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Working Paper
August 31, 1993

Residential Waste Generation Model for King County

PART A: PRESENTATION OF THE MODEL.

The quantity of residential waste generation that enters the King County system can be identified by the following equation:

Waste Generation = Recycling + Solid Waste Collection + Solid Waste Self-Haul.

Each component of the waste generation equation is assumed to be a function of demographic characteristics as well as the level of recycling and waste reduction programs available to the population.

Hauler report data is used to estimate the recycling[1] and solid waste collection functions. Because this data is location specific, it is possible to estimate the relationship between the quantities of recycling and solid waste collection in a given location and the characteristics and programs available within that location. Survey data is used to estimate the percentage of self-haul solid waste that came from each location. Multiplying actual tonnage by the estimated percentage from each location yielded an estimate of location specific self-haul solid waste that could be used to complete the waste generation equation.[2]

The waste generation model treats each component of waste generation (recycling, solid waste collection, and solid waste self-haul) as an endogenous variable[3] which is a function of the characteristics and programs available in each city.[4] For each endogenous variable I converted tonnage to pounds per household per day.[5] This conversion allows for consistent and simplified interpretations of the estimation results. Each location (each city and unincorporated King county) represents an observation that was used in estimating the model.

The recycling, solid waste collection, and solid waste self-haul equations, were estimated

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The hauler report data includes curbside collection as well as some drop site collection. Private recycling occurs that is not picked up by the haulers and therefor is not included in the hauler report data.

It is assumed that there is no systematic bias between the independent variables in the model and the location specific tonnage data obtained from the surveys.

Endogenous variables are also referred to as dependent variables and as choice variables.

The programs and characteristics for individual cities and unincorporated areas are referred to as the independent variables or as the exogenous variables.

Data on the number of households within a given area were obtained from the Washington state office of financial management. They provide intercensul estimates of population and housing. It is assumed that multifamily households with four units or more are excluded from the collected residential solid waste data. They are probably included as commercial waste. Therefor, in the solid waste collection equation, multifamily households with more than four units are subtracted from the household data.

simultaneously using multivariate least squares regression.[6] This method of estimation allows the interdependencies of the endogenous variables to be incorporated in the model.

For each function, the independent variables include demographic characteristics, price data, and data on the recycling programs available in each city and in unincorporated King county. The demographic characteristics included in the equations are: population per household (pop), per capita income (inc), and households per square mile (dens).[7] A variable indicating the change in population between 1992 and 1991 (growth) is also included in the model. This variable is included to control for differences in the measured dependent variable that may be do to differences in growth rates between communities. Also, in areas experiencing rapid growth, households may be less familiar with the recycling programs available in a community. In addition, a zero one dummy variable is included to distinguish rural areas (r) from urban areas (1 indicates rural).

There are two price variables included in the model. The price of garbage collection (price) is defined as the difference between the one and two can collection rates. The price of recycling (prec) is the additional subscription fee customers must pay for participating in curbside programs. The price of recycling is the sum of yard waste fees and other curbside recycling fees.

Variables representing the recycling programs available in different communities include: a curbside recycling variable, a curbside yard waste variable and a variable representing the use of bins for recycling collection. The variable representing curbside recycling programs (curb) is the fraction of households for which curbside recycling is available. For cities with both single and multifamily curbside programs, this variable equals one. For communities with no curbside programs, this variable equals zero, and for cities with only single-family curbside recycling, this variable equals the fraction of households in the data set which are single family households.[8] A zero one dummy variable is used to indicate the presence of a curbside yard waste program (YW). A one indicates the presence of a yard waste program while a zero indicates the absence of a yard waste program. A dummy variable is also used to distinguish curbside recycling programs that use multiple bins for collection (1 indicates bins) from those that use a single toter. Also, a dummy variable for contract haulers (cntrct) is included in the recycling and solid waste collection equations (1 indicates contract hauler). The significance of this variable probably reflects differences in data reporting. Because the city of Skykomish has a free drop box for solid waste which is included in the hauler collection tonnage, a dummy variable for Skykomish is included in the solid waste equations (1 indicates Skykomish). Finally, dummy variables are also included to account for differences in quarters (1,2,3). To prevent singularity of the covariance matrix, a dummy variable for the fourth quarter is omitted.

The solid waste collection equation is labeled as equation A, the recycling equation is labeled as equation B, and the self-haul solid waste equation is labeled as equation C. The parameters for each equation start with the letter associated with each equation. So, the coefficient ACURB represents the

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The use of multivariate least squares estimation incorporates the simultaneous nature of the model into the estimation procedure. However, it is also possible to estimate each equation separately using ordinary least squares. Ordinary least squares will provide an efficient estimation of the parameters if the error terms associated with each of the equations are independent and uncorrelated. Because the endogenous variables are jointly determined, independence of the error terms is probably an invalid assumption. Nevertheless, estimation results using ordinary least squares are reported in appendix A.

In the self-haul disposal and disposal collection equations, the density variable was highly insignificant and did not impact the other parameters of interest. It was therefore excluded from those equations.

The curbside variable can also be interpreted as the probability that a given household in the community will have access to curbside recycling.

curbside variable for the solid waste collection equation while the coefficient BCURB represents the curbside variable for the recycling equation. Likewise, the coefficient BINC represents the income variable for the recycling equation while the coefficient CINC represents the income variable for the self-haul solid waste equation. Finally, a constant (CONST) term is included in each equation.

The dependent variable for the solid waste collection equation (equation A) is pounds of solid waste collected per household per day. The dependent variable for the recycling equation (equation B) is pounds of recycling collected per household per day. The dependent variable for the self-haul equation (equation C) is the natural logarithm of pounds of self-haul solid waste dropped off per household per day.[9] Estimation results are reported in table 1.

For the self-haul equation, both the independent variables and the dependent variable were converted to their natural logarithms. The logarithms provided a significantly better fit than using the untransformed data for the self-haul equation.

TABLE 1.

MULTIVARIATE REGRESSION

Parameter	Coefficient Estimate	Standard Error	t-statistic
ACONST	2.79503	1.21784	2.29507
A1	.299643	.194016	1.54442
A2	.591716	.192174	3.07906
A3	.706368	.192156	3.67602
APRICE	-.206296	.043567	-4.73518
APREC	.051518	.027882	1.84775
ACURB	-.965830	.336216	-2.87265
AYW	-1.02412	.264343	-3.87421
AINC	.033330	.752840E-02	4.42723
APOP	.714934	.443161	1.61326
AGROWTH	-.078426	.057038	-1.37497
AR	-.324267	.232733	-1.39330
ASKY	15.1511	.672161	22.5408
ABIN	.637176	.193661	3.29016
ACNTRCT	.494896	.197419	2.50684
BCONST	-4.70735	.959368	-4.90672
B1	-.117307	.200076	-.586314
B2	.524548	.196693	2.66684
B3	-.156503	.196734	-.795507
BPRICE	.067036	.043977	1.52434
BPREC	-.128624	.027769	-4.63197
BCURB	.981357	.317265	3.09318
BYW	1.14987	.263308	4.36703
BINC	.070597	.760063E-02	9.28832
BPOP	1.19503	.385389	3.10086
BDEN	.389093E-03	.193497E-03	2.01085
BGROWTH	-.215663	.058287	-3.70004
BR	.303789	.259025	1.17282
BBIN	-.309100	.195805	-1.57861
BCNTRCT	.378303	.192674	1.96343
CCONST	4.59105	1.83010	2.50863
C1	-.270304	.388435	-.695880
C2	-.139607	.387233	-.360524
C3	.269435	.387232	.695796
CPRICE	-.017803	.058447	-.304601
CPREC	-.342653E-02	.027005	-.126886
CCURB	-.153662	.068718	-2.23613
CYW	.015987	.529064	.030218
CINC	-1.08206	.391207	-2.76594
CPOP	-1.69279	1.95038	-.867929
CR	-.811779	.432580	-1.87660
CSKY	-12.3647	1.45860	-8.47704
CBIN	.472809	.385566	1.22627

TABLE 1 (continued).

LOG OF LIKELIHOOD FUNCTION = -421.123
NUMBER OF OBSERVATIONS = 108

Equation A

Dependent variable: DISP = pounds of solid waste collected per household per day.

Mean of dependent variable = 4.24511	Std. error of regression = .705764
Std. dev. of dependent var. = 3.27069	R-squared = .953009
Sum of squared residuals = 53.7951	Durbin-Watson statistic = 2.58490
Variance of residuals = .498103	

Equation B

Dependent variable: RECT = pounds of recycling collected per household per day.

Mean of dependent variable = 1.80094	Std. error of regression = .722621
Std. dev. of dependent var. = 1.52791	R-squared = .774235
Sum of squared residuals = 56.3955	Durbin-Watson statistic = 2.30464
Variance of residuals = .522181	

Equation C

Dependent variable: LSH = logarithm of pounds of self-haul solid waste delivered per household per day.

Mean of dependent variable = -.488324	Std. error of regression = 1.42277
Std. dev. of dependent var. = 2.53314	R-squared = .681689
Sum of squared residuals = 218.623	Durbin-Watson statistic = 2.09905
Variance of residuals = 2.02429	

PARAMETER:	INDEPENDENT VARIABLE.
Aconst, Bconst, Cconst:	constant term.
A1, A2, A3:	1st quarter.
A2, B2, C2:	2nd quarter.
A3, B3, C3:	3rd quarter.
Aprice, Bprice, Cprice:	solid waste collection price.
Aprec, Bprec, Cprec:	recycling collection price.
Acurb, Bcurb, Ccurb:	curbside recycling variable.
Ayw, Byw, Cyw:	yard waste curbside dummy variable.
Abin, Bbin, Cbin:	dummy variable for the use of multiple bins to collect curbside recycling.
Asky, Csky:	dummy variable for the city of Skykomish.
Acntrct, Bcntrct:	dummy variable to indicate contract haulers.
Agrowth, Bgrowth:	percentage change in population growth.
Apop, Bpop, Cpop:	population per household.
Ainc, Binc, Cinc:	per capita income (in thousands of dollars).
Bden:	households per square mile.
Ar, Br, Cr:	rural area.

The overall fit on the solid waste collection equation is outstanding. The model explains 95% of the variation in disposal collection ($R^2 = .953$). This is very high for models using cross section data.

The overall fit for the recycling equation and for the self-haul solid waste equation is also quite good. With an R^2 of .682, the model is explaining about 68% of the variation for self-haul solid waste, while with an R^2 of .774 the model is explaining 77% of the variation in recycling.

The coefficients in the preceding equations can be interpreted as the change in the dependent variable associated with a change in a particular independent variable.[10] For example, the coefficient AINC can be interpreted as the change in pounds of disposal collected per household per day associated with a change in per capita income. This coefficient tells us that as income rises by $1,000, solid waste disposal collected rises by approximately 0.033 lbs. per household per day. Similarly, the coefficient for curbside yard waste programs in equation B (BCURB) represents the average change in recycling collected associated with the availability of a curbside yard waste program. This coefficient tells us that curbside yard waste programs increase recycling collected by approximately .98 lbs. per household per day. So, the coefficients for equation A represent the change in pounds of disposal collected per household per day due to a change in the independent variable, while the coefficients in equation B represent the change in pounds of recycling collected per household per day due to a change in the independent variable.

The coefficients for equation C are also interpreted as the change in the dependent variable associated with a change in the independent variable. However, since equation C is in log form, the direct interpretation of each coefficient is different from equations A and B. For equation C, the coefficients (for continuos variables) represent the percentage change (divided by 100) in pounds of self-haul solid waste dropped off per household per day associated with a percentage change (divided by 100) in the dependent variable.[11] For dummy variables, the precise formula for the percentage change in the dependent variable is derived from the following equation:

$$PC = 100\ (\exp(c)-1),$$

where PC represents the percentage change in the dependent variable and c represents the estimated coefficient.[12]

The confidence levels associated with the coefficients are a function of the standard errors. In general, (with 94 degrees of freedom), plus or minus one standard error represents a confidence level of approximately 68% while plus or minus two standard errors represents a confidence level of about 95%. Similarly, the t-statistic (which equals the coefficient divided by the standard error) provides a test that the estimated coefficient is different from zero. For a two tailed test (which is appropriate when

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A positive sign indicates that the independent variable causes an increase in the dependent variable while a negative sign indicates that the independent variable causes a decrease in the dependent variable.

For continuos variables, the estimated coefficient represents the partial derivative of the log of self-haul (sh = self-haul) with respect to the log of the independent variable (x). This equals (dsh/sh)/(dx/x), which represents the percentage change (divided by 100) in self-haul associated with a percentage change (divided by 100) in the independent variable.

For a derivation of this formula, see:

Halvorsen, Robert and Raymond Palmquist, "The Interpretation of Dummy Variables in Semi-Logarithm Equations, "American Economic Review," Vol. 70, No. 3, 1980.

the sign of the coefficient is not predicted by the model), the 95% confidence level requires a t-statistic of 1.99 while the 90% confidence level requires a t-statistic of 1.67. For a one tailed test (which is appropriate when the sign of the coefficient is predicted by the model), the 95% confidence level requires a t-statistic of 1.67 while the 90% confidence level requires a t-statistic of 1.29. If the calculated t-statistic exceeds the critical value for a given confidence level, we can conclude that the coefficient is significantly different from zero.

Interpretations of the estimation results are presented below. I have divided the results into three categories: demographic results, price results, and recycling program results.

PART B: DEMOGRAPHIC RESULTS.

As mentioned earlier, the coefficient AINC can be interpreted as the change in pounds of disposal collected per household per day associated with a change in per capita income. This coefficient tells us that as income rises by $1,000, solid waste disposal collected rises by approximately 0.033 lbs. per household per day. Similarly, the coefficient BINC tells us that a $1,000 increase in income increases recycling by about .07 lbs. per household per day.[13] As we would expect, the income coefficient for the self-haul equation CINC is negative, indicating that as income rises, self-haul disposal declines. In addition, the magnitude of the variable is close to one indicating that as income rises by fifty percent, self-haul disposal falls by about fifty percent.

The population per household variable is positive and significant for both the solid waste collection equation and the recycling equation. In the disposal collection equation, APOP is .71 indicating that adding another person to a household increases disposal collected by .71 lbs. per household per day. Similarly, the population per household coefficient for the recycling equation (BPOP) is 1.19, Indicating that an extra person in a household increases household recycling by about 1.19 lbs. per day. It is interesting to note that the estimated impact of an extra person in a household is higher in the recycling equation than in the disposal equation. This difference may be due to random error,[14] or it may be that higher population rates are indicative of families with young children who may tend to recycle more. In the self-haul equation, the population per household variable was negative (CPOP = -1.69) but with a standard error of 1.95, the coefficient is insignificant. Thus, population per household did not seem to have a significant impact on self-haul.

The density variable (households per square mile) was positive and significant in the recycling equation, indicating that more densely populated areas tend to recycle more.

The growth variable (the percentage change in population between 1991 and 1992) was negative and significant for both the recycling and solid waste collection equations. As indicated earlier, this variable may reflect differences in awareness in recycling programs due to new people moving into a community. However, I believe it is more likely that the variable is picking up differences in the measured dependent variable that are due to differences in growth rates between communities.

Finally, The rural variable in the self-haul equation (CR) is both negative and significant. By using the formula discussed on page 6, we can calculate the percentage change in self-haul associated with

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It is important to remember that we are using cross section data for our analysis, so income is likely to pick up other characteristics associated with a given community than just income alone. We expect income to be correlated with characteristics such as education and perhaps a general willingness to participate in recycling programs. Thus, while we can conclude that higher income communities have higher recycling levels, it is inappropriate to conclude that increasing income alone will increase recycling levels by the estimated .07 lbs. per household per day.

The difference between the estimated coefficients (APOP and BPOP) is not statistically significant at the 90% confidence level.

rural communities. Results are reported below:

Parameter	Estimate	Standard Error	t-statistic
RUR	-55.5933	19.2095	-2.89405,

where RUR = (exp(CR)-1)100, Thus rural communities dispose of about 55.6% less self-haul than their urban counterparts. This difference may be due to differences in travel distance to transfer stations.[15]

PART C: PRICE RESULTS.

It is interesting to look at the impact that garbage rates have on both disposal and recycling choices. As indicated earlier, I define the price of solid waste collection as the difference between one and two can collection rates. I feel that this difference represents the price that typical households perceive when faced with choices on disposal quantities. The impact of price on disposal is strong and significant. The price coefficient (-.206296) indicates that a one dollar increase in disposal price would reduce disposal collection by approximately 0.21 lbs. per household per day. The price elasticity for solid waste collection is defined as the percentage change in disposal collected divided by the percentage change in price. Evaluated at the data means, the price elasticity for solid waste collection (PELASD = APRICE(disp/price), where disp is the mean quantity of disposal collected and price is the mean price of collection) is:

Parameter	Estimate	Standard Error	t-statistic
PELASD	-.202034	.042667	-4.73518

A price elasticity of -0.20 indicates that a 100% increase in the price of collection would reduce the quantity of solid waste collected by 20%.

We can also evaluate the impact that garbage collection prices have on the quantity of recycling collected. The coefficient BPRICE indicates that a $1 increase in the price of garbage collection increases recycling by about .067 lbs. per household per day. So, of the estimated .21 lbs. of solid waste collection reduced due to a $1 price increase, about one third (.067 lbs.) of that amount is shifted into recycling. By multiplying BPRICE times the average quantity of recycling collected then dividing by the average price of garbage collection, we can calculate the elasticity of recycling with respect to garbage collection rates (PELASR) evaluated at the sample means.

Parameter	Estimate	Standard Error	t-statistic
PELASR	.154750	.101519	1.52453

This result indicates that a 100% increase in the price of garbage collection would increase recycling by about 15%, other things being equal.

It is also interesting to examine the impact that recycling fees have on both the quantity of solid waste disposal and on the quantity of recycling collected. I define the price of recycling to be the sum of monthly subscription fees charged for both curbside recycling and curbside yard waste. The coefficient APREC indicates that a $1 increase in recycling fees increases disposal collection by about .05 lbs. per household per day. Similarly, the coefficient BPREC indicates that a $1 increase in recycling fees

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The rural variable was negative in the disposal collection equation and positive in the recycling equation. However, using a two-tailed test, neither variable was significant at the 90% confidence level.

reduces recycling by about .129 lbs. per household per day. The discrepancy between the two variables indicates that less than half of the reduction in recycling due to recycling collection fees is associated with an increase in solid waste collection. The rest of the reduction in recycling collected is probably shifted into private recycling. It may be that the types of individuals who are prevented from participating in curbside programs because of a fee are also the type of individuals who are already recycling in the private sector (perhaps through buy back stations).

The recycling price elasticity with respect to disposal collection (PRELASD) is the percentage change in the quantity of solid waste collected divided by the percentage change in the price of recycling. The recycling price elasticity with respect to recycling fees (PRELASR) is the percentage change in the quantity of recycling collected divided by the percentage change in the price of recycling. These elasticities are evaluated at the sample means and the results are reported below:

Parameter	Estimate	Standard Error	t-statistic
PRELASD	.027150	.014693	1.84775
PRELASR	-.159776	.034494	-4.63197

These elasticities indicate that a 100% increase in the price of recycling would reduce the quantity of recycling by about 16%, while increasing the quantity of solid waste collection by about 2.7%.

Reductions in solid waste collection associated with increases in collection prices may be off-set by increases in self-haul disposal. Therefor, it is important to also consider the impact of collection prices on self-haul solid waste. Because the self-haul equation is a logarithmic function, the price coefficients for equation C represent the price elasticities directly. The estimated coefficient in the self-haul equation with respect to disposal collection prices (CPRICE) was found to be negative (-0.017803) but was not significantly different from zero (t-statistic = .304601), It is therefor assumed that the potential off-set in self-haul disposal due to collection rates is not significant. Similarly, the coefficient associated with the price of recycling (CPREC) is negative (-.00343) but insignificant (t-statistic = -.126886), indicating that recycling fees do not significantly impact self-haul disposal.[16]

PART D: RECYCLING PROGRAM RESULTS.

The impact that curbside recycling programs have on solid waste collection is estimated in equation A. The coefficient AYW estimates the change in per household disposal collected due to a change in the availability of a curbside yard waste program. This coefficient indicates that , other things being equal, curbside yard waste programs reduce disposal collected by 1.02 lbs. per household per day. Similarly, The coefficient ACURB indicates the change in household disposal associated with a change in the availability of general curbside recycling. This coefficient tells us that, other things being equal, the availability of curbside recycling reduces disposal collected by about 0.966 lbs. per household per day.[17]

Just as the coefficients ACURB and AYW represent the effects of curbside recycling programs on

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In the self-haul equation, both the impact of garbage collection prices and the impact of recycling collection fees were found to be negative but insignificant. In both cases I was expecting to see positive price coefficients. Since self-haul disposal can be used as a substitute for both disposal collection, and recycling collection, I would expect an increase in collection rates to increase self-haul disposal. This substitution effect was not found.

This interpretation assumes that single toters are used to collect commingled recycling. The use of multiple bins to collect source separated recycling was found to have a smaller impact on disposal. A discussion of the findings for bins is included in section D.

solid waste collection, the coefficients BCURB and BYW represent the effect of curbside recycling programs on the amount of recycling collected. The coefficient BYW tells us that a yard waste program increases recycling by about 1.15 lbs. per household per day[18]. The coefficient for general curbside recycling (BCURB) indicates that curbside programs increase recycling by about 0.98 lbs. per household per day, other things being equal. Each of these coefficients are highly significant.

To look at the total effect of curbside programs on solid waste disposal, we need to examine the combined effect of these programs on both solid waste collection (equation A) and on self-haul solid waste (equation C.) The coefficient CCURB tells us that the availability of a general curbside recycling program reduces self-haul solid waste by about 15.4%. This variable is significant at the 95%. On the other hand, the curbside yard waste coefficient (CYW) is .016 with a t-statistic of only .03, indicating that we do not see a reduction in self-haul disposal associated with curbside yard waste programs. Using the formulas discussed on page 6, we can calculate the impact of curbside programs on self-haul solid waste evaluated at the data means. Results are reported below (where YWSH1 = (exp(CYW)-1)sh, CRBSH1 = CCRB(sh/curb), sh = mean pounds of self-haul per household per day, and curb = mean fraction of households with access to curbside recycling);

Parameter	Estimate	Standard Error	t-statistic
YWSH1	.021812	.727628	.029977
CRBSH1	-.250867	.112188	-2.23613

The above coefficients represent the change in pounds of self-haul solid waste per household per day associated with the curbside programs. The yard waste (YWSH1) program does not seem to have a significant impact on self-haul disposal.[1198] However, the general recycling program does significantly reduce self-haul disposal.

By adding the impact on self-haul to the impact on disposal collection we can look at the total impact that general curbside recycling has on solid waste disposal (evaluated at the data means):

The estimated impacts associated with curbside yard waste programs may not reflect the full impact associated with these programs in a typical year. This is because the data used for the estimation procedure was from 1992. In that year, a water shortage led to restrictions on lawn watering throughout most of King county.

18 The curbside yard waste program probably has a larger impact on self-haul than what is indicated by these statistics. This is because the survey from which the self-haul data were obtained was not conducted during the second quarter of 1992, necessitating the use of first quarter survey data to estimate second quarter self-haul. Because yard waste programs primarily impact second and third quarter solid-waste, the estimated coefficient associated with curbside yard waste is probably an under estimate of the annual impact of such programs on self-haul.

Parameter	Estimate	Standard Error	t-statistic
CRBDT	-1.12670	.354503	-3.43212

Where CRBDT = CRBSH1 + ACURB. This result tells us that general curbside recycling programs reduce solid waste by nearly 1.13 lbs. per household per day.

From the preceding results we can see that curbside recycling programs significantly impact both recycling and solid waste disposal. Somewhat surprisingly, we also see that the amount of recycling collected from curbside recycling programs is about the same as the quantity of waste reduction associated with each program. An analysis of the difference between increases in recycling associated with each curbside program and decreases in solid waste disposal associated with each curbside program was conducted. Results are reported below where YRDPV = AYW + BYW + (exp(CYW)-1)sh, CRBPV = ASF + BSF + (CSF)sh/curb, and where sh = pounds of self-haul collected per household per day evaluated at the sample mean and curb = the mean fraction of households with access to curbside recycling.

Parameter	Estimate	Standard Error	t-statistic
YRDPV	.147567	.873771	.168885
CRBPV	-.235341	.517990	-.454335

A significantly positive value for either of the above parameters would indicate that the quantity of recycling collected from curbside programs is larger than the solid waste reduction associated with these programs. This would indicate that some of the recycling collected was merely being diverted from private recycling programs. However, as we can see from the above results, the difference between increases in recycling and decreases in solid waste are not significantly different from zero. In fact, the coefficient for the general recycling program is slightly negative indicating that there is a greater reduction in solid waste disposal associated with this program than there is an increase in recycling. This could be due to a greater consciousness on the part of the public when the program is instituted. However, with a t-statistic of only 0.45, the difference is not significant. I interpret these results to indicate that the amount of recycling collected from curbside programs appears to come directly out of solid waste disposal. There does not appear to be a significant amount of diversion from private recycling associated with these programs.

Another interesting variable is the dummy variable associated with the use of bins for recycling collection (bins are used to collect source separated recycling as opposed to single containers that collect commingled recycling.) We see that the use of bins is associated with lower levels of recycling (BBIN = -.309) and higher levels of solid waste collection (ABIN = .637). It is tempting to interpret these coefficients as an indication that the use of bins for curbside recycling programs is less effective at reducing solid waste than the use of single containers. However, it may be inappropriate to draw that conclusion. The use of bins may be correlated with specific haulers. To the extent that the choice of bins is correlated with the choice of haulers, these coefficients may reflect differences in data reporting.[19] Also, to the extent that the use of bins for recycling collection also results in a higher level of contaminated recycling, the full impact of using bins instead of single containers may not show up in the residential solid waste data. That is, contaminated recycling could re-enter the land fills through the commercial sector. Until we can examine the commercial sector and try to control for this possibility, it may be premature to conclude that bins are less effective at reducing solid waste than single

19 The magnitude of the bin coefficient seems inappropriately high (especially in the solid waste equations). I believe that this variable is probably correlated with a left out variable. Unfortunately, I was unable to find such a variable.

containers.

PART E: CONCLUSIONS:

The preceding basic model is very flexible. We can add new variables to this basic model to examine the statistical impact of new programs or to examine changes in existing programs. Whenever we can obtain data on programs or characteristics affecting residential waste, we can incorporate such data into the model to examine its statistical impact.

APPENDIX A:

Estimation results using ordinary least squares (estimating equations A, B, and C independently.)

EQUATION: A

LOG OF LIKELIHOOD FUNCTION = -115.576
NUMBER OF OBSERVATIONS = 108

Parameter	Estimate	Standard Error	t-statistic
ACONST	2.56618	1.32228	1.94072
A1	.303487	.209043	1.45179
A2	.592428	.207028	2.86158
A3	.706915	.207008	3.41492
APRICE	-.202577	.047011	-4.30910
APREC	.052581	.030049	1.74982
ACURB	-.932562	.364608	-2.55771
AYW	-1.00732	.285067	-3.53363
AINC	.033306	.811402E-02	4.10475
APOP	.778649	.479445	1.62406
AGROWTH	-.077291	.061468	-1.25741
ASKY	15.3296	.735069	20.8547
ABIN	.643890	.208774	3.08415
ACNTRCT	.509918	.213053	2.39338
AR	-.328799	.250745	-1.31129

Equation EQA

Dependent variable: DISP

Mean of dependent variable = 4.24511	Std. error of regression = .760312
Std. dev. of dependent var. = 3.27069	R-squared = .953032
Sum of squared residuals = 53.7609	Adjusted R-squared = .945961
Variance of residuals = .578074	Durbin-Watson statistic = 2.58553

EQUATION: B

LOG OF LIKELIHOOD FUNCTION = -118.147
NUMBER OF OBSERVATIONS = 108

Parameter	Estimate	Standard Error	t-statistic
BCONST	-4.68211	1.04312	-4.48856
B1	-.117953	.215641	-.546989
B2	.524385	.211939	2.47422
B3	-.156562	.211984	-.738556
BPRICE	.063846	.047824	1.33501
BPREC	-.127329	.030096	-4.23075
BCURB	.979522	.345235	2.83726
BYW	1.14111	.284415	4.01211
BINC	.070002	.824410E-02	8.49117
BPOP	1.20668	.418020	2.88665
BDEN	.378422E-03	.214690E-03	1.76264
BGROWTH	-.216108	.063820	-3.38622
BBIN	-.300587	.211720	-1.41974
BCNTRCT	.360791	.210535	1.71369
BR	.285298	.281042	1.01514

Equation EQB

Dependent variable: RECT

Mean of dependent variable = 1.80094	Std. error of regression = .778632
Std. dev. of dependent var. = 1.52791	R-squared = .774281
Sum of squared residuals = 56.3829	Adjusted R-squared = .740302
Variance of residuals = .606268	Durbin-Watson statistic = 2.29768

Equation: C

Parameter	Estimate	Standard Error	t-statistic
CCONST	4.39457	1.95514	2.24770
C1	-.262100	.413828	-.633355
C2	-.139386	.412526	-.337884
C3	.269806	.412526	.654034
CPRICE	-.030853	.062814	-.491179
CPREC	-.706047E-04	.028862	-.244627E-02
CCURB	-.134258	.073834	-1.81837
CYW	-.01603	.564025	-.028430
CINC	-1.11201	.417560	-2.66311
CPOP	-1.29191	2.08745	-.618892
CR	-.821412	.461292	-1.78068
CSKY	-12.0818	1.57244	-7.68344
CBIN	.474872	.411711	1.15341

Standard Errors computed from quadratic form of analytic first derivatives (Gauss)

Equation EQC

Dependent variable: LSH

Mean of dependent variable = -.488324	Std. error of regression = 1.51571
Std. dev. of dependent var. = 2.53314	R-squared = .682129
Sum of squared residuals = 218.250	Adjusted R-squared = .641977
Variance of residuals = 2.29737	Durbin-Watson statistic = 2.09081

The estimation results using ordinary least squares are very similar to the estimation results using simultaneous equation estimation. Again we see that the explanatory power of the solid waste collection equation is very high with R^2 of .953. The over-all fit for the self-haul and recycling equations is more typical of results using cross section data with R^2 s of .682 and .774 respectively.

All of the parameters separately evaluated with respect to the simultaneous least squares model were also analyzed using the ordinary least squares model. Results are presented below:

Parameter	Estimate	Standard Error	t-statistic
YWSH1	-.021531	.751264	-.028659
CRBSH1	-.219189	.120541	-1.81837
CRBDT	-1.15175	.120541	-9.55481
YRDPV	.112254	.284415	.394683
CRBPV	-.172229	.345235	-.498876
PELASR	.147386	.110400	1.33501
PRELASR	-.158169	.037385	-4.23075
PELASD	-.198392	.046040	-4.30910
PRELASD	.027709	.015836	1.74982
RUR	-56.0190	20.2881	-2.76118