Chapter 4. Statistical Estimates of Program Efficiency

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The Model

Our empirical model of California recycling utilizes data collected for the administration of the bottle bill program and publicly available county data. In the recycling program data, we observe the number of containers, by container type, that are sold in California and we observe the disposition of the containers by county. In this section, we model the disposition of containers as a function of elements of the distribution and disposition chain.

These containers (and the beverages in them) are sold by distributors to retail outlets (including vending machines, traditional food stores and cold cases in other types of stores). Figure 1 depicts this flow for the simpler case of two counties (Alameda and Contra Costa in the example and two types of disposal, recycling centers and curbside). The data includes the number of containers that are sold, but they do not contain the county where the final sale takes place. The containers are purchased by consumers. The consumers then consume the beverages and dispose of the containers. The disposal of the containers is observed: data include the county of disposal, type of container, the method of disposal, and the date the disposal was reported.

Thus one observes state wide sales (by container type) and then disposition by type of program and county. There is one way for containers to enter this system, but we have categorized their possible return into 168 ways: three modes of return for each of 56 included counties (Alpine and Sierra counties were not included because of lack of data.).

The first step in the modeling process is to explain the distribution of the containers to counties, given the total number of containers distributed in the state. To begin with, the demand for beverages is a function of consumer income, the price of beverages including their cost of disposal, the price of other goods, population, and environmental variables like temperature. One expects higher beverage consumption in hotter weather, when income is higher, or when prices are lower. For these reasons, one expects a higher fraction of the containers sold in the state to be sold in those counties that are higher in income or are hotter. Similarly, more beverages are sold at times of the year when it is hotter. There is no measure of price variation for beverages within the state (on a quarterly basis) so this variable is not used. These considerations lead to the first stage of the model: The containers in a county are a function of the total number of containers in the state, weather, and county income. In terms of figure 1, these are the variables that determine the split into counties.

Given the number of containers emptied in a county in a calendar quarter, the consumers have a choice of how to dispose of these containers. For the purposes of this study, we have grouped all disposal methods into four groups: (1) return for deposit, (2) return not for deposit, (3) curbside pickup, (4) all other means. Containers can be returned for deposit at certified recycling centers. The "cost" to the consumer of returning a container in this mode is mainly the time and effort to sort the containers and physically return them, while the benefits are the CRV and any satisfaction that comes from not landfilling the containers. The value of time increases with income so higher income leads to less use of return for deposit. Lower unemployment rate has the same effect. The CRV and the scrap value are monetary incentives to use return for deposit. The degree of urbanity, both in terms of density of population or in number of apartment dwellers may be proxies for either unmeasured ease of return of bottles in urban areas or taste for recycling per se. In California, there are “convenience centers” within ½ mile of every major food store. These centers keep limited hours. Since the centers are not within the food store and not necessarily open when the consumer would otherwise be shopping, there is a probability that the return of containers requires a separate trip and hence has a higher time cost. This probability decreases as the number of hours that the centers are open increases. Thus we include in our model the average number of hours that the convenience centers are open. The distance to the nearest certified recycling center may also be a detriment to the use of this mode of disposal, so we include a variable that measures the density of centers in the county and another variable that measures the density of the population.

The mode of returning bottles without deposit is attractive to consumers who wish to recycle, but are willing to forgo receiving the deposit in exchange for a more convenient way to recycle. Many certified recycling centers have lines and can take significant amounts of time and effort to accomplish the recycling task. Drop off centers typically permit the rapid recycling of both large and small volumes of material, usually including newspaper, cardboard and aluminum that are not within the program, all in the same trip.

The third modality of recycling is curbside pickup programs. These programs were not initially widespread and have, over the sample period, included many more households. (Another section of this report gives the details of the curbside program.) Thus the percent of households that were served by curbside is an important variable for determining the mode of recycling. The last mode of disposal is not directly measured: it is containers that are either landfilled or are improperly disposed of.

The data are observations on the volumes collected by these modalities and these volumes are not determined only by consumer choice of mode of disposal One purpose of a container recycling program is to induce other people to redirect the flow of containers from landfilling and inappropriate disposal to return for deposit. The same incentive causes these agents (commonly called scavengers) to redirect material from curbside to return for deposit. The bottom loop of figure 1 shows the effect of scavengers. Unemployment and low income should both be positively associated with greater scavenging, both from inappropriate disposal sites and from material placed for collection at curbside. (Another section of this report examines this phenomenon in greater detail.) Density of residential settlement makes scavenging more profitable (less distance traveled per container diverted) and so the density variables should also help capture the scavenging effect.

Rural places differ from cities in that they do not have curbside garbage pickup. In this case, the time commitment to recycle and the time commitment to simply discard a beverage container may be the same. All garbage is taken by the consumer to a dumping facility and it is common for there to be a recycling option at the dump itself. For this reason, it may be that recycling is more common in rural areas.

There is one other determinant of recycling that we have not explored: the role of preference for recycling. It may be that counties with higher proportions of consumers who value recycling per se recycle more. Proxies for these preferences might include voting records on environmental initiatives and party affiliation.

Based upon these considerations, the variables including in the econometric model are defined in the table 1. The sample period is 1994 to 2000.

One property of this model is that the number of containers that are returned cannot exceed the number that is sold (at least in the long run.) In order to enforce this constraint upon the estimation and on the predictions, we chose to model returns as follows. We run separate regressions for each material type. The dependent variable in our regression is the percent of material returned in a specific program in a specific county divided by the percent of material not returned in the state. For example, the percent of state-wide cans sold that are returned in curbside programs in Alameda county divided by the percent of cans not returned in any program statewide. Of course, we have observations on these dependent variables for every quarter in our sample and for every county in our sample. The appendix gives a technical description of this estimation which includes the possibility of using a Tobit estimator to account for the non-negativity of the sample shares. The current estimation is done within the least squares framework, however.

Results

The regressions were run in the form described above and the regression coefficients, their standard errors, asymptotic t statistics, probability greater than t, and 95 percent confidence intervals are reported in tables 2-10. The tables also report the number of observations, the R^2, and the root mean squared error. The R^2 for the recycling center regressions were all over 70 percent while some of the dropoff and curbside regressions fit with only 35 percent of the variable explained. As most of the variance is across counties, rather than across time, these fits are quite good.

Response of Recycling to Change in Container Value

Recycling responds strongly to a change in the CRV. Figures 2-4 show the recycling rate for aluminum, glass and plastic that is predicted by our regressions for CRV values from 0.25 cents to 7 cents for a small container. Each figure has three lines. The middle line is the predicted response; the upper and lower lines are the upper and lower limits of the 90% confidence interval for the predicted response. The confidence intervals were constructed using a bootstrap technique. The figures show that increasing the CRV to the level prevalent in other "bottle bill" states, 5 cents, will result in a California recycling rate for aluminum of 93%, for glass of 86%, and for plastic of 86%. The numbers for plastic are extremely high compared to current rates and should be treated with extreme caution. Further increasing the CRV to 7 cents would bring glass up to a rate of 91 percent.

Increasing the CRV provides incentives both for consumers to return their own containers and for scavengers to remove containers from curbside and return them for deposit. Figures 5-7 show the response, by program, for percent of aluminum returned as CRV changes from 0.25 cents to 5.0 cents. The volumes in dropoff and in curbside both decrease substantially and become de-minimus. For glass, figures 8-10 show the response by program to CRV. Neither curbside nor dropoff are severely affected by an increase in CRV. Figures 11-13 show the predicted results for plastic and show an increase for all programs.

Scrap value (scrapval) is also an important component of container value, particularly for aluminum. The overall response of the recycling rate to a 10% increase in each variable is shown in table 11. In this table, the first column is the variable that is increased by ten percent, the second column is the predicted value after the ten percent change, the third and fourth columns are the lower an upper bounds of the 90 percent confidence interval and the fifth column is the arc elasticity (the percentage change in the percent recycled incident upon a one percent change in the variable.) Table 12-14 give the marginal responses by program. In these tables the first column gives the name of the variable that is to be increased by ten percent of its value, the second column gives it value for the state as a whole. The third column gives the recycling rate predicted by the regression if the variable were increased by ten percent and the fourth column gives the arc elasticity (the percent change in the percent recycled incident upon a one percent change in the variable. For scrap value, these tables show a similar pattern of sensitivity to that of CRV value. For aluminum the effect of increasing scrap value is nearly as strong as the effect of increasing CRV, while is it more moderate for glass.

Response of the State Fund to a Doubling of the CRV

The State collects the deposits from beverage containers and ultimately disperses the deposits from this fund for cancelled containers and for the subsidy of the convenience centers and other parts of the recycling chain. Doubling the CRV will increase the size of the fund (assuming a very low elasticity of beverage demand) by double, but it will also result in a higher fraction of the fund being paid out for returned containers. Using the predicted (median) values from the regression, one can calculate the change in the size of the fund. For aluminum (year 2000) the fund returned $178 million and the regression predicted rate of recycling was 81 percent. Based upon these numbers the apparent contribution of aluminum to the fund was $40 million. When the CRV is doubled, the payout would be 93% (predicted by the regression) which would lead to a contribution to the fund of $30 million. Similarly the numbers for glass are $39 million currently and predicted at $28 million dollars; for plastic $47 million currently and predicted at $25 million. The result of a doubling of CRV is that the size of the fund available to subsidize recycling will decrease considerably.

Response of Recycling to Change in Center Availability

There are three measures of ease of recycling in this study, hours open for convenience centers, density of recylcing centers, and percentage covered by curbside. Statewide recycling rates should increase in all of these variables since they are all measures of how easy it is to recycle. All three of these variables have the posited positive effect and all three are statistically significant. Increase in hours open or in the density of recycling centers increases the amount recycled in these centers and decreases the amount in curbside. A one percent change in the hours open (an extra 23 minutes per week on average) leads to a .9, 2.5, and 16 percent increase in returns for aluminum, plastic, and glass respectively through the certified recycling centers. It also leads to a decrease in the returns at curbside (except for plastic.) The effect of increasing the number of centers per capita has a very similar effect. The effects of increasing curbside coverage reflective of a very strong scavenging effect: increasing curbside coverage for aluminum and glass results in lower collections through this medium while redemptions rise. This is indicative of very strong scavenging activity in counties with high curbside collections.

Response of Recycling to Income and Employment

The gross response of recycling rates for aluminum, glass, and plastic to higher unemployment or higher income are all positive. The effect on unemployment is expected to be positive because in times or places of high unemployment, the value of time, the primary ingredient for recycling, is lower than at times of low unemployment. This manifests itself both in a higher willingness of people to return their own containers and in an expansion of the supply of scavengers. The overall percent increases in recycling incident upon a one percent increase in the unemployment rate (the elasticity) are .9 for aluminum, 1.3 for glass and 9 for plastic. (In all cases the 90% confidence interval does not include a change in recycling rate of zero). A ten percent increase in the unemployment rate, in this sample, is equivalent to an increase from unemployment from 5.1 to 5.6 percent. The response of the recycling rate to the increase would be for aluminum's rate to increase from .75 to .82; glass's rate from .54 to .60 and plastic's rate from .26 to .49. These are relatively large effects, the effect for plastic so large as to be implausible. Looking at the level of the individual programs, the increase in recycling rate for glass and aluminum comes largely from an increase in return for deposit. Curbside collections actually decrease, indicating that with higher unemployment people put fewer containers out for curbside collection, even though scavengers are more willing to collect the containers that are available. For plastic, all programs benefit.

The response of recycling to higher income is dominated by the tendency of higher income counties to consume more beverages. The data measures total containers distributed in California and the return of containers, by county, by program. Counties with higher income use more beverages than counties with lower income, so there is are more containers available for recycling in the higher income counties. Higher income, on the other hand, makes time more expensive (both for consumers and scavengers) and so one would expect that a lower percent of these containers would be returned for deposit. The net of these two effects, more containers and lower propensity to return for deposit, yields a Statewide income elasticity of return of .8, 1.4, and 9 for aluminum, glass and plastic respectively. (All of these effects significant at the 5% level of significance) The percent collected in curbside and for deposit increases with county income for all three materials, though for aluminum and glass in curbside the additional amounts collected in curbside are extremely small and not significantly different from zero. This finding would be consistent with lower income people in higher income counties diverting all the additional volume from curbside to for deposit centers.

Response of Recycling to Temperature and Quarter

There are more returns at times and in counties with higher temperatures, which is a direct reflection of higher sales in those counties. The first quarter of the year is the quarter with the highest returns. Given the large holiday sales of beverages, return early in the first quarter is to be expected.

Effect of Other Demographic Variables on Recycling

Increased population, population density, and increased apartment units all lead to increases in the recycling of all three materials. Increased population leads to increased sales. Population density and apartments, however, reflect life style issues and people's propensity to make material available for recycling or the ease with scavengers can reclaim material not made available for recycling by consumers.

Response of Recycling to No Program Alternative

The no Bottle Bill alternative is simulated by setting the CRV, the density of centers, and hours open all to zero. The results are not significantly different from just setting the

CRV to zero. The increase in curbside recycling does not make up for the decrease in the use of centers. For aluminum, curbside increases from 4 to 12 percent, while center recycling falls to 49 percent in this simulation. The simulation is well outside of the data on which the regression is based and so it is not surprising that it does not predict no recycling. However the regression does not support the theory that all volume will be picked up by curbside; much to the contrary the evidence is that a great deal of the volume will be lost. For glass, all programs decrease with a cessation of the CRV payments and similarly for plastic. Based upon the experience of the last several years, reducing the CRV and eliminating the certified recycling centers would severely reduce the level of recycling.

Appendix: Technical Aspects of the Regression Model

Econometric Model of County-Level Recycling

Let q_{ijt} denote the quantity (weight, or volume) of recyclable material (aluminum, plastic, or glass) in county $i = 1, \ldots, K$ returned through program $j = 1, 2, 3$ (certified recycling center, dropoff program or curbside program respectively), or not recycled through any program and thrown out as trash or litter ($j = 4$) in period $t = 1, \ldots, T$. We do not observe non-returned quantities of recyclable materials by county. In addition, material that is purchased in one county may be recycled or thrown out as trash or litter in other counties in the state. However, we do have data on the total quantity (sales) of the recyclable material in the state, Q_t. While there is the potential for some quantities of beverage containers to cross into or out of the state between the date of sales and the date of disposal, the net effect of this flow should be quite small and on average approximately zero. We therefore include the net outflow of recyclable material from the state as part of total non-returns.

We seek to explain and predict recycling rates by material type, county, program, and time period subject to non-negativity constraints and a latent adding up condition, $\sum_{i=1}^{K}\sum_{j=1}^{4} q_{ijt} \equiv Q_t \;\forall\; t$, for each material. Our strategy, taken from demand analysis, is to define recycling shares, $w_{ijt} \equiv q_{ijt}/Q_t$, and model the behavior of the w_{ijt} as non-negative quantities that sum to one. We proceed by defining the total proportion of Q_t not returned in the state in time period t, $\sum_{i=1}^{K} w_{i4t} \equiv 1-\sum_{i=1}^{K}\sum_{j=1}^{3} w_{ijt} > 0 \;\forall\; t$. Next, define the ratio of the proportion the material that is returned in county i under program j in period t to the total proportion of material that is not returned in any program in period t,

$$y_{ijt} = \frac{w_{ijt}}{1-\sum_{k=1}^{K}\sum_{\ell=1}^{3} w_{k\ell t}},\; i=1,\ldots,K,\; j=1,2,3,\; t=1,\ldots,T. \tag{1}$$

Note that $w_{ijt} \geq 0 \;\forall\; i,j,t$ implies that $y_{ijt} \in [0,\infty) \;\forall\; i,j,t$. We therefore impose these non-negativity conditions with a Tobit regression framework,

$$y_{ijt} = \max\left\{\boldsymbol{x}'_{ijt}\boldsymbol{\beta}_{ij} + u_{ijt}, 0\right\}, \tag{2}$$

where u_{ijt} is an *iid* $n(0,\sigma_j^2)$ random error term and the county-specific subscript i is included on the parameter vector $\boldsymbol{\beta}_{ij}$ to account for the possibility of county-level fixed effects. We consider generalizations of the *iid* hypothesis in the empirical analysis, including robust heteroskedasticity consistent estimation methods, autocorrelation in the error terms, and general correlations within counties and among programs as well as across material types. Even so, it is worth noting that we can estimate equation (2) consistently with single equation methods. We also note that the share ratios defined in (1) and the Tobit specification in (2) is a minimally restrictive way to impose the non-negativity of all recycling shares and the latent adding up condition in our econometric framework.

The prediction equations for the econometric model are obtained from the well-known mean of the censured regression equation,

$$E\left(y_{ijt}\right)=\Phi\left(\frac{x_{ijt}'\beta_{ij}}{\sigma_j}\right)\left[x_{ijt}'\beta_{ij}+\sigma_{ij}\lambda\left(\frac{x_{ijt}'\beta_{ij}}{\sigma_j}\right)\right], \quad (3)$$

where $\lambda\left(\frac{x_{ijt}'\beta_{ij}}{\sigma_j}\right)=\varphi\left(\frac{x_{ijt}'\beta_{ij}}{\sigma_j}\right)\Big/\Phi\left(\frac{x_{ijt}'\beta_{ij}}{\sigma_j}\right)$ is the inverse Mill's ratio, while $\varphi(\cdot)$ and $\Phi(\cdot)$ are the pdf and cdf, respectively, for the standard normal probability distribution. If we denote the consistent, asymptotically normal parameter estimates for the Tobit regression model by $\hat{\beta}_{ij}$ and $\hat{\sigma}_j$, then the predicted values of the mean share ratios in (3), $\hat{y}_{ijt}$, are calculated by substituting the parameter estimates for their true values in (3). The median consistent prediction for the total proportion of recyclable material not returned is then equal to

$$1-\sum_{i=1}^{K}\hat{w}_{i4t}=\frac{1}{1+\sum_{k=1}^{K}\sum_{\ell=1}^{3}\hat{y}_{k\ell t}}\in(0,1]\;\forall\, t, \quad (4)$$

by the non-negativity of each of the $\hat{y}_{ijt}$. The median consistent prediction for the proportion of recyclable material returned in county i under program j then equals

$$\hat{w}_{ijt} = \frac{\hat{y}_{ijt}}{1+\sum_{k=1}^{K}\sum_{\ell=1}^{3}\hat{y}_{k\ell t}} \in [0,1)\ \forall\ i=1,\ \forall\ j=1,2,3,\ \forall\ t\,. \tag{5}$$

Asymptotic standard errors of prediction can be readily calculated for (4) and (5) using Slutsky's theorem and the delta method. Alternatively, a parametric bootstrapping method can be used to calculate the finite sample distributional properties of these prediction equations. This latter approach would be particularly useful in the presence of heteroskedasticity and/or serial correlation in the error terms.

Table 1. Data Description and Sources

Variable	Description	Mean	Standard Deviation	Min	Max	Source
County Population Dynamics						
Nonmetro	Urbanization index, equals 1 if non-metropolitan area	0.32	0.47	0	1	US Department of Housing and Urban Development Income Limit Dataset Variable used: Metropolitan Statistical Area (MSA) http://www.huduser.org/datasets
Pop	Population (in millions)	0.6151	1. 4125	0.0036	9.7161	Yearly data from RAND All race and age series http://ca.rand.org/stats/popdemo/popraceage.html
Density	Number of people (in tens of thousands, 10,000) per square mile	0.0519	0.1252	0.0001	0.7889	Area obtained from: California State Association of Counties http://www.csac.counties.org/counties_close_up/ county_web/county_mileage.html
ApptUnits	Suburbanization index: percent of dwellings that are multi-unit housing	0.20	0.11	0.04	0.69	California Department of Finance, Demographics Research Unit *City/County Population and Housing Estimates, 1991-2000, with 1990 Census Counts.* Sacramento, California, May 2000. http://www.dof.ca.gov/HTML/DEMOGRAP/drupubs.htm Report E-5

Variable	Description	Mean	Standard Deviation	Min	Max	Source
County Economic Characteristics						
MFI	Median Family Income (in hundred thousand dollars, $100,000)	0.2781	0.0689	0.1761	0.5053	US Department of Housing and Urban Development Income Limit Dataset – Median Family Income for California http://www.huduser.org/datasets
Unemp	Unemployment rate	5.12	2.02	0.33	9.73	RAND California Employment and Unemployment Statistics http://ca.rand.org/stats/economics/employment.html
County Weather Conditions						
AverTemp	Average Temperature (in thousand degrees F, 1,000 F)	0.0583	103.36	297.55	931.13	National Climactic Data Center Monthly Surface Data Element Type: MNTM Monthly mean temperature http://lwf.ncdc.noaa.gov/oa/ncdc.html

Variable	Description	Mean	Standard Deviation	Min	Max	Source
Recycling Program Characteristics						
PS	Percent population served by curbside programs	0.47	0.35	0	1	California Department of Conservation, Division of Recycling FTP site – Data – Curbside. zip http://www.consrv.ca.gov/dor ftp://ftp.consrv.ca.gov/pub/dor/Data/
Hours Average	Average number of hours per week (in thousand 1,000 hours) open for recycling centers	0.038	0.008	0	0.066	California Department of Conservation, Division of Recycling http://www.consrv.ca.gov/dor
rcpopdens	Number of Recycling Centers per county over time divided by population	41	85	0	599	California Department of Conservation, Division of Recycling FTP site—Data – Recycler.zip http://www.consrv.ca.gov/dor ftp://ftp.consrv.ca.gov/pub/dor/Data/

Variable	Description	Mean	Standard Deviation	Min	Max	Source
Price Effect						
CRV	Container Redemption Value over time for California, adjusted for inflation with the consumer price index	0.031	0.002	0.028	0.034	California Department of Conservation, Division of Recycling http://www.consrv.ca.gov/dor CPI is from the US Department of Labor, Bureau of Labor Statistics http://www.bls.gov/cpi/
ScrapVal	Aluminum scrap value over time for California	30.98	4.8	24.12	42.09	California Department of Conservation, Division of Recycling http://www.consrv.ca.gov/dor American Metal Market Scrap Prices from the Recycling Manager services http://www.amm.com
Constants						
_cons	constant					
-lq_i	Quaterly dummy for quarter i					

Table 2. Regression for Aluminum in Recycling Centers

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf. Interval]	
Nonmetro	-0.0625	0.0058	-10.87	0.000	-0.0738	-0.0512
_lq_2	-0.0762	0.0105	-7.25	0.000	-0.0968	-0.0556
_lq_3	-0.0463	0.0124	-3.73	0.000	-0.0707	-0.0219
_lq_4	-0.0148	0.0095	-1.55	0.121	-0.0335	0.0039
Pop	0.1340	0.0116	11.53	0.000	0.1110	0.1570
MFI	-0.0799	0.0481	-1.66	0.097	-0.1740	0.0144
AverTemp	0.6050	0.3910	1.55	0.122	-0.1620	1.3720
Density	-0.1790	0.0248	-7.20	0.000	-0.2270	-0.1300
CRV	8.2645	1.7436	4.74	0.000	4.8445	11.6846
ScrapVal	0.0023	0.0009	2.64	0.008	0.0006	0.0041
Hours Average	-0.5357	0.4633	-1.16	0.248	-1.4443	0.3730
rcpopdens	9.9552	3.1019	3.21	0.001	3.8709	16.0395
PS	0.0230	0.0067	3.42	0.001	0.0098	0.0361
Unemp	0.0019	0.0011	1.83	0.068	-0.0001	0.0040
ApptUnits	-0.0681	0.0263	-2.59	0.010	-0.1196	-0.0166
_cons	-0.2550	0.0532	-4.79	0.000	-0.3593	-0.1506

Regression with Robust Standard Errors

Number of obs=	1563
R-squared=	0.7313
Root MSE=	0.1091

Table 3. Regression for Aluminum in Dropoff

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf. Interval]	
Nonmetro	-0.0004	0.0001	-2.84	0.005	-0.0006	-0.0001
_lq_2	-0.0010	0.0003	-3.54	0.000	-0.0015	-0.0004
_lq_3	-0.0008	0.0004	-1.93	0.054	-0.0015	0.0000
_lq_4	-0.0001	0.0002	-0.51	0.610	-0.0006	0.0003
pop	0.0008	0.0001	8.54	0.000	0.0006	0.0010
MFI	0.0113	0.0013	8.71	0.000	0.0088	0.0139
AverTemp	0.0179	0.0127	1.41	0.158	-0.0070	0.0427
Density	0.0002	0.0007	0.35	0.725	-0.0011	0.0016
CRV	0.0144	0.0369	0.39	0.696	-0.0579	0.0868
ScrapVal	0.0000	0.0000	2.16	0.031	0.0000	0.0001
Hours Average	0.0362	0.0048	7.49	0.000	0.0267	0.0457
rcpopdens	0.0389	0.0426	0.91	0.362	-0.0447	0.1226
PS	-0.0021	0.0002	-8.82	0.000	-0.0025	-0.0016
Unemp	0.0000	0.0000	-0.79	0.429	-0.0001	0.0000
ApptUnits	0.0010	0.0004	2.57	0.010	0.0002	0.0018
_cons	-0.0055	0.0016	-3.50	0.000	-0.0085	-0.0024

Regression with Robust Standard Errors

Number of obs=	1320
R-squared=	0.3546
Root MSE=	0.0023

Table 4. Regression for Aluminum in Curbside

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf. Interval]	
Nonmetro	0.0018	0.0003	6.24	0.000	0.0012	0.0023
_lq_2	-0.0056	0.0005	-10.39	0.000	-0.0067	-0.0046
_lq_3	-0.0046	0.0007	-6.76	0.000	-0.0059	-0.0032
_lq_4	-0.0014	0.0004	-3.14	0.002	-0.0022	-0.0005
pop	0.0035	0.0003	12.82	0.000	0.0030	0.0041
MFI	0.0437	0.0022	19.55	0.000	0.0393	0.0480
AverTemp	0.1090	0.0235	4.63	0.000	0.0627	0.1550
Density	-0.0053	0.0009	-5.91	0.000	-0.0071	-0.0036
CRV	-0.1124	0.0861	-1.31	0.192	-0.2814	0.0566
ScrapVal	0.0001	0.0000	3.74	0.000	0.0001	0.0002
Hours Average	-0.0010	0.0201	-0.05	0.959	-0.0404	0.0383
rcpopdens	1.5202	0.2073	7.34	0.000	1.1136	1.9269
PS	0.0001	0.0004	0.29	0.774	-0.0006	0.0008
Unemp	0.0000	0.0000	-0.28	0.781	-0.0001	0.0001
ApptUnits	0.0083	0.0020	4.13	0.000	0.0044	0.0122
_cons	-0.0166	0.0027	-6.22	0.000	-0.0219	-0.0114

Regression with Robust Standard Errors

Number of obs=	1320
R-squared=	0.3546
Root MSE=	0.0023

Table 5. Regression for Glass in Recycling Centers

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf.	Interval]
Nonmetro	-0.0161	0.0023	-7.04	0.000	-0.0206	-0.0116
_lq_2	-0.0073	0.0036	-2.02	0.044	-0.0145	-0.0002
_lq_3	0.0013	0.0046	0.29	0.773	-0.0078	0.0104
_lq_4	-0.0072	0.0032	-2.26	0.024	-0.0135	-0.0010
pop	0.0586	0.0042	13.97	0.000	0.0503	0.0668
MFI	0.0421	0.0194	-2.17	0.030	-0.0801	-0.0040
AverTemp	-0.5570	0.1450	-3.84	0.000	-0.8420	-0.2720
Density	-0.0201	0.0119	-1.69	0.092	-0.0434	0.0033
CRV	4.5710	0.9929	4.60	0.000	2.6234	6.5187
ScrapVal	0.0001	0.0003	0.16	0.872	-0.0006	0.0007
Hours Average	-0.4061	0.1985	-2.05	0.041	-0.7953	-0.0168
rcpopdens	6.6002	1.0685	6.18	0.000	4.5044	8.6961
PS	0.0070	0.0027	2.61	0.009	0.0017	0.0122
Unemp	0.0005	0.0005	0.89	0.374	-0.0006	0.0015
ApptUnits	-0.0429	0.0097	-4.43	0.000	-0.0619	-0.0239
_cons	-0.0791	0.0214	-3.69	0.000	-0.1212	-0.0370

Regression with Robust Standard Errors

Number of obs=	1563
R-squared=	0.7840
Root MSE=	0.0398

Table 6. Regression for Glass in Dropoff

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf. Interval]	
Nonmetro	-0.0004	0.0001	-3.96	0.000	-0.0006	-0.0002
_lq_2	-0.0010	0.0003	-3.51	0.000	-0.0015	-0.0004
_lq_3	-0.0008	0.0004	-2.27	0.023	-0.0015	-0.0001
_lq_4	-0.0006	0.0002	-2.78	0.006	-0.0011	-0.0002
pop	0.0009	0.0001	6.25	0.000	0.0006	0.0012
MFI	0.0072	0.0011	6.57	0.000	0.0051	0.0094
AverTemp	0.0009	0.0100	0.09	0.928	-0.0187	0.0205
Density	0.0066	0.0009	7.59	0.000	0.0049	0.0083
CRV	0.2876	0.0680	4.23	0.000	0.1543	0.4210
ScrapVal	0.0000	0.0000	-0.40	0.689	-0.0001	0.0000
Hours Average	0.0362	0.0061	5.99	0.000	0.0244	0.0481
rcpopdens	-0.1525	0.0512	-2.98	0.003	-0.2530	-0.0521
PS	-0.0003	0.0002	-2.07	0.039	-0.0006	0.0000
Unemp	0.0000	0.0000	-0.50	0.614	-0.0001	0.0000
ApptUnits	0.0008	0.0006	1.36	0.173	-0.0003	0.0019
_cons	-0.0107	0.0017	-6.14	0.000	-0.0141	-0.0073

Regression with Robust Standard Errors

Number of obs=	1320
R-squared=	0.4512
Root MSE=	0.0024

Table 7. Regression for Glass in Curbside

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf. Interval]	
Nonmetro	0.0032	0.0005	6.78	0.000	0.0023	0.00410
_lq_2	-0.0058	0.0008	-7.17	0.000	-0.0073	-0.00419
_lq_3	-0.0054	0.0010	-5.32	0.000	-0.0074	-0.00342
_lq_4	-0.0038	0.0007	-5.69	0.000	-0.0051	-0.00248
pop	0.0050	0.0004	13.22	0.000	0.0042	0.00571
MFI	0.0686	0.0032	21.31	0.000	0.0623	0.07490
AverTemp	0.0410	0.0350	1.17	0.242	-0.0277	0.11000
Density	-0.0097	0.0019	-5.10	0.000	-0.0135	-0.00598
CRV	0.4440	0.1550	2.87	0.004	0.1399	0.74810
ScrapVal	0.0001	0.0001	1.87	0.062	0.0000	0.00021
Hours Average	-0.0560	0.0251	-2.23	0.026	-0.1053	-0.00668
rcpopdens	2.6227	0.2803	9.36	0.000	2.0727	3.17272
PS	0.0006	0.0006	1.11	0.266	-0.0005	0.00178
Unemp	0.0000	0.0001	0.35	0.726	-0.0001	0.00019
ApptUnits	0.0264	0.0037	7.17	0.000	0.0192	0.03358
_cons	-0.0356	0.0046	-7.69	0.000	-0.0446	-0.02649

Regression with Robust Standard Errors

Number of obs=	1095
R-squared=	0.7444
Root MSE=	0.0065

4.26

Table 8. Regression for Plastic in Recycling Centers

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf. Interval]	
Nonmetro	-0.0625	0.0058	-10.87	0.000	-0.0738	-0.0512
_Iq_2	-0.0762	0.0105	-7.25	0.000	-0.0968	-0.0556
_Iq_3	-0.0463	0.0124	-3.73	0.000	-0.0707	-0.0219
_Iq_4	-0.0148	0.0095	-1.55	0.121	-0.0335	0.0039
Pop	0.1340	0.0116	11.53	0.000	0.1110	0.1570
MFI	-0.0799	0.0481	-1.66	0.097	-0.1740	0.0144
AverTemp	0.6050	0.3910	1.55	0.122	-0.1620	1.3720
Density	-0.1790	0.0248	-7.20	0.000	-0.2270	-0.1300
CRV	8.2645	1.7436	4.74	0.000	4.8445	11.6846
ScrapVal	0.0023	0.0009	2.64	0.008	0.0006	0.0041
Hours Average	-0.5357	0.4633	-1.16	0.248	-1.4443	0.3730
rcpopdens	9.9552	3.1019	3.21	0.001	3.8709	16.0395
PS	0.0230	0.0067	3.42	0.001	0.0098	0.0361
Unemp	0.0019	0.0011	1.83	0.068	-0.0001	0.0040
ApptUnits	-0.0681	0.0263	-2.59	0.010	-0.1196	-0.0166
_cons	-0.2550	0.0532	-4.79	0.000	-0.3593	-0.1506

Regression with Robust Standard Errors

Number of obs=	1563
R-squared=	0.7313
Root MSE=	0.1091

Table 9. Regression for Plastic in Dropoff

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf. Interval]	
Nonmetro	-0.0003	0.0001	-2.58	0.010	-0.0006	-0.0001
_lq_2	-0.0005	0.0003	-1.85	0.065	-0.0011	0.0000
_lq_3	-0.0006	0.0004	-1.50	0.134	-0.0014	0.0002
_lq_4	-0.0001	0.0002	-0.54	0.589	-0.0005	0.0003
pop	0.0009	0.0001	9.19	0.000	0.0007	0.0011
MFI	0.0111	0.0016	6.79	0.000	0.0079	0.0143
AverTemp	0.0274	0.0133	2.06	0.040	0.0013	0.0534
Density	0.0030	0.0010	2.85	0.004	0.0009	0.0050
CRV	0.1243	0.0490	2.54	0.011	0.0282	0.2204
ScrapVal	0.0000	0.0000	-1.03	0.305	-0.0001	0.0000
Hours Average	0.0395	0.0062	6.39	0.000	0.0274	0.0516
rcpopdens	0.0217	0.0393	0.55	0.582	-0.0555	0.0989
PS	-0.0024	0.0003	-8.72	0.000	-0.0030	-0.0019
Unemp	-0.0001	0.0000	-2.20	0.028	-0.0001	0.0000
ApptUnits	-0.0013	0.0003	-4.12	0.000	-0.0019	-0.0007
_cons	-0.0071	0.0017	-4.19	0.000	-0.0105	-0.0038

Regression with Robust Standard Errors

Number of obs=	1320
R-squared=	0.3631
Root MSE=	0.0024

Table 10. Regression for Plastic in Curbside

y_al_crc	Coef.	Robust Std. Err.	t	p>|t|	[95% Conf.	Interval]
Nonmetro	0.0014	0.0004	3.05	0.002	0.0005	0.0022
_lq_2	-0.0020	0.0008	-2.37	0.018	-0.0037	-0.0003
_lq_3	-0.0005	0.0012	-0.42	0.675	-0.0029	0.0019
_lq_4	-0.0007	0.0007	-1.09	0.276	-0.0020	0.0006
pop	0.0064	0.0007	8.59	0.000	0.0049	0.0078
MFI	0.0447	0.0035	12.75	0.000	0.0378	0.0516
AverTemp	-0.0164	0.0398	-0.41	0.681	-0.0945	0.0618
Density	-0.0131	0.0017	-7.82	0.000	-0.0164	-0.0098
CRV	1.4990	0.2604	5.76	0.000	0.9880	2.0101
ScrapVal	-0.0001	0.0001	-1.77	0.078	-0.0003	0.0000
Hours Average	-0.0816	0.0352	-2.32	0.021	-0.1506	-0.0126
rcpopdens	2.2603	0.2845	7.95	0.000	1.7021	2.8184
PS	0.0006	0.0006	1.10	0.271	-0.0005	0.0017
Unemp	0.0001	0.0001	1.29	0.196	-0.0001	0.0004
ApptUnits	0.0175	0.0034	5.13	0.000	0.0108	0.0242
_cons	-0.0525	0.0057	-9.17	0.000	-0.0637	-0.0413

Regression with Robust Standard Errors

Number of obs=	1072
R-squared=	0.6838
Root MSE=	0.0077

Table 11. Marginal Effects: Recycling Rate with a 10% Increase in Variables

Aluminum	Median	5th Percentile	95th Percentile
Pop	0.8264	0.8125	0.8396
MFI	0.8141	0.7985	0.8277
AverTemp	0.8182	0.8031	0.8321
Density	0.8140	0.7992	0.8276
CRV	0.8398	0.8280	0.8505
ScrapVal	0.8258	0.8091	0.8398
Hours Average	0.8140	0.7986	0.8283
rcpopdens	0.8157	0.7997	0.8290
PS	0.8138	0.7991	0.8270
Unemp	0.8157	0.8011	0.8291
ApptUnits	0.8156	0.7999	0.8290

Glass	Median	5th Percentile	95th Percentile
Pop	0.6270	0.5971	0.6525
MFI	0.6118	0.5829	0.6369
AverTemp	0.6028	0.5743	0.6283
Density	0.6002	0.5695	0.6291
CRV	0.6515	0.6264	0.6768
ScrapVal	0.6033	0.5724	0.6312
Hours Average	0.5981	0.5672	0.6275
rcpopdens	0.6043	0.5731	0.6318
PS	0.6011	0.5698	0.6285
Unemp	0.6040	0.5726	0.6311
ApptUnits	0.6044	0.5736	0.6307

Plastic	Median	5th Percentile	95th Percentile
Pop	0.5171	0.4182	0.5921
MFI	0.4923	0.3993	0.5698
AverTemp	0.4790	0.3747	0.5581
Density	0.4869	0.3860	0.5649
CRV	0.5805	0.5113	0.6358
ScrapVal	0.4842	0.3784	0.5607
Hours Average	0.4866	0.3866	0.5644
rcpopdens	0.4885	0.3955	0.5655
PS	0.4887	0.3891	0.5657
Unemp	0.4928	0.3924	0.5645
ApptUnits	0.4905	0.3931	0.5654

Note: Base Case for

Aluminum = 0.7500
Glass = 0.5362
Plastic = 0.2587

Table 12. Marginal Effects for Aluminum

Certified Recycling Centers

Variable	CRC Share Before	CRC Share After	Elasticity
Pop	0.6951	0.7783 *	1.20
MFI	0.6951	0.7508 *	0.80
AverTemp	0.6951	0.7647 *	1.00
Density	0.6951	0.7611 *	0.95
CRV	0.6951	0.7980 *	1.48
ScrapVal	0.6951	0.7705 *	1.09
Hours Average	0.6951	0.7584 *	0.91
rcpopdens	0.6951	0.7627 *	0.97
PS	0.6951	0.7648 *	1.00
Unemp	0.6951	0.7638 *	0.99
ApptUnits	0.6951	0.7590 *	0.92

Certified Dropoff Programs

Variable	CDP Share Before	CDP Share After	Elasticity
Pop	0.0092	0.0090	-0.18
MFI	0.0092	0.0116 *	2.65
AverTemp	0.0092	0.0097 *	0.58
Density	0.0092	0.0093 *	0.18
CRV	0.0092	0.0082	-1.10
ScrapVal	0.0092	0.0097 *	0.53
Hours Average	0.0092	0.0103 *	1.25
rcpopdens	0.0092	0.0093 *	0.09
PS	0.0092	0.0086	-0.63
Unemp	0.0092	0.0092 *	0.00
ApptUnits	0.0092	0.0095	0.36

Curbside Programs

Variable	CS Share Before	CS Share After	Elasticity
Pop	0.0458	0.0375 *	-1.81
MFI	0.0458	0.0471	0.29
AverTemp	0.0458	0.0414	-0.95
Density	0.0458	0.0387 *	-1.55
CRV	0.0458	0.0315 *	-3.11
ScrapVal	0.0458	0.0391 *	-1.45
Hours Average	0.0458	0.0392 *	-1.45
rcpopdens	0.0458	0.0389 *	-1.50
PS	0.0458	0.0385 *	-1.61
Unemp	0.0458	0.0384 *	-1.61
ApptUnits	0.0458	0.0402 *	-1.23

Note: A * denotes significance at the 5% level.

Table 13. Marginal Effects for Glass

Certified Recycling Centers

Variable	CRC Share Before	CRC Share After	Elasticity
Pop	0.3824	0.5162 *	3.50
MFI	0.3824	0.4682 *	2.24
AverTemp	0.3824	0.4705 *	2.30
Density	0.3824	0.4865 *	2.72
CRV	0.3824	0.5464 *	4.29
ScrapVal	0.3824	0.4864 *	2.72
Hours Average	0.3824	0.4799 *	2.55
rcpopdens	0.3824	0.4879 *	2.76
PS	0.3824	0.4891 *	2.79
Unemp	0.3824	0.4882 *	2.77
ApptUnits	0.3824	0.4786 *	2.52

Certified Dropoff Programs

Variable	CDP Share Before	CDP Share After	Elasticity
Pop	0.0208	0.0182	-1.25
MFI	0.0208	0.0207	-0.03
AverTemp	0.0208	0.0191	-0.79
Density	0.0208	0.0192	-0.75
CRV	0.0208	0.0247	1.87
ScrapVal	0.0208	0.0182	-1.23
Hours Average	0.0208	0.0204	-0.19
rcpopdens	0.0208	0.0185	-1.10
PS	0.0208	0.0183	-1.19
Unemp	0.0208	0.0185	-1.11
ApptUnits	0.0208	0.0188	-0.94

Curbside Programs

Variable	CS Share Before	CS Share After	Elasticity
Pop	0.1331	0.1105 *	-1.69
MFI	0.1331	0.1361	0.23
AverTemp	0.1331	0.1193 *	-1.03
Density	0.1331	0.1128 *	-1.53
CRV	0.1331	0.1076 *	-1.92
ScrapVal	0.1331	0.1163 *	-1.26
Hours Average	0.1331	0.1129 *	-1.52
rcpopdens	0.1331	0.1141 *	-1.43
PS	0.1331	0.1134 *	-1.48
Unemp	0.1331	0.1133 *	-1.49
ApptUnits	0.1331	0.1207 *	-0.93

Note: A * denotes significance at the 5% level.

Table 14. Marginal Effects for Plastic

Certified Recycling Centers

Variable	CRC Share Before	CRC Share After	Elasticity
Pop	0.1692	0.4801 *	18.37
MFI	0.1692	0.4340 *	15.64
AverTemp	0.1692	0.4375 *	15.85
Density	0.1692	0.4478 *	16.46
CRV	0.1692	0.5252 *	21.03
ScrapVal	0.1692	0.4429 *	16.17
Hours Average	0.1692	0.4422 *	16.13
rcpopdens	0.1692	0.4501 *	16.59
PS	0.1692	0.4511 *	16.66
Unemp	0.1692	0.4508 *	16.64
ApptUnits	0.1692	0.4422 *	16.13

Certified Dropoff Programs

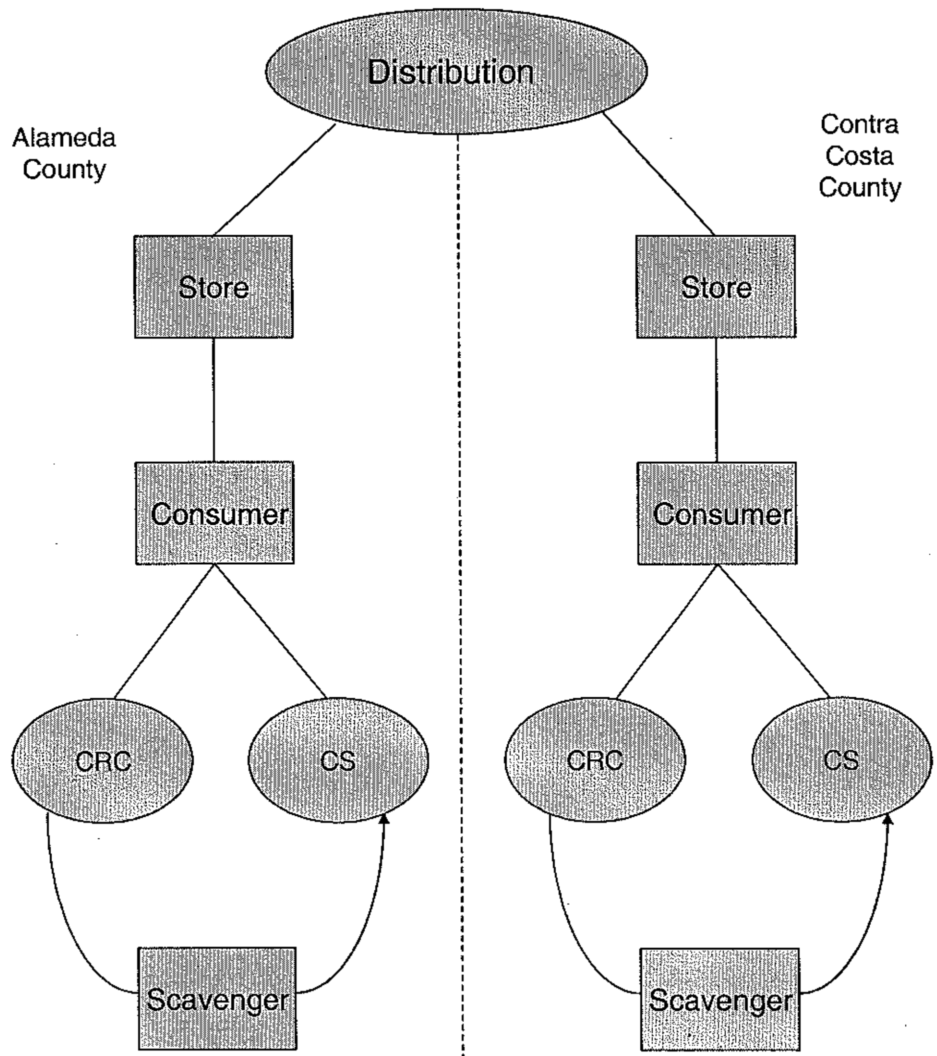
Variable	CDP Share Before	CDP Share After	Elasticity
Pop	0.0134	0.0192 *	4.25
MFI	0.0134	0.0241 *	7.96
AverTemp	0.0134	0.0222 *	6.55
Density	0.0134	0.0199 *	4.80
CRV	0.0134	0.0194 *	4.44
ScrapVal	0.0134	0.0191 *	4.23
Hours Average	0.0134	0.0219 *	6.32
rcpopdens	0.0134	0.0194 *	4.45
PS	0.0134	0.0180 *	3.37
Unemp	0.0134	0.0191 *	4.23
ApptUnits	0.0134	0.0192 *	4.26

Curbside Programs

Variable	CS Share Before	CS Share After	Elasticity
Pop	0.0760	0.0870 *	1.45
MFI	0.0760	0.1008 *	3.26
AverTemp	0.0760	0.0870 *	1.44
Density	0.0760	0.0854 *	1.24
CRV	0.0760	0.1078 *	4.19
ScrapVal	0.0760	0.0840 *	1.05
Hours Average	0.0760	0.0845 *	1.11
rcpopdens	0.0760	0.0870 *	1.44
PS	0.0760	0.0866 *	1.40
Unemp	0.0760	0.0866 *	1.39
ApptUnits	0.0760	0.0914 *	2.02

Note: A * denotes significance at the 5% level

Fig. 1. Flow Chart of Continuous Disposal



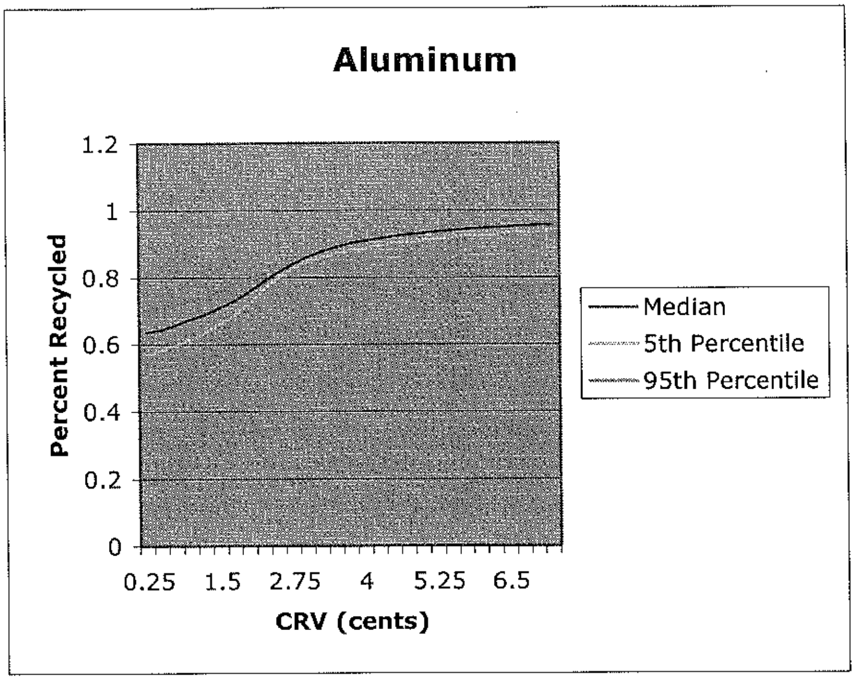


Fig. 2. Percent Recycled by CRV for Aluminum

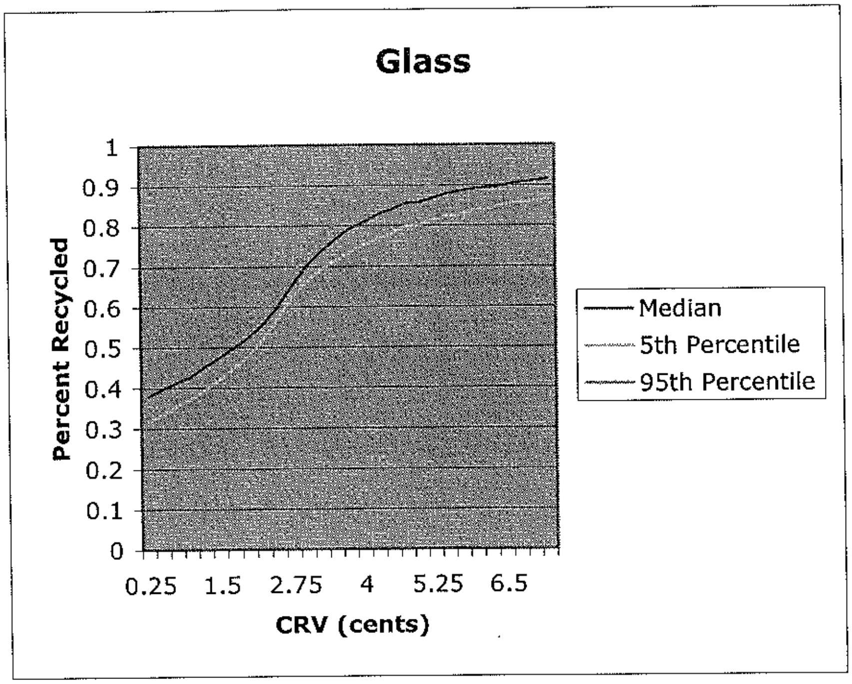


Fig. 3. Percent Recycled by CRV for Glass

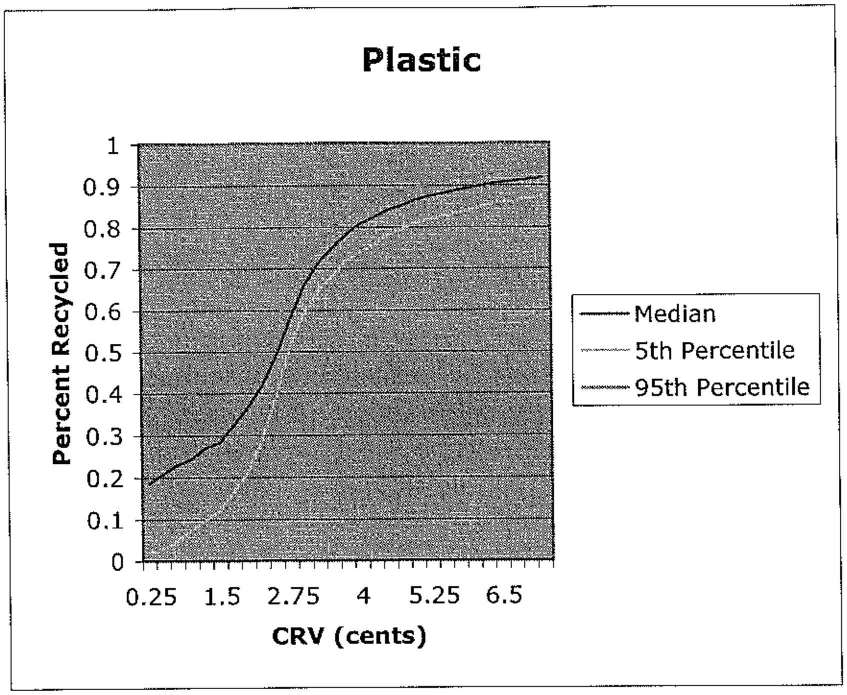


Fig. 4. Percent Recycled by CRV for Plastic

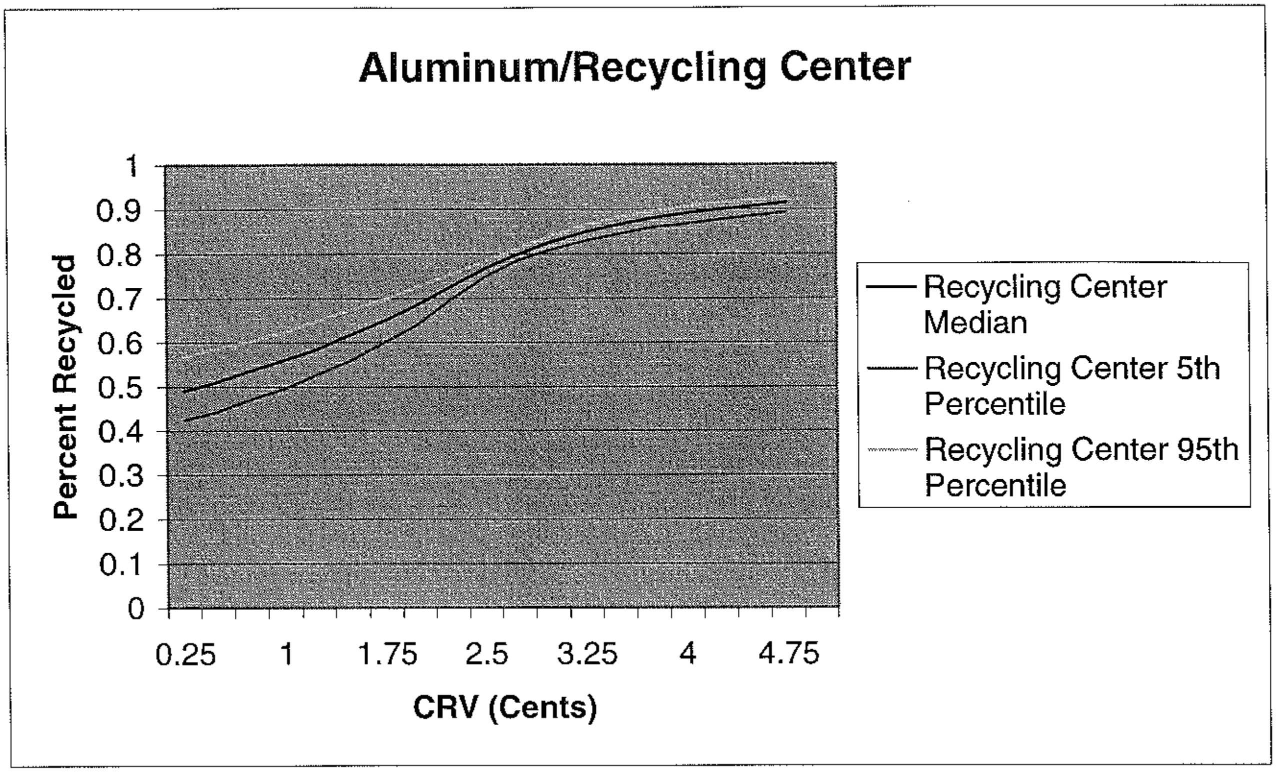


Fig. 5. Percent Recycled in Recycling Centers by CRV for Aluminum

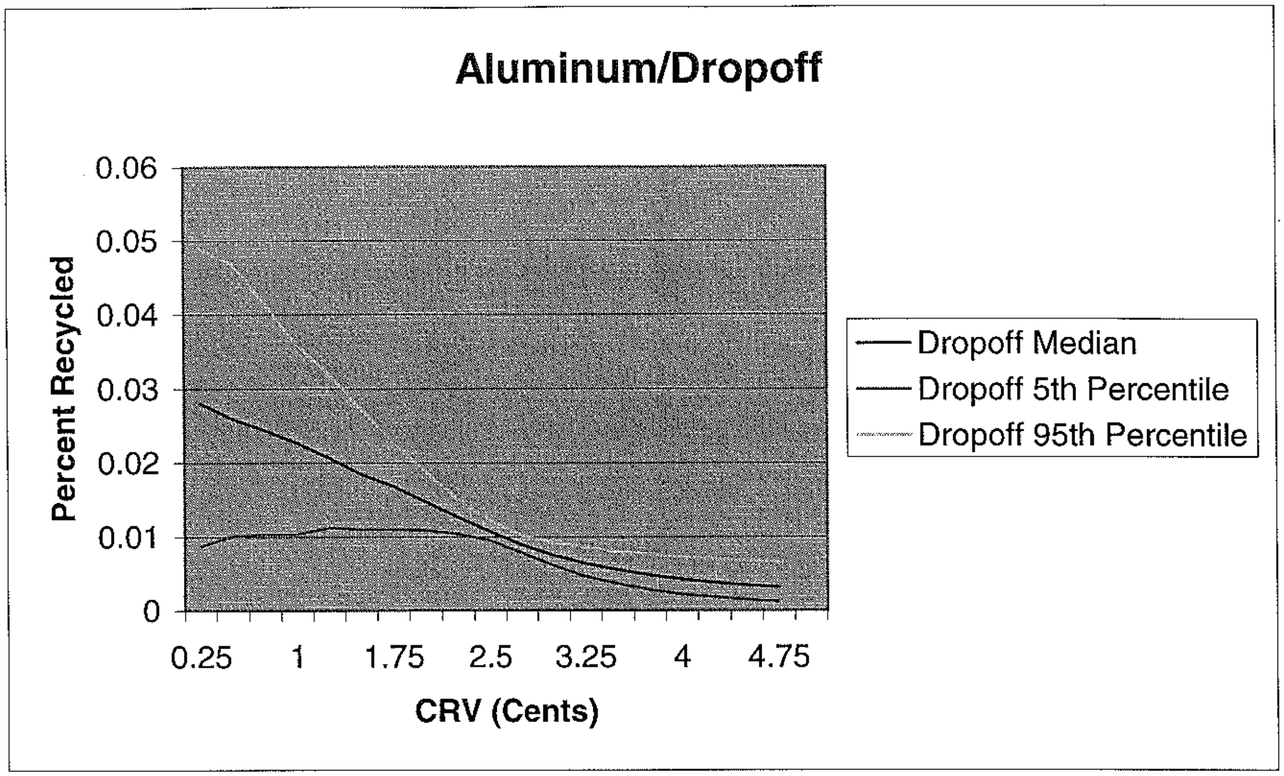


Fig. 6. Percent Dropoff Recycled by CRV for Aluminum

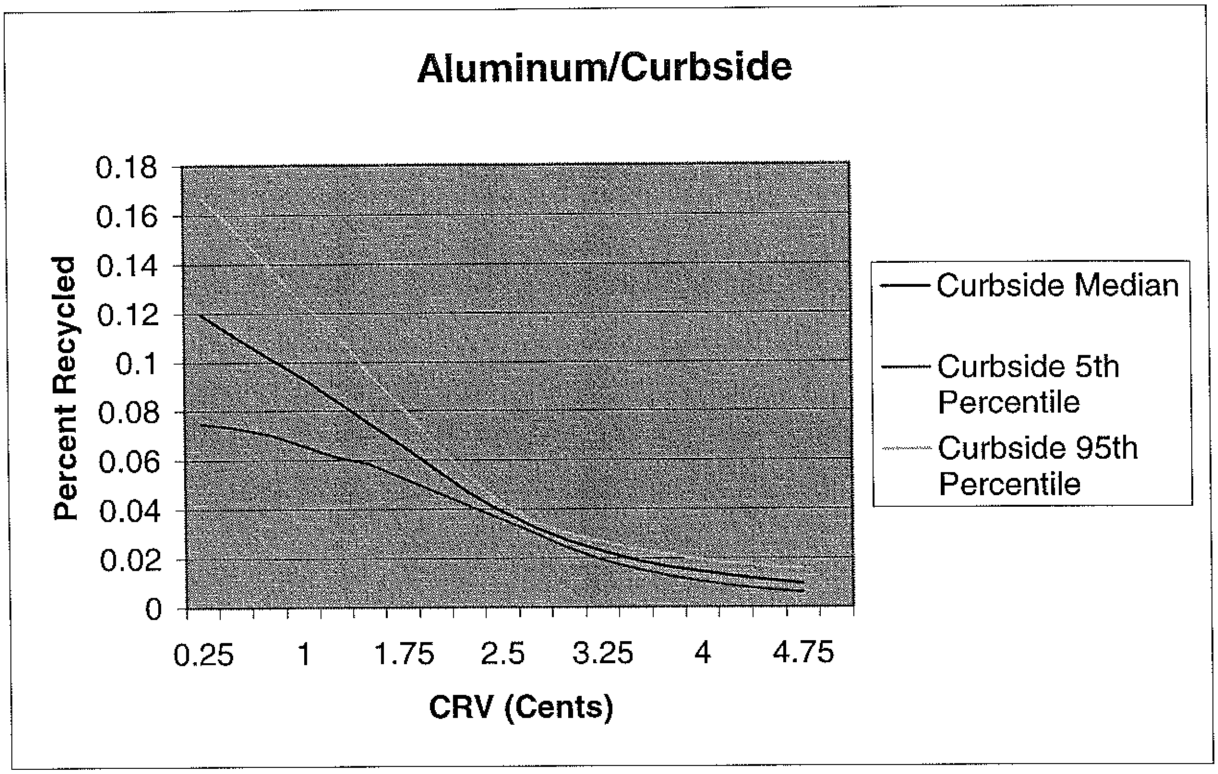


Fig. 7. Percent Curbside Recycled by CRV for Aluminum

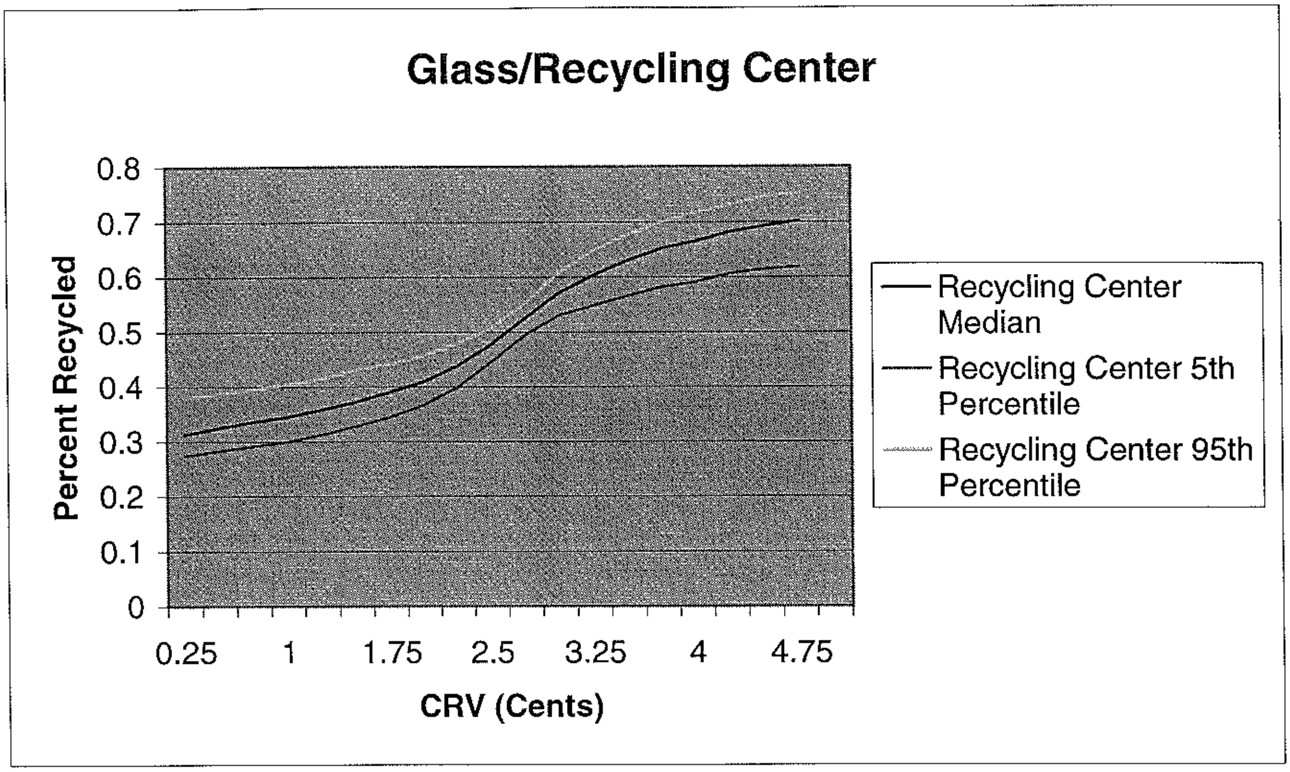


Fig. 8. Percent Recycled in Recycling Center by CRV for Glass

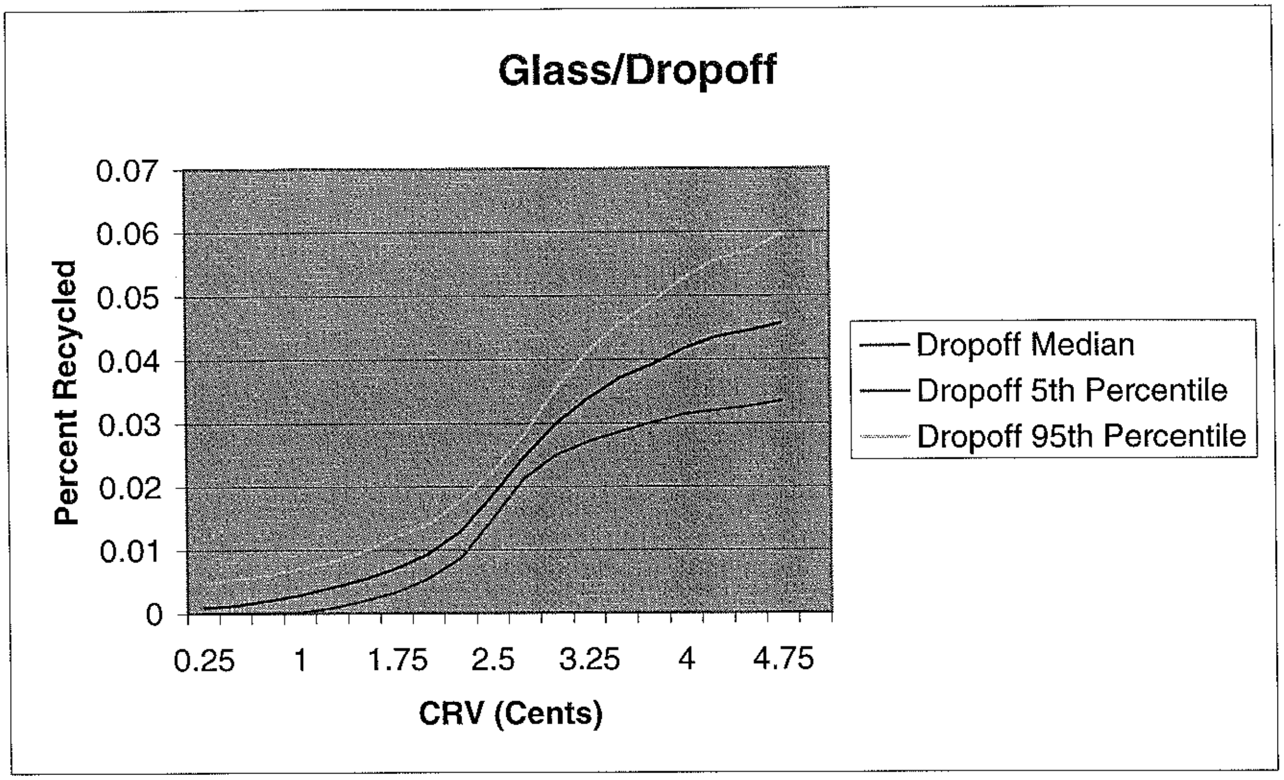


Fig. 9. Percent Dropoff Recycled by CRV for Glass

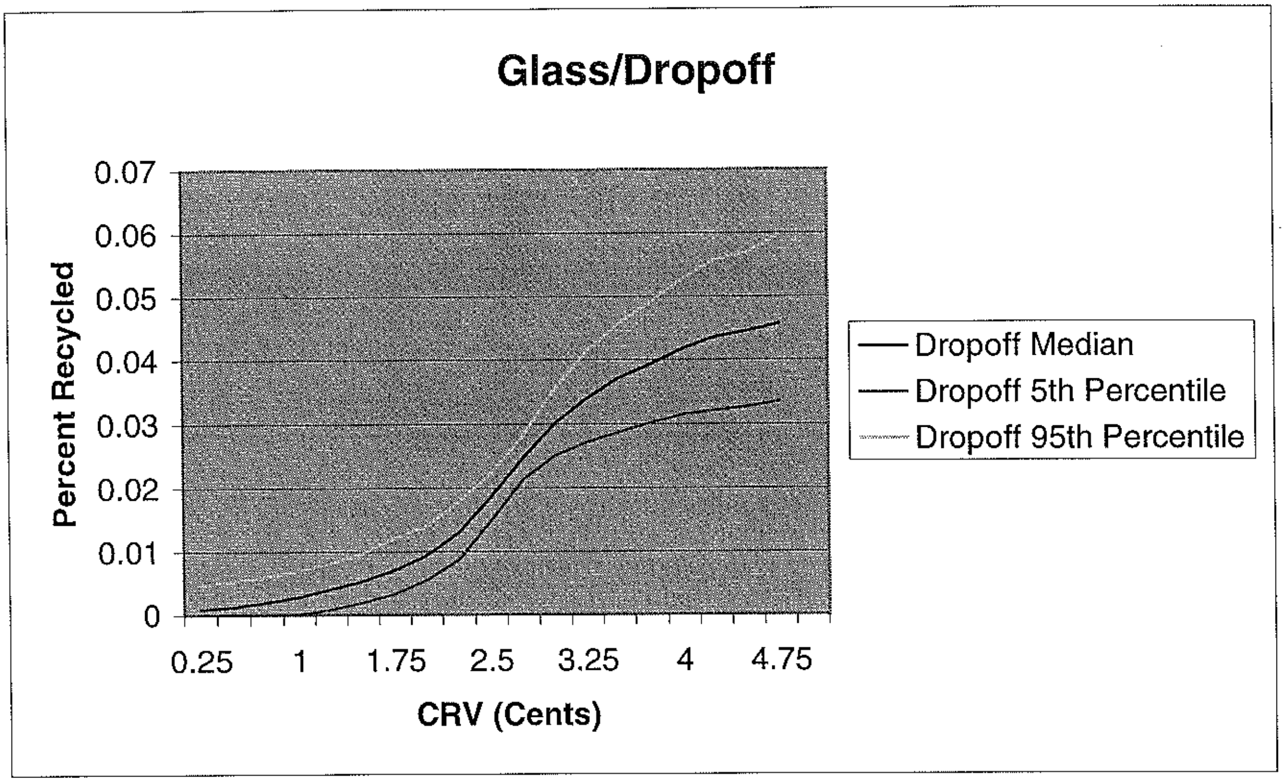


Fig. 9. Percent Dropoff Recycled by CRV for Glass

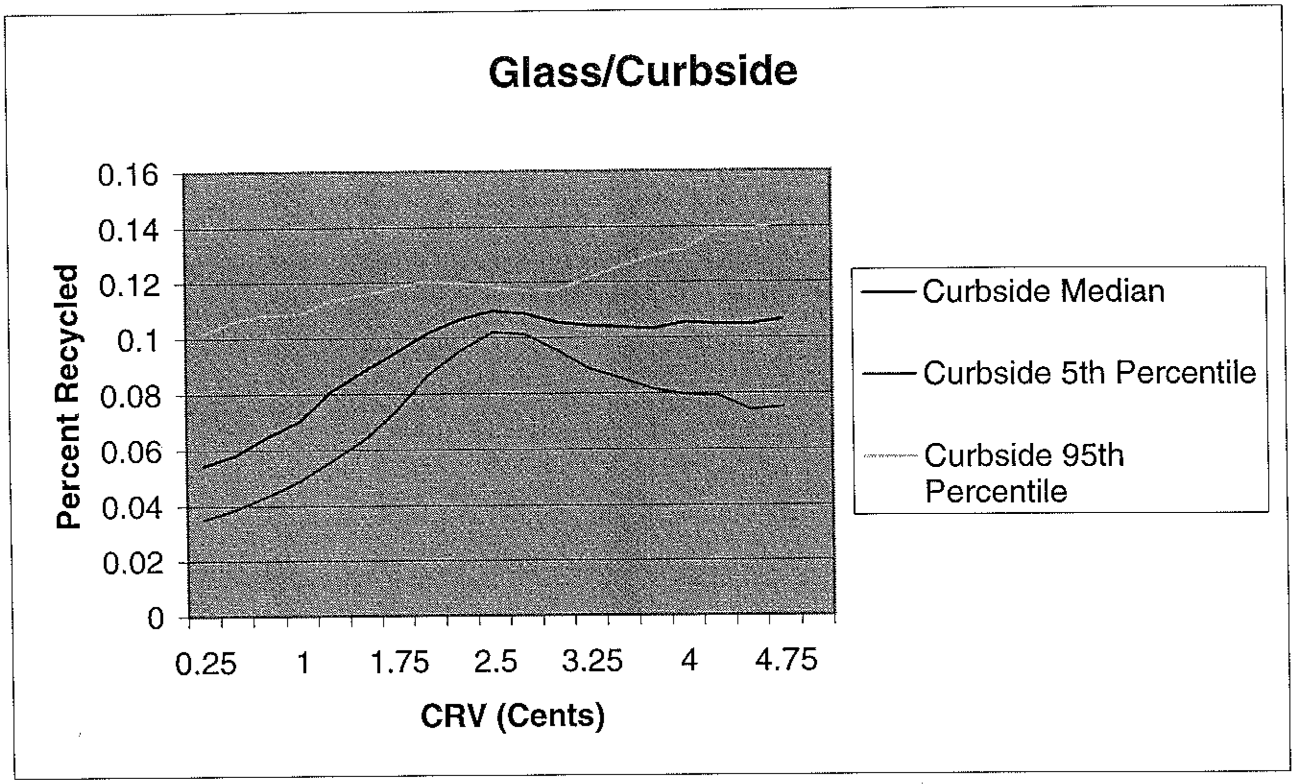


Fig. 10. Percent Curbside Recycled by CRV for Glass

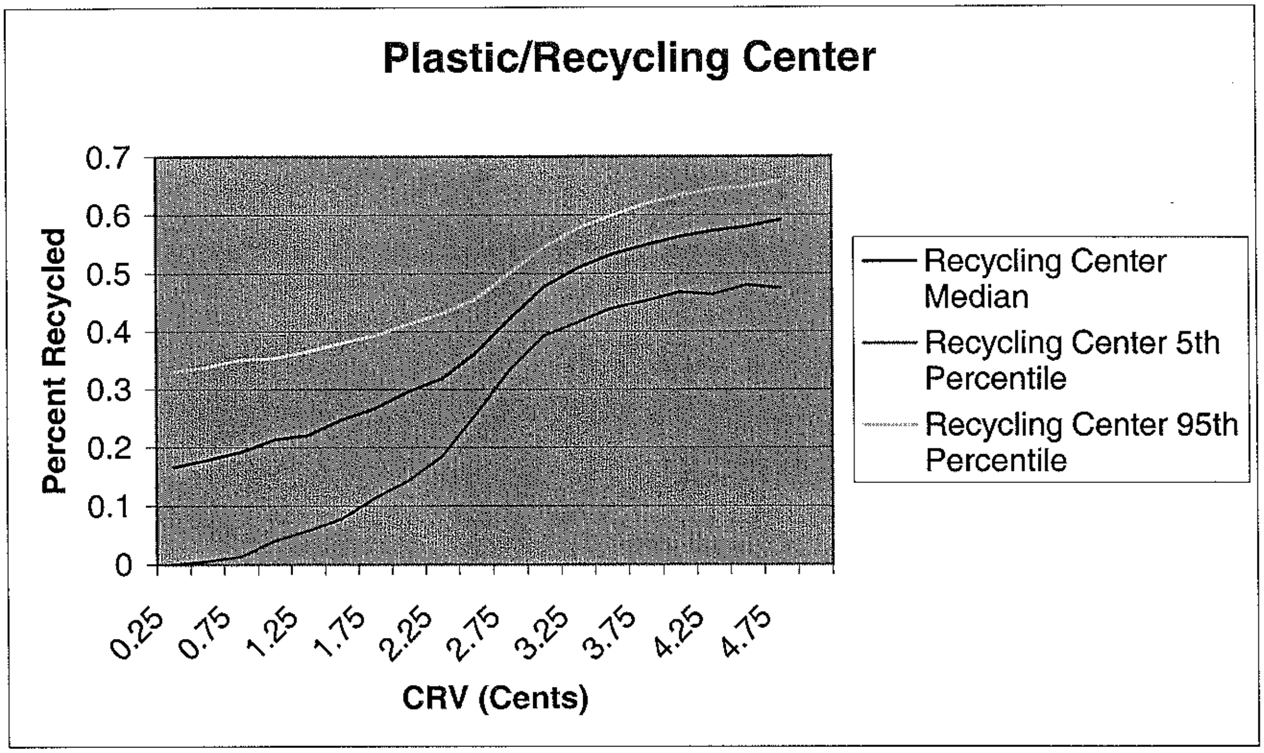


Fig. 11. Percent Recycled in Recycling Center by CRV for Plastic

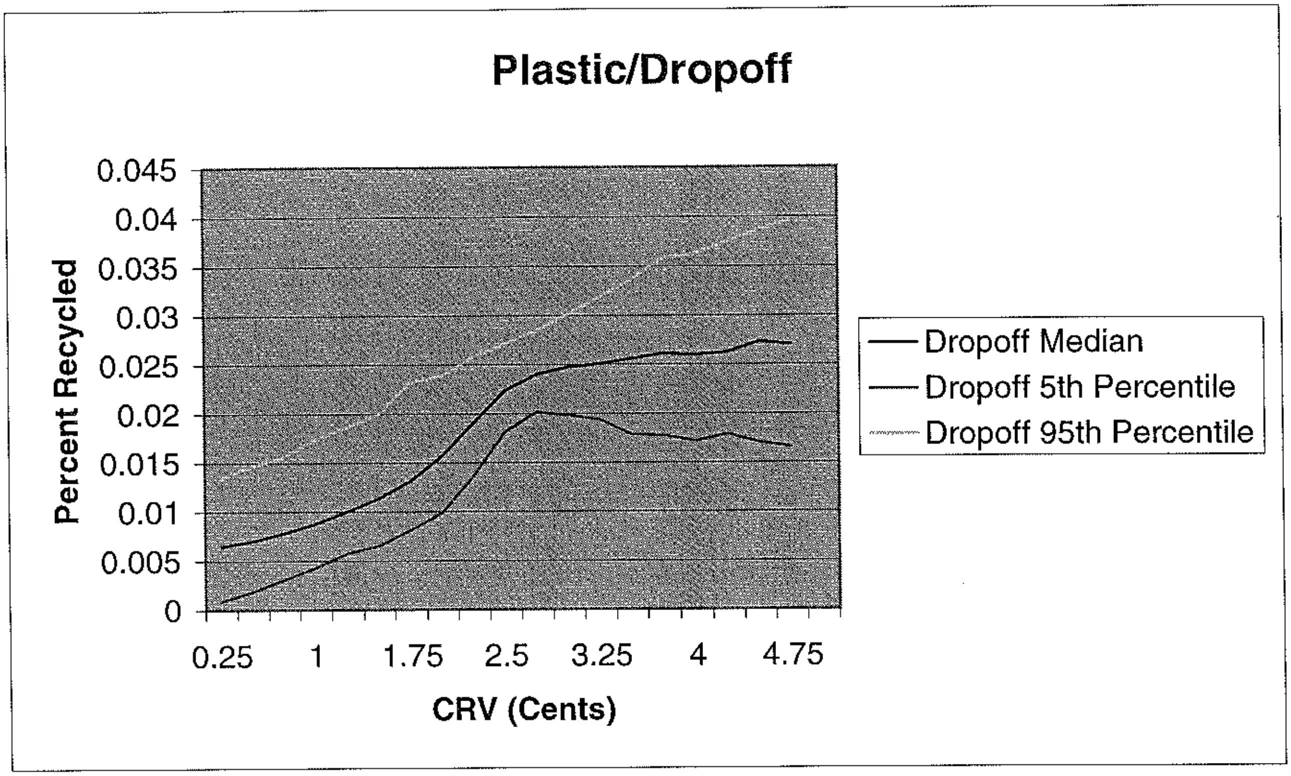


Fig. 12. Percent Dropoff Recycled by CRV for Plastic

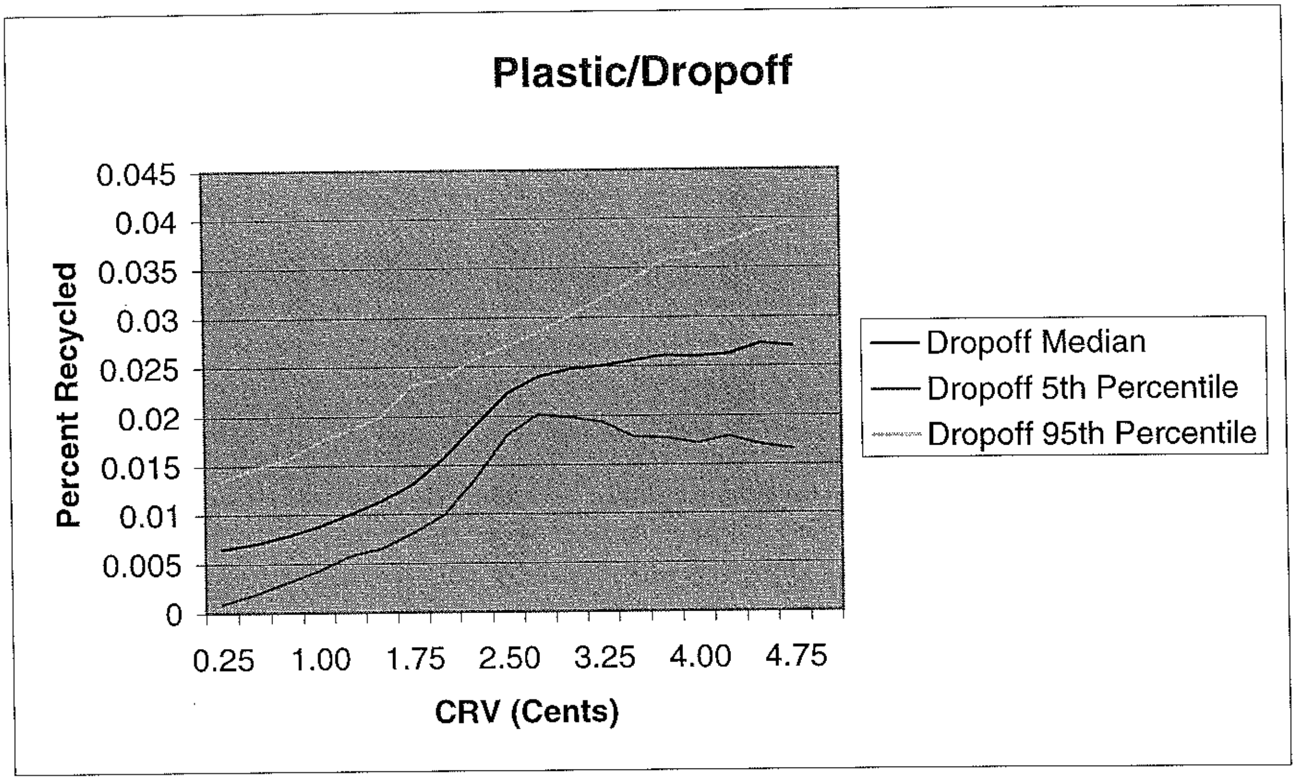


Fig. 13. Percent Curbside Recycled by CRV for Plastic