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Garbage and Recycling with Endogenous Local Policy*

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This paper estimates the impact of garbage fees and curbside recycling programs on garbage and recycling amounts. Without correction for endogenous policy, a price per bag of garbage has a negative effect on garbage and a positive cross-price effect on recycling. Correction for endogenous local policy increases the effect of the user fee on garbage and the effect of curbside recycling collection on recycling. Introducing a fee of $1 per bag is estimated to reduce garbage by 412 pounds per person per year (44%), but to increase recycling by only 30 pounds per person per year.

Most communities in the United States pay for municipal solid waste services using general revenues or monthly fees that do not vary per unit of garbage collected at the curb. Thus households think that more garbage is free. This public provision might be warranted if the service were nonrival, but the marginal cost of collecting and disposing of another unit of garbage is decidedly nonzero. The community must pay for additional labor, truck space, and tipping fees at regional landfills or incinerators.

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Similarly, free public provision might be warranted if the service were nonexcludable, but providers can indeed extract a price per unit of garbage collected. An increasing number of communities have begun to sell special stickers or tags that must be attached to any bag of garbage at the curb—or else it will not be collected.

This local policy innovation can have several beneficial effects. The price per bag of garbage can help reduce household generation of garbage that must be put in a landfill, help raise revenue, alleviate budget problems, and allow property tax reductions. It provides incentives for recycling, composting, and even for source reduction—demanding less packaging at stores. Unfortunately, these policies also have costs. The new programs must be advertised, promoted, administered, and enforced. And the price per bag of garbage might induce households to litter or burn their garbage, or dump it in vacant lots.

Many communities have also adopted curbside recycling programs to help deal with their solid waste problems. A curbside recycling program can be expensive to operate, but reduces disposal costs at the landfill and could produce revenue if collected materials are sold.

Both of these local solid waste management policies are still relatively new and more could be known about their effectiveness at reducing garbage and increasing recycling. Communities considering the adoption of curbside recycling and a user fee (price per bag of garbage) could benefit from economic estimates of the incidence of these policies. The U.S. EPA [23] describes case studies of 17 communities with pricing programs, and Jenkins [7, 8] uses a panel of 14 communities to initiate a growing econometric literature that estimates the demand for garbage collection as a function of the price per bag, the presence of a free curbside recycling program, and household demographic characteristics.

Our paper makes three main contributions to this literature. First, we collect original data from a significantly larger cross-section of communities. No existing econometric study uses data with more than 12 communities with a user fee.[1] We started with a list of 32 communities with user fee programs from the U.S EPA [23], and through extensive probing and

[1] Jenkins [7, 8] and Repetto *et al*. [17] estimate fixed effects using a monthly panel of 14 communities, 9 with a user fee, for a total of 636 observations. Podolsky and Spiegel [16] use a cross-section of 180 cities, 12 with a user fee. Miranda *et al*. [12] show data from 21 communities before and after implementation of a user fee but do not use econometrics to control for changes in other variables. Other kinds of data have been used as well. Aggregate time series from one city are employed by Efaw and Lanen [3] and Skumatz and Breckinridge [20]. Household surveys with self-reported garbage and recycling behavior appear in Hong, Adams, and Love [5] and Reschovsky and Stone [18]. Fullerton and Kinnaman [4] take direct measures of garbage and recycling weight and volume for 75 households before and after the implementation of a user fee program.

word-of-mouth communications, we expanded this list to include 114 communities with a user fee. We called each of these communities on the phone to find the appropriate solid waste official and to ask about the pricing program, the recycling program, actual tonnages of residential garbage and recycling (for 1991), and whether they knew of any other communities that charge a price per unit of garbage at the curb.[2] We combine this original data with similar information for 845 communities without a user fee but with and without curbside recycling. This second set of data is provided by the International City Managers Association (ICMA [6]). We use U.S. Census data for demographic characteristics of all these communities and data published by *Biocycle* magazine's annual survey for regional tipping fees and any state mandates expected to affect garbage and recycling (Steuteville and Goldstein [21]).[3]

Second, while other studies estimate the demand for garbage collection or for recycling collection, we estimate both as comparable functions of the price of garbage, the presence of a curbside recycling program, and other relevant variables. Thus we can estimate the cross-price effect of garbage price on recycling quantity.[4] In addition, the comparable estimation of both garbage and recycling demands allows us to infer changes in source reduction or other possibly illegal methods of disposal: as discussed below, the user fee decreases the weight of garbage by more than it increases recycling.

Third, and perhaps most important, we allow for the possibility of endogenous policy choices. As pointed out by Besley and Case [1, p. 1], "If state policy making is purposeful action, responsive to economic and political conditions within the state, then it may be necessary to identify and control for the forces that lead policies to change if one wishes to obtain unbiased estimates of a policy's incidence." No existing study of

[2] After collecting much of this information, we discovered that some towns had provided us an estimate of their aggregate garbage (our dependent variable) that was obtained by multiplying their local population times the EPA estimate of the U.S. average garbage per person! We did not include these communities in our sample. We also excluded towns that were unable to provide data on residential waste separately from commercial waste.

[3] See an earlier unpublished version of this paper (Kinnaman and Fullerton [10]) for a detailed written description of the data gathering process. Enough years of a panel could be used to estimate a fixed-effects model, but that effort will have to wait.

[4] Several papers mentioned above estimate the demand for garbage collection, but not recycling amounts. Using a survey of 2298 households, Hong, Adams, and Love [5] are able to estimate the frequency that households recycle. Using a different survey of 1422 households, Reschovsky and Stone [18] estimate the probability that a household will recycle, for each material. Tawil [22] estimates the probability of adopting curbside recycling. Only Browne [2] estimates the amount of household recycling as a function of a user fee for garbage collection, and other variables, using 34 communities (16 with a user fee). None of these studies estimates both garbage and recycling quantities.

garbage demand includes a correction for the endogeneity of local government decisions about the price per bag of garbage collected and whether to implement curbside recycling.[5]

The bias in the estimate of a policy's incidence from treating the policy variable as exogenous could go in either direction. Both the positive effect on recycling and the negative effect on garbage could be *overstated* if the estimation processes omit an unobservable variable such as the environmental awareness of the community. The omitted variable might (i) increase the probability that a community implements "green" policies such as a user fee and curbside recycling program, (ii) increase the observed quantity of recycling by these "environmentally aware" citizens, and (iii) consequently reduce the observed quantity of garbage. On the other hand, the effects of such policies could be *understated* if the likelihood of implementing these local policies is a positive function of the quantity of garbage collected in the community. Such a relationship could exist if the benefits of implementing these policies (including the expected reduction in garbage) are larger for towns with relatively large quantities of garbage collected. In general, previous estimates of the effect of price or curbside recycling could be biased in either direction if they leave in the error term these unobserved characteristics that are correlated with the price or curbside recycling variables.

To control for the possibility of endogenous policy choices, we model the local government's decisions about curbside recycling, whether to charge a price and what price to charge. These local policy choices are estimated as functions of observable exogenous variables such as the region-wide tipping fee, the population density, several state policy variables, and demographic characteristics. We then use the predicted values for these policy variables to correct for possible endogeneity in the garbage and recycling demand equations using two-stage least squares (2SLS).

Relative to the results obtained from treating these policies as exogenous, we find that this correction increases the estimated impact of a user fee on garbage quantities, and it increases the effect of curbside recycling on the quantity of recycling. That is, previous studies may have underestimated the effects of these programs on garbage and recycling totals. Thus, our results confirm the second scenario described in the paragraph above.

[5] Most studies assume the price is exogenous. Hong, Adams, and Love [5] correct for the endogeneity that arises from the fact that the household's quantity choices determine its location on a fixed price schedule, but they do not deal with the setting of the price schedule. Browne [2] considers endogeneity of the town's chosen price, and rejects it. Tawil [22] corrects for the self-selection of towns into curbside recycling programs, to estimate the probability of adopting such programs. None of these papers corrects for this kind of self-selection or endogeneity in the estimation of garbage or recycling quantities.

Accounting for endogeneity in local policy choices, we find that raising the fee from 0 to $1 per bag reduces collected garbage from 942 to 530 pounds per capita (by 44%). Of the 412-pound decrease, we estimate that approximately 30 pounds goes into local recycling. At present we are unable to trace the remaining 382 pounds. Clearly, the wisdom of garbage collection fees depends critically on the ultimate whereabouts of these 382 pounds of missing garbage; it is an important topic for future research.

I. A MODEL OF HOUSEHOLD DEMAND FOR GARBAGE AND RECYCLING

Our full model involves a sequence of decisions by different agents. In order to explain the model, we start with the household's waste disposal choices, and then work our way back to the local government's policy choices.

Assume that a community with a single local government is composed of N households. Each household buys a single composite consumption good c, and each generates waste in three forms. All waste must appear as regular garbage collection (with amount g), recycling (with amount r), or illicit burning and dumping (with amount b). Household preferences among these three disposal methods may depend on a set of demographic characteristics, α . Thus each household maximizes utility:[6]

$$u = u[c, g, r, b; \alpha] \tag{1}$$

subject to

$$m = c + p_g g + p_r r + p_b b \tag{2}$$

where m is income, the consumption good c is numeraire, and p_j denotes the price of disposal option j for $j = g, r, b$. This maximization process yields demand functions for each method of waste removal:

$$g = g(p_g, p_r, p_b, m, \alpha) \tag{3a}$$

$$r = r(p_g, p_r, p_b, m, \alpha) \tag{3b}$$

$$b = b(p_g, p_r, p_b, m, \alpha). \tag{3c}$$

The price of garbage collection facing the household (p_g) may include the value of a user fee charged by the community (P), plus time and effort

[6] As pointed out by a referee, utility could be a function only of consumption c, where c is produced at home using purchased inputs, household time, and disposal (g, r, and b). Then that home-production function for c can be substituted into utility to obtain Eq. (1). Our formulation is somewhat more general, however, in that it allows for the possibility that altruistic households do care directly about their own g, r, and b.

to store garbage and to put it out to the curb.[7] We have no data on the time and effort components, but we assume they are functions of household income and demographic characteristics (m, α). Other variables might also affect the household cost of disposing of garbage. First, several states prohibit yardwaste from entering landfills. We define the indicator variable $I^{YW} = 1$ if the community bans yardwaste from the garbage, and 0 otherwise. We expect such a ban to increase the cost of disposing of yardwaste. Second, many states require local mandates for household curbside recycling ($I^{MAN} = 1$, and 0 otherwise).[8] This law increases the cost of disposing of garbage at the curb by the expected fine for not recycling. These considerations explain the first of our three price equations:

$$p_g = p_g(P, m, \alpha, I^{YW}, I^{MAN}) \tag{4a}$$

$$p_r = p_r(I^R, m, \alpha, I^{DR}, I^{MAN}) \tag{4b}$$

$$p_b = p_b(m, \alpha, D, D^2) \tag{4c}$$

where all variables are carefully defined in Table 1.

In Eq. (4b), the household's price of recycling (p_r) includes the cost of separating, storing, transporting, and possibly paying a firm to accept the recycled material (this last component could be negative). Time costs can be functions of household income and demographic characteristics (m, α). The presence of a curbside recycling program diminishes these costs significantly, since transportation and payments to firms are handled by the community. Let $I^R = 1$ if the community has free curbside recycling collection, and 0 otherwise. Several states have a deposit-refund program for certain types of drink containers. We define $I^{DR} = 1$ for communities in such states, and 0 otherwise. A refund for bottles returned to the store might increase the cost of putting those bottles into curbside collection.

The household's price for burning or dumping (p_b) is not a market price, but it includes implicitly the time required to find a suitable dump site, the costs of traveling to the dump site, and the possible fine for breaking a local litter ordinance.[9] We tried to collect information on litter

[7] Throughout this paper we use lower case letters to denote household variables and upper case letters to denote community variables.

[8] In most cases, this decision is imposed by the state and is therefore exogenous to the community. We treat all state policy variables defined in the paper as exogenous in order to focus on local choices about whether to implement a curbside recycling program and a pricing program.

[9] Some of these costs may be fixed or marginal. Implicitly, therefore, we allow for the possibility that a higher price for garbage could induce the household to incur the fixed cost of dumping, and thus to reduce both its garbage and its recycling (Kinnaman and Fullerton [9]).

TABLE 1
Definitions of Variables

Endogenous variables:	
G	Pounds per person per year of collected residential garbage
R	Pounds per person per year of collected recyclable material
I^R	1 if city-wide, free curbside recycling collection (0 otherwise)
$P1$	Price of first 32-gallon bag or can, divided by local price index
$P2$	Price of second 32-gallon bag or can, divided by local price index
Exogenous variables in household demand (X_i in Eq. (6)):	
m = INCOME	Per capita income in 1000's of dollars, divided by local price index
RETIRE	The percentage of all persons that are 65 years and older
FAM SIZE	Average number of persons per household
EDUC	Percentage of those 25 years or older with bachelor's degree or higher
OWNER	The percentage of households that own their own home
D = DENSITY	The number of 1000's of persons per square mile
I^{YW}	1 if a state law prohibits yardwaste from landfills (0 otherwise)
I^{DR}	1 if the state has a deposit/refund system for bottles (0 otherwise)
I^{MAN}	1 if the state mandates that households recycle (0 otherwise)
Exogenous variables in probability of recycling (Z_i^R in Eq. (7)) include X_i plus:	
P_T	The region-wide tipping fee, divided by the local price index
I^{SH}	1 if state helps incentives to buy recycled materials (0 otherwise)
I^{SB}	1 if state agencies must buy recycled materials (0 otherwise)
$Q = QUOTA$	State mandated minimum for the recycling rate, $R/(R+G)$
$QTIME$	Number of years until quota takes effect
I^{SL}	1 if state law "requires" the city to collect recycling (0 otherwise)
Exogenous variables in the optimal price (Z_i^P in Eq. (9)) include the Z_i^R plus:	
I^{PT}	1 if state law limits the town's property taxes (0 otherwise)
I^{MUN}	1 if collection is handled by municipal employees (0 otherwise)

laws and fines in each community, but enforcement varies widely. Adequate data on penalties are not available. Instead, we hypothesize that easier opportunities for illegal dumping are provided in areas where population density is very high or very low: urban areas with commercial dumpsters and rural areas with remote spots for dumping. Communities with middle densities (suburbs and residential communities) provide fewer opportunities to dump. Suburban areas could also provide greater social pressure not to dump. We therefore enter density (D) in a nonlinear fashion, using both population density and its square in the regressions. Hence (4c) above.

Upon substitution of (4a–c) into 3(a–c), we get demands for garbage (G), recycling (R), and burning or dumping (B) as functions of observed variables defined above:

$$G = G(I^R, P, m, \alpha, D, D^2, I^{YW}, I^{DR}, I^{MAN}) \tag{5a}$$

$$R = R(I^R, P, m, \alpha, D, D^2, I^{YW}, I^{DR}, I^{MAN}) \tag{5b}$$

$$B = B(I^R, P, m, \alpha, D, D^2, I^{YW}, I^{DR}, I^{MAN}). \tag{5c}$$

We do not observe each community's quantity of burning or dumping (B) and, therefore, do not estimate (5c). Though the system of equations in (5) is simultaneously determined, the bias from estimating one equation at a time is zero since the set of independent variables is the same in all equations. The reason for discussing B, however, is two-fold. First, the instruments for the *price* of burning and dumping can affect the quantities of observed garbage and recycling in (5a) and (5b). Second, the availability of this third option (B) to households implies that the two observed options (G and R) are not *necessarily* substitutes.

A linear econometric specification of these equations is:[10]

$$Y_i = \beta_0 + I_i^R\beta_1 + P_i\beta_2 + X_i\beta_3 + \mu_i \tag{6}$$

where Y_i denotes either the per capita weight of garbage (G) or recycling (R) for community i (where $i = 1, \dots, M$), I_i^R is the indicator variable for the presence of a curbside recycling program, P_i denotes the (observed) price of garbage collection, X_i is a vector of exogenous variables in (5) defined in Table 1, and μ_i is an error term. The vector X_i includes variables such as income, demographic characteristics, population density, its square, and state laws (m, α, D, D^2, I^{YW}, I^{DR}, and I^{MAN}).

Summary statistics appear in Table 2. We gathered information on two types of user fee pricing systems. The first is a "subscription" system, in which residents pay a monthly fee for a specified number of cans each week. The second is a "bag or tag" program, where residents must purchase special program bags or stickers to place on each of their own garbage containers. Because different communities state prices for different bag or can sizes, we convert all observations to a price per 32-gallon container.

Although we gather data from 959 towns, 50 had implemented "subscription" pricing programs. For reasons explained below, we eliminate these communities from most of our regressions—which reduces our sample size to 909. (For comparison, we also estimate the model with the full sample including "subscription" programs.) All remaining 909 communi-

[10] One might naturally include an interaction term to account for the idea that curbside recycling ($I^R = 1$) could increase the effect of the price (P). Without curbside recycling, households have few options to reduce their garbage and might react to a fee by dumping illegally. Probably for this very reason, no city in our sample has a positive price without curbside recycling. That is, every town with $I^R = 0$ also has $P = 0$. The interaction term is exactly colinear with P and cannot be included separately in (6). Thus the coefficient on P should always be interpreted as the effect of price *given* curbside recycling collection.

TABLE 2

Summary Statistics

	Mean	SD	Min.	Max.	No.
Endogenous Variables					
G (in pounds per person per year)	911.68	392.17	88.75	2115.	756[a]
R (in pounds per person per year)	47.84	103.41	0	1155.	658[b]
I^R (curbside recycling is in place)	0.44	0.50	0	1	909
$P1$ (price of first bag of garbage)	0.08	0.31	0.00	2.76	909
$P2$ (price of second bag of garbage)	0.07	0.28	0.00	2.18	909
Household demand (X_i in Eq. (6)):					
INCOME (per capita, in \$000)	12.69	5.31	4.46	51.2	909
RETIRE (% $\geq$ 65 years of age)	14.12	6.07	2.10	56.0	909
FAM SIZE (number per household)	2.57	0.29	1.80	4.13	909
EDUC (% with bachelor's)	23.60	13.51	2.76	82.8	909
OWNER (% homeowners)	64.12	13.30	17.6	98.3	909
DENSITY (1000's per square mile)	2.59	2.10	0.03	21.0	909
I^{YW} (ban on yardwaste in garbage)	0.39	0.49	0	1	909
I^{DR} (state has deposit-refund)	0.17	0.37	0	1	909
I^{MAN} (mandatory recycling)	0.48	0.50	0	1	909
Curbside recycling (Z_i^R in Eq. (7)):					
P_T (regional tipping fee)	26.07	20.70	2.41	107.7	909
I^{SH} (state help to recycling)	0.55	0.50	0	1	909
I^{SB} (state buys recycled materials)	0.72	0.45	0	1	909
Q (quota for min % recycled)	0.12	0.17	0	0.5	909
$QTIME$ (years before quota)	1.74	3.07	−1	9	909
I^{SL} (state law on city recycling)	0.11	0.31	0	1	909
Optimal price (Z_i^P in Eq. (9)):					
I^{PT} (property tax limitation)	0.38	0.49	0	1	909
I^{MUN} (municipal collection)	0.52	0.50	0	1	909

[a] Number of towns with garbage quantity data available.

[b] Number of towns with recycling quantity data available.

ties are used in first-stage regressions, but only 756 report data on garbage quantity (for garbage regressions) and 658 report data on the quantity of recyclable materials (for recycling regressions). Garbage averages 911.68 pounds per person per year. Recycling averages only 47.84 pounds per person per year, but the third row of Table 2 shows that only 44% of the communities have curbside collection.

In some towns, residents pay one price ($P1$) for their first bag of garbage each week and another price ($P2$) for the second bag. Households may *have* to use at least one bag each week, so we use $P2$ as the marginal price for additional garbage in most of our regressions. We compare these results to those using $P1$, below, and find that the results are fairly robust to alternative specifications of price. The price variable ($P2$) ranges from zero to \$2.18 per 32-gallon bag, and it averages \$.07 per 32-gallon bag.

Table 2 also shows that our communities display considerable variation in income and demographic characteristics. Using the U.S. Census, per capita income varies from \$4,461 per person to \$51,170 per person. The retired population varies from 2 to 56%, family size varies from 1.8 to 4.1, the fraction with college degrees varies from 3 to 83%, and the fraction that own homes varies from 18 to 98%. The overall average fraction for homeowners in our sample is 64%, closely matching the overall average for the United States. Population density varies from 32 per square mile to 21,040 per square mile. Finally, 39% of our communities ban yardwaste from their garbage, 17% are located in states with deposit-refund systems, and 48% require households to recycle.

Previous studies have estimated (6) directly by ordinary least squares (OLS) or generalized least squares (GLS). Estimates of β_1 and β_2 are used to interpret the effects of free curbside recycling and of the user fee. These OLS estimates are biased, however, if I_i^R and P_i are endogenous. The next section describes instruments for these variables.

II. A MODEL AND ESTIMATION OF LOCAL GOVERNMENT BEHAVIOR

Each local government has several policy instruments available to control the quantities of garbage, recycling, and illegal dumping. The two primary policies of concern are free curbside recycling and a user fee for garbage.

A. The Choice to Implement a Curbside Recycling Program

1. *A Probit Model.* Each local government is assumed to compare the costs and benefits of implementing a curbside recycling program. The first benefit to the community is the reduction in garbage collected (ΔG) times the tipping fee that must be paid to the regional landfill (P_T). As shown in Table 2, the average tipping fee faced by our communities is \$26 per ton and varies from \$2.41 to just over \$107. The reduction in garbage collected depends on the vector X_i of variables in the household's demand for garbage collection in equation (6) above. A second benefit to the community is the price that it receives (P_R) for the collected recycling times any increase in recycling (ΔR). This latter amount also depends on household income and characteristics in X_i of Eq. (6).[11] For the price P_R, we use two proxies described below.

The cost to the community of curbside recycling includes the total cost of labor and capital to collect the recycled materials from the household

[11] In the reduced form below, the probability of curbside recycling depends directly on household characteristics X_i, so the policymaker's decision can equivalently be said to depend directly on local voter preferences rather than on a formal cost-benefit test.

(TC_R). We have no data on the labor or capital costs of collection, but proxy it with the population density of the community. Recycling trucks in communities with high densities do not have to drive as far between houses. The benefits and costs of curbside recycling might also be affected by a number of state laws described below. These considerations give us the following equation for I_i^{R*}, a latent variable defined as the net benefits to the community from providing curbside recycling collection:

$$I_i^{R*} = Z_i^R \gamma + \varepsilon_i \tag{7}$$

where $\varepsilon \sim N(0,1)$, and γ is a vector of parameters to be estimated. The vector Z_i^R includes all of the variables that help determine household choices (the X_i), and it includes other exogenous variables defined in Table 1 (and discussed below).

We do not observe the net benefits from having curbside recycling. Instead, we only observe whether a community has implemented such a program. We assume:

$$I^R = 1 \qquad \text{iff } I^{R*} > 0 \tag{8a}$$

$$I^R = 0 \qquad \text{otherwise.} \tag{8b}$$

We use the Probit model to estimate the γ, and then we use these coefficients to generate a predicted probability that each town will choose to implement curbside recycling. This predicted variable is used to replace the actual (endogenous) variable I^R in Eq. (6) to estimate household demands.

2. *Results of recycling Probit.* Results from the Probit model defined in Eqs. (7) and (8) are presented in Table 3. The third column of Table 3 presents the marginal effect of a change in any independent variable on the probability that a government implements free curbside recycling. The probability of this program is estimated to decrease by about 20% for an additional person per household and to increase by 0.77% for a 1-point increase in the percentage of citizens with bachelor degrees. Perhaps college-educated residents have greater preference for a clean environment and thus encourage their local government to implement curbside recycling. An increase of 1000 persons per square mile is estimated to increase the likelihood of this recycling program by 3.9%.

We estimate that communities in states with deposit-refund programs are 18% less likely to implement curbside recycling collection. Households in these states can take recyclable materials directly to stores for a refund. A community in one of these states would therefore realize fewer benefits from implementing curbside recycling.

TABLE 3
Probit Estimation of the Probability of Curbside Recycling
(Dependent Variable: I^R (= 1 iff Curbside Recycling))

Variable	Coefficient	Standard error	Marginal effects
CONSTANT	−1.3436	(0.8956)	
INCOME	−0.0195	(0.0190)	−0.0062
RETIRE	−0.0014	(0.0139)	−0.0044
FAM SIZE	−0.6218*	(0.3426)	−0.1995
EDUCATION	0.0241***	(0.0073)	0.0077
OWNER	0.0092	(0.0071)	0.0030
DENSITY	0.1199*	(0.0665)	0.0385
DENSITY SQUARED	−0.0064	(0.0049)	−0.0020
I^{YW} (yardwaste ban)	0.3854	(0.3346)	0.1236
I^{DR} (deposit refund)	−0.5501**	(0.2718)	−0.1765
P_T (tipping fee)	0.0242***	(0.0046)	0.0078
I^{SH} (state helps)	0.4026	(0.3210)	0.1292
I^{SB} (state buys)	0.2115	(0.2105)	0.0679
Q (quota)	−0.0072	(0.9924)	−0.0023
$QTIME$	0.0357	(0.0740)	0.0115
$Q \times TIME$	0.0730	(0.2092)	0.0234
I^{SL} (state law)	−0.2041	(0.2306)	−0.0655
Sample size		909	
ZM statistic		0.570	
Likelihood ratio index		0.363	
−2[L(0) − L(b)]		452.6639***	

Note. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively. The ZM statistic and Likelihood ratio index measure goodness of fit. The last row jointly tests whether all coefficients are equal to zero.

The model also suggests that the probability of implementing a curbside recycling program increases with the regional tipping fee (P_T). Faced with additional costs for disposing of garbage in landfills, these communities can use curbside recycling to decrease collections of garbage. Indeed, much of the previous literature attributes the recent popularity of curbside recycling programs to higher tipping fees. Our data support these claims. After controlling for other relevant variables, we find that the likelihood of implementing a curbside recycling program increases by 7.8% with every \$10 increase in the regional tipping fee.

We do not have direct observations of the price received for recycling (P_R), but we have a couple of proxies. First, we have an indicator variable $I^{SH} = 1$ if the state helps stimulate demand by providing economic incentives to firms that purchase recycled materials (and 0 otherwise). Second, we have another indicator variable $I^{SB} = 1$ if the state buys recycled materials for its own operation (and 0 otherwise). Though the estimated effects are positive, the coefficients are not statistically different from zero.

Several states have implemented quotas that require communities to recycle more. For example, every community in the state of California must recycle 50% of its waste by the year 2000. The effect of such a quota (Q) may depend on the time until it must be achieved ($QTIME$). For completeness, we include Q, $QTIME$, and their interaction in the regression, but we find none of these to be significant.

Some states like New Jersey have passed laws requiring all communities to implement curbside recycling ($I^{SL} = 1$, and 0 otherwise). This law does not guarantee that communities actually implement the required program, but it may increase the probability. The final choice still remains with the community, and only 57% of communities in these states had implemented curbside recycling in the year of our data. Controlling for other variables in the model, results in Table 3 indicate that this mandate has *no* effect on a community's decision to implement a curbside recycling program.

Though results in Table 3 are useful and interesting in their own right, the major purpose of estimating this Probit model is to generate a prediction to substitute for the endogenous dummy variable I^R in the estimation of Eq. (6) above. Before estimating those demand equations, however, we still need to calculate an instrument for the price per unit garbage.

B. The Choice to Implement a User Fee

1. *A Tobit Model.* In order to decide whether to charge a price per bag, community officials first calculate the optimal price to charge. This optimal fee, P^*, is determined by a tradeoff between benefits and costs at the margin. A higher fee might generate more revenue (if demand is inelastic), reduce the amount of garbage that has to be sent to the landfill, and increase the amount of curbside recycling that can be sold by the community. Unfortunately, it may also increase the quantity of illegal dumping. The locations of the marginal cost and benefit curves and thus P^* will vary across communities. Each town implements the program only if its optimal price is positive.[12]

Thus we expect the chosen price per bag of garbage to depend upon marginal conditions that are proxied by many of the variables that entered

[12] Marginal curves may not include the fixed costs necessary to print and distribute the stickers or bags, to promote the program, and to enforce litter laws. Thus an alternative specification might say that the town finds P^* and then implements the program only if the net social gain is positive. A problem with this alternative is that net social benefits are not monotonic in price, since a higher price might increase dumping. Thus the decision to implement would not be based on any threshold involving P^*.

into the curbside recycling equation above, including the region's tipping fee (P_T), the price received for recycled materials (P_R, or its proxies I^{SH} and I^{SB}), and the household's determination of G and R (which depend upon income and household characteristics in X_i). We add two additional variables to this list. First, the revenue from a higher user fee might help alleviate the problem of dealing with a state limitation on local property taxes. We define a dummy variable $I^{PT} = 1$ if the community is located in a state with a property tax limitation (and 0 otherwise). Second, the marginal cost of the program may depend on whether garbage collection is conducted by the municipality or by a private regulated firm. Private firms may be more efficient. We define a dummy variable $I^{MUN} = 1$ if the community employs municipal resources for collection and 0 for those that franchise or contract the collection service to a single private firm.[13] These considerations together suggest that the optimal price to charge is a function of exogenous variables:

$$P_i^* = Z_i^P \delta + u_i \tag{9}$$

where Z_i^P is the vector of exogenous variables for community i (defined in Table 1), $u_i \sim N(0, \sigma_u^2)$, and δ is a vector of parameters to be estimated.

We do not observe the optimal price. We observe only the user fee that is charged by each community (P_i):

$$\begin{aligned} P_i &= P_i^* \qquad && \text{if } P_i^* > 0 \\ P_i &= 0 && \text{otherwise.} \end{aligned} \tag{10}$$

We use the standard Tobit model to estimate Eq. (10).[14]

[13] Cities with multiple private haulers are excluded; we wish to model the city's endogenous determination of price, not a competitive market determination of price.

[14] As an alternative, we estimated a censored regression model where the dichotomous decision is based on whether the optimal price P^* is above or below some "stochastic unobserved threshold" (Maddala [11, pp. 174–178]). A problem, however, is that such a model uses a Probit on the decision to implement a positive fee, the inverse Mills ratio to correct the estimation of P^* for those with a positive price, and the predicted optimal price $\hat{P}^*$ for all communities in the sample (with or without user fees) to replace the endogenous price in the garbage demand Eq. (6). That P^* may be quite high for a community that faces a high administrative cost and chooses not to implement that price. Yet households in (6) generate garbage in response to the actual price of zero, not the hypothetical high price P^*. The predicted $\hat{P}^*$ is very weakly correlated with actual price, and its use in (6) would not help determine household behavior. Instead, we need an instrument for both positive prices and zero prices, given that communities choose endogenously whether to implement a fee. Such an instrument is provided by the Tobit estimation of (10) which provides a prediction of the actual price, whether zero or positive. The correlation coefficient between the actual price and the predicted price generated from the Tobit estimation of (10) is 0.67.

Next, to obtain a consistent estimate of the effect of price in Eq. (6), we use the predicted price $\hat{P}_i$ calculated from (10) as an instrument for P_i.

2. *Results of the user fee Tobit*. Results for the Tobit model are presented in Table 4. The coefficient on income is negative and significant, as a $1000 increase in per capita income reduces the optimal user fee by $.20. One explanation for this negative coefficient is that communities using property taxes to pay for garbage collection enable their residents to deduct those local taxes against Federal income tax. User fees are not deductible. Communities with high per capita incomes have more residents who itemize, and who face high income tax rates, so they find a user fee to be costly in terms of lost deductions.

Education is the only demographic variable that has a significant effect on the value of the user fee. We estimate that the optimal user fee increases by $.37 for a 10% increase in the percentage who are college graduates. Perhaps these communities find that educated individuals are less likely to engage in illegal dumping. Education might raise the opportu-

TABLE 4
Tobit Estimation of the Optimal User Fee
(Dependent Variable: P (Price per Bag of Garbage))

Variable	Coefficient	Standard error
CONSTANT	−8.0053	(18.61)
INCOME	−0.1955***	(0.0452)
RETIRE	0.0182	(0.0272)
FAM SIZE	0.0564	(0.7183)
EDUCATION	0.0368**	(0.0125)
OWNER	0.0115	(0.0111)
DENSITY	−0.1060	(0.1433)
DENSITY SQUARED	−0.0001	(0.0158)
I^{YW} (yardwaste ban)	1.8391***	(0.4733)
I^{DR} (deposit refund)	0.2863	(0.3548)
P_T (tipping fee)	0.0345***	(0.0084)
I^{SH} (state helps)	0.4909	(0.5253)
I^{SB} (state buys)	4.2700	(18.50)
Q (quota)	−8.6695***	(1.845)
$QTIME$	0.3634***	(0.1012)
$Q \times QTIME$	0.3604	(0.4004)
I^{SL} (state law on recycling)	−0.7995	(0.5802)
I^{PT} (property tax limit)	0.2022	(0.4307)
I^{MUN} (municipal collection)	0.4756**	(0.2237)
Inverse Mills ratio	1.1212***	(0.1208)
Sample size	909	

Note. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively.

nity cost of time, and thus raise the fee necessary to induce behavioral changes, but this regression controls for income (another proxy for wage rate).

A user fee might generate more illegal burning and dumping. This response may be greater in areas with very low population density (where garbage can be dumped in the woods) and with very high density (where garbage can be dumped in commercial dumpsters). Knowing this, the community may think that household dumping in response to the implementation of a user fee is a non-linear function of the population density.[15] Results do not substantiate this hypothesis, since the coefficients on density and density-squared are insignificant. Either communities are not worried about illegal dumping when they consider the implementation of a user fee, or we have a weak proxy for the household "price" of illegal disposal.

Many have conjectured that the optimal user fee increases with the tipping fee. Our results support this conjecture; a \$10 increase in the regional tipping fee (per ton at the landfill) is estimated to increase the local user fee by \$0.35 per bag. Also, the user fee is predicted to increase in states that ban yardwaste from landfills. Lastly, the significant effect of a quota and *QTIME* are difficult to explain.[16]

Results in Tables 3 and 4 provide the necessary instruments for estimation of household demands, but they also provide an interesting analysis of local policy making. These results show how local government decisions respond to state mandates, demographic variables such as education, and economic variables such as income.

III. THE EFFECTS OF POLICY ON GARBAGE AND RECYCLING

In the last stage of this process, we use Eq. (6) to regress aggregate garbage or recycling quantities on the exogenous variables in X_i and on the predicted values of the curbside recycling variable from (8) and user fee variable from (10).

A. Estimating the Demand for Garbage Collection

The garbage regressions use only 756 towns without "subscription" programs and with complete data on garbage. The first column of Table 5a presents estimates from the endogenous choice model (two-stage least squares). The coefficient on the user fee ($P2$) is negative and significant at

[15] Fines for littering and the level of enforcement could also play a role in determining the costs of household dumping, but we were not able to obtain data on these variables.

[16] Indeed, using the coefficients on *QUOTA* and its interactive term (and using the mean of *QTIME*), we calculate that a higher recycling quota decreases the optimal user fee.

the 1% level.[17] By these estimates, the change in price from zero to one dollar would reduce garbage per person per year by 412.37 pounds.

To better interpret the magnitude of this price coefficient, we provide three calculations of the price elasticity of demand. We assume the mean price (0.075) and quantity of garbage (911.7) are on one point along a linear demand curve with slope -412.37. The price elasticity at this point is only $(-412.37)(0.075/911.7) = -0.034$, because the average price (0.075) is very low. Most towns in our sample had not implemented a user fee program and thus charged a price of zero. Among towns *with* user fee programs, the average price charged is 0.999 (i.e., one dollar). Evaluated at this point on the same linear demand curve, the price elasticity is $(-412.37)(1/530.17) = -0.778$. Finally, the arc-elasticity resulting from an increase in price from 0 to \$1.00, which is the same as the point-elasticity at a price of 50 cents, is -0.28. This final calculation is perhaps the one that is most appropriate to compare with elasticity estimates provided by the previous literature, but our estimate of -0.28 is larger than most of these previous estimates.[18]

The last two columns of Table 5a present OLS estimates from a model of the type used in the previous literature. These OLS estimates do not account for the possible endogeneity of the user fee or recycling dummy variables. The coefficient on the user fee is negative and significant, but the point estimate provided by the OLS model is only -275.08. Thus, consideration of endogenous choice raises the absolute value of the estimated coefficient by 50% (from 275 to 412). A test of the null hypothesis that these two coefficients are equal is rejected with 90% confidence. Therefore, we conclude that the OLS model underestimates the true impact of the implementation of a user fee.

Our introduction outlines two opposing possible sources of bias. Results here tend to reject the idea that an omitted variable such as "environmental awareness" increases the user fee and decreases the garbage amount. Instead, results here suggest that the bias may be the result of unobserved variables that jointly make a community more likely to implement a user fee and that also increase the amount of garbage. Or, the bias may be attributable to community self-selection. Communities with large per capita

[17] Most packages correct the standard errors for the use of a fitted value on the right-hand side, but this model mixes fitted values from both Probit and Tobit on the right-hand side. Thus the standard errors may be biased, and significance tests may be misleading.

[18] Using household data for one town's change in price from zero to 80 cents, Fullerton and Kinnaman [4] find an arc-elasticity of -0.075. Others have estimated the point-elasticity of demand for garbage to be -0.12 (Jenkins [7]), -0.15 (Wertz [24]), -0.26 and -0.22 (Morris and Byrd [13], in two communities), -0.14 (Skumatz and Breckinridge [20]), and -0.42 (Podolsky and Spiegel [16]).

TABLE 5a

Determinants of the Annual Weight of Garbage
(Dependent Variable: G (Pounds of Garbage per Person per Year))

	Endogenous choice		OLS	
Variable	Coefficient	Standard error	Coefficient	Standard error
CONSTANT	732.70***	199.2	752.59***	196.3
I^R (curbside recycling)	83.551	135.7	−36.210	31.91
$P2$	−412.37***	110.9	−275.08***	50.67
INCOME	19.149***	5.171	21.160***	4.891
RETIRE	−0.2020	3.358	−0.0226	3.313
FAM SIZE	19.789	74.72	4.2845	72.43
EDUCATION	−7.7338***	1.899	−7.3566***	1.755
OWNER	1.9534	1.589	1.9128	1.551
DENSITY	2.2680	15.20	6.0992	14.06
DENSITY SQUARED	0.0773	1.063	0.0267	1.043
I^{YW} (yardwaste ban)	−29.273	40.18	−30.919	34.08
I^{DR} (deposit refund)	−52.404	38.79	−55.227	38.27
I^{MAN} (mandatory recycling)	−88.796*	45.67	−52.146	31.46
Sample size	756		756	
R^2	0.088		0.109	

Note. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively.

quantities of garbage may be more likely to implement a user fee than communities with lower per capita garbage totals.[19]

The implementation of curbside recycling is estimated to *increase* garbage by 83.55 pounds per person per year. This estimate differs considerably from the OLS estimate of −36.21, but neither estimate is statistically different from zero. The fact that the data are not able to establish a significant negative effect of curbside recycling on garbage quantities is an interesting result in itself. Although the estimated effect of a curbside recycling program on garbage totals appears to vary rather dramatically across model specifications (OLS vs 2SLS), this difference is not statistically significant.

Other estimates in Table 5a are similar to those in previous studies. The coefficient on income is positive and significantly different from zero at the 1% level. The income elasticity calculated from this coefficient is

[19] A joint Hausman test for correlation between the error and the price variable and recycling dummy does not reject the null hypothesis that no correlation is present in the garbage equation ($F[2,741] = 0.481$) but does reject the null in the recycling equation ($F[2,643] = 11.662$) estimated below. Monte Carlo simulations have shown that the Hausman test has poor power (the probability of accepting a false null is high).

TABLE 5b

Estimated Responses to Policy Using Other Price Definitions
(Dependent Variable: G (Pounds of Garbage per Person per Year))

Specification	Variable	Endogenous choice Coefficient	Endogenous choice Standard error	OLS Coefficient	OLS Standard error
Include subscription	I^R (curbside)	15.059	122.1	−50.111	31.63
	$P2$ (user fee)	−172.35**	77.82	−105.28**	33.11
Include subscription	I^R (curbside)	21.211	128.4	−54.492*	31.99
	$P1$ (user fee)	−133.98**	63.07	−62.578**	26.92
Use only subscription	I^R (curbside)	**18.895**	**116.5**	−43.872	32.91
	$P2$ (user fee)	**−22.669**	**73.85**	−1.7768	42.43
Use only subscription	I^R (curbside)	**65.662**	**125.5**	−43.788	33.20
	$P1$ (user fee)	**−61.722**	**61.89**	−1.4089	31.34
Exclude subscription	I^R (curbside)	131.37	142.7	−37.592	31.97
	$P1$ (user fee)	−443.39***	114.3	−249.35***	48.02

Note. Table 5b omits the estimated coefficients on all variables other than the two policy variables.

0.262.[20] Households with high income not only have more waste material to remove, but they also face a high opportunity cost of time spent recycling or dumping. Therefore, these households throw out more garbage. Also, the quantity of garbage decreases significantly with education. Better educated citizens may have greater preference for a clean environment, switching some of their disposal from regular garbage to recycling (as seen in the next section).

We also estimate the impact of state policies on garbage totals, but most are not significant. Communities in states that mandate household recycling ($I^{MAN} = 1$) generate 89 fewer pounds per person per year.[21]

Table 5b tests alternative specifications. First, we provide estimates of the effect of a user fee on garbage amounts using additional observations for communities that have implemented "subscription" programs. Recall that subscription programs require households to pay extra for a second

[20] Others have estimated this income elasticity to be 0.242 (Richardson and Havlicek [19]), 0.279 and 0.242 (Wertz [24]), 0.2 (Petrovik and Jaffee [15]), 0.41 (Jenkins [7]), 0.049 (Hong, Adams, and Love [5]), 0.22 (Reschovsky and Stone [18]), 0.57 (Podolsky and Spiegel [16]), and 0.05 (Fullerton and Kinnaman [4]).

[21] Some variables in Z^R and Z^P are excluded from X (every variable in Table 3 or 4 that is not in Table 5). To check for overidentification, we test the null hypothesis that the coefficients on these variables are jointly equal to zero, but we cannot reject the null. Therefore, the model does not appear to be overidentified.

can each week, but each household must pre-commit to a number of cans and is charged for those cans whether empty or full. Thus the true cost to the household for a marginal increase in garbage may be zero. Since "bag and tag" programs provide better marginal incentives, Nestor and Podolsky [14] predict that subscription programs are less effective at reducing garbage. The first panel of Table 5b reports estimated coefficients of the curbside recycling and user fee variables when subscription programs are included in the sample. The effect of price ($P2$) falls from -412.37 (Table 5a) to only -172.35 (Table 5b). The bold-faced values of Table 5b report estimated coefficients among *only* those communities that have implemented subscription programs. The effect of price on garbage disappears. Thus we find that "bag and tag" programs reduce garbage more than "subscription" programs.

Second, we test the specification of price. Table 5b also shows a separate set of estimations using $P1$ (the price of the *first* bag of garbage) in place of $P2$. The final row is comparable to the results in Table 5a where "subscription" programs are excluded from the sample. The estimated coefficient on price is fairly robust to the specification of price (-443.39 compared to -412.37).

B. Estimating the Demand for Recycling

The first column of Table 6a corrects for possible endogeneity in the town's choices about whether to collect recycling and whether to charge a price for garbage. The second column provides OLS results for comparison. In this regression, we used all 658 observations for communities with complete data on recycling quantity (and without "subscription" programs).

The implementation of a user fee ($P2$) is estimated using the endogenous choice model to increase the quantity of recycling by 30 pounds per person per year. This coefficient is not significantly different from zero, but it is almost exactly the same size as the significant coefficient in the OLS regression. Given this similarity of coefficients, the OLS estimate may not be biased. According to this estimate, the cross-price arc-elasticity of demand for recycling collection is 0.220 (evaluated at $P2$ equal to 50 cents).[22]

The implementation of a curbside recycling program in the endogenous choice model increases the quantity of curbside recycling by an average of 195.64 pounds per person per year, 81 pounds more than is estimated by the OLS model. Given the small standard errors, these two estimates are statistically different from one another at the 1% confidence level. Thus the OLS-estimated impact of curbside recycling may be biased downward.

[22] The U.S. EPA [23] estimates this cross-price elasticity to be 0.49, 0.48, and 0.06 for various different communities. Browne [2] finds it to be 0.102 for glass and cans, and -0.02 for paper recycling. Fullerton and Kinnaman [4] find 0.074 for all recycling.

TABLE 6a
Determinants of the Annual Weight of Recycling
(Dependent Variable: R (Pounds of Recycling per Person per Year))

Variable	Endogenous choice Coefficient	Endogenous choice Standard error	OLS Coefficient	OLS Standard error
CONSTANT	−121.46**	49.50	−147.96**	45.13
I^R (curbside recycling)	195.64***	28.26	114.63***	7.860
$P2$	30.221	26.08	28.974**	12.16
INCOME	−0.8818	1.279	−0.6275	1.148
RETIRE	1.1461	0.8351	1.5386**	0.7553
FAM SIZE	26.330	17.89	26.947*	16.48
EDUCATION	0.2656	0.4744	0.8215**	0.4124
OWNER	0.6527*	0.3877	0.7925**	0.3546
DENSITY	−6.2523*	3.767	−2.0681	3.267
DENSITY SQUARED	0.2742	0.2569	0.1454	0.2343
I^{YW} (yardwaste ban)	−8.6427	10.24	14.362*	7.978
I^{DR} (deposit refund)	−11.727	10.00	−11.689	9.211
I^{MAN} (mandatory recycling)	−9.4474	9.623	2.2907	7.260
Sample size	658		658	
R^2	0.294		0.401	

Note. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively.

Again, this bias seems not to be caused by omitting a variable such as "environmental awareness" (which would increase both recycling and the probability of free curbside collection). Instead, the bias could be caused by unobservable variables that jointly decrease the quantity of recycling and increase the probability that a community implements curbside recycling. We cannot think of examples of such variables. More likely, then, this bias may be the result of community self-selection. Communities with low recycling amounts prior to curbside recycling may be more likely to implement a curbside program. Officials in these communities probably see the potential for large benefits from the implementation of curbside recycling.

Notice that the estimated increase in recycling attributable to a user fee (30 pounds per person per year) does not match the estimated decrease in garbage attributable to a user fee (412 pounds per person per year). In fact, an estimated 382 pounds per person per year has seemed to disappear. In response to the user fee, households may increase their other disposal options such as source reduction, composting, burning, or illegal dumping. These data do not allow us to determine which of these methods is used.[23]

[23] Using other data, Fullerton and Kinnaman [4] estimate the reduction of garbage at the curb attributable to a user fee, and that dumping may account for 28 to 43% of it.

The estimated increase in recycling brought on by a curbside collection program (196 pounds) exceeds the decrease in garbage (84 pounds in Table 5a). In response to a curbside recycling program, perhaps households begin to recycle an extra 112 pounds per person per year that were previously dumped or burned in the absence of the curbside recycling program.

We expect various offsetting effects of income on aggregate recycling amounts. First, if an increase in income leads to more consumption, it could generate more waste material for disposal in all three forms, including more recycling. Second, a higher wage increases the opportunity cost of time spent recycling, so it could decrease aggregate recycling. Third, the higher wage increases the opportunity cost of time spent illegally dumping waste, so the net effect on recycling could depend on which type of disposal is more time-intensive. The estimated coefficient on income in Table 6a is negative (but insignificant), suggesting that the second effect could be slightly stronger than the others.

Demographic characteristics also play a role in determining aggregate recycling quantities. At least in the OLS model, significantly more recycling per person is generated in communities where households are older, larger, more educated, and own more of their own homes. Retired individuals may have more time to separate and store recyclable waste. Educated individuals may be more aware of recycling opportunities and may also have greater taste for a clean environment. Owner-occupants may generate more waste and therefore recycle more, especially if they have more room to store and separate recyclable material. Population density has a significant negative effect on recycling per person, but again the square term is not significant.

Table 6b shows the results of regressions with alternative specifications. As in Table 5b, the results are robust to the specification of price ($P1$ vs $P2$). Also, "bag and tag" programs increase recycling more than "subscription" programs.

IV. CONCLUSION

Using original data and correcting for endogenous local policy choices, this paper contributes to the empirical literature estimating the effects of policies designed to reduce solid waste and increase recycling. We have learned that endogeneity does matter. That is, policy making appears to be a "purposeful action, responsive to economic and political conditions" (Besley and Case [1]). Estimation linked these policy choices to various observable exogenous variables.

We have also learned that the previous empirical literature may have underestimated the impact of these local programs by assuming the policy variables to be exogenous. It seems that the likelihood that a community

TABLE 6b

Estimated Responses to Policy Using Other Price Definitions (Dependent Variable: R (Pounds of Recycling per Person per Year))

		Endogenous choice		OLS	
Specification	Variable	Coefficient	Standard error	Coefficient	Standard error
Include subscription	I^R (curbside)	176.95***	24.94	113.18***	7.723
	$P2$ (user fee)	15.008	23.56	24.078**	10.02
Include subscription	I^R (curbside)	171.90***	26.32	113.79***	7.760
	$P1$ (user fee)	20.649	23.75	18.310**	9.123
Use only subscription	I^R (curbside)	167.18***	24.70	108.08***	7.702
	$P2$ (user fee)	−133.33	92.32	9.5832	17.08
Use only subscription	I^R (curbside)	173.45***	24.60	108.31***	7.730
	$P1$ (user fee)	−63.392	53.00	2.5586	14.20
Exclude subscription	I^R (curbside)	182.59***	28.82	114.77***	7.859
	$P1$ (user fee)	43.686*	25.89	26.467**	11.38

Note. Table 6b omits the estimated coefficients on all variables other than the two policy variables.

implements a user fee or curbside recycling increases with the quantity of garbage. Ignoring this possibility produces biased estimates.

Finally, we estimated that the implementation of a \$1 user fee could decrease the quantity of garbage by 412 pounds per person per year but increase recycling by only 30 pounds per person per year. Where did the extra garbage go? The difference could be explained partly by waste reduction at the source, or by composting, but it also could be explained partly by other less-attractive alternatives like burning or dumping. Towns are turning increasingly to user fees to help reduce garbage, but the advisability of this policy depends crucially on the unestimated extent of illegal dumping. Thus this paper points to the importance of future research on the methods of reducing garbage at the curb.

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