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Publication Date

1999-04-01

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DEPARTMENT OF AGRICULTURAL AND RESOURCE ECONOMICS AND POLICY/
DIVISION OF AGRICULTURE AND NATURAL RESOURCES
UNIVERSITY OF CALIFORNIA AT BERKELEY.

WORKING PAPER NO. 881

PRICE AND NON-PRICE INFLUENCES ON WATER
CONSERVATION: AN ECONOMETRIC MODEL OF
AGGREGATE DEMAND UNDER NONLINEAR
BUDGET CONSTRAINT

by

Leonardo Corral, Anthony C. Fisher, and Nile W. Hatch
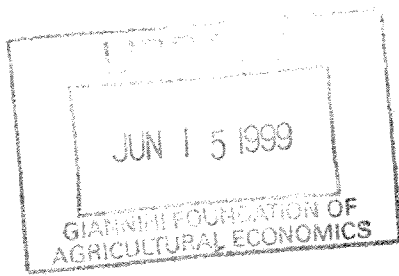
Price and Non-Price Influences on Water Conservation:

An Econometric Model of Aggregate Demand under

Nonlinear Budget Constraint

April 1999

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Price and Non-Price Influences on Water Conservation: An Econometric Model of Aggregate Demand under Nonlinear Budget Constraint

Abstract

This paper develops a model of residential water demand under a nonlinear budget constraint. The theoretical model for an individual consumer is adapted to yield an aggregate model that preserves the structure of the individual demand function, and that can be used with aggregate (water district level) data. The model is used to study the influence of pricing and non-price conservation programs on consumption and conservation behavior in three water districts in the San Francisco Bay Area, over a 10-year period that includes both drought and normal years. Empirical results show that pricing can be effective in reducing water consumption, particularly during the annual dry season, and during longer drought episodes. The effect is mitigated when non-price conservation programs are included in the analysis. Among these, use restrictions and landscaping audits appear to be particularly effective in inducing conservation.

1   Introduction

The increased frequency of droughts, diminishing supplies of high quality water, and reduced reliability of current supplies in nearly all parts of the U.S. have raised awareness of the need to understand both residential water consumption and conservation behavior. It has become increasingly difficult to add to current water supplies both in terms of costs, including environmental costs, and supply reliability, hence water district managers have turned their attention to improved management of existing supplies. In this paper, we study the effectiveness of their efforts which include the manipulation of price structures and the introduction of non-price measures to induce conservation.

In this paper we consider residential water consumption and conservation behavior in three water districts in the San Francisco Bay Area. Beginning with the rainy season of 1987-1988, the Bay Area suffered from a drought that ultimately lasted seven years. As the drought continued, all water districts responded with policy measures to reduce demand and induce conservation.

One of the principal tools a water district has to influence consumption behavior is price structure. Until the 1970's many urban water utilities employed decreasing block rates based on the the rationale that this pricing scheme encouraged the exploitation of economies of scale in delivering water to consumers. Later, utilities began switching to flat rates and, more recently, increasing block rate structures have been instituted in numerous districts. By charging a lower price for small amounts of consumption, and a higher price for units above a certain threshold, increasing block pricing may induce conservation.

The use of block pricing by some water utility districts raises issues of appropriate modeling of demand and empirical estimation. Detailed attention is given to this issue in this paper, since it has been the cause of much debate in the literature on water demand. Typically, empirical studies that have modeled demand, given nonlinearity in budget sets, have used micro-level data for their analysis. This empirical approach requires expensive survey techniques to gather relevant data. We develop an aggregate model of water demand that preserves structure of individual demand

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functions. This model requires data on the distribution of consumers across the block rate pricing structure, but is less demanding and less expensive than models of individual demand that require micro-level survey data.

Most previous empirical studies of water demand have limited their analysis to data in which the price structure remains constant through the duration of the analysis. In our study, price structure varies both within and across the water districts for which we have data. In particular, one of the districts moved from decreasing to increasing block rates while another changed from increasing block rates with two blocks to flat rates to increasing with several blocks. We formulate an empirical specification that allows us to make use of all available data.

Non-market tools are also frequently used by water utility districts in their efforts to induce conservation. For this study, variables have been created to represent the influence of a variety of conservation programs on water consumption. Most of these programs were instituted as a response to the drought. The conservation variables can be categorized as use restrictions, education, billing information, landscaping, and plumbing (retro-fit) programs.

Water pricing as well as conservation policies might be more effective under certain conditions. In particular, during the summer season households have more discretionary water use and hence, pricing policies could induce a greater response. Likewise, in periods of drought households might become more sensitive to pricing and conservation policies. We address these issues and provide empirical tests.

The paper is organized as follows. First, a brief literature review is presented. The next section describes residential water consumption and conservation efforts in the three districts. Section 4 presents a theoretical model of residential water demand that allows for non-linear pricing. In section 5, the demand functions derived from section 4 are aggregated to accommodate the available data and the empirical model is formulated. Section 6 describes the data, estimation procedure, and results. Conclusions and policy implications are discussed in section 7.

2 Literature Review

The literature on residential water demand is extensive. At the core of the literature lie the complexities in theoretical and econometric modeling arising from the block rate structure of prices prevalent in most municipal water districts. Taylor (1975) and Nordin (1976) were the first to propose a model that accounted for the increasing or decreasing block rate structure of prices. These papers proposed what has become known in the literature as the *difference* variable, where *difference* is defined as the amount the consumer actually gets billed minus what the consumer would have been billed if all consumption was charged at the same price as the price for the last unit of consumption. A theoretical argument was made that this variable should be of equal magnitude, but opposite in effect, to income in the case of increasing block rates, where it acts as a tax, and vice versa with decreasing block rates, where it acts as a subsidy. This gave rise to a number of papers which tried to test this relation empirically.[1] Econometric estimation of these models has used instrumental variables and two- or three-stage least squares techniques to try to correct for the bias that arises in simple OLS estimation due to the co-determination of quantity, price and *difference*.[2]

A few papers in the water demand literature have studied the effectiveness of prices and conservation programs as tools for influencing water demand in the face of a drought. One example is Moncur (1987), which uses panel data on single family residential customers of the Honolulu Board of Water Supply to estimate demand for water as a function of price, income, household size, rainfall and a dummy variable denoting a water restrictions program. Moncur (1987) concludes that marginal price can be used as an instrument to achieve reduction in water use, even during a drought episode, and that the conservation program would mitigate the necessary increase

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[1] Many studies using the Taylor and Nordin price specification have performed this test. These include Acton, Bridger & Sohlberg (1980), Billings & Agthe (1980), Foster Jr. & Beattie (1981), and Howe (1982). The only study to actually obtain estimates of the income and difference variables that were equal but opposite in sign was Schefter & David (1985), which used simulated data.

[2] See, for example, Chicoine, Deller & Ramamurthy (1986), Deller, Chicoine & Ramamurthy (1986), Jones & Morris (1984), Nieswiadomy & Molina (1989).

in price, but only slightly. In a study of two Santa Barbara County communities, Renwick & Archibald (1998) find that pricing, use restrictions, and low-flow plumbing programs are effective in reducing demand during a drought.

Similarly, the recent study of Fisher, Fullerton, Hatch & Reinelt (1995) compares the cost-effectiveness of price-induced water conservation with other drought management tools such as building a dam and conjunctive use of ground and surface water. They find that a combination of conjunctive use and conservation pricing are the least cost technique of managing a 25% reduction in supply. On the other hand, Gilbert, Bishop & Weber (1990) argue that, during a drought, price elasticity studies are of limited use in predicting the impact of price changes on consumption because other, drought related, forces have a stronger influence on consumption decisions.

Until recently, few attempts had been made to explicitly model the discrete choice embedded in the decision process of the consumer facing a multi-tiered price schedule for water. The early study by Terza & Welch (1982) constructed a demand function from non-linear budget constraints where the consumer's decision to locate on a particular block is determined by consumer surplus rather than indifference curves.[3] By directly modeling the discrete and continuous choice, using the two error model originally proposed in the labor supply literature by Burtless & Hausman (1978), Hewitt & Hanemann (1995) solve the co-determination problem in the context of household water demand. We employ a similar model that directly accounts for the block rate structure of prices in its theoretical model and econometric specification but do so in the context of aggregate demand. In addition, we contribute to the current literature by including non-price conservation efforts in the econometric specification to gain some insights into price and non-price influences on urban water conservation.

Our paper is most similar in objectives and results to that of Renwick & Archibald (1998). They study the effectiveness of pricing and conservation programs in reducing demand during

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[3]The use of consumer surplus as compared to indifference curves reduces the complexity of the statistical techniques. However, Terza & Welch (1982) do not estimate a demand curve using their model and we are aware of no papers that have used it for estimation of water demand since.

the 1987-1995 drought in Southern California. In particular, they find that increased prices, use restrictions, and programs promoting water-conserving capital stock are significant in reducing demand. They also show that different pricing and conservation policies result in higher water conservation burdens for low income households compared to high income households.

Our paper differs from the Renwick and Archibald study in several respects. Although they do incorporate the traditional "difference" variable, they do not explicitly account for the discrete/continuous nature of the water consumption decision emphasized in Hewitt & Hanemann (1995). In contrast, our paper derives a model for aggregate demand that preserves the discontinuous structure of the individual demand curve. In contrast to both Hewitt and Hanemann, and Renwick and Archibald, who rely on expensive or hard-to-get micro-level data, our model is designed to work with aggregate, or district-level, data.[4] Further, it is sufficiently general that we can estimate aggregate demand under decreasing, increasing, and constant block rate structures, even allowing for changes from one to another during the sample period. Since our data span a period of normal (pre-drought) and drought conditions, we are able to study the conservation efforts before and during a drought as well as estimate the interaction effect of the drought and the price mechanism. This allows us to make comparisons of aggregate demand and conservation behavior during a drought episode and a "normal" episode. We also explore the effectiveness of a wider variety of conservation programs than previous studies, including billing information, conservation education, use restrictions, landscaping programs, and low-flow plumbing.

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[4]While the Renwick and Archibald paper uses individual-level data, it sidesteps the complexities of non-linear budget constraints by assuming constant pricing in constructing the demand model. This modeling assumption is at odds with the actual use of increasing block rate pricing by the water districts in their study.

3 Residential Water Consumption and Conservation in the San Francisco Bay Area

In this section we present a brief summary of the 1987-95 drought and conservation efforts in the Bay Area. The San Francisco Bay Area is both demographically and geographically diverse. From the foggy coastal regions to the arid inland valleys, temperatures, precipitation, incomes, and house and lot sizes vary widely. As a result, water consumption varies as well. The rainy season of the Bay Area runs from approximately November through February or March. In the inland areas, summers are dry and hot. On the coast, however, the months of June, July, and August bring heavy fog and cool temperatures. Communities that lie around the San Francisco Bay typically experience temperatures between these two extremes.

For the first year or two of the drought, many water districts did little to encourage residential water conservation. Instead, they relied on stored water reserves (typically reservoirs) and waited for precipitation patterns to return to normal. As the drought continued, all water districts responded with conservation measures that varied widely in scope and intensity. Many districts raised prices and/or imposed increasing block rate prices. A variety of conservation programs, which we categorize as use restrictions, education, billing information, landscaping, and plumbing (retro-fit) programs, were also tried. The result was a substantial reduction in consumption.

In this study we consider the residential water consumption patterns of three Bay Area water districts.[5] These water districts serve the communities of Great Oaks, San Leandro, and San Mateo. Summary statistics of monthly consumption and other relevant variables before and during the drought are listed in Table 1 for each of the communities.

The Great Oaks Water Company is relatively small, serving an area, Great Oaks, of approximately six square miles near San Jose in the southern part of the Bay Area. It is also unusual in

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[5] Our data collection efforts originally focused on nine Bay Area water districts that correspond to those included in the study by Bruvold (1979) of conservation during a previous drought in the San Francisco Bay Area. Unfortunately, due to data limitations we are able to analyze conservation and demand at only three districts.

Table 1: Summary Statistics for the Water Districts

Great Oaks	Before the Drought		During the Drought	
variable	mean	std. dev.	mean	std. dev.
household consumption (ccf)	33.55	9.85	27.02	6.57
household income	$63,426	2812.8	$77,552	5234.3
number of households	8542.5	695.56	8799.4	897.98
household size	3.06	0.015	3.08	0.032
temperature	60.49	7.66	61.37	8.11
precipitation (inches)	1.05	1.33	0.93	1.44

San Leandro	Before the Drought		During the Drought	
variable	mean	std. dev.	mean	std. dev.
household consumption (ccf)	10.82	2.92	8.36	1.40
household income	$36,766	5669.8	$50,308	2705.8
number of households	22,168	745.3	21,666	1170.5
household size	2.35	0.010	2.35	0.019
temperature	59.62	5.79	59.99	5.71
precipitation (inches)	2.15	2.72	1.25	1.79

San Mateo	Before the Drought		During the Drought	
variable	mean	std. dev.	mean	std. dev.
household consumption (ccf)	12.81	3.77	11.39	2.58
household income	$47,247	8162.9	$66,882	4086.9
number of households	22,646	643.34	22,344	112.46
household size	2.35	0.025	2.37	0.018
temperature	57.62	5.50	58.71	5.73
precipitation (inches)	1.84	2.40	1.10	1.54

that all of the water consumed is from underground aquifers. Officials from the Great Oaks Water Company are confident that their supply of water is safe and, thus, was relatively insulated from the effects of the drought. It is not surprising that consumption in this community is the highest in our sample. This district is the only one in our sample that uses decreasing block rate prices (marginal price falls as consumption rises).

In the undated "management plan," the Great Oaks Water Company states that it does not have an active conservation agenda. Consequently, the district's conservation programs are relatively modest. Some education programs, including presentations to homeowners and school children, and a period of distribution of low-flow shower heads and toilets comprise much of the district's conservation efforts. The most aggressive conservation program was a use restriction program initiated in 1989. Initially, a 25% mandatory reduction in consumption was set. Later the goal was revised to a 20% cutback and then, in 1991, was relaxed to a request for a voluntary reduction of 25% from 1987 usage levels. Figure 1 shows the consumption history of the Great Oaks community from 1985 through 1992.

Located south of Oakland, San Leandro receives its water from East Bay Municipal Utility District (EBMUD). EBMUD is a large provider serving many of the communities on the east, or inland side of the bay. It is also quite aggressive in pursuing water conservation. When the drought began and again when the drought became especially severe, the district raised prices and invoked relatively steeply increasing block rates.

EBMUD also initiated an impressive array of conservation programs. Education efforts included the printing and distribution of a variety of flyers and brochures asking people to conserve, telling how much water various activities use, and teaching water-saving techniques such as drip irrigation and water conserving landscaping. They also made presentations at schools, teaching water conservation habits. Their education efforts even extended into advertisements on radio, television, and newspapers. Finally, the district imposed a variety of use restrictions to avoid "wasteful" uses such as water for fountains, washing vehicles, or swimming pools. The conserva-

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tion efforts were successful as the district reduced consumption substantially. Figure 2 shows the history of average household consumption from 1980 through 1992 for the San Leandro community.

The third district included in our study is the San Mateo Water District. The county of San Mateo is located just south of San Francisco on the western peninsula of the Bay Area. The district receives its water through the California Water Service Company, a private, investor-owned water utility that serves 20 other water districts. As a result, the City of San Mateo passes all ordinances relating to water. The district appears to make only limited use of block rate pricing to influence consumption. For most of our sample, they used a relatively mild increasing block rate pricing structure. When the drought began, the district abandoned the two-tiered pricing scheme for constant prices. In fact, when adjusted for inflation, the real price of water remains level or even falls during the drought.

The California Water Service Company has published literature containing water conservation tips, as well as conservation coloring and activity books. In our sample, the San Mateo district made the greatest use of billing information to educate consumers on their water usage, often urging them to conserve. The water company has also used periodic advertising to promote awareness of water conservation. Well into the drought, the San Mateo customers were subjected to a variety of use restrictions, including prohibitions of use above a monthly allocation, excessive landscaping, and use for washing hard surfaces (buildings/sidewalks). After a warning, use restrictions were enforced with flow restricting devices. The district's conservation goals from 1990 to 1993 were a 25% reduction in summer usage and 15% reduction in winter consumption.

4   A Model of Residential Water Consumption

Contrary to traditional consumer demand analysis, the demand function for a good facing block rate pricing is typically nonlinear, nondifferentiable and often includes discrete jumps. Conse-
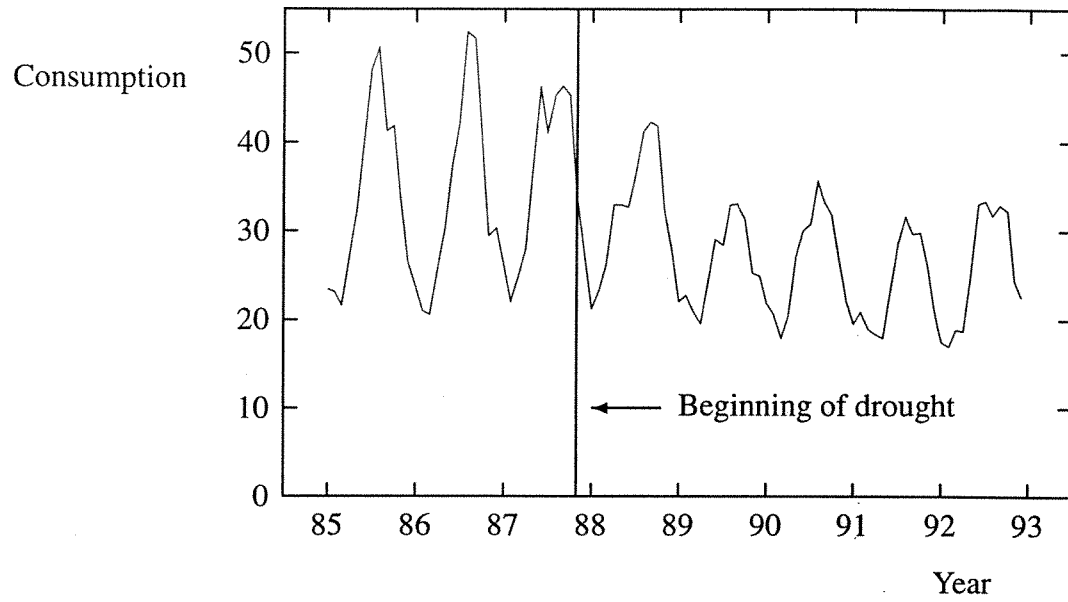
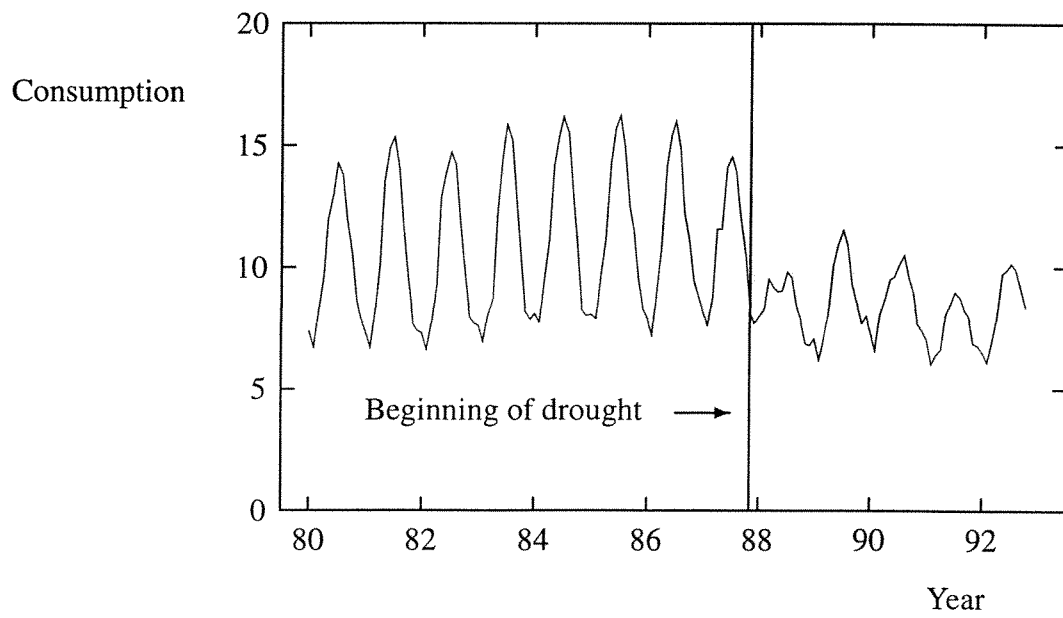Figure 1: Consumption per Household for the Great Oaks Water District

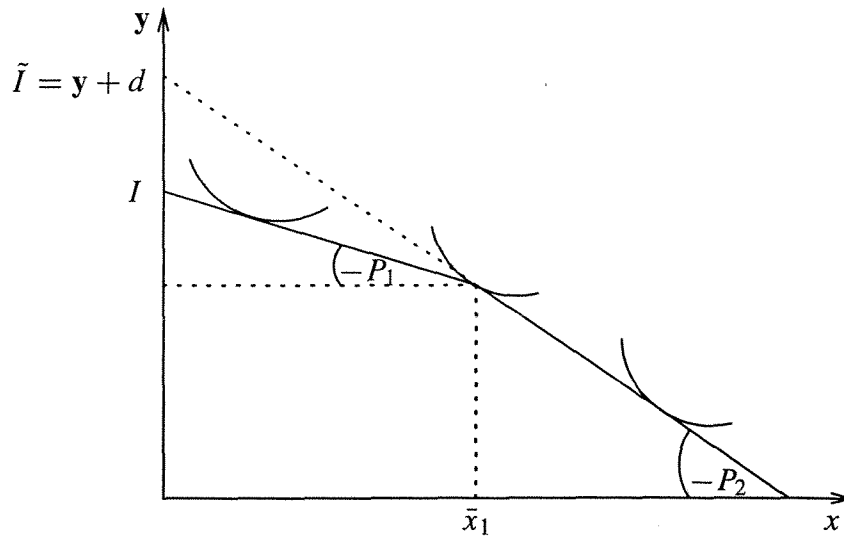Figure 2: Consumption per Household for the San Leandro Region of EBMUD

Figure 3: Budget Constraint for a Two Tiered Pricing Scheme

quently, conventional demand curves cannot adequately represent consumer behavior when facing a nonlinear budget constraint. The derivation of the correct demand function is relatively straightforward. However, the resulting demand function often changes the comparative statics results of consumer demand and is relatively cumbersome for empirical estimation.[6]

Block rate pricing implies that consumers face a kinked budget constraint. This can be seen in Figure 3 which illustrates the budget constraint for a two tiered block pricing scheme where I is income, x is water consumption, $\bar{x}_1$ is level of consumption at which the price changes, and y is a vector of all other goods. P_i represents the price of x on the ith segment of the budget constraint and y is the *numeraire*. When the multi-tiered pricing structure incorporates increasing block rates, the budget set is convex; when rates are decreasing over blocks, the budget set is nonconvex. It is possible to have budget constraints that are both concave and convex. Initially, we consider the case of a convex budget set (concave budget constraint) with m piecewise linear segments. The

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[6]The survey by Moffitt (1986) provides a general derivation of the demand function. Also see Hewitt & Hanemann (1995) for a careful derivation of the demand function in the context of water demand with a three tiered block rate pricing structure.

budget set is given by

$$I = P_1 x + y + fc \qquad \qquad \text{if } x \leq \bar{x}_1$$

$$I = P_1 \bar{x}_1 + P_2(x - \bar{x}_1) + y + fc \qquad \qquad \text{if } \bar{x}_1 < x \leq \bar{x}_2$$

$$\vdots \qquad \qquad \qquad \vdots$$

$$I = P_1 \bar{x}_1 + P_2(\bar{x}_2 - \bar{x}_1) + \ldots + P_m(x - \bar{x}_{m-1}) + y + fc \qquad \text{if } \bar{x}_{m-1} < x \leq \bar{x}_m$$

where fc represents fixed costs, such as hook-up fees. We simplify the budget set by incorporating the difference variable first suggested by Taylor (1975) and Nordin (1976). The difference variable is defined as the difference between how much the consumer would have paid if she had been charged the marginal rate for all units and what the consumer actually paid for water. Typically, any fixed charges are included in the difference variable as well. If we let d_i denote the difference variable in the ith block, then

$$d_i = -fc - \sum_{j=1}^{i-1}(P_j - P_{j+1})\bar{x}_j. \qquad (1)$$

Note that $d_1 = -fc$.[7] Using equation (1), we can express the budget constraint more succinctly:

$$I + d_1 = P_1 x + y \qquad \text{if } x \leq \bar{x}_1$$

$$I + d_2 = P_2 x + y \qquad \text{if } \bar{x}_1 < x \leq \bar{x}_2$$

$$\vdots \qquad \qquad \vdots$$

$$I + d_m = P_m x + y \qquad \text{if } \bar{x}_{m-1} < x \leq \bar{x}_m. \qquad (2)$$

The income plus difference variable term in equation (2) is equivalent to the virtual income variable

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[7]The difference variable proposed by Taylor (1975) and Nordin (1976) is actually the negative of that defined in equation (1). In words, it is defined as the difference between how much the consumer actually pays for water and what the consumer would have paid if she had been charged the marginal rate for all units.

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which is more commonly used in studies with piecewise-linear constraints and is found in Figure 3. We incorporate the difference variable instead of virtual income since the difference variable is so common in the water demand literature.[8]

The consumer's problem is to maximize a strictly quasi-concave utility function $U(x, y)$ subject to the budget constraint in equation (2). Since the budget constraint is clearly nondifferentiable, optimization requires two stages. Conceptually, the optimization stages correspond to the continuous and discrete choices faced by the consumer. In the first stage of maximization, we choose the optimal level of consumption for each segment of the kinked budget constraint. This stage results in the conditional demand function

$$
\begin{aligned}
x &= x_1^*(P_1, I + d_1), & &\text{if } x < \bar{x}_1, \\
x &= x_2^*(P_2, I + d_2), & &\text{if } \bar{x}_1 < x < \bar{x}_2 \\
&\ \ \vdots & &\ \ \vdots \\
x &= x_m^*(P_m, I + d_m), & &\text{if } \bar{x}_{m-1} < x < \bar{x}_m \\
x &= \bar{x}_i & &\text{if } x = \bar{x}_i \text{ for } i = 1, 2, \ldots, m - 1,
\end{aligned} \tag{3}
$$

which gives the optimal level of consumption conditional on being located on a particular segment or kink.

In the next stage, the consumer chooses the segment with the conditional demand that maxi-

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[8]In the literature on the econometrics of piecewise-linear budget constraints, it is more typical to model the budget constraint, with two segments, as

$$
\begin{aligned}
I &= P_1 x + y & &\text{if } x \leq \bar{x}_1 \\
\tilde{I} &= P_2 x + y & &\text{if } x > \bar{x}_1
\end{aligned}
$$

where $\tilde{I} = I + (P_2 - P_1)\bar{x}_1$ is often referred to as "virtual income" (Burtless & Hausman 1978) and denotes the intercept of the second segment of the budget constraint extended to the axis. Virtual income provides a convenient representation of the situation faced by consumers in the second block. Note that $\tilde{I} = I + d_2$. For the sake of its similarity to virtual income, we define the difference variable to be the negative of the variable traditionally used in the water demand literature.

mizes overall utility. If we denote the conditional indirect utility function as

$$V_i(P, I) = \max_{x_i, y_i} U_i(x, \mathbf{y})$$

$$= U[x_i^*(P_i, I + d_i), I + d_i - P_i \cdot x_i^*(P_i, I + d_i)],$$

then the second stage problem is

$$\max\{V_1(\cdot), V_2(\cdot), \ldots, V_m(\cdot)\}.$$

Using the conditional indirect utility function and the assumptions of a concave utility function and convex budget set, the utility maximizing choice of segments can be reduced to (see Moffitt (1986)):

$$\begin{aligned}
&\text{Choose segment 1 if} && x_1^*(P_1, I + d_1) \leq \bar{x}_1 \\
&\text{Choose segment } i \text{ if} && \bar{x}_{i-1} < x_i^*(P_i, I + d_i) \leq \bar{x}_i \\
& && \text{for } i = 2, 3, \ldots, m - 1 \\
&\text{Choose segment } m \text{ if} && \bar{x}_{m-1} < x_m^*(P_m, I + d_m) \\
&\text{Choose the } i^{th} \text{ kink if} && x_{i+1}^*(P_{i+1}, I + d_{i+1}) \leq \bar{x}_i < x_i^*(P_i, I + d_i) \\
& && \text{for } i = 1, 2, \ldots, m - 1 && (4)
\end{aligned}$$

Finally, combining the solutions to the continuous (equation (3)) and discrete choice (equation (4)) optimization problems gives the unconditional demand function. We can express this function as

$$\begin{aligned}
x = {}& b_1 x_1^*(P_1, I + d_1) + b_2 x_2^*(P_2, I + d_2) + \ldots + b_m x_m^*(P_m, I + d_m) + \\
& c_1 \bar{x}_1 + c_2 \bar{x}_2 + \ldots + c_{m-1} \bar{x}_{m-1}
\end{aligned} \qquad (5)$$

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where

$$b_1 = 1 \quad \text{if } x_1^*(P_1, I + d_1) \leq \bar{x}_1; \qquad b_1 = 0 \text{ otherwise;}$$

$$b_i = 1 \quad \text{if } \hat{b}_{i1} > 0 \text{ and } \hat{b}_{i2} > 0; \qquad b_i = 0 \text{ otherwise;} \quad \text{for } i = 2, 3, \ldots, m - 1$$

$$b_m = 1 \quad \text{if } \bar{x}_{m-1} < x_m^*(P_m, I + d_m); \quad b_m = 0 \text{ otherwise;}$$

$$c_i = 1 \quad \text{if } \hat{c}_{i1} > 0 \text{ and } \hat{c}_{i2} > 0; \qquad c_i = 0 \text{ otherwise;} \quad \text{for } i = 1, 2, \ldots, m$$

and

$$\hat{b}_{i1} = \bar{x}_i - x_i^*(P_i, I + d_i);$$

$$\hat{b}_{i2} = x_i^*(P_i, I + d_i) - \bar{x}_{i-1};$$

$$\hat{c}_{i1} = x_i^*(P_i, I + d_i) - \bar{x}_i;$$

$$\hat{c}_{i2} = \bar{x}_i - x_{i+1}^*(P_{i+1}, I + d_{i+1}).$$

It is straightforward to derive the demand function for the nonconvex budget set. In that setting, the budget constraint and conditional demand function are identical to those in equations (2) and (3). The function defining the choice of segments is

$$\text{Choose segment } i \text{ if } \quad V_i(P, I) \geq V_j(P, I) \quad \text{for all } j \neq i \tag{6}$$

Therefore, the demand function is

$$x = b_1 x_1^*(P_1, I + d_1) + b_2 x_2^*(P_2, I + d_2) + \ldots + b_m x_m^*(P_m, I + d_m) \tag{7}$$

where

$$b_i = 1 \quad \text{if } \hat{b}_{ij} > 0 \quad \text{for all } i \neq j; \quad b_i = 0 \quad \text{otherwise}; \quad \text{for } i = 1, 2, \ldots, m;$$

$$\hat{b}_{ij} = V_i(\cdot) - V_j(\cdot).$$

5 Aggregation and an Empirical Model

We now specify an econometric model to estimate the water demand function. Previous empirical studies that employ models that account for the nonlinear budget constraint and resulting endogeneity of prices, have used micro-level data for their analysis. This requires expensive survey techniques to gather the relevant data. Instead, we utilize much cheaper and more readily available aggregate data, in this case from three water districts in the Bay Area. This approach requires that the demand functions in equations (5) and (7) be aggregated to accommodate the available data.

Initially, we sum the demand functions over all the consumers in the district. For the demand functions based on increasing block rates (convex budget set), we get

$$X = \sum_{i=1}^{m} [b_1 x_{i1}^*(P_1, I + d_1) + b_2 x_{i2}^*(P_2, I + d_2) + \ldots + b_m x_{im}^*(P_m, I + d_m)]$$

$$= X_1(P_1, I + d_1) + X_2(P_2, I + d_2) + \ldots + X_m(P_m, I + d_m)$$

$$= n_1 \cdot q_1(P_1, I + d_1) + n_2 \cdot q_2(P_2, I + d_2) + \ldots + n_m \cdot q_m(P_m, I + d_m).$$

where $x_{ij}^*(\cdot)$ refers to the conditional demand of the ith consumer in the jth block, $X_j = \sum_{i=1}^{n} b_j x_{ij}^*(\cdot)$, and n_j and q_j are the number of consumers and the average consumption on the jth segment. The discrete choice component of the consumer choice problem determines the number of households on the jth segment n_j, while the continuous choice problem defines the average household consumption $q_j(\cdot)$ conditional on being located in the jth block. Thus, the structure of the unconditional demand function for micro-data (equation (5) is essentially preserved in the aggregate de-

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mand function. The notable exception is that we are unable to consider the question of consumers locating at the kinks because our aggregate data do not allow us to identify such consumers. We will return to this problem shortly.

To control for population differences between water districts, we normalize by the total number of consumers in each district. The aggregate demand function becomes

$$q = \frac{X}{n} = \frac{n_1}{n} q_1(P_1, I + d_1) + \frac{n_2}{n} q_2(P_2, I + d_2) + \ldots + \frac{n_m}{n} q_m(P_m, I + d_m) \tag{8}$$
$$= s_1 \cdot q_1(P_1, I + d_1) + s_2 \cdot q_2(P_2, I + d_2) + \ldots + s_m \cdot q_m(P_m, I + d_m)$$

where q is average consumption per household and s_j is the fraction of consumers located in the jth price block. Although we cannot identify consumers located at the kinks, our data are rich enough to identify the share of consumers and average consumption in each block.

One of the principal contributions of the piecewise-linear budget constraint model is its stochastic specification. In contrast to traditional models of consumer demand, studies of demand subject to a piecewise-linear budget constraint usually separate the error into heterogeneity and "measurement" error components. The heterogeneity error explicitly accounts for the variation in consumer preferences, while the measurement error incorporates all other error types. The heterogeneity error produces clustering of consumers around kinks because there is a range of preferences that lead to utility maximization through consumption at the kinks (Moffitt 1986).[9] Therefore, the importance of analyzing consumer behavior at the kinks is in relation to the degree of clustering around the kinks.

We believe that our inability to identify consumers at the kinks is a relatively small problem given the lack of clustering evident in our consumption data. In Figures 4 and 5, we present the distribution of consumers across levels of consumption from representative summer months for the

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[9]In the case of decreasing block rates, heterogeneity error would cause dispersion of consumers away from the kink since it is never an optimal location for consumption.

Great Oaks, and San Leandro municipal water districts.[10] There is strikingly little clustering (or dispersion in the case of the Great Oaks Water District) in these data sets. It is impossible to know from the data available why there is so little clustering.

In past studies, the water demand literature has recognized the importance of climate, socioeconomic variables and the water-consuming capital stock (landscaping, swimming pools, bathrooms, plumbing fixtures, etc.) in determining water consumption. We incorporate these commonly used variables in our econometric model, but also include less frequently used variables such as specific conservation measures employed by the different water districts to induce conservation. Including these additional variables and a stochastic specification gives us our econometric model of water demand:

$$q_t = s_{1t} \cdot q_{1t}(P_{1t}, I + d_{1t}, Z_t \mid \beta) + s_{2t} \cdot q_{2t}(P_{2t}, I + d_{2t}, Z_t \mid \beta) +$$
$$\ldots + s_{mt} \cdot q_{mt}(P_{mt}, I + d_{mt}, Z_t \mid \beta) + \varepsilon_t \tag{9}$$

where t denotes the time subscript, Z represents the matrix of climate, socioeconomic, capital stock and conservation variables, β is the vector of unknown coefficients, and ε is the unobserved error term.

For convenience, we assume linear conditional demand curves. With this assumption, the unconditional demand function in equation (9) simplifies to

$$q_t = \beta_0 + \beta_1 \left(\sum_{i=1}^{m} s_{it} \cdot p_{it} \right) + \beta_2 \left(\sum_{i=1}^{m} s_{it} \cdot (I + d_{it}) \right) + \delta Z_t + \varepsilon_t \tag{10}$$

where δ is a vector of unknown parameters associated with the matrix of climate, socioeconomic, and capital stock variables, Z. It would be inappropriate to estimate equation (10) using the observed probabilities of being located on a particular segment s_i because they, like the conditional

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[10]Note that there appears to be a small clustering of consumers around the kink at 30 ccf in Figure 5. This does not seem to be the result of heterogeneity error because the clustering at 30 ccf persists even when the kink point moves far from 30 ccf in other periods.
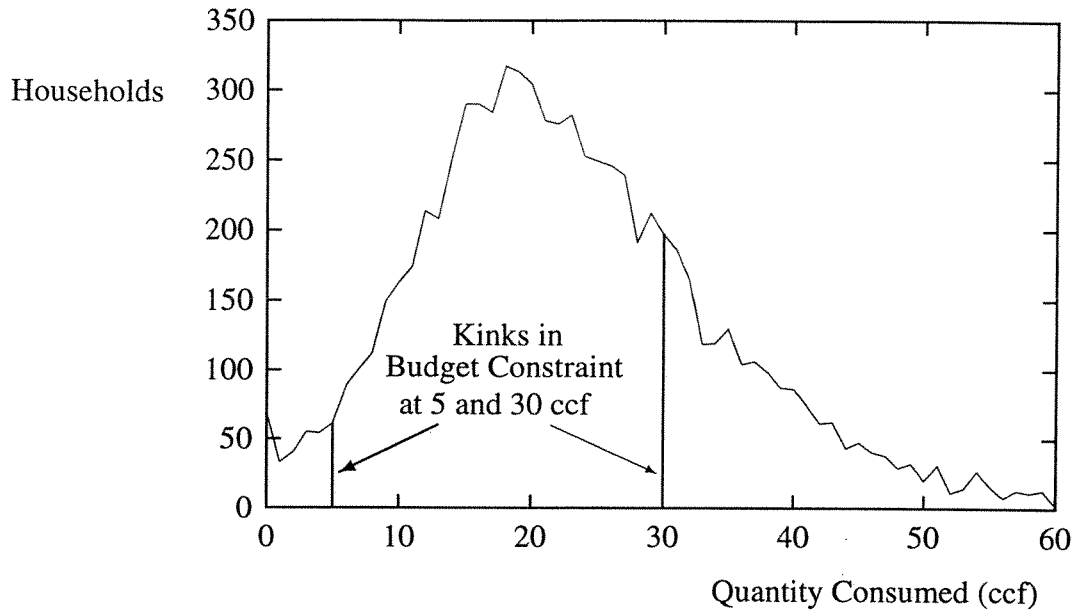
18

Figure 4: Frequency Distribution of Great Oaks Water Consumers
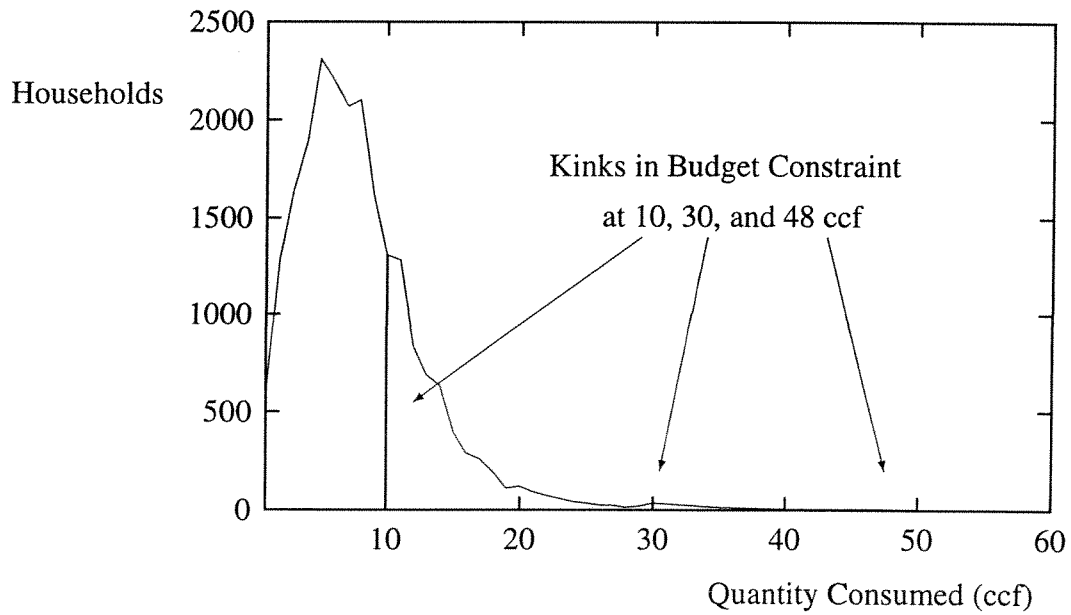

Figure 5: Frequency Distribution of San Leandro Water Consumers

demands, are functions of preferences and are determined by the consumer's discrete choice problem. Therefore, they are correlated with the error term ε. To deal with this issue, we estimate equation (10) in stages that are parallel to the discrete and continuous stages of optimization of the consumer's choice problem. We first estimate the proportion of households located in the different blocks, $\widehat{s_i}$, using a Multinomial logit model.

The general format of the multinomial logit model is

$$\text{Prob[choice i]} = \frac{e^{\beta_i' X_t}}{\sum_i e^{\beta_i' X_t}}, \quad i=0,1,\ldots,M \tag{11}$$

A possible $M+1$ unordered outcomes can occur. This model is typically employed for individual or grouped data in which the X variables are characteristics of the observed individuals, not the choices. The characteristics are the same across all outcomes. Here, the observed dependent variable is a proportion, s_i. X is a matrix of time-specific characteristics such as temperature, precipitation, income and household size. Given this specification, we estimate the proportion of households located in each block at time t in each district. We then utilize the predicted proportions for each of the districts in our sample and estimate the unconditional demand function for all three districts.

Schefter & David (1985) propose a new aggregation technique in which average marginal price is constructed as an average of the marginal prices of each rate block weighted by the distribution of consumers across the block structure. This aggregation technique preserves the structure of the individual demand function when aggregated, in contrast to the more common technique of using the marginal price paid by the average consumer which results in biased estimates of the price effect.[11] It is noteworthy that the model specification in equation (10), derived through the straightforward aggregation of the piecewise-linear demand function, is similar to that of Schefter

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[11]Due to a lack of data on the distribution of consumers across rate blocks, Schefter & David (1985) were forced to use simulations rather than actual average marginal price in their study. We know of no study since that has used their proposed technique to estimate aggregate demand. As mentioned earlier, we have data on the distribution of consumers across rate blocks that allow us to appropriately aggregate prices.

& David (1985). The major difference between our model and theirs is our provision for how the probabilities of being on a particular segment are determined.[12] In other words, they do not correct for the endogeneity between quantity and price so their consumer demand model does not explicitly incorporate the discrete choice problem. Notice that if the error term is large, then observed average household consumption must be large, which implies that a larger fraction of consumers must be located in the higher blocks. Thus, the observed probabilities s_i are positively correlated with the error term.

6 Data, Estimation, and Results

The data utilized for this analysis consist of variables collected for the three residential water districts, Great Oaks, San Mateo and San Leandro. The data span 10 years, from January 1982 to October 1992 and include variables on quantity, price structure, socio-economic, climate and conservation.

The quantity variables include the total single family residential monthly consumption of water for the district in ccf (100 cubic feet), the total number of single family residential households in the district per month, the number of single family residential households located in each block per month. From the quantity variables we obtain our dependent variable q, which denotes monthly water consumption of the average household for the district.

The price structure variables collected include the fixed monthly charge, the marginal price associated with each block, and the quantity of water at which each kink occurs. All prices are deflated. The socio-economic variables include deflated average monthly income, I, which is collected separately for each district, and annual average household size, HHS, for each district.[13]

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[12]Schefter & David (1985) also differ in that the difference variable is not included in income.

[13]Ideally, we would incorporate the average monthly income and household size weighted by the distribution of consumers over the billing structure. Unfortunately, this information is not available to the water districts and would require micro-level data to include. Since our objective is to understand the forces driving aggregate demand and conservation as opposed to the distribution of the conservation burden, this data limitation does not pose a severe problem.

Table 2: Construction of Conservation Dummies

Conservation Program	0	1	2	3
Billing Information	Total only	Use for period last year	1 + allotment message	1 + 2 + bill insert
Conservation Education	None	Flyers only	1 + speakers bureau	1 + 2 + in-school educaation
Use Restrictions	None	% reduction or allotment	1 + use restrictions	1 + 2 + enforcement
Landscaping Program	None	Education (flyers, etc.)	1 + restrictions or limits	1 + 2 + landscape audits
Low-flow Plumbing	None	Retro-fit kits available	1 + rebates	1 + 2 + new construction code

The climate variables are temperature ($Temp$) and precipitation ($Precip$), both collected on an average monthly basis and separately for each district. Temperature is measured in degrees Fahrenheit and precipitation is measured in inches. Conservation variables were created to measure the degree to which the residential water districts implemented the different conservation programs available to them. Table 2 contains a description of the codes used.

Fifteen dummy variables were created to capture the effect of conservation programs on water demand. Billing information ($Bill$) refers to information accompanying the billing statement. There are three dummy variables under this heading. When the statement includes the amount of water used in the same period last year, a value of 1 is assigned to the variable ($Bill1$), otherwise 0 is assigned. When the billing statement includes the amount of water used last year for the same period in addition to an allotment message a value of 1 is assigned to $Bill2$, otherwise 0 is assigned. When a billing insert is included in addition to an allotment message and last year's period consumption the Bill variable ($Bill3$) is assigned a value of 1, otherwise 0 is assigned.

Similarly, there are three dummy variables under the heading Conservation education (Ed).

$Ed1$ is given a value of 1 when flyers containing conservation information are distributed by the water district, a value of 0 otherwise. A value of 1 is assigned to $Ed2$ when in addition to flyers the district has a speaker bureau, 0 otherwise. $Ed3$ represent flyers, speaker's bureau and an in-school program. A value of 1 is given if all three are present, otherwise 0.

There are three dummy variables corresponding to levels of use restrictions (UR). $UR1$ gets a 1 when a request is made to consumers in the district to reduce their consumption by a given percentage amount, otherwise 0 is assigned. When use restrictions are mandatory a 1 is assigned to $UR2$, otherwise 0. When the use restriction is enforced a 1 is coded, if not, 0 is assigned to $UR3$.

The landscaping program variables $(Land)$ and Low Flow Plumbing program variables $(Plumb)$ are similarly coded. $Land1$ is given a value of 1 when landscaping education is provided, 0 otherwise. $Land2$ is equal to 1 when in addition to education there are restrictions or limits to landscaping activities, 0 otherwise. $Land3$ is 1 if landscape audits are performed, otherwise 0. $Plumb1$ equals 1 if retro-fit kits are available, otherwise 0. $Plumb2$ is 1 when rebates are offered, 0 otherwise, and $Plumb3$ is 1 when new construction codes are in effect, 0 otherwise.

To measure the influence of price, we create the variable average marginal price, $\widehat{AMP}$. We use the predicted proportions $\hat{s}$ estimated using (11) to create $\widehat{AMP} = \sum_{i=1}^{m} \hat{s}_{it} \cdot p_{it}$. This price variable represents the mean marginal price faced in the district.[14] The variable $\hat{d}$ is also created using $\hat{s}$ and represents the mean *difference* faced by all households.

The main results are summarized in Tables 3 – 7. Values in parentheses are t-ratios. All specifications of the model were estimated employing a set of assumptions on the disturbance co-variance matrix that gives a cross-sectionally heteroskedastic and time-wise autoregressive model as described in Kmenta (1986).[15]

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[14]Schefter & David (1985) were the first to note that the correct marginal price to use in an aggregate setting is the mean marginal price and not the marginal price faced by the average consumer.

[15]The preferred technique for estimating equation (10) would be a two error maximum likelihood technique that simultaneously estimates the discrete and continuous choice problems. We use the two stage approach described because the price specifications (number of segments, increasing vs. decreasing block rates) vary within and across the

We estimate four different specifications of the demand function. Model 1 is the standard model of water demand and includes the basic variables included in practically all water demand studies. Model 2 expands the standard model by introducing the variables created to measure the districts' conservation efforts, as described in table 2. Originally all conservation dummy variables were introduced, but only $UR2$ and $Land3$ proved significant. High collinearity between conservation programs likely affected the individual estimated influence attributed to the different programs. $UR3$ and $Land3$ were used exclusively by San Leandro. These programs were implemented simultaneously at the beginning of the drought, and lasted for the duration of the available data. Thus, we cannot separate their individual effects on water consumption. $UR2$ was implemented in the Great Oaks district, also as a response to the drought.

We use Model 3 to test whether households responded differently to water prices during the drought. In other words, was there a structural shift in consumer behavior due to the drought? We create a dummy variable, D, which takes on the value of 1 during the drought, and 0 otherwise, and look at the interaction of $\widehat{AMP}$ and drought. For purposes of estimation, we define the beginning of the drought as April 1988. The regular rainy season in the Bay Area ends by the end of March. Therefore, expectations of additional rain are insignificant by April. What we are trying to estimate is whether or not households behave differently once they realize there is a state of drought. We control for precipitation, therefore any change in behavior must be due to knowing there is a drought, and not because of a lack of precipitation.

While the estimates of Model 3 tell us whether or not households behaved differently with respect to water prices during the drought, the estimates of Model 4 gives us different slope coefficient measures for price during the drought and during normal periods of rainfall. We make use of $C = 1 - D$ to accomplish this. $D \cdot \widehat{AMP}$ reflects the influence that price had on consumption decisions during the drought, whereas $C \cdot \widehat{AMP}$ reflects the estimated influence that price has on

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districts we consider. Since the pricing structures vary over time within some districts (San Leandro and San Mateo use both constant and increasing block rates during our sample), we cannot use the maximum likelihood technique previously used in Hewitt and Hanemann's (1995) paper.

consumption during normal periods of precipitation.

Table 3 and Table 5 differ in the data sets used for estimation of the different models. The models presented in Table 3 were estimated using all the months of the year, from January 1982 to October 1992; in all, 130 observations per water district. The models in Table 5 were estimated using only the non-rainy months in the Bay Area, from April to October of 1982 to 1992; in all, 77 observations per water district. We believe households have more discretionary water needs during the non-rainy period, and this should magnify the influence different variables, particularly $\widehat{AMP}$, have on conservation and consumption household decisions.

Regression results presented in Tables 3 and 5 were estimated using the 2-stage procedure described in section 5. For comparison purposes, we present Tables 4 and 6 which contain results of models estimated using observed proportions (s_i) to construct AMP. Since the s_i's, like the conditional demands, are functions of preferences, they are correlated with the disturbance term ε of equation (10) and hence these results are biased. Correcting for the endogeneity of s_i, and thus AMP, through the 2-stage procedure should strengthen the estimated influence of price on consumption behavior. This result is to be expected, since two of the three districts considered employed increasing block rates. With increasing block rates, the higher the quantity consumed, the higher the price paid, hence without correcting for the endogeneity a spurious positive relationship between price and quantity might be obtained.

When we compare across Tables 3 and 5 the first thing we notice is the enhanced influence all variables seem to have on consumption during the non-rainy months. In both tables all coefficients are of the expected sign. As was anticipated, more discretionary water needs associated with the non-rainy months, such as watering lawns, filling swimming pools, washing cars and sidewalks, etc., are associated with larger impacts of changes in explanatory variables, including price.

In Model 1 of Table 3 all estimated coefficients have p-values of less than 0.05, except for $\widehat{AMP}$, which has an associated p-value of 0.12. The coefficient on price is used to obtain the elasticity measure presented in Table 7 of -0.1710, which indicates a relatively inelastic price

response. Once we control for the influence of the conservation programs (use restrictions and landscape audits) on household consumption decisions in Model 2, the effect of average marginal price on consumption is mitigated, and becomes statistically insignificant at conventional levels, though the sign is still "correct". In Model 3 we interact average marginal price with the drought episode and find that there in fact was a structural shift. The coefficient on $D \cdot \widehat{AMP}$ is -2.4133 with a p-value of 0.0055, confirming our believe that households responded differently to price signals during the drought than during normal periods of rainfall. From the coefficients on $D \cdot \widehat{AMP}$ and $C \cdot \widehat{AMP}$ in Model 4 we construct price elasticities during the drought and during periods of normal precipitation. These are presented in Table 7. When we consider all months, and include the non-price conservation variables, the effect price has on consumption during normal periods is negligible, at an elasticity measure of -0.00051. During the drought, the price effect is inelastic at -0.12050. In other words, if during the drought, the mean marginal price was increased by 10%, the average household would have consumed 1.2% less water. The estimated influence of all other included variables stayed similar across all specifications of the model in Table 3. Using the coefficients presented in Model 3, we can construct elasticity measures for mean marginal income $(I + \hat{d})$ temperature, precipitation and household size. A 10% increase in mean marginal income would imply a 2.5% increase in the water consumption of the average household. A 10% increase in temperature would lead to a 7.6% increase in water consumption, a result that has implications for policy to deal with global warming. A 10% reduction in local precipitation leads to a 0.16% increase in water consumption. The employment of use restrictions, even without enforcement, proves to be effective, as does the auditing of landscaping restrictions.

Looking at Table 5 we observe similar patterns as those found in Table 3, but the estimated influence on consumption of the different included variables is stronger. In particular, the effect average marginal price has on consumption is enhanced. As was discussed previously, if price can be used effectively as a conservation tool, it would have to be during periods when households can be more discriminating on their water use. One noticeable distinction between Table 5 and Table

Table 3: Regression Results for All Months

Model	1	2	3	4
Constant	-57.765	-66.697	-68.101	-68.101
	(-7.7829)	(-11.183)	(-11.447)	(-11.447)
$\widehat{AMP}$	-4.4031	-2.8720	-0.14947	
	(-1.5227)	(-1.0918)	(-0.0541)	
$I + \hat{d}$	0.00189	0.0009	0.001148	0.001148
	(1.9085)	(0.94567)	(1.2832)	(1.2832)
HHS	22.476	27.369	26.919	26.919
	(6.4277)	(9.4840)	(9.5605)	(9.5605)
Temp	0.20902	0.21960	0.22418	0.22418
	(7.8114)	(8.5199)	(8.7996)	(8.7996)
Precip	-0.13422	-0.17390	-0.18497	-0.18497
	(-2.6424)	(-3.4399)	(-3.6492)	(-3.6492)
UR2		-7.3257	-6.4111	-6.4111
		(-3.0560)	(-2.6415)	(-2.6415)
Land3		-2.8163	-1.8099	-1.8099
		(-5.2275)	(-2.9561)	(-2.9561)
$D \cdot \widehat{AMP}$			-2.4133	-2.5627
			(-2.7915)	(-1.0192)
$C \cdot \widehat{AMP}$				-0.14947
				(-0.0541)
n (per district)	130	130	130	130
Buse R^2	0.3257	0.5044	0.5198	0.5198

Table 4: Regression Results Using Observed Proportions (All Months)

Model	1	2	3	4
Constant	-59.552	-67.986	-69.595	-69.595
	(-8.0327)	(-11.463)	(-11.756)	(-11.756)
AMP	-2.5742	-1.0824	2.0196	
	(-0.91482)	(-0.42026)	(0.74549)	
$I + \hat{d}$	0.001464	0.00043	0.00067	0.00067
	(1.4967)	(0.46195)	(0.76244)	(0.76244)
HHS	23.368	28.173	27.749	27.749
	(6.6881)	(9.8241)	(9.9156)	(9.9156)
Temp	0.20626	0.21622	0.22037	0.22037
	(7.7208)	(8.4269)	(8.7189)	(8.7189)
Precip	-0.13389	-0.17721	-0.18922	-0.18922
	(-2.6264)	(-3.5001)	(-3.7450)	(-3.7450)
UR2		-7.2516	-6.2090	-6.2090
		(-3.0245)	(-2.5574)	(-2.5574)
Land3		-2.9576	-1.8197	-1.8197
		(-5.6416)	(-3.0256)	(-3.0256)
$D \cdot AMP$			-2.7318	-0.71218
			(-3.1768)	(-0.28928)
$C \cdot AMP$				2.0196
				(0.74549)
n (per district)	130	130	130	130
Buse R^2	0.3252	0.5077	0.5241	0.5241

3 is that in going from Model 1 to Model 2 by introducing conservation measures, the price effect is enhanced in Model 2. This result might indicate that there exists some kind of synergy between conservation programs and price during non-rainy periods that is lost when we consider all months of the year, or that misspecification biases of Model 1 due to excluded variables is stronger when we use all months in estimation. Again, from Model 3 we see that there was a structural shift in households' perception of price when in periods of drought. The coefficient on the drought interaction term $D \cdot \widehat{AMP}$ is -2.1471 with a p-value of 0.0866. From the estimated coefficients of Model 4 we get elasticity measure for years of drought and of normal precipitation during non-rainy months. In episodes of drought, during non-rainy months, a 10% increase in average marginal price would reduce water consumption of the average household by 3%, a reduction almost three times greater than when we consider all months. This result again implies that even in periods of drought, households have more discretionary needs during the non-rainy season in the Bay Area. In normal periods of precipitation, a 10% increase in mean marginal price would reduce the consumption of the average household by 1.38%. Using the coefficient of Model 3, the mean marginal income elasticity during non-rainy seasons is 0.545, almost twice as large as when all months are used in estimation. This empirical finding implies that water during the non-rainy season responds more elastically to increases in income, as in price, than in other seasons of the year. The temperature elasticity is 0.766 which is practically identical to the elasticity estimated using all months. Households seem to be equally responsive to temperature changes in all seasons with respect to their water use. Similar findings apply for precipitation and household size. Use restrictions and landscaping audits prove useful in inducing conservation behavior from households in non-rainy seasons.

Table 5: Regression Results for Non-rainy Months

Model	1	2	3	4
Constant	-61.356	-78.188	-78.779	-78.779
	(-7.3241)	(-12.730)	(-13.220)	(-13.220)
$\widehat{AMP}$	-6.3995	-6.7084	-4.9108	
	(-1.4007)	(-1.7573)	(-1.2638)	
$I + \hat{d}$	0.00296	0.00229	0.002845	0.002845
	(1.8570)	(1.6210)	(2.0541)	(2.0541)
HHS	23.708	31.361	30.320	30.320
	(5.6861)	(9.4953)	(9.4263)	(9.4263)
Temp	0.20346	0.23435	0.24152	0.24152
	(3.1169)	(3.8141)	(3.9481)	(3.9481)
Precip	-0.43555	-0.46923	-0.4881	-0.4881
	(-2.3400)	(-2.6271)	(-2.7262)	(-2.7262)
UR2		-12.745	-11.799	-11.799
		(-6.5841)	(-6.0511)	(-6.0511)
Land3		-3.1927	-2.2556	-2.2556
		(-3.7478)	(-2.3310)	(-2.3310)
$D \cdot \widehat{AMP}$			-2.1471	-7.0579
			(-1.7211)	(-1.9212)
$C \cdot \widehat{AMP}$				-4.9108
				(-1.2638)
n (per district)	77	77	77	77
Buse R^2	0.4025	0.7315	0.7484	0.7484

Table 6: Regression Results Using Observed Proportions (Non-rainy months)

Model	1	2	3	4
Constant	-63.167	-79.360	-79.927	-79.927
	(-7.5869)	(-13.032)	(-13.504)	(-13.504)
AMP	-4.5474	-5.2010	-3.3799	
	(-1.0333)	(-1.3937)	(-0.88548)	
$I + \hat{d}$	0.002577	0.001875	0.00245	0.00245
	(1.6650)	(1.3411)	(1.7946)	(1.7946)
HHS	24.657	32.242	31.137	31.137
	(5.9463)	(9.8448)	(9.7587)	(9.7587)
Temp	0.19557	0.2267	0.23423	0.23423
	(3.0051)	(3.6913)	(3.8306)	(3.8306)
Precip	-0.43823	-0.4734	-0.49279	-0.49279
	(-2.3564)	(-2.6430)	(-2.7442)	(-2.7442)
UR2		-12.744	-11.760	-11.760
		(-6.5759)	(-6.0239)	(-6.0239)
Land3		-3.3277	-2.3426	-2.3426
		(-3.9984)	(-2.4523)	(-2.4523)
$D \cdot AMP$			-2.2366	-5.6164
			(-1.7934)	(-1.5609)
$C \cdot AMP$				-3.3799
				(-0.88548)
n (per district)	77	77	77	77
Buse R^2	0.3989	0.7328	0.7493	0.7493

Table 7: Price Elasticities (at means)

Model	1	2	4	
			Drought	Normal
Non-rainy Months	-0.21801	-0.22853	-0.30262	-0.13782
	(-1.4007)	(-1.7573)	(-1.9212)	(-1.2638)
All Months	-0.17100	-0.11154	-0.12050	-0.00051
	(-1.5227)	(-1.0918)	(-1.0192)	(-0.05412)

7 Conclusions

Growing populations in arid regions are placing strains on the ability of water districts to deliver all the water that is demanded. As demand grows and supplies remain fixed or even diminish, water managers and policy makers are looking for measures to "quench the thirst" of their clients with less water. In this paper, we study the effectiveness of their efforts to induce conservation by analyzing consumption and conservation behavior for the San Francisco Bay Area utilizing aggregate panel data comprised of three water utility districts. We derive an aggregate demand function that preserves the structure of the individual demand function and estimate the effect of pricing and non-price conservation programs on water consumption.

Our results indicate that water pricing as well as conservation policies are more effective in inducing conservation under certain conditions. In particular, pricing policies influence water consumption during non-rainy months (summer and parts of spring and fall), whereas pricing policies are less significant in winter. Households can exercise greater discretion during summer months where outdoor activities such as filling swimming pools, washing cars and sidewalks and watering lawns are common. Also, water consumption in the Bay Area is low compared to Southern California. In fact, Southern California's water consumption in 1991, the most severe year of the drought, was approximately equivalent to the Bay Area's consumption in 1986, the last year of normal precipitation before the drought began (Dixon, Moore & Pint (1996)). This empirical observation implies that consumption in the Bay Area is closer to subsistence levels, so the response to price changes should be expected to be low.

Our results also show price policies to be significant in combating the drought. The influence that price has on consumption was shown to be greater in periods of drought. It is not clear whether this result is due to consumers' reaction from perceiving change in price policy as a signal of the severity of the drought, or whether this result truly represents a price effect.

Conservation programs such as use restrictions and landscaping programs proved effective in lowering water demand during the drought. The experience shared by water utility managers of

the Bay Area during the drought shows that using a proper mix of market and non-market policies to combat droughts can successfully induce conservation behavior from their customers.

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