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Reduce, Reuse, Redeem: Deposit-Refund Recycling Programs in the Presence of Alternatives*

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Abstract

We estimate consumer preferences and willingness to pay for current beverage container recycling methods, including curbside pick-up services, drop-off at government-subsidized recycling centers, and drop-off at non-subsidized centers. Using a representative online and telephone survey of California households, we estimate a discrete choice model that identifies the key attributes explaining consumers' beverage container disposal decisions: the refund amount (paid to consumers only if they recycle at drop-off centers), the volume of recyclable material generated by the household, and the effort associated with bringing recyclable materials to recycling centers. Additionally, we use counterfactual policy analysis to show that increasing the refund amount increases overall recycling rates, with the largest changes in consumer surplus accruing to inframarginal consumers, who are on the boundary between taking containers to recycling centers and recycling using curbside pick-up, namely white and higher income consumers. Conversely, we show that eliminating government-subsidized drop-off centers does not significantly alter consumer surplus for any major demographic group, and has little impact on recycling rates.

Keywords: recycling; discrete choice; deposit-refund program; consumer convenience; Bottle Bill

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1 Introduction

In 2018, an estimated 359 million tons of plastic were produced worldwide, with nearly one third of this going to single-use plastics (Vidal, 2020). Hence, figuring out how to reduce food and beverage container waste is an often overlooked, but important element of creating environmentally sustainable value chains. One way that policymakers have historically approached this problem has been to promote the recycling of container waste, especially for beverage containers such as plastic bottles. Yet in the US, recycling services and policies are often under the jurisdiction of local or state governments rather than the federal government, and hence vary greatly from state to state. For instance, while in 2016 approximately 94% of the US population had some form of recycling program available to them, this access is highly heterogeneous; 30% had curbside collection only, 43% had both curbside programs and access to drop-off programs, and 21% had access to drop-off programs only (Sustainable Packaging Coalition, 2016).[1] Understanding how consumers value the attributes of such recycling methods is imperative in crafting sustainable recycling policies, since incorporating information about consumer preferences and behavior can ensure policies are both effective and efficient. In this paper, we will explore the Californian setting where most consumers have multiple recycling method options (including a deposit-refund system at drop-off centers, curbside pick-up services, and recycling at other locations) in order to estimate consumer valuation of these options and to simulate potential policy changes going forward.

When recycling programs first took off in the US in the 1970s and 1980s, the go-to policy was a deposit-refund system, which is a type drop-off program .[2] These systems generally work as follows. Upon purchasing a beverage in an eligible container, a small fee (or "deposit")—usually between 1-10 cents—is levied on consumers. However, consumers can get this deposit refunded if they return the container post-consumption to a retail store that sells the corresponding beverage or to other designated recycling centers. These stores and centers, who are legally mandated to accept such recycled containers, are then tasked with sorting returned containers for pickup by the beverages' original distributors, who are legally responsible for then recycling these containers. The requirement that all retailers of an eligible beverage also accept the containers for refunds ensures that purchasers of such beverages also have convenient access to their fee-deposit refund. In this way, deposit-refund systems can promote recycling without greatly reducing consumer welfare.

California's deposit-refund system, our focus in this paper, was established in the 1987 "Bottle Bill" (formally called the Beverage Container Recycling and Litter Reduction Act), and works a bit differently.[3] Like

[1] These estimates align with those made by the U.S. Environmental Protection Agency 2013.

[2] Deposit-refund systems have been adopted and implemented by Oregon (1972), Vermont (1973), Maine (1978), Michigan (1978), Iowa (1979), Connecticut (1980), Massachusetts (1983), New York (1983), California (1987), and Hawaii (2005) (Container Recycling Institute, 2020). Such laws currently affect 27% of the population of the US. Container deposit-refund systems also exist in Canada, Australia, Denmark, Finland, Germany, The Netherlands, Norway, and Sweden, to name a few.

[3] Hawaii's program also deviates from the description above, and is more similar to California's.

in other states, consumers are charged the deposit—known as the California Redemption Value (CRV)[4]—upon purchase of eligible containers, yet California's policy relies on existing recycling center infrastructure, rather than retail stores and distributors, to collect containers and distribute refunds to consumers (Naughton et al., 1990).[5] Specifically, the California Department of Resources Recycling and Recovery (CalRecycle) relies on existing recycling centers (which buy materials from consumers and resell them for their scrap value), to also collect CRV eligible containers, pay consumers their CRV refund, and recycle containers as they would any other material. In return, CalRecycle provides a small payment to these centers called a "processing fee" for participation in the CRV program.

Yet, given that under California's system consumers cannot receive their CRV refund at retail locations, there is the potential of generating negative welfare impacts for beverage consumers who face high costs of travelling to a recycling center, such as low income consumers. To mitigate this potential loss, CalRecycle made provisions in the Bottle Bill that aimed to encourage more drop-off centers to open in "convenient" locations. Specifically, grocery stores with over 2 million dollars in annual sales are required by the bill to have a drop-off center in operation within a half-mile radius of their location.[6] If the recycling center within this half-mile boundary does not receive a high enough volume of containers to be profitable, then it receives additional subsidies from CalRecycle (beyond the aforementioned processing fees) called "handling fees" in order to help it stay in business, as to remain a convenient recycling option for consumers. We refer to these heavily subsidized centers here as "handling fee centers," and all other recycling centers participating in the CRV program as "processing fee" centers (as they only receive the processing fees).

While California and other states attempted to increase recycling by promoting such drop-off programs, governments also greatly expanded access to curbside pick-up throughout the country in the 1990s and 2000s. In fact, curbside programs grew from 2,000 in 1990 to more than 9,700 in 2000 (Beatty et al., 2007) and more than 70% of the US population had access to curbside programs by 2016 (Sustainable Packaging Coalition, 2016). Given the current widespread availability of a curbside collection alternative in California, a major concern is that continuing to offer a CRV payment for bottles returned to drop-off centers may not increase overall recycling rates, but rather induces substitution between curbside pick-up and drop-off recycling. More specifically, individuals do not receive a CRV refund if they recycle their containers by curbside pick-up, while they do receive this payment from dropping containers off at a center. Given this, it is a well-known fact that so-called "scavengers" will take CRV refund-eligible containers out of others' curbside bins, and

[4]The CRV is currently five cents on bottles and cans under 24 ounces, and a ten cents on beverage containers that exceed 24 ounces, excluding glass bottles and some specialty containers.

[5]This is because supermarket and beverage industries lobbied significantly against the establishment of such a policy in California, given that collecting, sorting, and handling all of the containers in such a large state would be very expensive for them (Reinhold, 1987).

[6]If there is not a drop-off center within a half mile of the grocery store, then the grocery store must pay daily penalties until a center is in operation.

bring them to a center to receive a refund, with some individuals even earning their livelihoods through this activity (Ashenmiller, 2009). Hence, our first research question is: Given the presence of a curbside pick-up alternative, how do overall recycling rates change when the CRV refund amount is changed, and specifically, which consumer demographics would be most greatly affected by such policy changes?

The continued support subsidies from CalRecycle to keep handling fee centers open (an artefact of California's policy which does not require retail locations to accept recycled cans) has also been a hotly contested issue. While the goal of giving all consumers convenient access to a drop-off program center (and hence their CRV refund) is important in mitigating consumer welfare losses, it also is costly for the government of California to keep open handling fee centers that are not profitable. Moreover, a key practical difference between handling fee centers and processing fee centers is that while consumers at processing fee centers are generally given their refunded CRV in the form of cash, at handling fee centers, consumers are often given a voucher which they can only redeem for cash at the corresponding supermarket for which the center is within the half-mile boundary. Hence consumers may not value handling fee centers because they do not want to receive their CRV refund as a voucher.[7]

Beyond this, recently there have been a string of closings of various processing fee centers throughout the state of California in response to China's 2017 decision to restrict imports of recyclable materials,[8] which rattled recycling markets and increased these centers' costs of hauling away recyclable materials (Katz, 2019). Perhaps one of the most high profile examples was RePlanet, which closed all of its almost 300 recycling centers in California in August of 2019 (Freedman, 2019).[9] The closing of so many centers also raises significant red flags, in that they further limit consumer access to drop-off program centers. Hence, our second research question is: what would happen to recycling rates if California stopped supporting some or all of these handling fee centers or when more processing fee centers potentially close? Will individuals travel further to access drop-off centers, switch to curbside pick-up recycling/recycling at other institutions, or choose not to recycle? We seek to understand how would this affect consumer welfare, and specifically, which groups of consumers would potentially stand to lose out from such a change.

To answer these policy questions, we designed and implemented a survey to simultaneously estimate California residents' willingness to pay (WTP) for various beverage container recycling alternatives. The survey was implemented online and via telephone for a representative sample of California households in

[7]Consumers may disprefer these vouchers for many reasons. Examples may include the additional transaction costs of obtaining the cash at the supermarket or the stigma associated with cashing in these vouchers at a supermarket (as this might be seen as a signal of having a low income).

[8]Beginning in the 1990's, China imported most of the world's scrap material. This came to an abrupt end in 2017 when China announced Operation National Sword, which banned 24 types of scrap material and implemented much stricter and more rigorous contamination standards. (Source: "America's new recycling crisis, explained by an expert," Vox.com, Online, *accessed 26 Mar. 2020*)

[9]About 7-8% of RePlanet's Centers were handling fee centers; the rest were processing fee centers.

June to July of 2017, and collected information on household demographics, knowledge of recycling options, and recycling behaviors over the past week. Using these data, we then estimate a discrete choice model for consumer preferences for the disposal options available to them (including processing fee recycling centers, handling fee recycling centers, curbside recycling pick-up, recycling at other establishments, and trash), where a choice is defined as a bundle of attributes (as in Huber and Train 2001; Revelt and Train (1999); McFadden and Train 2000; Train 2009). These attributes include the ability to receive the CRV, the time and effort required for disposal, the proximity to a grocery store, and the proximity to home, among others. From the model parameters, derived using random coefficient logit specifications (Revelt and Train, 1999; Huber and Train, 2001), we obtain estimates for the average willingness to pay (WTP) for these various recycling method attributes. In so doing, this paper provides researchers and policymakers with the first estimates of the average WTP and of the empirical distribution of the WTP for multiple recycling options in California. In addition, given observable demographic information and geo-coded locations of recycling centers near the surveyed consumers, we test whether the type of recycling center visited ("handling fee" versus "processing fee") affects WTP.

Moreover, to address the policy questions above, we estimate simulated choices under alternative recycling policies. First, we simulate changes in the CRV amount, and consider how this would change household beverage container recycling choices, as well as how consumer surplus changes across demographic characteristics as a result of this policy. Second, we simulate the closure of handling fee centers, and estimate the resulting welfare changes for various demographic groups, measured as changes in the distribution of consumer surplus.

We find that potential recyclers in California choose their recycling method primarily based on the CRV refund amount, the volume of recyclable material generated by the household, and the effort associated with bringing recyclable materials to recycling centers, conditional on options known and available to the household. In our counterfactual policy simulations, we find that an increase in the CRV leads to the largest improvements in consumer surplus for the group of inframarginal consumers who are on the boundary between taking containers to recycling centers and recycling using curbside (which means they do not receive the CRV), namely white and higher income respondents. An increase in the CRV also increases recycling overall; however, the majority of the change in recycling is associated with a change in recycling methods, rather than from a reduction in containers entering trash streams. In addition, we find that eliminating the subsidized handling fee centers does not significantly alter consumer surplus for any major demographic group. Moreover, reducing the number of recycling centers reduces frequent recycling center use, but only leads to a minor reduction in overall recycling rates. In other words, individuals simply recycling more material less often. Hence the benefits of a minor increase in recycling may not outweigh the costs of subsidizing handling fee centers. Both of these results have important implications for the future of beverage container recycling policies.

The rest of the paper proceeds as follows. Section 2 summarizes this study's contribution to the literature. Section 3 describes the empirical setting, the research design, and the data. Section 4 outlines the model to estimate consumer choices and willingness to pay for disposal option attributes. Section 5 presents the results of the choice model and a brief discussion. Section 6 derives the methodology and presents the results of the counterfactual policy simulations. Section 7 concludes with a discussion of policy applications.

2 Contribution to the Literature

This study adds to body of literature that estimates the WTP for recycling programs in various contexts. A summary of relevant literature is listed in Table 1, including information about the year, sample size, and setting of the study, the average estimated WTP, and the recycling method considered. Notably, all of the papers only consider one recycling method each, with the most common being curbside pick-up. Additionally, even accounting for differences in the recycling method studied and length of the time period considered, estimates of WTP tend to vary somewhat across contexts. For instance, monthly WTP for curbside ranges between $1 and $10. Our study simultaneously evaluates a set of recycling programs (rather than a single option) within a unified framework and obtains the resulting WTP estimates.

In terms of studies of WTP for drop-off recycling options, Jakus et al. (1996) and Tiller et al. (1997) both consider the context of convenience centers in Williamson County, Tennessee. As this is a rural area, with households that are few and far between, offering curbside recycling pick-up services (and for some consumers trash pick-up services as well) is not profitable, and hence dropping materials off at a center is the only disposal option for most consumers. Jakus et al. (1996) survey intercepted consumers at a disposal center, use a two-stage procedure to estimate recycling demand while controlling for selection, and find an average WTP for drop-off recycling of about $5.68. On the other hand, Tiller et al. (1997) use a similar survey method, but estimate WTP using a contingent valuation (CVM) method which asks consumers their hypothetical willingness to pay for more drop-off centers. The authors in this case find estimates of average WTP that range from $4.05 for non-recyclers who do not have curbside trash pick-up, to $11.74 for recyclers who do have curbside trash pick-up.

Other studies considered use a variety of methods across contexts to calculate WTP for curbside recycling pick-up services. Here we will highlight a few. One common context in which many of these studies take place is in the US state of Utah. For instance, both Aadland and Caplan (1999) and Aadland and Caplan (2003) study the WTP of households in Utah for curbside recycling programs, using CVM questions regarding

WTP for either their current or hypothetical recycling services. The authors estimate average WTP of about \$2 (in Ogden, Utah) and about \$7 (in Utah more generally), in the two papers respectively. Yet they find that when the estimate in the latter (based on stated preference data) is corrected by their revealed preference data, the WTP estimate falls by up to a \$1.00 a month. In terms of heterogeneity, they find that young, well-educated women who are members of environmental organizations, who recycle out of an ethical responsibility for the environment, who are not frequent drop-off users, and who reside in large households are willing to pay the most for a curbside service. Caplan et al. (2002) also consider the WTP for recycling in Ogden, Utah and specifically for the combination of curbside recycling and green waste pick-up. Using a contingent ranking (CR) method where respondents provide an ordinal preference ranking of various programs at various prices, they find a WTP of between \$6 and \$10 a month for the combined program. Various studies also estimate WTP for curbside services in other geographical contexts; for example Blaine et al. (2005) look at the WTP for curbside recycling in Lake County, Ohio. They use two CVM techniques: a single bounded referendum and a payment card. The authors find that the results obtained from these valuation methods differ significantly, but that the willingness to pay for curbside recycling is between \$1.00 and \$2.00 dollars monthly for most consumers. Perhaps most geographically representative of all of the papers listed, Aadland and Caplan (2006) uses a phone survey to elicit WTP for curbside across 40 cities (with populations of 50,000 or more) in the Western United States. Using CVM and supplemented with "cheap talk" statements that alert participants about the potential bias in their statement of WTP using hypothetical elicitation methods, they estimate a mean WTP of \$5.61, or \$2.97 when calibrated to control for the hypothetical bias imposed by CVM methods.

This paper meaningfully contributes to the WTP for recycling literature in four ways. First, while much of the literature focuses on WTP for a single recycling methods, (such as only considering willingness to pay for curbside pick-up), our study simultaneously evaluates a set of recycling programs (rather than a single option) within a unified framework. Second, while many of the studies discussed above have a more narrow geographic focus, this study is able to consider the large-scale context of the entire state of California (the World's 5th largest economy by GDP). We are able to conduct our analysis using a representative sample of California residents, with a relatively large sample size compared to many of the studies listed in Table 1. Third, we largely avoid hypothetical bias problems involved with CVM methods by asking individuals to recall their actual recycling behavior, and hence learn about individuals' revealed recycling preferences.[10] Fourth, we obtain the zip codes of our respondents, and can thus match respondents to their nearest recycling center. This allows us to create individual-specific measures of recycling center convenience.

[10] Admittedly, we may then introduce an additional issues of recall bias, given that consumers are asked about recycling behavior over the past week. Yet, given that one week is a relatively short recall period, the issue likely will not cause substantial distortion. People may also misreport recycling behavior due to experimenter demand effects.

Given our scope to simulate counterfactuals under various policy scenarios, this paper also contributes to the literature on recycling policy more generally. Various papers, such as Fullerton and Wolverton (2000) and Ashenmiller (2009), study deposit-refund systems (of which California's CRV is an example). The merits of these deposit-refund systems have been debated in the literature. Porter (1978), for instance, shows that the desirability of mandatory deposit systems on efficiency alone is not indisputable. Moreover, it depends critically on the average value of the time it takes consumers to return empty containers, the average value of the benefits associated with decreased beverage container litter. On the other hand, Calcott and Walls (2005) identify a rationale for recycling markets and associated deposit refunds, even when curbside recycling is available. Although they acknowledge that recycling markets may come with transaction costs, they argue that the existence of such markets encourages greater "Design for Environment" and more recycling than there would be with only curbside recycling. Additionally, the authors note that when there is incomplete sorting of recyclables (meaning some recyclables end up in the trash), a deposit–refund applied to all products works along with the disposal fee to attain the constrained optimum. Viscusi et al. (2013) also conduct a phone and online survey of over 3,000 representative US consumers and using simple cross-sectional regression of reported recycling behaviors on household characteristics, show that respondents from states with stringent recycling laws and bottle deposits have greater recycling rates. Yet they also note that the impact of the "warm glow" from being an environmentalist and an environmental group member on recycling rates is about equal to that of a 5-cent bottle deposit.

Various literature has also considered the optimal value of the deposit refund amount. For instance, Palmer and Walls (1997) calculate the optimal deposit-refund scheme and find the deposit must equal the refund and both must be set equal to the marginal social cost of disposal. Similarly, Numata (2011) argues that the refund should be equal to the sum of the following three components: (1) the suppliers' marginal net revenue from collecting and treating used deposit–refund goods, (2) the marginal negative externality, and (3) the deposit multiplied by the share of the unredeemed deposits that the government and the recycler collect from the supplier. Porter (1983) also debunked the perhaps intuitive-seeming notion that higher deposit-refund amounts necessarily lead to higher return rates. To do this, Porter compares Michigan, which had relatively high deposit-refund amounts of 5-10 cents, to other US states at the time with deposit-refund amounts of 2-5 cents, and notes that recycling rates in Michigan were not necessarily higher. We build on this literature by using our structural model to estimate how consumers will alter their beverage disposal behavior under various CRV amount regimes. Moreover, we are able to measure heterogeneous impacts of such CRV changes on various demographic groups, for whom understanding welfare impacts may be of particular interest for policymakers. These include, for instance, low-income and minority consumers.

Additionally, other important policy questions surround the issue of what types of recycling options should optimally be offered by policymakers who want to increase recycling rates. Beatty et al. (2007) consider what would happen to overall recycling rates in California if access to curbside pick-up services was extended to more consumers. Using a panel regression framework where material recycled is regressed on share of the population with access to curbside services, they find that marginal gains from extending these services are small, as they mostly induce consumer switching from drop-off to curbside recycling. Best and Kneip (2018) also consider the impact of curbside access on overall recycling rates in the context of Cologne, Germany, using propensity score matching and differences-in-differences approaches. They find that a curbside scheme has no effect on paper recycling but increases recycling participation by between 10-25% points for plastic and packaging. In the UK, Abbott et al. (2017) use a 3 stage least squares approach and find that while there is no trade-off between recycling in curbside and non-curbside methods when curbside access is expanded, there is a trade-off when expanding non-curbside provision. Similarly to above, we contribute to this literature by estimating policy impacts of closing various government-subsidized handling fee centers in the Californian context, and simulating how this might drive consumers either to recycle less or switch to other recycling methods.

Table 1: Literature on Willingness to Pay for Recycling Services

Authors	**Year**	**Program Type**	**Time Period**	**WTP**	**Approx. Sample Size**	**Setting**
Jakus, Tiller, and Park	1996	dropoff	month	$5.78	284	Williamson County, TN
Lake, Bateman, and Parfitt	1996	curbside	year	£35.69	285	Hethersett, South Norfolk, UK
Tiller, Jakus, and Park	1997	dropoff	month	$4.05- $11.74	481	Williamson County, TN
Aadland and Caplan	1999	curbside	month	$2.05	401	Ogden, UT
Kinnaman	2000	curbside	quarter	$23.12	100	Lewisberg, PA
Caplan, Grijalva, and Jakus	2002	curbside (and green waste pickup)	month	$6.44-$9.66	350	Ogden City, UT
Aadland and Caplan	2003	curbside	month	$6.00-$7.00	1000	UT
Blaine, Lichtkoppler, Jones, and Zondag	2005	curbside	month	$1.08-$2.35	2000	Lake County, OH
Aadland and Caplan	2006	curbside	month	$2.97-$5.61	4000	40 Western US cities
Jamelske and Kipperberg	2006	upgrade to automatic/ single stream	month	$3.17-$3.18	301	Madison, WI
Bohara, Caplan, and Grijalva	2007	curbside	month	$5.48	400	Logan, UT
Karousakis and Birol	2008	curbside	month	£2.68/material	188	London, UK
Troske, Blomquist, Hardesty, Koford, and Hughes	2009	curbside	month	$2.29	600	Lexington, KY
Gillespie and Bennett	2013	curbside (fortnightly collection)	year	AU$131.49	600	Brisbane, AU

3 Survey Data and Summary Statistics

The National Opinion Research Center (NORC) at the University of Chicago administered our survey to a representative sample of Californian adults using their AmeriSpeak Panel.[11] During the survey, we collected information about the beverage containers purchased by each household in the week prior to the survey, as well as the disposal methods chosen for each of those containers. After determining the method(s) of disposal, we asked respondents to provide information about the disposal decisions they made. For example, if a respondent reports that they went to a recycling center, we asked why they chose their preferred center over other centers, as well as why they chose to dispose of their containers at a recycling center as opposed to other options (such as curbside disposal). In addition, we looked to capture respondents' knowledge of their potential options; we asked individuals if they knew the CRV refund amount, if they knew the location of their nearest recycling center, and if they had access to curbside recycling. Finally, we asked respondents if they would recycle their beverage containers at a recycling center given a (randomly assigned) change in the CRV. Demographic information collected from each respondent in the AmeriSpeak panel was also provided by NORC.

The survey had a total of 1,005 respondents, with 899 of the respondents responding that they had purchased beverage containers over the previous week, and 893 providing information on their disposal method. For people who were estimated to take the survey in only one sitting (with a response time of less than 100 minutes), respondents completed the approximately 30 question survey in an average 12.70 minutes. The number of questions a respondent faced differed depending on the choice of disposal method(s). Summary statistics of the survey data are presented in Tables 2–4 and Figure 1. Table 2 presents the demographic makeup of the survey respondents in column 1, the demographics of the weighted sample in column 2, and the demographic composition of California residents in column 3. The weighted sample include post-stratification weights to balance the survey respondents to the California population's breakdown of age, race, and education. Column 4 represents the difference between the weighted sample and the California populace. Overall, our weighted sample is representative of the California population, with the exception that high income residents (above $125,000 household income) and currently married residents are underrepresented whereas low income residents (under $30,000 household income) and not married residents are overrepresented by roughly 10 percentage points.

In Table 3, we present survey response summary statistics for disposal method choices of the CRV beverage containers purchased over the previous seven days. Respondents were able to choose more than

[11] The AmeriSpeak Panel has over 2800 participants from California. NORC compensates participants upon completion of the survey. NORC obtains representative samples by offering surveys (1) by either internet or telephone and (2) in either English or Spanish. NORC also has protocols for encouraging responses, if needed, and weighting the responses to make the answer representative.

Table 2: Demographic characteristics of the households in the unweighted sample and the weighted sample, compared to the demographics of California residents

	Unweighted	Weighted	CA Benchmark	Difference
Household Income				
Less than $30,000	27.4	28.5	17.4	11.1
$30,000 to $74,999	36.3	37.4	32.3	5.1
$75,000 to $124,999	22.2	21.4	24.1	-2.7
$125,000+	14.1	12.7	26.2	-13.5
Age				
18 -34	30.5	31.3	31.8	-0.5
35 - 49	19.7	26.3	25.8	0.5
50 - 64	26.8	24.5	24.5	0.0
65+	23.0	17.9	17.9	0.0
Race/Ethnicity				
Non-Hispanic White	46.0	41.6	41.6	0.0
Non-Hispanic Black	7.2	5.7	5.7	0.0
Hispanic	27.5	34.5	34.5	0.0
Non-Hispanic Asian/Pacific Islander	11.8	10.7	16.0	-5.3
Non-Hispanic Others	7.6	7.5	2.2	5.3
Education Status				
Less than High School	6.8	15.2	15.2	0.0
High School Equivalent	12.8	23.1	23.1	0.0
Some College	40.1	29.9	28.6	1.3
Bachelor's Degree	23.9	18.8	21.7	-2.9
Graduate Degree	16.4	12.9	11.4	1.5
Household Ownership				
Owner Occupied	52.3	52.6	56.7	-4.1
Renter Occupied/Other	47.7	47.4	43.3	4.1
Children in Household				
1+ Under 18 years	29.9	35.0	37.3	-2.3
No Children Under 18	70.1	65.0	62.7	2.3
Marital Status				
Currently Married	40.9	43.0	52.0	-9.0
Not Currently Married	59.1	57.0	48.0	9.0
Gender				
Male	41.0	48.8	48.8	0.0
Female	59.0	51.2	51.2	0.0

Note: These balance weights were constructed using 1,005 respondents that completed any portion of the survey. The benchmark data for California come from the Current Population Survey, March Supplement 2016.

one method of disposal. Of the 893 respondents that purchased CRV beverage containers in the previous week, 23% said that they had visited a recycling center to dispose of their containers purchased over the previous week, 43% saved their containers for a future visit to a recycling center, 37% recycled the containers in curbside collection or in places outside of the home, and 9% put the containers in the trash.

Household income was a major factor correlated with different recycling method choices, as indicated in

Table 3: How did you (or someone in your household) dispose of the eligible beverage containers that your household purchased in the last week?

	(1) Respondents (#)	(2) Respondents (share)
Redeemed at a recycling center	205	23%
Saved them to redeem for money later	394	43%
Curbside collection	294	32%
Recycled at a place of work, education, worship, or entertainment	49	5%
Put them in the trash	81	9%
Other	44	5%

Note: Column 1 is the weighted sample of survey respondents who said they used the method of disposal for at least one beverage container purchased that week, rounded to the nearest integer, and Column 2 is the corresponding weighted share of respondents.

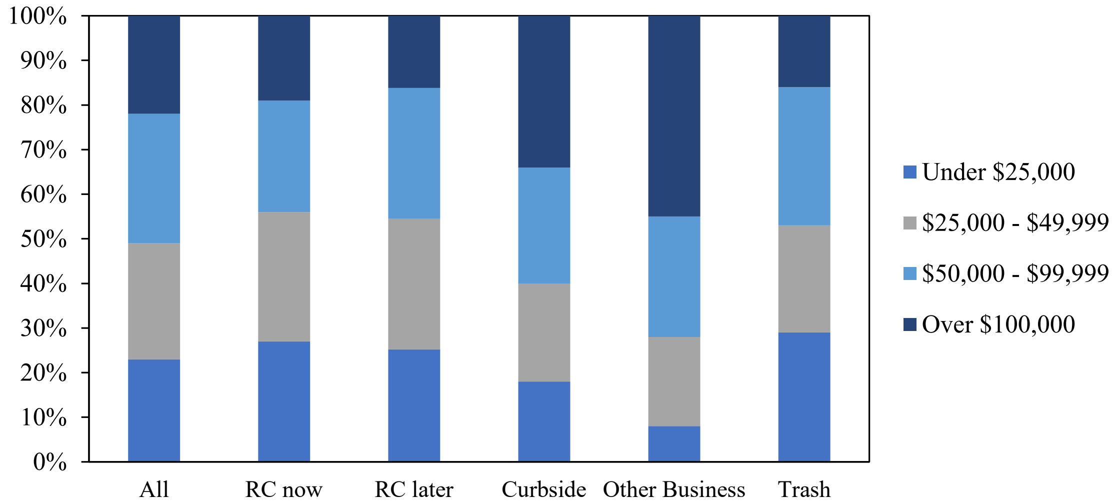
Figure 1. In this figure, we split the sample into four roughly equal annual household income bins—under \$25K, \$25-50K, \$50-100K, and over \$100K.[12] We find that respondents under \$50K are slightly more likely to report using recycling centers, while those over \$50K are much more likely to use curbside recycling and to recycle at other businesses away from home.

The choice of recycling method also varies across other demographics, as shown in Appendix Table A.1. Households with more than 4 individuals make up 40% of the sample, but 50–55% of households using recycling centers. This is as expected since we find larger households also consume more containers, and thus may face a lower per-container cost of transportation to a recycling center. In addition, non-Hispanic, white respondents are more likely to use curbside recycling, Hispanic respondents are more likely to use recycling centers (and to have visited a center in the previous week), and Asian respondents are more likely to recycle at other businesses (i.e., places of education, work, religion, and entertainment). Those with higher educations are more likely to recycle using curbside or other businesses, as well as to dispose of containers in the trash, while those with lower educations are more likely to frequent recycling centers. Recycling methods are largely consistent across age and gender, the exception being recycling at other businesses, which is higher for men.

We estimate how far a respondent is from their nearest recycling center using the zip code of their home address. To do this, we geocode the centroid of the zip code and find the minimum distance from that centroid to the locations of the recycling centers in California. Using this approach, on average, the respondents in our sample live an estimated 3.55 miles away from their nearest recycling center. Additionally, respondents

[12] For reference, the median income in California for 2015 was \$64,500.

Figure 1: Income shares by disposal method



Note: "All" indicates all 893 households purchasing CRV containers in the previous week. "RC now" indicates that the household shopper went to a recycling center to return the CRV beverage containers purchased within the last week. "RC later" signifies that the household shopper saved their CRV containers to return to a recycling center in the future. "Curbside" indicates that the consumer put their CRV beverage containers in a curbside bin. "Other Business" signifies that the consumer brought their CRV containers to a school, a workplace, or a place of worship to recycle. "Trash" indicates that the consumer put their CRV containers in the garbage. Each survey respondent had the opportunity to choose more than one of these options.

who state they live too far away from their nearest recycling center to use one, live an estimated 4.40 miles away from their nearest center.

With respect to curbside recycling access, over 97% of the survey respondents live in a municipality that offered some level of curbside recycling services, although 16% of our respondents say that they do not personally have access to curbside recycling. For households that report disposal of CRV-eligible containers in the trash, 42% report not having access to curbside recycling. On average, the respondents who dispose of their beverage containers using curbside collection purchased 10 to 20 fewer containers than those using a recycling center (either now or later), suggesting the volume of beverage containers purchased is correlated with disposal choice.

Table 4 shows the results when we ask respondents if they would recycle their beverage containers at a recycling center if there was a hypothetical change in CRV for containers under 24 ounces. The current value of the CRV is five cents per container, but only 29 percent of the sample knew this before we informed them in the survey. The potential change in CRV varied randomly across the respondents.[13] In alignment with our expectations, the proportion of people who report they would take their containers to a recycling center increases with an increase in the CRV refund. The response rates vary based on current recycling methods,

[13]Respondents were shown a randomly-assigned hypothetical CRV value of either $0.07, $0.10, $0.15, $0.20, or $0.40. All of these are larger than the current CRV refund for containers under 24 ounces of $0.05.

specifically between respondents who currently place beverage containers in curbside bins and respondents who currently place containers in the trash, as seen in the second and third panels of Table 4. People who currently recycle via curbside and/or put their containers in the trash are less likely to visit a recycling center at every CRV-level. However, the curbside recyclers are more likely to change their behavior to recycling centers under a low shift in CRV than those who dispose via trash. We validate these estimates via regression analysis in Section 5.4, after running our mixed logit model.

Table 4: If the money you received for redeeming one small CRV-eligible beverage container increased to the following number of cents from 5 cents, would you redeem your household's CRV-eligible containers at a recycling center?

	7 cents	10 cents	15 cents	20 cents	40 cents	Total
All Survey Respondents						
Yes	0.66	0.71	0.83	0.86	0.89	0.79
	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
No	0.34	0.29	0.17	0.14	0.11	0.21
	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
Total	173	210	164	164	182	893
Current Curbside Recyclers						
Yes	0.34	0.41	0.68	0.75	0.86	0.58
	(0.11)	(0.07)	(0.07)	(0.08)	(0.05)	(0.04)
No	0.66	0.59	0.32	0.25	0.14	0.42
	(0.11)	(0.07)	(0.07)	(0.08)	(0.05)	(0.04)
Total	53	71	53	53	54	284
Currently Disposes via Trash						
Yes	0.11	0.35	0.75	0.83	0.82	0.68
	(0.08)	(0.14)	(0.11)	(0.10)	(0.08)	(0.06)
No	0.89	0.65	0.25	0.17	0.18	0.32
	(0.08)	(0.14)	(0.11)	(0.10)	(0.08)	(0.06)
Total	10	15	21	21	20	87

Note: Standard errors are in parentheses. Each weighted respondent was assigned randomly to one of the five following changes in CRV value, and were asked whether or not they would change their recycling behavior under the change.

These descriptive statistics provide a preview of our main finding, namely that transaction costs are essential in understanding the recycling methods that people choose. Those who live farther from recycling centers and those with fewer CRV-eligible containers are less likely to use recycling centers. Furthermore, consumers appear to conduct a cost-benefit analysis, weighing the CRV benefit against the effort costs associated with a particular disposal method.

3.0.1 Selection and Representativeness

In order to estimate WTP for recycling options of Californians, we rely on a random, representative sample (after the appropriate weighting). However, we still may be concerned that those respondents who have convenient access to recycling centers is a selected sample: individuals who choose to live somewhere with access to a recycling center may inherently value recycling centers more. We can partially alleviate these concerns by relying on a relatively exogenous temporal shock to the number of recycling centers in existence, which came with the passage of the Bottle Bill. Within four months after the implementation of the Bottle Bill, the number of recycling centers increased in the short term by 1723 centers. For context, there only are approximately 400 centers in operation across California today. If sorting of residents based on location of recycling centers occurred, we would expect people who are more likely to use recycling centers to move into zip codes where recycling centers were in operation in response to the shock.

To test this hypothesis, we look at key demographic variables in zip codes that received recycling centers in 1987 as well as those that did not receive a new recycling center during this period. While we only have decennial census data to evaluate, Table 5 shows observable demographic factors which are highly correlated with recycling center use from 1970 to 2000 (periods before and after the passage of the bill). None of the p-values for the difference-in-means tests are statistically significant. This suggests that the zip codes that received these recycling centers were not substantially different in demographic makeup than the zip codes that did not receive centers. In addition, this did not change after the passage of the bottle bill, giving us confidence that we plausibly identify the WTP for attributes of various disposal methods for Californians in general, and not just those who particularly value recycling.

4 Empirical Strategy to Estimate Willingness to Pay for Recycling Methods

In evaluating the impact of types of recycling options on consumer choice, we define disposal methods as a bundle of attributes, providing the framework to compute consumer choices and implied consumer WTP for product attributes in a straightforward way. The survey data, which includes individual choices along with demographic information, allows us to consider heterogeneous preferences in a discrete choice framework. Similar to the work by McFadden and Train (2000) and Train (2009), we use a random utility framework where the error and the product attributes enter linearly. Our utility function is as follows:

$$U_{ji} = X_j\beta_i + \alpha \; distance_j + \epsilon_{ji} \tag{1}$$

Table 5: Demographic characteristics of the zip codes that received a new recycling center after the Bottle Bill passed in 1987, compared to zip codes that did not get a new center

	Zip Codes with new centers Mean	Other Zip Codes Mean	Difference in Means p-value
White Population (Percent)			
1970	0.9402	0.9373	0.7882
1980	0.8383	0.8552	0.4692
1990	0.7919	0.8064	0.6217
2000	0.7224	0.7291	0.8234
Hispanic Population (Percent)			
1970	0.12044	0.09452	0.3181
1980	0.1713	0.1424	0.3516
1990	0.2174	0.1923	0.468
2000	0.2634	0.2485	0.6845
Education (Percent)			
Less than 9th Grade, 1970	0.1413	0.1355	0.5758
Less than 9th Grade, 1980	0.10515	0.09061	0.1684
Less than 9th Grade, 1990	0.07707	0.06897	0.4316
Less than 9th Grade, 2000	0.06539	0.0637	0.8579
Some High School/College, 1970	0.3667	0.3708	0.7793
Some High School/College, 1980	0.4135	0.4174	0.8133
Some High School/College, 1990	0.4597	0.4556	0.816
Some High School/College, 2000	0.4604	0.4446	0.359
College Degree, 1970	0.05004	0.05519	0.3797
College Degree, 1980	0.08321	0.09344	0.2386
College Degree, 1990	0.1107	0.1127	0.8671
College Degree, 2000	0.1284	0.1338	0.7094

Note: Data in this table comes from the American Community Survey (ACS) provided by IPUMS.

Here, the matrix X_j is composed of attributes of the disposal methods j, and β_i is the marginal utility that the individual i places on the respective attributes. $distance_j$ is the distance to travel to option j (estimated as explained in Section 3), with corresponding marginal utility α. If a respondent waits to take their containers to a recycling center, distance is scaled down to reflect the reduced frequency in traveling to recycling containers. On average, respondents who wait to take their containers to a recycling center go monthly, so, for respondents who wait, distance is scaled down to 25% of the distance faced by respondents who go to recycling centers weekly.

A respondent will choose a disposal method based on whether it maximizes their utility, such that the probability of choosing a disposal method can be written as:

$$Pr(Choice_j) = Pr(U_{ji} > U_{hi} = Pr(X_j\beta_i + \alpha \ distance_j + \epsilon_{ji} > X_h\beta_i + \alpha \ distance_k + \epsilon_{hi}), \forall h \neq j \quad (2)$$

The following closed form solution of equation 2 can be derived for the probability that a respondent's disposal choice corresponds to disposal method j:

$$Pr(Choice_j, respondent_i) = \frac{\exp^{X_j\beta_i+\alpha\ distance_j}}{\sum_{k=0}^{N}\exp^{X_k\beta_i+\alpha\ distance_k}}. \tag{3}$$

Distributional assumption about β_i and ϵ_{ji} drive the econometric model choice. We assume that ϵ_{ji} is distributed i.i.d. extreme value. We run a conditional logit model, specifying that $\beta_i = \beta_0 + \beta_1 D_i$, where D_i are consumer demographics. We also run a random coefficients logit model, allowing β_i to vary for each respondent by the structure $\beta_i = \beta_0 + \beta_2\nu_i$, where ν_i is a normal random variable that captures heterogeneity in preferences for attributes of the disposal methods. Finally, we run a mixed logit specification, such that $\beta_i = \beta_0 + \beta_1 D_i + \beta_2\nu_i$.

While we explicitly ask each respondent how often they visit recycling centers, it is necessary in terms of estimation for the distance vector to be associated with the same marginal utility parameter for all people in the sample, in order to estimate the consumer surplus. This may be of concern, given that some individuals are choosing to wait to recycle less frequently, as we've currently modeled those visiting recycling centers as doing so on a weekly basis. We deal with this issue by weighting the distance vector by 0.25 for individuals who respond that they wait to visit a recycling center, since the majority of those who go to recycling centers less frequently do so on a monthly basis. Therefore, our assumption is that the effort required to take containers to a recycling center infrequently is on average 25% of the effort required to take recycling materials to a center on a weekly basis, for respondents in the same zip code. Otherwise, the valuations of other characteristics vary depending on the attributes of the household (such as the amount of CRV redeemed, going to a handling-fee center over a processing fee center, choosing an environmentally friendly option, etc.). The mean utility of the option to throw beverage containers into the trash is normalized to zero, as the outside option. We believe that there is some utility gained from disposing of containers in a variety of recycling methods, such as through curbside or another business, even if it is manifested only in feeling good about doing something positive for the environment.

By normalizing the mean utility of the outside option to zero, the predicted probabilities simplifies to:

$$Pr(Choice_j, respondent_i) = \frac{\exp^{X_j\beta_i+\alpha\ distance_j}}{1+\sum_{k=1}^{N}\exp^{X_k\beta_i+\alpha\ distance_k}} \tag{4}$$

Using the results of our estimations, we are able to estimate the WTP for attributes of disposal methods, by dividing the marginal utility of the attribute by absolute value of the parameter of the distance α_j. For example, the willingness to pay for a handling fee center is given by:

$$WTP_{handling} = \frac{\beta_{handling}}{|\alpha_j|} \tag{5}$$

Finally, we are able to relate the estimated willingness to pay to each respondents' demographics by estimating the equation:

$$WTP_i = \gamma_0 + \gamma_1 D_i + \epsilon_i \tag{6}$$

where WTP_i is a vector of all the respondents' individually estimated willingness-to-pay for CRV and estimated willingness-to-pay for a recycling center being a handling fee center. D_i are the demographic characteristics of respondent i, and γ_0 and γ_1 are estimated parameters.

5 Results

First, we present the results from the conditional logit specification in order to determine if the value placed on disposal method attributes vary based on observable characteristics of the respondents. Then we explore more flexible random coefficient logit and mixed logit choice models. We use the Akaike information criterion (AIC) in order to compare the models and to better understand the best specification. Given the choice estimates, we find the implied marginal utilities for CRV and handling-fee centers.

5.1 Conditional Logit Estimates

In Table 6, we present the estimates of the conditional logit choice model specification, where the dependent variable in all of the columns is an indicator variable that is equal to one if an individual chose a specific disposal method or combination of disposal methods, and equal to zero otherwise. For example, a choice to only recycle containers curbside is considered separately from a choice to recycle some containers curbside and take others to a handling fee center weekly, and is also separate from recycling containers curbside and waiting to go to a handling fee center on an infrequent basis. This leads to 23 total possible combinations of disposal methods and timings.

In Column (1), the right hand side variables are the distance, a "Handling" dummy that is equal to one if a recycling center is a handling fee center and equal to zero otherwise, an "Other Recycling" dummy that is equal to one if an alternative involves recycling, but not physically going to a recycling center (i.e.

Table 6: Logit Choice Estimates

	(1) Choice=0/1	(2) Choice=0/1
Distance	-0.204***	-0.205***
	(0.046)	(0.046)
CRV	0.521***	0.636***
	(0.079)	(0.106)
Handling	-0.542***	-0.543***
	(0.164)	(0.164)
Other Recycling	3.224***	3.221***
	(0.373)	(0.373)
Inc_CRV		-0.004
		(0.004)
White_CRV		-0.026
		(0.035)
Age_CRV		0.008
		(0.010)
Edu_CRV		-0.013*
		(0.007)
Qty_CRV		0.000*
		(0.000)
Constant	-5.022***	-5.014***
	(0.351)	(0.350)
Num of Obs.	20539	20539
Log Likelihood	-3458.393	-3441.765
AIC	6926.787	6903.529

Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.
Note: The table displays the estimates of Logistic regressions where the dependent variable is equal to one if an alternative if chosen and equal to zero otherwise.

curbside recycling or recycling at work), and "CRV", which is equal to five cents if an alternative is going to a recycling center, and is scaled down if multiple options beyond recycling centers are chosen. For example, for respondents that took containers to a recycling center and recycled through curbside, the "CRV" value is scaled down to 2.5 cents, because half of the options chosen do not lead to getting the CRV back.

From the estimates in Column (1), we see that the coefficient of distance is negative and significant, meaning that an increase in distance from a recycling center will decrease the incentive to recycle containers at a center. The coefficient on CRV is positive, suggesting that there is an appeal to using recycling centers in order to retrieve the value of the CRV. The handling-fee center attribute is negative and significant. Handling-fee centers often pay in vouchers rather than in cash, making it a potentially less desirable choice if there are multiple recycling centers in a person's immediate area. Additionally, we see that the attribute of recycling at a location other than a recycling center is positive and significant. This may be due to the "warm glow" feeling of helping the environment or helping family and friends receive the value of the CRV (when donating their recyclables to others).

In Column (2), we further interact demographic characteristics such as age, income, education, and quantity of containers purchased. Education interacted with the CRV is significant at the 10% level, suggesting that with higher education, the value of going to a recycling center to redeem beverage containers is less appealing. The quantity of beverage containers interacted with the CRV is also significant at the 10% level, suggesting that the value of a recycling center increases for households with more containers to redeem. The lower AIC in the second model suggests that the second specification is preferred. We turn next to a flexible choice specification, where the average taste parameters are allowed to vary randomly for the respondents in the mixed logit specification.

5.2 Random Coefficients Logit Choice Estimates

The average marginal utility and individual's marginal utility are estimated using simulated maximum likelihood, using the methods of Revelt and Train (1999).[14] Estimates are presented in Table 7.

In the first two columns of Table 7, we present the estimates of the random coefficients logit choice model specification. The dependent variable is an indicator variable for the disposal choice(s), as specified above. The right-hand-side variables include indicators for handling-fee centers, indicators for outside recycling options, the CRV, and distance from a recycling center. Columns (1) and (2) differ by the number of these variables which we allow to have the random unobserved heterogeneity. In column (1), the CRV and handling-fee indicator are flexible, and in column (2), the CRV, handling-fee indicator, and outside recycling options are allowed to have random unobserved heterogeneity.

The top of Table 7 reports the average estimated marginal utilities. Similar to the conditional logit models, distance from a recycling center and handling fee centers have significant and negative coefficients, while non-center recycling options and the CRV have positive and significant coefficients.There is significant heterogeneity in the marginal utility of the CRV and other recycling options, given the significant and positive coefficients for the standard errors of the marginal utilities reported in the bottom of Table 7. We therefore investigate whether a random coefficient mixed logit is the preferred specification to move forward in estimating WTP, before we choose a model for the counterfactual analysis.

5.3 Mixed Logit Choice Estimates

In the third column of Table 7, we present the estimates of the mixed logit choice model specification, where β_i varies across demographics as well as across individual respondents. The dependent variable and

[14] The estimation of each β_i is a conditional average of the βs of the respondents similar to them, defined by demographic characteristics and similar choices when presented with the same options.

Table 7: Random Coefficient and Mixed Logit Choice Estimates

	(1) Choice=0/1	(2) Choice=0/1	(3) Choice=0/1
Mean			
Distance	-0.201***	-0.196***	-0.195***
	(0.043)	(0.043)	(0.042)
Other Recycling	2.352***	7.938***	8.242***
	(0.273)	(1.312)	(1.430)
CRV	1.248***	2.705***	6.970***
	(0.340)	(0.558)	(1.736)
Handling	-0.404***	-0.403***	-0.406***
	(0.125)	(0.125)	(0.126)
Inc_CRV			-0.055
			(0.071)
White_CRV			-1.369**
			(0.664)
Age_CRV			0.101
			(0.163)
Edu_CRV			-0.445***
			(0.136)
Qty_CRV			0.012**
			(0.005)
SD			
CRV	5.379***	-5.185***	4.851***
	(1.073)	(1.236)	(0.869)
Handling	-0.002	0.059	0.168
	(0.192)	(0.320)	(0.323)
Other Recycling		-11.248***	-12.177***
		(1.791)	(1.972)
Num of Obs.	20539	20539	20539
Log Likelihood	-2048.434	-1979.163	-1945.992
AIC	4108.867	3972.325	3915.983

Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.
Note: The table displays the estimates of the Mixed Logistic regressions where the dependent variable is equal to one if an alternative if chosen and equal to zero otherwise.

right hand side variables are the same as in the specifications in the random coefficients logit model, but the right-hand-side variables include demographic characteristics interacted with the CRV. In general, the sign, magnitude, and significance of the disposal method attributes do not change across the specifications, except with respect to CRV and Other Recycling attributes, which increase in magnitude. Households that identified as white interacted with CRV is also now significant, as are education and quantity of containers purchased. It is useful to note that in order to interpret point estimates for the attribute of interest, we can obtain the mean marginal utility of the CRV by taking the coefficient on CRV, and then adding the marginal utility with respect to a demographic characteristic, multiplied by the proportion of people with that characteristic.

The random coefficient mixed logit specification has the lowest AIC out of all of the models. Therefore, we use this as the specification to estimate the distribution of marginal utilities for different attributes, the distribution of the WTP, as well as the counterfactual policy simulations.

5.4 The effects of increasing the CRV on recycling center use

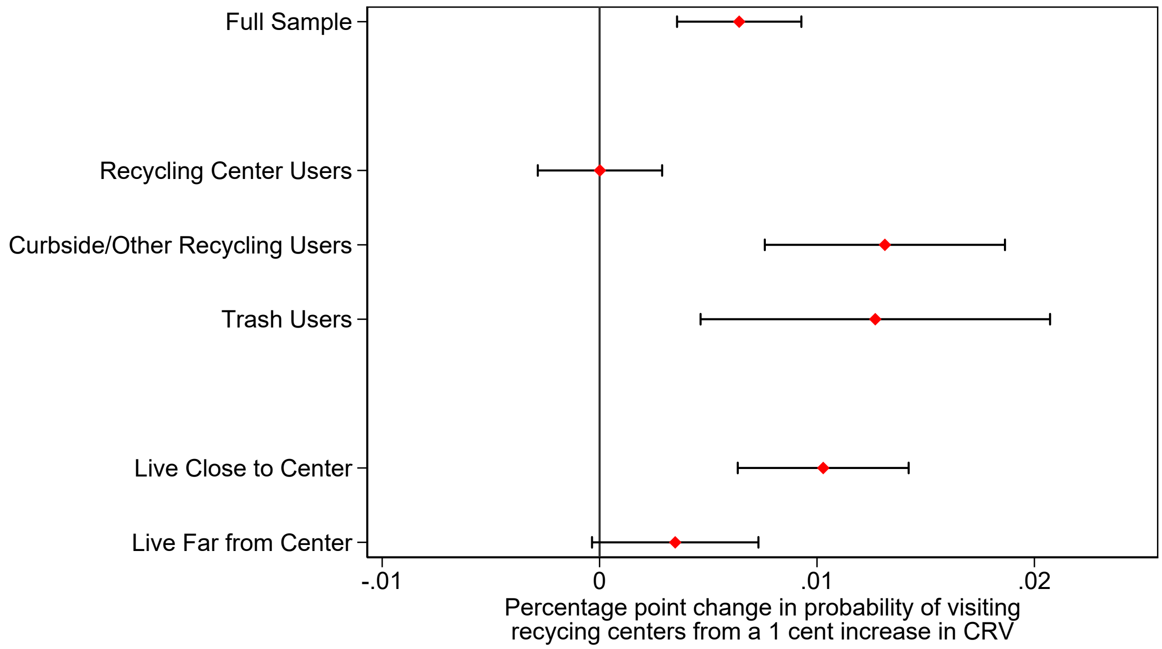
How would people respond to a hypothetical increase in the CRV level? Figure 2 shows the regression results when we ask respondents if they would recycle their beverage containers at a recycling center if there was a hypothetical change in CRV for containers. We use a linear probability model to estimate how a one-cent increase in the CRV would effect the reported likelihood that a respondent would visit a recycling center, estimated for the full sample and for subsamples of respondents. For the full sample, Figure 2 reveals that a one-cent increase in CRV would lead to a 0.64 percentage point increase in the probability of visiting a recycling center. Given 60 percent of respondents report using recycling centers with a CRV of 5 cents, a 0.64 percentage point increase equates to a 1 percent increase in the likelihood of visiting a recycling center.

Next we estimate the effects of a hypothetical change in CRV for subsamples of respondents by how they disposed of their actual containers in the previous week. As we expect, increasing the CRV has no effect on those already using recycling centers at 5 cents. Conversely, a one-cent increase in CRV leads to a 1.31 and 1.27 increase in the likelihood of visiting recycling centers for those who recycle via curbside or other businesses and for those that put containers in the trash, respectively. We also split the sample in half by whether respondents live above or below the median sample distance to a recycling center, which is 2.04 miles. We find that those living farther away from recycling centers would need the CRV to increase by 3 times as much as those living closer to a center to have the same increase in the probability of visiting a recycling center. Specifically, a one-cent increase in CRV would lead to a 1.03 and 0.35 percentage point increase in the probability of visiting a recycling center for those living closer and farther from recycling centers, respectively. These results, once again, show that respondents value having convenient recycling options and would need to be compensated to travel farther to a recycling center.

6 Choice Changes and Welfare Changes in Counterfactual Policy Simulations

Next, we ask the question of what would happen to respondents' choices and to consumer welfare in two counterfactual scenarios: if there was an change in the CRV, or if there were no handling fee centers. In order to answer these questions, we perform simulations and compute the utility-maximizing choices for each

Figure 2: Effect of Increasing CRV on Probability of Visiting Recycling Center



Note: Figure presents the results from a linear probability model for the following question, "If the money you received for redeeming one small CRV-eligible beverage containers increased to the following number of cents from 5 cents, would you redeem your household's CRV-eligible containers at a recycling center?" Respondents saw a randomly generated increase in CRV from 2 to 35 cents. The model was estimated for the full Sample of 893 households purchasing CRV containers in the previous week, and for the following subsamples: "Recycling Center Users" indicates households that reported either taking their containers to a recycling center in the previous week or saving their containers to take to a recycling center. "Curbside/Other Recycling Users" indicates the households that reported putting their beverage containers in a curbside bin or recycling at business away from home. "Trash Users" indicates the households that reported putting their containers in the garbage. "Live Close to (Far from) Center" indicates the households living below (above) the median sample distance from a recycling center.

respondent in the counterfactual scenarios. With these choices, we are able to simulate the new choices of the respondents, leading to an estimation of the distribution of changes in consumer surplus. We project these changes in consumer surplus on the demographic characteristics of our respondents, in order to better understand the "winners" and "losers" under these policy changes.

6.1 Simulating Individual Counterfactual Choices

For each counterfactual scenario, we keep the estimated marginal utilities for the attributes of the recycling opportunities the same as in the mixed logit model displayed in Column (3) of Table 7. We then estimate the probability of each disposal method or combination of disposal methods of being chosen pre-simulation, in order to estimate the baseline choices for all of the respondents. Once we change the vector of attributes, based on the predicted policy change, we recalculate the probabilities for each individual under the new attribute set. For example, simulating a closure of handling fee centers changes the distance for many of our households from the nearest recycling center. We recompute the travel cost of getting to a recycling center with this closure of centers. This also eliminates the "handling-fee" center indicator variable from the attributes.

We follow the procedure set out by Small and Rosen (1981), where the change in consumer surplus corresponds to an individual's compensating variation for a change in product attributes. Expected consumer surplus is defined as:

$$CS_i(j=1) = \frac{1}{|\alpha|} \ln \sum_j \exp X_j \beta_j - \alpha price_j$$

We estimate the consumer surplus under the original choice set, and re-estimate the consumer surplus with respect to the predicted choices made with the changed attributes. This allows us to estimate the average change in consumer surplus and relate these changes to individual characteristics, by estimating the equation:

$$\Delta(CS)_i = \delta_0 + \delta_1 D_i + \epsilon_i$$

Here, $\Delta(CS)_i$ is a vector of the estimated changes in consumer surplus for each respondent, under the policy change, and D_i are the demographic characteristics of respondent i.

6.2 Policy simulation of an increase in the CRV

We seek to understand the distributional effects of a change in the CRV. We simulate a change in the CRV from 5 cents for small containers (under 24 oz) and 10 cents for large containers (over 24 oz) to 10 cents for all containers. First, we estimate the predicted probabilities of the choices for each of the disposal methods (or combination of disposal methods) without a change in the CRV. These choices are depicted in the left panel of Figure 3. Although the predicted probabilities for each type and combination of disposal method were calculated, note that the diagram only depicts the predicted choices for a single disposal method for clarity. Here, choice 1 is taking containers to a handling fee recycling center, choice 2 is waiting to bring containers to a handling fee recycling center at some point in the future, choice 3 is using curbside for recycling or recycling containers at a school, place of work or worship, choice 4 is putting containers into the trash or some other type of disposal method, choice 5 is taking containers to a non-handling fee recycling center, and choice 6 is waiting to take containers to a non-handling fee recycling center in the future. Next, we update the CRV attribute column to reflect an increase in the CRV for each of the disposal methods and re-estimate the predicted probabilities for the updated choice set. These results can be seen in the right column of Figure 3. With an increase in the CRV, the predicted probability of using curbside and trash decreases, while the popularity of using recycling centers for disposal increases significantly. From a total welfare perspective, this decrease in the number of containers thrown in the trash could reduce the environmental costs, and increase returns to recycling centers.

Figure **??** provides a more comprehensive breakdown of how an increase in the CRV changes the consumer surplus for individuals. The consumers most affected by the policy changes are the consumers who change their behavior, since a CRV redemption means that a consumer is only getting back what they paid in the original tax. The people who benefit from the increase in the CRV are the consumers who were on the fence about going to a recycling center or not (white, higher income consumers). With an increase in the CRV to ten cents, it is clear that going to a recycling center will be worth their time and effort. To clarify this point, Figure 5 depicts how a decrease in the CRV to 2.5 cents changes consumer surplus. The people who lose from a decrease in the CRV are the middle and high-income consumers who had previously found it worthwhile to go to a recycling center, and are no longer doing so. The poorer population still finds it worth the effort to get their money back, and so their welfare losses are largely not statistically different from zero.

Figure 3: Estimated Changes in Consumer Surplus for a change in CRV from 5 to 10 cents

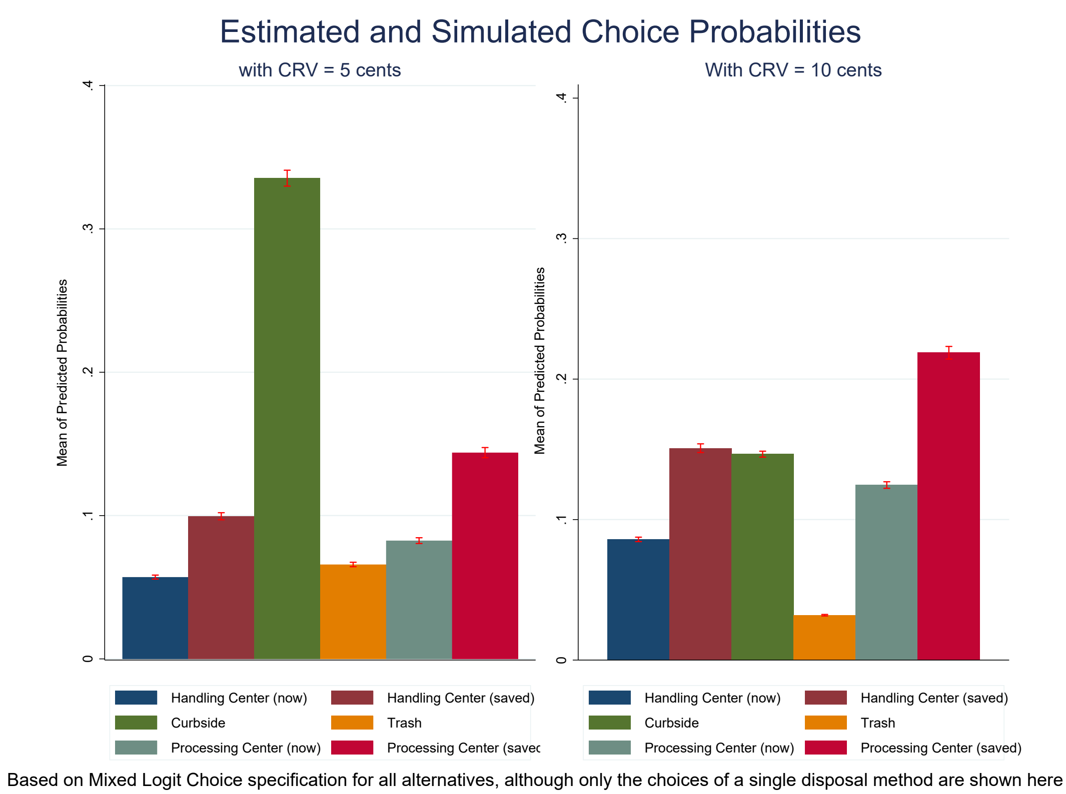
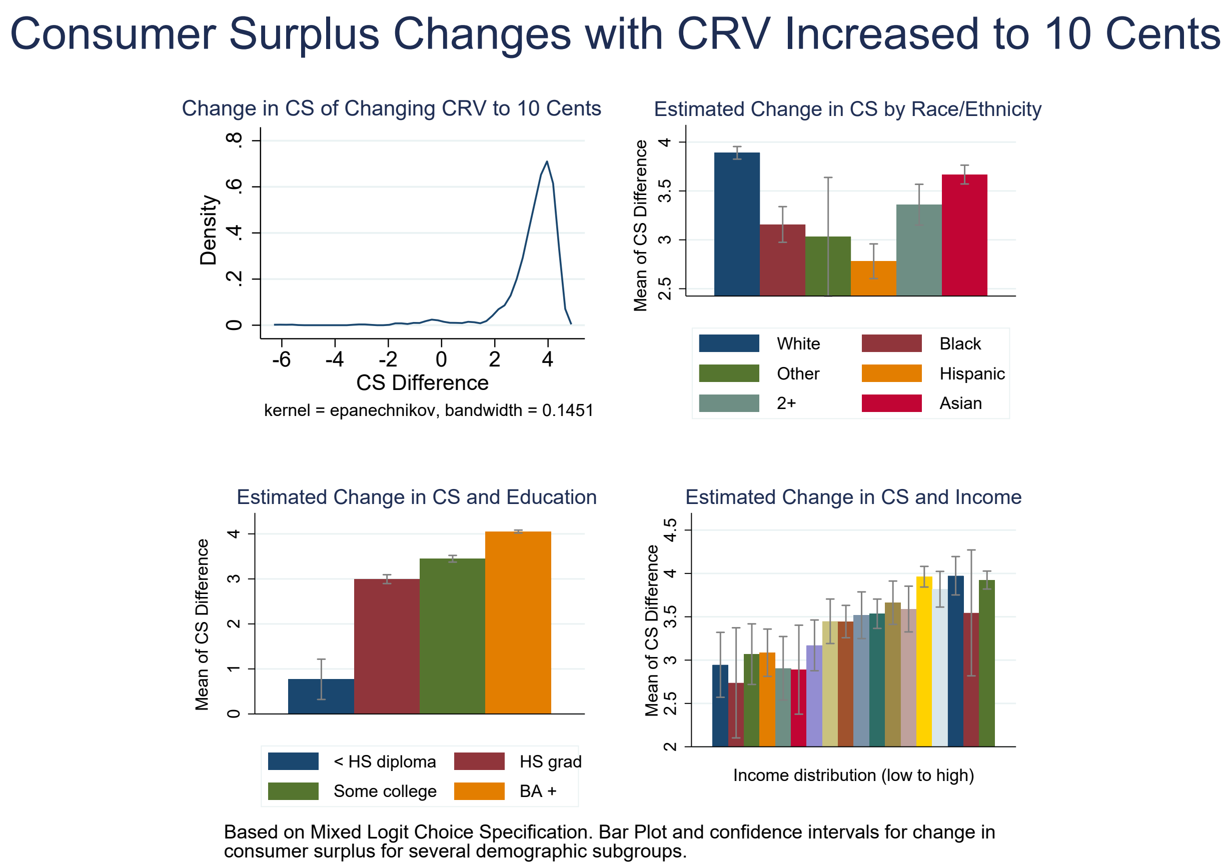


Figure 4: Estimated Changes in Consumer Surplus for a change in CRV from 5 to 10 cents



6.3 Policy simulation of the elimination of handling fee centers

Next, we turn to a different counterfactual policy analysis, to evaluate the change in consumer surplus with respect to a closure of all handling fee centers. Here, the attribute set changes in two dimensions. First, the distance to the nearest centers changes for almost half of the sample set, with the elimination of the handling fee centers. Secondly, the handling fee indicator variable is removed from the attribute list. This is important because handling fee centers, while there are largely located in convenient areas for shoppers, have some undesirable attributes for consumers (as indicated by the significant, negative coefficient in the mixed logit model), such as the fact that most handling fee centers pay in vouchers that can only be redeemed for cash within the grocery store. When asked about this attribute in the survey, 33% of respondents said that paying directly in cash was a specific reason for why they chose their preferred recycling center. Therefore, in estimating this counterfactual, there are both positive (lower travel costs) and negative (not paying in cash) attributes that are removed from the choice set.

Figure 5: Estimated Changes in Consumer Surplus for a change in CRV from 5 to 2.5 cents

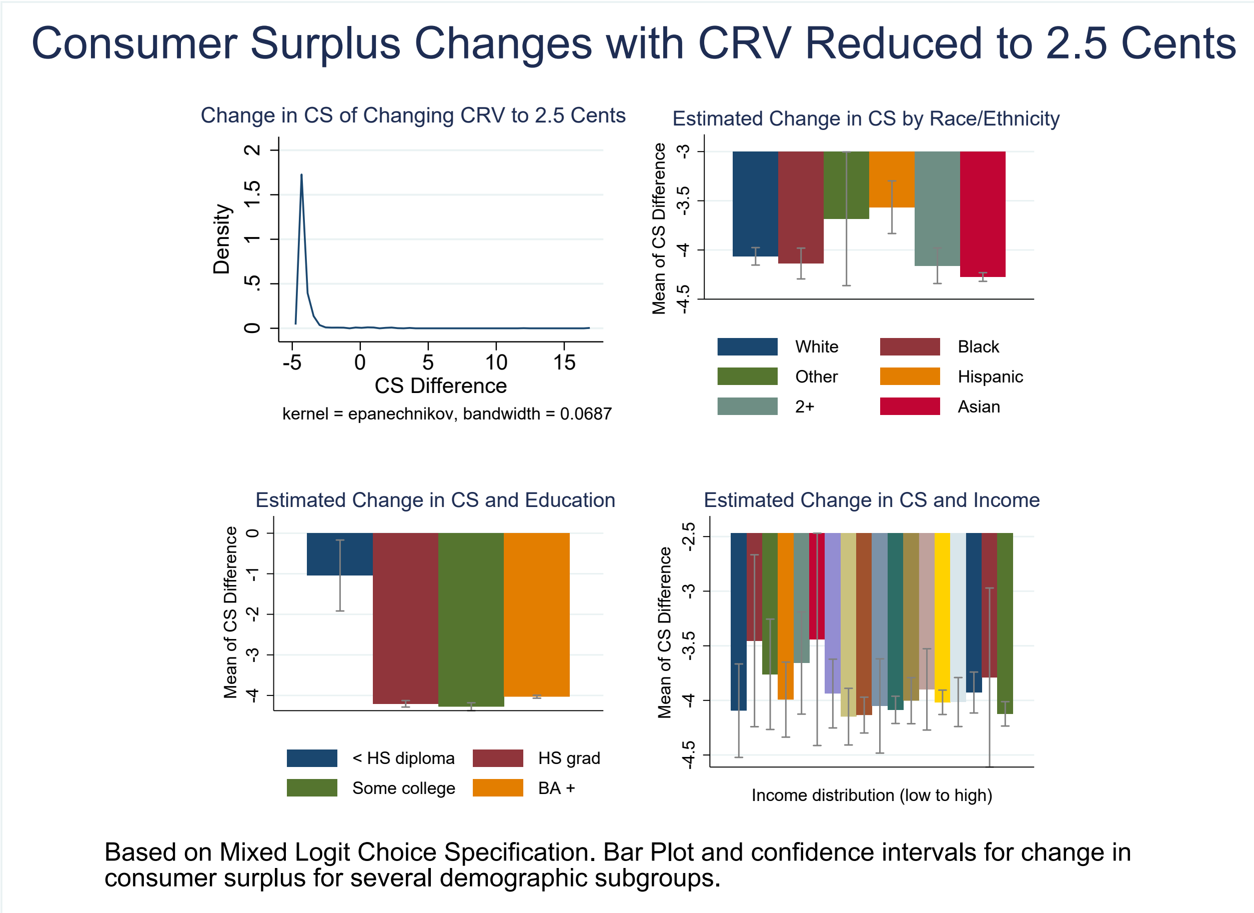
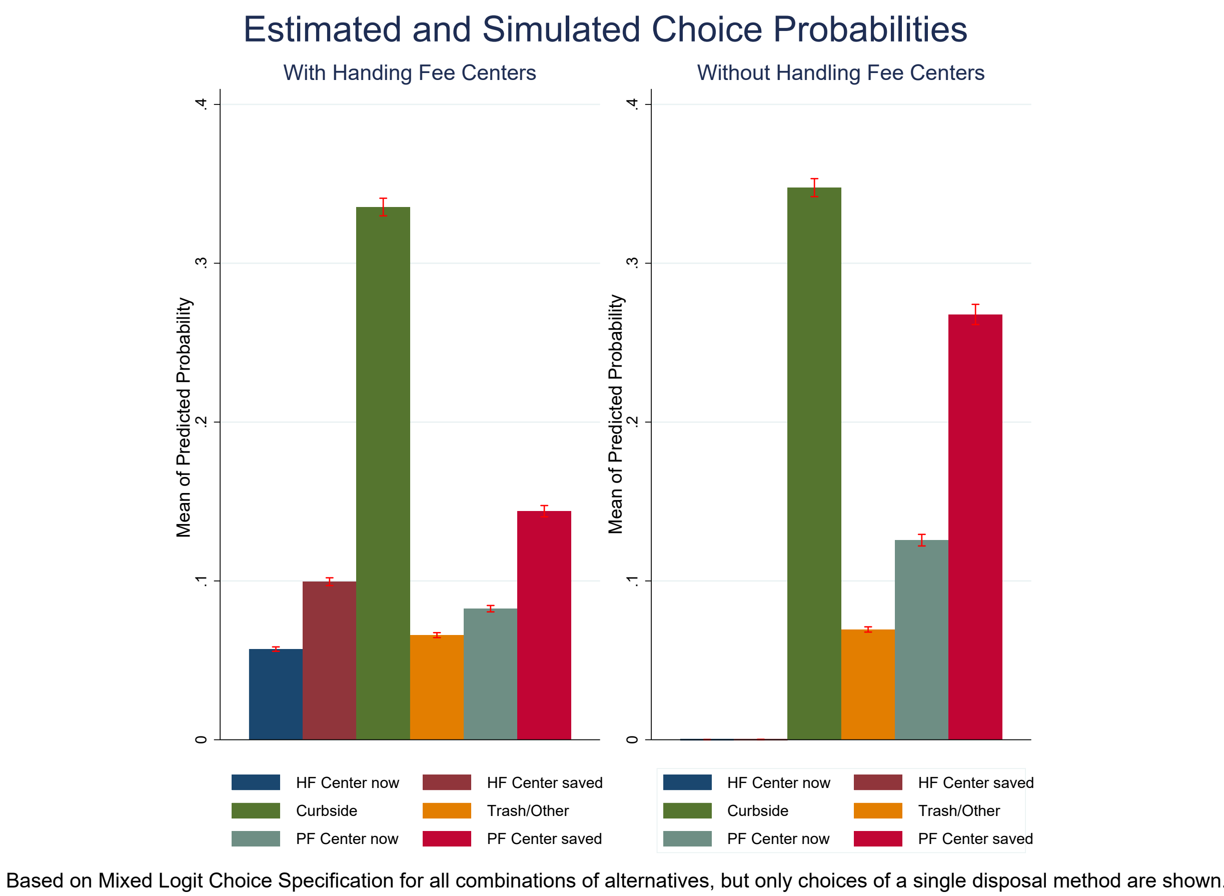


Figure 6 depicts the estimated and simulated choice probabilities under this counterfactual scenario. The estimated choice probabilities in the left panel of Figure 6 are the same estimated choice probabilities found in Figure 3. We see that after the removal of handling fee centers from the set, no one takes containers to handling fee centers, and the predicted probabilities for recycling containers via curbside, trash, or processing fee centers jump up. The magnitude of the change in the predicted probabilities for disposal through curbside and trash is much smaller than the change in probability of recycling at a processing fee facility. In addition, the probability of waiting to recycle at a processing fee facility (therefore going less frequently) shoots up, suggesting that the longer distance to a recycling center reduces the number of trips a household would take.

Figure 7 depicts the estimated changes in consumer surplus for the closure of the handling fee centers. The results are largely insignificant. The kernel density estimate for the change in consumer surplus is inconsistent, and changes in consumer surplus across various demographic traits are not significant, in line with the results of the mixed logit model. This suggests that handling fee centers are not providing major

Figure 6: Estimated and Simulated Choice Probabilities for a Closure in Handling Fee Centers

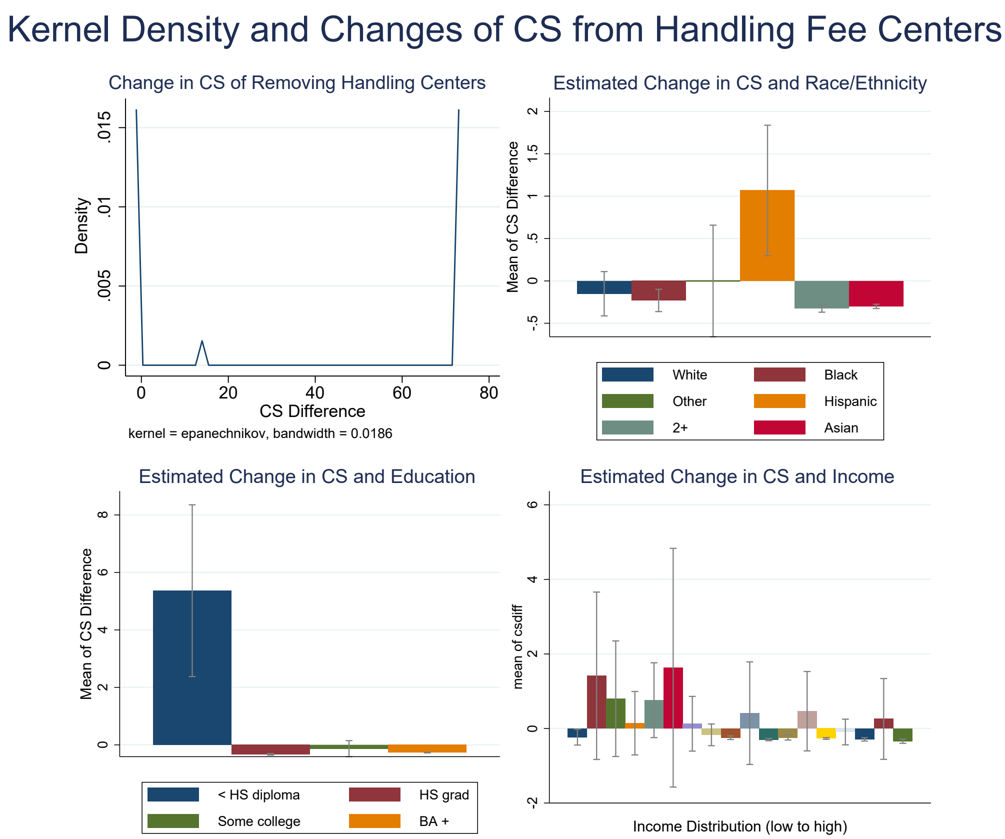


benefits to consumers, even as we break this down across demographic groups, except for small positive increases in consumer surplus for Hispanic consumers and those without a high school diploma. 97% of respondents who went to recycling centers drove, so a couple of additional miles added to their route does not seem to be a deterrent. Since handling fee centers take in only a small volume of the total containers recycled at recycling centers, it is expected that the removal of handling fee centers would not affect a large portion of the population, since demand for these centers is low. What is important and surprising is that the removal of the handling fee centers does not seem to disproportionately negatively affect any demographic group.

7 Conclusion

In this study, we sampled California residents on their stated recycling choices and estimated a structural choice model to infer their willingness-to-pay for various disposal methods of beverage containers. We used

Figure 7: Estimated Changes in Consumer Surplus for a Closure of Handling Fee Centers



Based on Mixed Logit Choice Specification. Bar Plot and confidence intervals for change in consumer surplus for several demographic subgroups.

an online survey to collect the data, asking California residents about their purchases of beverage containers, their knowledge of various recycling methods, their methods of disposal, and the reasons behind their choices. Using the survey, we estimated a flexible mixed logit discrete choice model for consumer preferences to obtain estimates for the average and the distribution of the willingness-to-pay for the different types of disposal methods and their attributes. We are the first paper to provide estimates of this sort, and this allows us to better understand how current CalRecycle policies may effect the distribution of welfare outcomes for consumers of CRV beverage containers. Our main results are robust in applicability to the demographic makeup of the California population.

We find that an increase in the CRV would, in general, encourage more recycling at recycling centers. Any positive benefits to consumers from an increase in the CRV are accrued by consumers that were on the fence between recycling their containers using curbside or taking their containers to a recycling center. With an increase in the CRV, this would reduce the number of containers entering both the curbside and trash streams, which could results in overall environmental gains. A decrease in the CRV would lead to the opposite implications. We also find that a closure of handling fee centers across California would not have a major impact on the welfare of California residents. The handling fee centers were put in place in order to best serve all of California residents, such that no one was burdened by the scope of the tax. However, our analysis shows that people who would have gone to a handling fee center will continue to go to processing fee recycling centers, just at a lower frequency than previously. This suggests that that the continual closure of handling fee centers may not negatively impact recycling opportunities for consumers, and may inform future decisions by CalRecycle as to whether to further subsidize handling fee centers.

References

Aadland, D. and A. J. Caplan (2003). Willingness to pay for curbside recycling with detection and mitigation of hypothetical bias. *American Journal of Agricultural Economics 85*(2), 492–502.

Aadland, D. and A. J. Caplan (2006). Curbside recycling: Waste resource or waste of resources? *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management 25*(4), 855–874.

Aadland, D. M. and A. J. Caplan (1999). Household valuation of curbside recycling. *Journal of Environmental Planning and Management 42*(6), 781–799.

Abbott, A., S. Nandeibam, and L. O'shea (2017). The displacement effect of convenience: the case of recycling. *Ecological Economics 136*, 159–168.

Ashenmiller, B. (2009). Cash recycling, waste disposal costs, and the incomes of the working poor: evidence from california. *Land Economics 85*(3), 539–551.

Beatty, T. K., P. Berck, and J. P. Shimshack (2007). Curbside recycling in the presence of alternatives. *Economic Inquiry 45*(4), 739–755.

Best, H. and T. Kneip (2018). Assessing the causal effect of curbside collection on recycling behavior in a non-randomized experiment with self-reported outcome. *Environmental and resource economics 72*(4), 1203–1223.

Blaine, T. W., F. R. Lichtkoppler, K. R. Jones, and R. H. Zondag (2005). An assessment of household willingness to pay for curbside recycling: A comparison of payment card and referendum approaches. *Journal of Environmental Management 76*(1), 15–22.

Bohara, A. K., A. J. Caplan, and T. Grijalva (2007). The effect of experience and quantity-based pricing on the valuation of a curbside recycling program. *Ecological Economics 64*(2), 433–443.

Calcott, P. and M. Walls (2005). Waste, recycling, and "design for environment": Roles for markets and policy instruments. *Resource and energy economics 27*(4), 287–305.

Caplan, A. J., T. C. Grijalva, and P. M. Jakus (2002). Waste not or want not? a contingent ranking analysis of curbside waste disposal options. *Ecological Economics 43*(2-3), 185–197.

Container Recycling Institute (2020). Current and proposed laws. *Bottle Bill Resource Guide*. http://www.bottlebill.org/index.php/current-and-proposed-laws/usa/additional-links.

Freedman, W. (2019, August). California's largest recycling center chain replanet closes all locations. *ABC 7 News*. https://abc7news.com/5447020/.

Fullerton, D. and A. Wolverton (2000). Two generalizations of a deposit-refund systems. *American Economic Review 90*(2), 238–242.

Gillespie, R. and J. Bennett (2013). Willingness to pay for kerbside recycling in brisbane, australia. *Journal of environmental planning and management 56*(3), 362–377.

Huber, J. and K. Train (2001). On the similarity of classical and bayesian estimates of individual mean partworths. *Marketing Letters 12*(3), 259–269.

Jakus, P. M., K. H. Tiller, and W. M. Park (1996). Generation of recyclables by rural households. *Journal of Agricultural and Resource Economics*, 96–108.

Jamelske, E. and G. Kipperberg (2006). A contingent valuation study and benefit-cost analysis of the switch to automated collection of solid waste with single stream recycling in madison, wisconsin. *Public works management & policy 11*(2), 89–103.

Karousakis, K. and E. Birol (2008). Investigating household preferences for kerbside recycling services in london: A choice experiment approach. *Journal of Environmental Management 88*(4), 1099–1108.

Katz, C. (2019, March). Piling up: How china's ban on importing waste has stalled global recycling. *Yale Environment 360*. https://e360.yale.edu/features/piling-up-how-chinas-ban-on-importing-waste-has-stalled-global-recycling.

Kinnaman, T. C. (2000). Explaining the growth in municipal recycling programs: The role of market and nonmarket factors. *Public Works Management & Policy 5*(1), 37–51.

Lake, I. R., I. J. Bateman, and J. P. Parfitt (1996). Assessing a kerbside recycling scheme: a quantitative and willingness to pay case study. *Journal of Environmental Management 46*(3), 239–254.

McFadden, D. and K. Train (2000). Mixed mnl models for discrete response. *Journal of applied Econometrics*, 447–470.

Naughton, M., F. Sebold, and T. Mayer (1990). The impacts of the california beverage container recycling and litter reduction act on consumers. *Journal of Consumer Affairs 24*(1), 190–220.

Numata, D. (2011). Optimal design of deposit–refund systems considering allocation of unredeemed deposits. *Environmental Economics and Policy Studies 13*(4), 303–321.

Palmer, K. and M. Walls (1997). Optimal policies for solid waste disposal taxes, subsidies, and standards. *Journal of Public Economics 65*(2), 193–205.

Porter, R. C. (1978). A social benefit-cost analysis of mandatory deposits on beverage containers. *Journal of Environmental Economics and management 5*(4), 351–375.

Porter, R. C. (1983). Michigan's experience with mandatory deposits on beverage containers. *Land Economics 59*(2), 177–194.

Reinhold, R. (1987, October). In california, truce in a bottle battle. *The New York Times*. https://www.theguardian.com/environment/2020/jan/02/year-plastic-pollution-clean-beaches-seas.

Revelt, D. and K. Train (1999). Customer-specific taste parameters and mixed logit. *University of California, Berkeley*.

Small, K. A. and H. S. Rosen (1981). Applied welfare economics with discrete choice models. *Econometrica: Journal of the Econometric Society*, 105–130.

Sustainable Packaging Coalition (2016). 2015-16 centralized study on availability of recycling. Industry report.

Tiller, K. H., P. M. Jakus, and W. M. Park (1997). Household willingness to pay for dropoff recycling. *Journal of Agricultural and Resource Economics*, 310–320.

Train, K. E. (2009). *Discrete choice methods with simulation.* Cambridge university press.

Troske, K., G. Blomquist, D. Hardesty, B. Koford, and M. Hughes (2009). Estimating willingness of citizens to pay for recycling. *Chicago IL: ISA-Industry Studies Association.*

U.S. Environmental Protection Agency (2013). Municipal solid waste in the united state: 2011 facts and figures.

Vidal, J. (2020, January). The plastic polluters won 2019 – and we're running out of time to stop them. *The Guardian*. https://www.theguardian.com/environment/2020/jan/02/year-plastic-pollution-clean-beaches-seas.

Viscusi, W. K., J. Huber, J. Bell, and C. Cecot (2013). Discontinuous behavioral responses to recycling laws and plastic water bottle deposits. *American law and economics review 15*(1), 110–155.

Table A.1: Proportion of respondents by demographic characteristics, for the entire sample and by disposal method

	All	RC now	RC later	Curbside	Other Business	Trash
Income						
Under $25K	0.23	0.27	0.25	0.18	0.08	0.28
$25–49K	0.26	0.29	0.29	0.22	0.20	0.24
$50–99K	0.30	0.25	0.29	0.26	0.27	0.31
Over $100K	0.22	0.19	0.16	0.34	0.45	0.16
Age						
18-29	0.23	0.25	0.26	0.21	0.35	0.29
30-44	0.29	0.32	0.30	0.33	0.38	0.26
45-59	0.25	0.20	0.24	0.24	0.17	0.26
60+	0.23	0.23	0.20	0.21	0.10	0.19
Race/Ethnicity						
White, non-Hispanic	0.39	0.22	0.36	0.47	0.32	0.40
Hispanic	0.37	0.53	0.44	0.26	0.28	0.31
Asian, non-Hispanic	0.10	0.11	0.07	0.12	0.20	0.12
Other, non-Hispanic	0.08	0.06	0.06	0.11	0.14	0.08
Black, non-Hispanic	0.06	0.07	0.07	0.03	0.07	0.09
Education Status						
Less than High School	0.16	0.30	0.17	0.15	0.05	0.11
High School Equivalent	0.23	0.21	0.29	0.15	0.19	0.20
Some College	0.31	0.29	0.33	0.25	0.29	0.26
Bachelor's Degree	0.30	0.21	0.21	0.45	0.48	0.43
Household Ownership						
Owner Occupied	0.52	0.48	0.51	0.54	0.64	0.32
Renter Occupied/Other	0.48	0.52	0.49	0.46	0.36	0.68
Household Size						
1	0.16	0.11	0.13	0.18	0.06	0.16
2	0.27	0.18	0.20	0.33	0.27	0.35
3	0.17	0.15	0.16	0.16	0.19	0.26
4+	0.40	0.55	0.50	0.33	0.48	0.22
Marital Status						
Not Currently Married	0.57	0.54	0.54	0.52	0.64	0.69
Currently Married	0.43	0.46	0.46	0.48	0.36	0.31
Gender						
Male	0.49	0.52	0.48	0.49	0.58	0.46
Female	0.51	0.48	0.52	0.51	0.42	0.54

Note: The column "RC now" indicates that the household shopper went to a recycling center to return the CRV beverage containers purchased within the last week. "RC later" signifies that the household shopper saved their CRV containers to return to a recycling center in the future. "Curbside" indicates that the consumer put their CRV beverage containers in a curbside bin. "Other Business" signifies that the consumer brought their CRV containers to a school, a workplace, or a place of worship to recycle. "Trash" indicates that the consumer put their CRV containers in the garbage. Each survey respondent had the opportunity to choose more than one of these options. The proportions for all sample respondents are represented in the column "All". The number of observations in each category are listed in the row "Total". These data come from the survey question, "Of the CRV-eligible containers that your household purchased in the last 7 days, how many were returned using the following disposal methods?".

An * indicates that the use of a particular method of disposal significantly varies by the demographic characteristic, at a 95% confidence level