age and gender are important predictors of people's willingness to drop off e-waste at recycling centers, and income is not. However, contingency table analyses erroneously suggest that political affiliation is an important predictor and that education is not.

In contrast to linear regression, it is not possible to directly compare estimates of β for OP and SNEOP, so we compare observed and predicted responses for each model. We find that SNEOP predicts the "Not very willing" and "Somewhat willing" categories better than OP, but not "Very willing." Indeed, OP predicts the correct answer 82.7% of the time for "Very willing," 69.0% for "Somewhat willing," but only a dismal 10.0% for "Not very willing"; by contrast, SNEOP's results are respectively 77.2%, 75.0%, and 25.0%. Overall, however, SNEOP provides only a slight improvement over OP: the Adjusted Count R^2 equals 0.38 for OP and 0.39 for SNEOP.

Results and Discussion

To analyze the impact of binary variables, we calculate discrete changes in the predicted probability of the willingness to recycle e-waste by changing one binary variable at a time and keeping all other variables at their baseline value (Long, 1997). Our baseline is a college-educated male who is between 36 and 65 years old and lives either in an urban or a suburban environment. He scores 42.6% on "Money and the environment," 45.7% on "General environmental attitudes," and 23.2% on "Environmental activism." We consider four cases based on the availability or not of curbside collection programs for conventional household recyclables (i.e., glass, metals, paper, and plastics) and the proximity of a drop-off recycling center for e-waste (within five miles or not). Results are presented in Table 5.

<Insert Table 5 approximately here>

Our first finding is that the availability of curbside collection for household recyclables really boosts the households' willingness to drop-off e-waste at recycling centers: a comparison of baseline probabilities for cases 1 and 2 with those of cases 3 and 4 respectively shows nearly a doubling of the probability of being in the "Very willing" category (from 0.188 to 0.325 for case 1 to case 3; from 0.308 to 0.607 for case 2 to case 4). We conjecture that when households have experience with recycling, they are much more willing to go the extra mile for other forms of waste, such as e-waste.

Convenience, however, is important. When a drop-off e-waste center is available within five miles of residences, the probability to be "Very willing" almost doubles (from 0.188 to 0.308 for case 1 to case 2; from 0.325 to 0.607 for case 3 to case 4). The impact of convenience is amplified by the availability of curbside collection for household recyclables: we see that the probability of being "Very willing" to recycle e-waste swells to 0.607 for case 4.

The effect of age is intertwined with convenience and experience with recycling. Respondents who are between 36 and 65 years old are always more willing to recycle, although not by much in case 1. The availability of either curbside collection for household recyclables or of an e-waste recycling center within 5 miles increases this difference (cases 2 and 3). With both, the probability to be in the "Very willing" category decreases by 0.215 (case 4) for people younger than 36 or older than 65.

The story is similar for education. Not having a college education decreases the willingness to drop-off e-waste at a recycling center for all cases, but without convenience or recycling habit, almost half of the change affects the "Somewhat willing" category (look at cases 2 and 3). When convenience and recycling habit are combined (case 4), not having a college education impacts most the "Very willing" category (-0.388) among the four discrete variables examined for each case.

The other two characteristics, gender and "living in a rural community," have a big impact on recycling. Women with otherwise similar characteristics as men are much more willing to recycle e-waste. Living in a rural community, is even more important across the board (except for case 4). Interestingly, it increases willingness to recycling most (0.502 for both case 2 and case 3) when either the nearest e-waste drop-off is more than 5 miles away or when households don't have curbside collection for conventional recyclables. Many rural communities do not have the same level of traditional household garbage pick-up as urbanized areas. We conjecture that, since residents must take their household garbage to collection sites, they may not feel that recycling e-waste at a drop-off location is a huge inconvenience. The presence of Mono County in our sample may also have influenced our results as local communities there have a long history of environmental awareness.

To examine the impact of the three factors (PC1-PC3; see Table 2), we follow Long (1997) and plot the predicted probabilities of being in any of the three categories characterizing willingness-to-recycle as a function of each factor. We start from a baseline corresponding to the profile of our typical respondent. We then change binary variables one at a time, keeping all other variables at their baseline values. Overall, PC1 appears to be most influential and PC3 is least influential.

<Insert Figure 1 approximately here>

Figure 1 graphs the predicted probability that a respondent is “Very willing” to drop-off e-waste at a recycling center as a function of PC1 (“Money and the environment”). A low value for PC1 indicates less willingness to pay for “green” electronics or to support a tax increase to protect the environment. As expected, predicted probabilities increase with PC1. Two cases are consistently above our baseline: rural respondents and women. The former have the highest overall predicted probability, which supports the hypothesis that rural respondents may be used to driving to recycle. The result for women is in-line with evidence in the environmental psychology literature. The difference between these probabilities and our baseline tends to decrease with PC1, but the reverse holds for the four cases below the baseline. Respondents with no college education are least likely to be in the “Very willing” category. Recycling convenience (living within 5 miles from the nearest e-waste drop-off center) and familiarity with recycling (for which the availability of curbside collection for conventional recyclables is a proxy) also appear important, especially at higher levels of PC1. Finally, age makes a difference at intermediate values of PC1: younger (age 18 to 35) or older adults (over 65) are again less likely to recycle e-waste.

<Insert Figure 2 approximately here>

Figure 2 illustrates the changes with PC1 in the predicted probability that a respondent is "Somewhat willing" to drop-off e-waste at a recycling center. Rural residents and women now have a smaller predicted probability than our baseline, which is expected since they had the highest predicted probabilities of being in the "Very willing" category (Figure 1). Interestingly, the probabilities for the four other cases are not monotonic with PC1: as PC1 increase from zero, respondents first become "Somewhat willing" before making the transition to being "Very willing."

A graph of the predicted probability of being "Not very willing" as a function of PC1 (not shown) indicates that the only cases with substantial probabilities are those below the baseline in Figure 1: the most important feature is the lack of a college education, and to a lesser extend the lack of convenience (drop-off >5 miles), closely followed by the lack of familiarity with recycling (no curbside collection), and age. In all cases, predicted probabilities decreases with PC1.

<Insert Figure 3 approximately here>

Figure 3 presents the change in predicted probabilities that a respondent is "Very willing" to drop-off e-waste at a recycling center as a function of PC2 ("general environmental attitudes"). In this case, predicted probabilities decrease with PC2 because higher values of PC2 entail a higher likelihood of prioritizing economic growth over environmental protection. First, we observe that PC2 has typically less impact on the willingness to recycle e-waste than PC1. A graph of the predicted probability for the "Somewhat willing" category (not shown) indicates that, with the exception of respondents without a college education, probabilities are monotonic with PC2; at higher values of PC2, respondents without a college education tend to move to the "Not very willing category."

An analysis of the impact of PC3 ("Environmental activism") shows that this factor has less impact on predicted probabilities than PC1 or PC2 (graphs are available from the authors).

Finally, we note that the order of importance of the different discrete variables is the same for all three factors: "rural" boost predicted probabilities the most, followed by gender. On the other hand, age, the lack of curbside collection for conventional recyclables, a large distance to the nearest drop-off for recycling e-waste, and the lack of a college education, most decrease the willingness to recycle e-waste.

Conclusions

The management of e-waste is a growing concern across regional, national, and international boundaries. Therefore, recycling programs need to be created and the recycling infrastructure needs to be developed in order to stop the accumulation of toxic metals in landfills, to comply with new regulations, and to prevent increasing exports of e-waste to developing countries with devastating consequences for people and the environment. To be effective, however, e-waste policies need to be informed by a sound understanding of people's willingness to recycle.

Although our findings should be extrapolated with caution given biases in our respondents, they yield a number of useful insights. First, results from our multivariate analysis highlight the importance of convenience and familiarity with recycling. People who live more than five miles away from the nearest drop-off recycling center are less likely to recycle; on the other hand, familiarity with recycling glass, paper, metal or plastics boosts the willingness to recycle e-waste. One option for boosting recycling convenience is to increase the number of e-waste drop-off centers. When public budgets are tight, as is currently the case, our findings suggest first establishing e-waste drop-off centers in communities that already have curbside collection programs for conventional recyclables. An alternative would be to contract with existing retail establishments so they agree to collect e-waste. Getting retailers of electronic products involved may, in the long run, influence electronic manufacturers to design more environmentally friendly products.

We also find that adults between 36 and 65 years old are more likely to recycle e-waste. Most adults in that age category are baby-boomers, so we conjecture they are more sensitive to environmental issues because they grew up with the environmental movement. Men in general and people without a college education are, however, less likely to recycle. This suggests creating educational programs for students all the way to high school, and targeting recycling campaigns at young adults, especially men. Enhancing e-waste recycling for older people may require periodic curbside collection programs instead.

Future research could investigate other recycling options and try to get a better understanding of the willingness to recycle by minority groups, especially Hispanics.

Acknowledgements

This research was supported in part by the Program in Industrial Ecology at UC-Irvine (UCI). This Program is supported by funds from the National Science Foundation (DMII 0223894); the University of California Toxic Substances Research and Teaching Program; the California Policy Research Center; the AT&T Foundation Industrial Ecology Faculty Fellowship; and the UC Research Discovery Program. Additional support was provided by the UCI School of Social Ecology and by the office of the Executive Vice Chancellor at UCI; their support is gratefully acknowledged.

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Table 1: Selected Demographic Characteristics of Respondents versus 2000 Census.

Characteristic	Respondents	2000 Census
Age	18-24: 2.0%; 50-64: 30.0% 25-34: 9.6%; ≥65: 21.9% 35-49: 36.4%;	18-24: 13.5%; 50-64: 18.7% 25-34: 21.4%; ≥65: 14.2% 35-49: 32.1%
Marital Status	Married: 68.3%: Divorced: 13.2% Widowed: 7.3%; Never married: 10.0% Separated: 1.2%	Married: 53.6%: Divorced: 9.7% Widowed: 5.4%; Never married: 29.0% Separated: 2.2%
Ethnicity	White: 79.0%; Hispanic: 9.8% Black: 2.1%; Asian: 6.1% Other: 3.0%	White: 55.2%; Hispanic: 23.3% Black: 5.6%; Asian: 10.7% Other: 5.2%
Education	High school or less: 12.8% Some college: 37.0% Bachelors degree: 28.2% Graduate or professional degree: 22.0%	High school or less: 38.3% Some college: 31.3% Bachelors degree: 19.5% Graduate or professional degree: 10.9%
Household Income	<$20K: 5.9%; $60K-$74K: 19.7% $20K-$39K: 16.9%; $75K-$99K: 10.6% $40K-$59K: 15.3%; >$99K: 31.6%	<$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: 86.5%; Rent: 13.5%	Own: 59.2%; Rent: 40.8%
Type of Dwelling	Single-family home: 82.8% Duplex: 7.0%; Mobile home: 4.1% Apartment: 5.5%; Other: 0.6%	Single-family home: 54.9% Duplex: 9.6%; Mobile home: 3.4% Apartment: 32.0%; Other: 0.1%
Household Size	1: 17.7%; 2: 39.0%; 3: 16.3% 4: 17.7%; >4: 9.3%	1: 23.1%; 2: 30.8%; 3: 16.4% 4: 15.0%; >4: 14.7%
Number of Children Under 18 per Household	0: 83.3%; 1 or more: 16.7%	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: the census data is for the six California counties surveyed (Alameda, Contra Costa, Kern, Mono, Orange, and San Diego).

Table 2: Principal Components Analysis of Environmental Attitudes and Behaviors

Survey Items and Principal Components	Eigenvectors and scoring coefficients	% Variance explained v; Cronbach's α; KMO; Bartlett.
PC1 – Money and the environment		v = 70.5%
1. Support for a tax increase for environmental protection	0.585	α = 0.880
2. Support to pay more for environmentally-friendly products	0.600	KMO = 0.801
3. Willingness to pay extra for electronic waste recycling	0.749	Bartlett: $p<0.001$
4. Willingness to pay extra for a "green" cellular telephone	0.878	
5. Willingness to pay extra for a "green" desktop computer	0.897	
PC2 – General environmental attitudes		v = 18.2%
1. Change in environmental quality over past 10 years	0.507	α = 0.808
2. Rating of U.S. environmental quality	0.640	KMO = 0.813
3. Rating of California environmental quality	0.762	Bartlett: $p<0.001$
4. Rating of local environmental quality	0.570	
5. Support for "environmental protection should be a priority, even if it slows economic growth and causes some job losses." (Low value if agrees, high if disagrees)	0.477	
6. Support for "economic growth and creating new jobs should be the top priority, even if the environment suffers."	0.455	
7. Attitude toward the nation's spending on environmental protection.	0.456	
PC3 – Environmental activism		v = 13.6%
1. Attend meeting or sign petition to protect the environment	0.592	α = 0.746
2. Contribute to environmental organizations	0.740	KMO = 0.684
3. Volunteer with environmental organizations	0.683	Bartlett: $p<0.001$

Notes. For PC1, a higher value indicates a greater support for the environment; likewise, a higher value of PC2 indicates that environmental quality is improving and other issues should have priority over the environment; for PC3, a higher score shows more involvement. Cronbach's α indicates how well a set of variables measures a single underlying construct; it is high when inter-item correlations are high. KMO measures sampling adequacy and tests whether partial correlations between variables are small; it should be >0.5 for a satisfactory factor model. Bartlett's test of sphericity checks whether the correlation matrix of the variables is significantly different from an identity matrix; if not, the factor model is inappropriate.

Table 3: Descriptive Statistics for Key Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Willingness to drop-off e-waste	2.47	.63	1	3
PC1 – Money and the environment	0.43	0.24	0	1
PC2 – General environmental attitudes	0.46	0.20	0	1
PC3 – Environmental activism	0.23	0.34	0	1
Curbside (yes = 1)	0.63	0.48	0	1
Distance to recycling center (>5 miles = 1)	0.43	0.50	0	1
Age between 36 and 65 years (yes = 1)	0.68	0.47	0	1
Gender (female = 1)	0.38	0.49	0	1
College education (yes = 1)	0.89	0.32	0	1
Rural community (yes = 1)	0.35	0.48	0	1

Notes: PC1, PC2, and PC3 are treated as continuous indexes; they are normalized to be between 0 and 1. The other variables are binary (0 or 1) indicator variables.

Table 4: Model Estimation Results

Variable	Ordered Probit Coefficient (Standard error)	SNEOP Coefficient (Standard error)
PC1 – Money and the environment	2.130***	1.853***
	(0.440)	(0.504)
PC2 – General environmental attitudes	-0.951**	-0.773*
	(0.466)	(0.414)
PC3 – Environmental activism	0.607**	0.387*
	(0.304)	(0.241)
Curbside collection for recyclables	0.518**	0.496**
(yes = 1)	(0.236)	(0.243)
Distance to recycling center	-0.548***	-0.533***
(>5 miles = 1)	(0.175)	(0.134)
Age between 36 and 65 years	0.367**	0.359***
(yes = 1)	(0.165)	(0.115)
Gender	0.439**	0.523***
(female = 1)	(0.188)	(0.158)
College education	0.876***	0.910***
(yes = 1)	(0.265)	(0.223)
Rural community	1.021***	0.810***
(yes = 1)	(0.255)	(0.305)
τ_2	0.269	0.269
	(0.466)	Set to OP value
τ_3	2.031	1.781
	(0.519)	(0.321)

Notes. Number of observations = 265. OP results: Log-likelihood = -177.14. LR Chi-Square (with 9 degrees of freedom) = 118.87; the corresponding p-value is <0.0001. SNEOP results: Log-likelihood = -167.84. Wald Chi-Square (with 9 degrees of freedom) = 18.25; the corresponding p-value is 0.032. Likelihood ratio test of the OP model against SNEOP model: Chi-square (with 2 degrees of freedom) = 18.58; the corresponding p-value is <0.001. The standard error is the Huber/White/Sandwich estimate. "***," "**,"and "*" indicate significance at the 1%, 5%, and 10% levels respectively.

Table 5: Discrete Change in the Probability of the Willingness to Recycle E-waste

Variable	Not very willing	Somewhat willing	Very willing
1. Curbside recycling for conventional recyclables: NO. Recycling center for e-waste <5 mi.: NO.			
Baseline probabilities:	*0.145*	*0.667*	*0.188*
Age 36-65 yrs (*yes* → no):	+0.174	-0.163	-0.011
College education (*yes* → no):	+0.445	-0.431	-0.014
Gender (*male* → female):	-0.110	-0.022	+0.132
Rural community (*no* → yes):	-0.126	-0.218	+0.344
2. Curbside recycling for conventional recyclables: YES. Recycling center for e-waste <5 mi.: NO.			
Baseline probabilities:	*0.037*	*0.655*	*0.308*
Age 36-65 yrs (*yes* → no):	+0.064	+0.040	-0.104
College education (*yes* → no):	+0.256	-0.125	-0.131
Gender (*male* → female):	-0.019	-0.274	+0.293
Rural community (*no* → yes):	-0.020	-0.482	+0.502
3. Curbside recycling for conventional recyclables: NO. Recycling center for e-waste <5 mi.: YES.			
Baseline probabilities:	*0.034*	*0.642*	*0.325*
Age 36-65 yrs (*yes* → no):	+0.057	+0.057	-0.114
College education (*yes* → no):	+0.239	-0.092	-0.147
Gender (*male* → female):	-0.016	-0.283	+0.299
Rural community (*no* → yes):	-0.017	-0.485	+0.502
4. Curbside recycling for conventional recyclables: YES. Recycling center for e-waste <5 mi.: YES.			
Baseline probabilities:	*0.018*	*0.375*	*0.607*
Age 36-65 yrs (*yes* → no):	+0.007	+0.207	-0.215
College education (*yes* → no):	+0.062	+0.326	-0.388
Gender (*male* → female):	-0.001	-0.261	+0.262
Rural community (*no* → yes):	-0.002	-0.347	+0.348

Notes. To generate the results above, we change discrete variables one at a time; other variables stay at their baseline value (underlined and in italics in the left-most column). Baseline probabilities are calculated for our baseline respondent: he is college-educated, between 36 and 65 years old, and he lives either in an urban or a suburban environment. He scores 42.6% on PC1 ("Money and the environment"), 45.7% on PC2 ("General environmental attitudes") and only 23.2% on PC3 ("Environmental activism"). These are the mean values for our respondents (see Table 3).

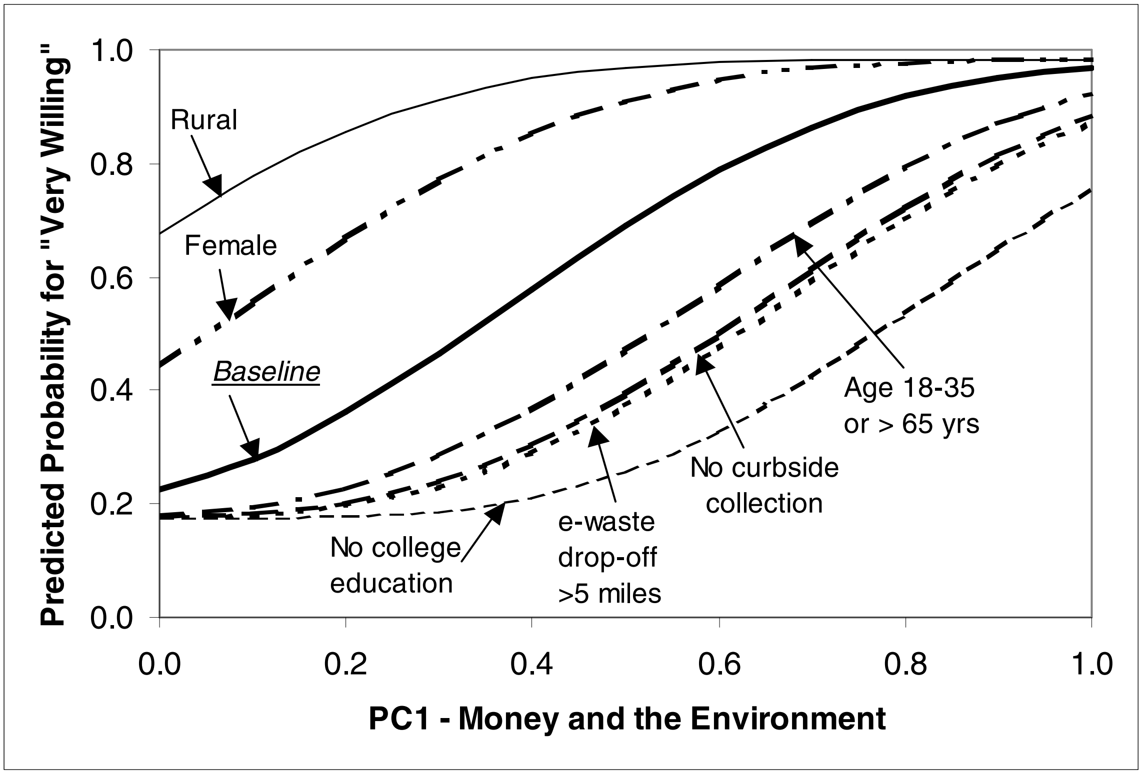

Figure 1: Predicted Probability of being "Very willing" to drop-off e-waste at recycling centers versus PC1.

Notes. Our baseline is a college-educated male who is between 36 and 65 years old and lives either in an urban or a suburban environment, within five miles of an e-waste recycling center; he has access to curbside recycling for conventional recyclables. He scores 45.7% on PC2 ("General environmental attitudes") and 23.2% on PC3 ("Environmental activism").

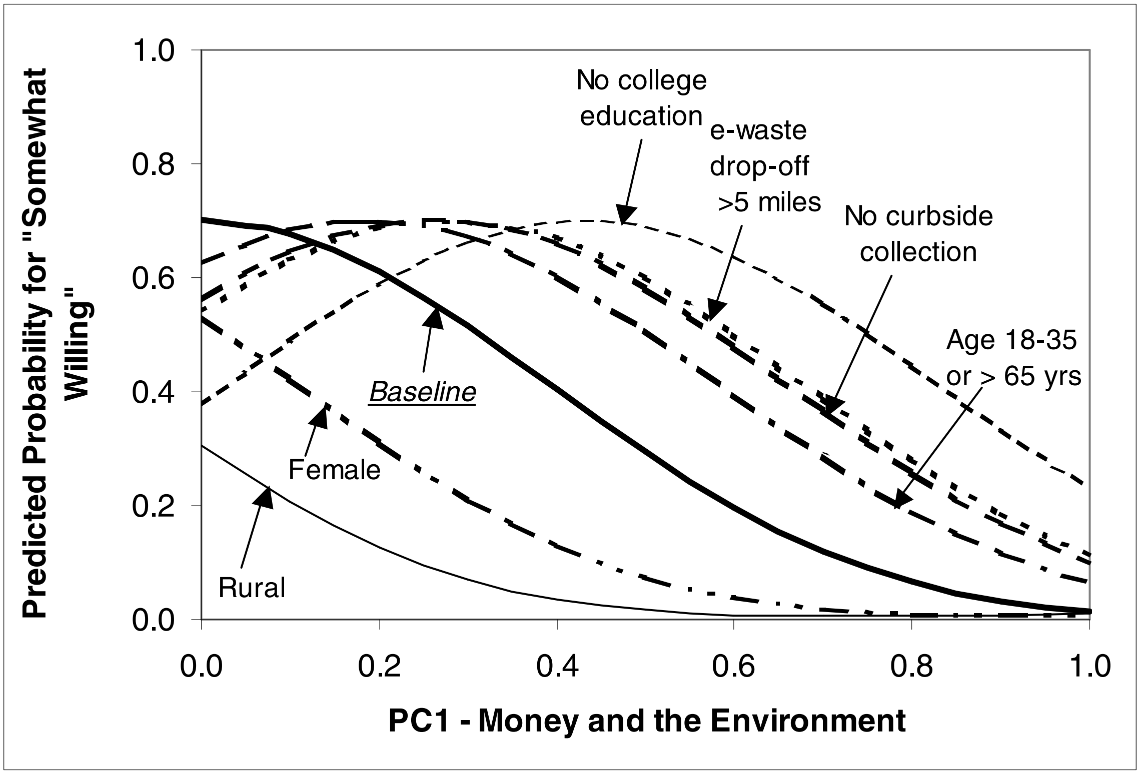

Figure 2: Predicted Probability of being "Somewhat willing" to drop-off e-waste at recycling centers versus PC1.

Notes. Our baseline is a college-educated male who is between 36 and 65 years old and lives either in an urban or a suburban environment, within five miles of an e-waste recycling center; he has access to curbside recycling for conventional recyclables. He scores 45.7% on PC2 ("General environmental attitudes") and 23.2% on PC3 ("Environmental activism").

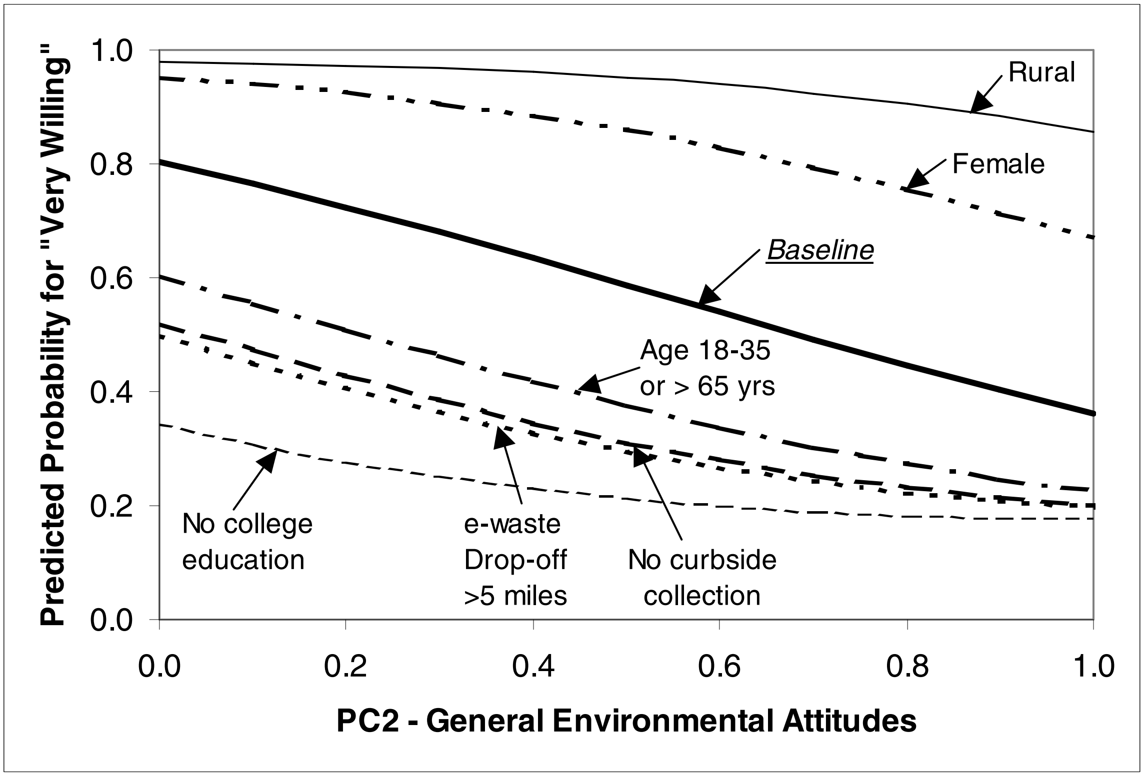

Figure 3: Predicted Probability of being "Very willing" to drop-off e-waste at recycling centers versus PC2.

Notes. Our baseline is a college-educated male who is between 36 and 65 years old and lives either in an urban or a suburban environment, within five miles of an e-waste recycling center; he has access to curbside recycling for conventional recyclables. He scores 42.6% on PC1 ("Money and the environment") and 23.2% on PC3 ("Environmental activism").