Household Responses to Increased Water Rates During the California Drought

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ABSTRACT. *This paper explores the use of fixed effects and maximum likelihood techniques to estimate household responses to water price increases during the California drought. Estimates are based on bimonthly meter readings from 599 single-family households in the Alameda County Water District over the period 1982–1992, before and after the introduction of a steeply increasing block rate price structure. I find that household and monthly fixed effects models are not successful in modeling water demand with these data. However, maximum likelihood models that explicitly consider the household's response to the rate structure result in plausible estimates of water demand.* (JEL Q25)

I. INTRODUCTION

Matching residential, business, and agricultural water demands with the available supply of water has long been a problem in the arid Western region of the United States. Growth in the U.S. economy and population, combined with increasing concerns about the environmental effects of water supply projects, have exacerbated this problem in the West. In other U.S. regions, increasing environmental standards are making water supplies more costly.[1] The possibility of global climate change adds greater uncertainty about weather patterns, and may lead to increasing variability in water supplies. The U.S. Environmental Protection Agency reported that water consumption already exceeded supply in the Colorado, Rio Grande, and Great Basins, and drier conditions caused by global warming could adversely affect the Pacific Northwest, California, the Great Plains, the Great Lakes region, the Mississippi delta, the Northeast, and the Southeast (Smith and Tirpak 1989).

Water utilities have traditionally focused on meeting expanding water demand by developing new sources of supply, and setting water prices to cover average costs. With the marginal cost of new water supplies rising, an average-cost pricing policy produces a predictable effect. If water demand continues to grow, water utilities will eventually be overinvesting in sources of supply, unless they are otherwise constrained. In some regions, constraints on the development of new water supplies, such as environmental objections, limited state and local government finance, and physical feasibility, may already be binding. In California, for example, both urban and agricultural water demand continue to grow at existing water prices, but no major new water supply projects have been built since the 1960s.

To an economist, the obvious first step to solving water allocation problems is to introduce marginal-cost pricing. This would ensure that available water supplies went to the most valuable uses, and that new water supplies were developed only if consumers were willing to pay for them. However, in practice, water utilities have been reluctant to use price to allocate water supplies, even in periods of drought. They have tended to rely on preachment and exhortation to induce water conservation, and if necessary, mandatory quantity and use restrictions. Quantity restrictions are often based on past levels of use, leading to perverse incentives to in-

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[1] In the Boston area, for example, household water and sewer bills are expected to triple within the next ten years to pay for the cleanup of Boston Harbor. See "Study Expects Rising Water Rates until 2005," *The Boston Globe*, May 1, 1993, pp. 1, 20.

crease water use during non-drought years. In addition, using quantity restrictions rather than price increases often leads to shortfalls in water agency revenues, which are later recouped by increases in average-cost prices.

To some extent, water agencies are legally and politically constrained in their pricing policies. Single-purpose water districts are not usually allowed to earn profits, and the profits and price structures of privately-owned water agencies are set by regulatory agencies. The profits of city-owned water utilities can be used to fund other city activities, but there is political pressure to keep water rates low. As a result, when marginal costs are above average costs, most water agencies are precluded from setting the water price at marginal cost because their profits would be too high. However, they are not generally prevented from using increasing block rate structures that would set price equal to marginal cost in the highest block, but not cause the agency to earn excessive profits.

Another reason why water agencies have tended not to use marginal-cost pricing is that estimates of price elasticity have been relatively low, and have been based on relatively small price variations. Water utility managers have been skeptical that price changes could result in sufficient levels of conservation, especially in times of drought. Estimates of point-elasticities of water demand have generally been in the range of −.2 to −.8 (Planning and Management Consultants, Ltd. 1990, 133–34), indicating that price increases of 25% to 100% would be needed to reduce residential consumption by 20% during a drought. The Mayor's Blue Ribbon Committee on Water Rates in Los Angeles, California, proposed a 65% price increase on residential water use above 175% of average use in order to raise price to marginal cost for the heaviest users (City of Los Angeles 1992). It is unlikely that previously estimated point-elasticities would be valid over such a large price range, yet few past studies of water demand have been able to provide estimates of arc-elasticities over wide price ranges, because the data simply have not been available. Therefore, water utility managers who seek to use price as a drought management policy or to raise water price to marginal cost face a great deal of uncertainty about the resulting effects on water use and total revenues.

This work is intended to provide estimates of water demand and price elasticity over a wider range of prices and consumption levels by using data from California households before and during the 1987–1992 drought. The California drought varied in its severity over time, and in different parts of the state. Water supply shortages were the greatest in 1991 for most parts of the state, with cutbacks of 15–30% required in many urban areas. A few water agencies used price increases as their main drought management policy, including the Alameda County Water District (ACWD), the East Bay Municipal Utility District (EBMUD), the City of Santa Barbara, and the Long Beach Water Department. At the most severe points of the drought, ACWD achieved a 27% reduction, EBMUD a 33% reduction, and Long Beach a 20% reduction in 1991 water use, while Santa Barbara reported a 62% reduction in 1990 single-family residential water use.[2]

The price changes implemented by these agencies cover a much wider range than those examined in previous studies. The real price increase at ACWD was almost 450% from the 1982 flat rate to the highest block rate in 1991. EBMUD's highest block price increased nearly 500% between 1986 and 1991, and Long Beach's highest block price increased over 300% during the same period. The most dramatic increase occurred in Santa Barbara, where the highest block price increased nearly 2,800% between 1986 and 1990.[3] In contrast, real price changes in Tuc-

[2] Moore, Pint, and Dixon (1993); Dixon, Moore, and Pint (1996); Spectrum Economics, Inc. and Sycamore Associates (1991).

[3] See Table 2 below for ACWD's prices over the period 1982–92. EBMUD's price structure changed from a flat $0.666 per hundred cubic feet (HCF) in 1986 to an increasing block structure with a charge of $3.94 per HCF for the highest block in 1991. Long Beach's highest block charge increased from $0.712 per HCF in 1986 to $3.003 per HCF in 1991. In Santa Barbara, prices changed from a flat rate of $1.02 per HCF to an increasing block structure with the highest block rate set at $29.43 per HCF during the period May–October 1990.

son, Arizona, one of the most heavily studied cities, were much smaller. The price in the mean-use block increased only 12% between 1974 and 1977, and fell back slightly over the remainder of the period studied.[4] Nieswiadomy and Molina's (1989) data set for Denton, Texas, shows a real price increase of 107% for the highest block rate between 1977 and 1985.[5]

Estimates reported in this paper are based on bimonthly meter readings for 599 single-family households over the period 1982–1992 from the Alameda County Water District, which used a steeply increasing block rate structure as a drought management policy from July 1991 to the end of the data collection period in July 1992. These data have been matched with 1992 tax assessor records on house size and lot size,[6] monthly weather data, median household income, and other variables from the 1980 and 1990 censuses at the block group level.[7]

Ordinary least squares estimates of demand curves using these data are inadequate because the increasing block rate structure creates a correlation between high price and high water use. As a result, the estimated demand curve begins to slope upward at higher prices. This paper explores two approaches for correcting this problem. The first approach is to use fixed-effects models that allow the intercept of the demand curve to vary among households, and that control for monthly weather effects. Although these models have much better explanatory power than OLS (the R^2 is more than doubled from .25 to .52), they still result in upward-sloping demand at high prices.

The second approach is to maximize a likelihood function that combines the probability that a household is in a particular block of the rate structure with a density function for water use, conditional on being in that block. I estimate three versions of the maximum-likelihood model (based on Hewitt 1993) with differing error structures. The "heterogeneous preferences" model allows for unobserved differences between households; the "error perception" model allows actual water use to differ from intended water use; and the "two-error" model combines the two sources of error. Both the heterogeneous-preferences model and the two-error model result in downward-sloping demand over the relevant range of prices. The heterogeneous-preferences model results in more accurate predictions of district-wide water consumption, but lower estimated elasticity of demand (ranging from $-.04$ to $-.29$) than the two-error model ($-.20$ to -1.24).

In Section 2, I discuss the previous literature on water demand and price elasticity estimates; Section 3 presents the data and OLS demand estimates; Section 4 shows the fixed-effects results; Section 5 shows the maximum-likelihood results; and Section 6 concludes. Detailed descriptions of the maximum-likelihood models are given in the Appendix.

II. REVIEW OF RELATED RESEARCH

The economics literature on water demand broadly supports the standard economic theory that the household demand function for water is downward-sloping in price, and shifts upward in income and household size. Weather variables explain a large percentage of the seasonal variation in water demand. Studies such as Howe and Lineweaver (1967), Hanke (1970), Foster and Beattie (1979), Danielson (1979) and others have generally found price elasticities in the range

[4] In Tucson, the price in the mean-use block increased from \$0.574 per HCF in 1979 dollars in 1974 to \$0.790 per HCF in 1977–78, and fell back to \$0.712 per HCF in 1982, the end of the period studied (Martin et al. 1984). Prices did not vary enough over the period 1974-76 to provide meaningful estimates of price elasticity, and these years had to be dropped from the sample.

[5] Prices in the highest use block increased from \$0.27 per 1,000 gallons to \$0.56 per 1,000 gallons in 1967 dollars over the period 1977–85.

[6] California's Proposition 13 and its successors freeze property values at their 1979 level, or the purchase price, if purchased after 1979. Therefore, data on the current value of properties is not available, and cannot be used as a proxy for household income.

[7] Household addresses were matched to their census block group using the geographic information system ARC/INFO. Directly collected data on household income, number of family members, etc., is not available for the households in the sample.

between 0 and -1, indicating that water demand is inelastic.

Generally speaking, water demand studies differ mainly in the type of data used and the treatment of the price variable. Hansen and Narayanan (1981), for example, used time series data on aggregate water consumption for a single community. Howe and Lineweaver (1967) used cross-sectional data on aggregate water consumption in 21 U.S. cities. Several studies, including Billings and Agthe (1980), Billings (1982), Billings and Day (1983), and Martin et al. (1984), have employed pooled cross-section and time series or panel data on household water use in Tucson, Arizona. For the purpose of studying the effects of price on household water consumption, more detailed household billing data seems most appropriate, and ideally it should be panel data rather than pooled time series and cross-section data.

The most serious debate in the literature involves the treatment of the price variable. Typically, water utilities have a fixed service charge as well as a commodity charge based on the amount of water used. The commodity charges can be uniform, increasing or decreasing across ''blocks'' of water used (i.e., either flat or an upward or downward step function). Many of the earlier water demand studies ignore the presence of block rates and employ either an average price for water (Foster and Beattie 1979) or the marginal price of water (Howe and Lineweaver 1967). As Billings and Agthe (1980) point out, the use of average price tends to introduce an upward bias in estimated price elasticity, particularly when the marginal price changes while intramarginal rates remain constant, because the change in average price is smaller than the change in marginal price. When only marginal price is used, the income effect of changes in intramarginal rates is ignored.

Borrowing from the literature on electricity demand (Taylor 1975; Nordin 1976), Billings and Agthe employ two price variables. The first is the marginal price in effect at the quantity purchased by the household, and the second is the difference between the household's actual utility bill and what would have been paid if all units of water had been purchased at the marginal price. This second variable captures the income effects of changes in intramarginal rates, and as a result, its estimated coefficient in the water demand function should be equal in value but have the opposite sign as the estimated coefficient on income itself. Although Billings and Agthe's estimated coefficient on the difference variable had the correct sign, its absolute value was much larger than the estimated coefficient on income.

In a comment on Billings and Agthe's formulation, Griffin and Martin (1981) point out that when the price paid by the consumer varies with his consumption, the use of standard OLS produces a biased estimate. This occurs because the observed price and difference correspond with observed consumption which, because of the error term in the regression model, differ from their true values. The larger the error term relative to the size of the blocks, the more likely that the observed marginal price is incorrect. Under increasing block rates, this produces a downward bias in the coefficient on marginal price and an upward bias in the coefficient on the difference variable.

Nieswiadomy and Molina (1989) compare the results of various suggested remedies to this problem using a panel data set from Denton, Texas, that includes periods of both decreasing and increasing block rates. They find that the OLS estimates of the price coefficient appear to be biased in the predicted direction for both increasing and decreasing block rates. They examine two techniques for correcting this bias. The first is to introduce separate price and difference equations, and to use predicted price and difference in the second stage as regressors. The second technique consists of regressing observed water demand on the rate schedule for each block, then using the actual rate schedule and predicted demand to obtain predicted marginal prices. The difference variable is calculated using the predicted marginal price, and the predicted price and difference are employed as instrumental variables in the final regression equation.

Although both the two-stage least squares and instrumental variable approaches appear to correct the bias in the price coefficient, the difference coefficient is statistically signifi-

TABLE 1
DESCRIPTIVE STATISTICS FOR VARIABLES USED IN ESTIMATIONS

Variable	Mean	Standard Deviation	Minimum Value	Maximum Value
Bimonthly Water Use (CCF)	27.05	16.78	0	190
House Size (sq. ft.)	1,485	377	528	2,887
Lot Size (sq. ft.)	6,646	1,484	4,687	17,292
Precipitation (inches in billing month)	1.15	1.43	0	7.17
Lagged Precipitation (inches in previous month)	1.25	1.62	0	7.17
Average Temperature (°F in billing month)	59.65	6.80	44	74
Lagged Average Temperature (°F in previous month)	59.46	7.00	44	74
Price (1992 $ per CCF)	0.93	0.26	0.66	3.69
Price^2	0.93	0.99	0.44	13.60

cant with the wrong sign in both cases. In this and other studies, there is relatively little empirical support for the hypothesis that the difference variable is equal in magnitude and opposite in sign to the income variable. This problem may occur because the difference variable is small relative to total household income, or because most studies use proxies for household income, since actual household income data is difficult to obtain.

Other economists, such as Chicoine and Ramamurthy (1986) and Nieswiadomy (1992) have argued that the measure of price to which consumers respond is an empirical question. Nieswiadomy uses a model developed by Shin (1985) to test whether consumers react to average or marginal prices. The premise is that it is costly for consumers to determine the true rate schedule. If the marginal benefit of learning the true rate schedule is less that the marginal cost, then consumers may respond to some proxy such as average price. If the marginal benefit exceeds the marginal cost, then consumers will be reacting to the true rate schedule. Nieswiadomy's results using cross-sectional data on aggregate water demand in 430 U.S. cities indicate that consumers tend to react to average prices. However, data on individual households would provide a better test of Shin's model.

Based on estimates using the Alameda County Water District data on household water use, it appears that the lack of variation in prices in some of the data sets used in the literature has masked more fundamental problems with the econometric techniques being used. Increasing and decreasing block rate structures create a correlation between high water use and high prices or low prices, respectively. Therefore, it is necessary to model the household's response to the price structure more directly than past studies have done.

Hewitt (1993) and Hewitt and Hanemann (1995) introduce a family of discrete/continuous choice, maximum-likelihood models that can be used to estimate households' responses to an increasing block rate structure more directly. Using the same panel data set from Denton, Texas, as Nieswiadomy and Molina (1989), they find a much higher price elasticity (-1.6) than previously published results based on regression models. This paper generalizes their models to the four-block rate structure used by Alameda County Water District, and also explores the use of fixed effects models as an alternative means of modeling household water demand.[8]

[8] Due to the computational complexity of the maximum-likelihood models, only three specifications were estimated. The maximum-likelihood models had to be programmed as nonlinear systems and estimated using computational algorithms that required hundreds of hours of off-peak computer processing time.

TABLE 2
ACWD Single-Family Residential Water Prices

Effective Date	Usage Level	Nominal Price	Real Price (1992=100)
January 1, 1982	All	$0.450	$0.6616
May 1, 1982	All	0.585	0.8550
January 1, 1983	All	0.585	0.8384
January 1, 1984	All	0.585	0.8114
July 1, 1984	All	0.673	0.9147
January 1, 1985	All	0.673	0.8843
January 1, 1986	All	0.673	0.8642
January 1, 1987	All	0.740	0.9187
January 1, 1988	All	0.777	0.9266
January 1, 1989	All	0.816	0.9292
January 1, 1990	All	0.857	0.9247
January 1, 1991	All	0.900	0.9349
July 1, 1991	0–28 CCF	0.900	0.9221
	29–38 CCF	1.800	1.8442
	39–48 CCF	2.700	2.7664
	>48 CCF	3.600	3.6883
January 1, 1992	0–28 CCF	1.008	1.0144
	29–38 CCF	1.800	1.8115
	39–48 CCF	2.700	2.7172
	>48 CCF	3.600	3.6223
July 1, 1992	0–30 CCF	1.008	1.0080
	31–48 CCF	1.260	1.2600
	49–64 CCF	1.512	1.5120
	65–80 CCF	1.764	1.7640
	>80 CCF	2.016	2.0160

Sources: Brown and Caldwell 1992; Alameda County Water District.
Note: CCF = hundred cubic feet

III. DESCRIPTION OF ACWD DATA AND OLS RESULTS

The data on water use come from Alameda County Water District (ACWD), which covers Fremont, Newark, and Union City, California, in the Southeast San Francisco Bay area, south of Oakland. Unlike many other California water utilities, which relied on quantity restrictions to reduce consumption, ACWD used a steeply increasing block rate structure as one of its drought management policies. It also had a uniquely comprehensive data set that covered water use by nearly 600 households over a 10-year period, including the drought.[9] As of 1991, ACWD served a population of about 270,000, with 69,000 customer accounts. Of these, approximately 63,000 are single-family household accounts, 2,200 multiple-family (e.g., apartment buildings), 2,400 commercial, 400 industrial, and 1,000 public authority accounts.[10]

The data used for this analysis were collected for a water demand forecast conducted by Brown and Caldwell Consultants (1992) for ACWD. Bimonthly meter readings for a sample of 599 single-family households were collected from January 1982 through July 1992. Clusters of households in various parts

[9] Most water agencies only retain 1–2 years of billing records in electronic format. Part of the data collected by ACWD for its demand analysis had to be retrieved from archived paper records (Brown and Caldwell 1992).

[10] This information was obtained from ACWD's response to the water agency survey reported in Dixon, Moore, and Pint (1996).

TABLE 3
SAMPLE PERCENTAGE OF BIMONTHLY HOUSEHOLD BILLS IN EACH BLOCK

Year	% in 0–28 CCF Block	% in 29–38 CCF Block	% in 39–48 CCF Block	% in >48 CCF Block
1982	60	20	9	11
1983	60	18	10	12
1984	57	16	12	15
1985	56	19	11	14
1986	55	19	11	15
1987	55	20	12	13
1988	63	19	10	8
1989	68	16	7	9
1990	65	18	9	8
1991	79	14	5	2
1992	77	13	6	4

of the district were sampled.[11] These data were matched with the ACWD price schedule; monthly precipitation and maximum, minimum, and average temperatures from the National Oceanic and Atmospheric Administration weather station in Newark; and Alameda County tax assessor data.[12] Means, standard deviations, and minimum and maximum values for each of the variables used in the estimates reported below are shown in Table 1. There were six addresses in the sample of 599 households that did not match to the tax assessor data. These households were dropped from demand estimates that used house size and lot size as regressors.

ACWD's commodity charges for water over the period 1982–92 are shown in Table 2. The nominal water price was raised infrequently during the early to mid-1980s, so prices were falling in real terms for some years.[13] As the drought began in the late 1980s, nominal prices were raised each year, and except for 1990, there was also a real price increase. In July 1991, ACWD introduced a steeply increasing block rate structure as a drought management policy. The base allowance per single-family household was 28 hundred cubic feet (CCF) per bimonthly billing period, or approximately 350 gallons per day.[14] If consumption stayed within the base allowance, households paid the flat rate price that had been in effect before the rate change. At higher levels of use, the water price was doubled, tripled, and quadrupled. The price for the base allowance was increased in January 1992, but the rest of the rate structure remained the same. In July 1992, the single-family household allowance was increased to 30 CCF per bimonthly period, or 400 gallons per day, and the rate of price increase over the higher blocks became less steep.

Annual changes in the sample distribution

[11] The sample was drawn by Brown and Caldwell based on street blocks. Households located on a total of 20 blocks were chosen to reflect each city's population: 13 blocks (65%) from Fremont, 4 blocks (20%) from Union City, and 3 blocks (15%) from Newark. The blocks were also chosen to be evenly distributed across the ACWD service area, including some blocks in the eastern hills, and to reflect the distribution of property values for the entire ACWD area (Brown and Caldwell 1992, 2–11 to 2–12).

[12] In addition, I obtained 1980 and 1990 census data regarding household size and composition, median incomes, etc., at the block group level for the census tracts corresponding to the ACWD service area and matched these data with the household data using the geographical information system ARC/INFO. However, census variables are not included in the models presented here because these variables resulted in coefficients that were insignificant and/or had the wrong sign. Median household income, for example, was positively correlated with house size and lot size, and often had a negative sign when all three variables were employed. It also tended to be less significant because of the greater measurement error involved in linking households with the median income for their block group rather than actual household income.

[13] Nominal water prices were converted to 1992 real prices using the Consumer Price Index for the western United States (Brown and Caldwell 1992, Appendix B).

[14] One hundred cubic feet of water is equivalent to approximately 750 gallons. Average household water use per billing period for the 600-household sample was 27 CCF, so the baseline was approximately equal to average use. (See Table 1.)

of bimonthly household bills among the four blocks of the rate structure that was in effect from July 1991 through June 1992 are shown in Table 3. During the pre-drought years (1982–87), 57% of bimonthly bills were in the 0–28 CCF block, 19% were in the 29–38 CCF block, 11% were in the 39–48 CCF block, and 13% were in the >48 CCF block. Usage shifted slightly toward the lowest block in the early drought years (1988–90), but the change was more dramatic in 1991–92. During the height of the drought, 78% of bimonthly bills were in the 0–28 CCF block, 14% were in the 29–38 CCF block, 5% were in the 39–48 CCF block, and 3% were in the >48 CCF block.

OLS Estimates

For illustrative purposes, Table 4 shows the best-fitting OLS estimate of a simple demand curve specification based on water prices, house size, lot size, and weather variables. The increasing block rate structure that was in effect from July 1991 through July 1992 created a positive correlation between high levels of use and high prices during those billing periods. As a result, OLS estimates yielded demand curves that slope downwards at low price levels, but began to slope upward at high price levels. The OLS demand estimate from Table 4 is evaluated at median house size and lot size and average winter and summer precipitation and temperatures and graphed in Figure 1. The figure clearly illustrates the problem of endogenous determination of price and consumption.

TABLE 4
OLS DEMAND CURVE ESTIMATE
(DEPENDENT VARIABLE: BIMONTHLY WATER USE IN CCF)

Variable	
Constant	−32.353
(*t* statistic)	(−22.19)
House size (sq. ft.)	0.0064
	(28.56)
Lot size (sq. ft.)	0.0011
	(19.62)
Precipitation (inches per month)	−0.3524
	(−5.14)
Lagged Precipitation	−1.0039
	(−16.72)
Monthly Average Temperature (F°)	0.2865
	(14.94)
Lagged Average Temperature	0.6483
	(34.95)
Price ($ per CCF)	−19.244
	(−13.81)
Price^2	6.7308
	(18.34)
Adjusted R^2	.2533

Note: During periods when the block rate structure was in effect, the price variable was set equal to marginal price at observed use.

IV. FIXED-EFFECTS MODELS

Fixed-effects models estimate household water use as a deviation from the household's average use, based on the deviations of the explanatory variables from their averages. The OLS regression models discussed in the previous section had the form:

$$\begin{aligned}\text{Water Use} = {} & \text{Constant} + \beta_1 \text{ House Size} \\ & + \beta_2 \text{ Lot Size} + \beta_3 \text{ Precipitation} \\ & + \beta_4 \text{ Lagged Precipitation} \\ & + \beta_5 \text{ Temperature} \\ & + \beta_6 \text{ Lagged Temperature} \\ & + \beta_7 \text{ Price} + \beta_8 \text{ Price}^2.\end{aligned}$$

The analogous fixed effects model has the form:

$$\begin{aligned}& \text{Water Use} - \text{Avg. Water Use} \\ & \quad = (\text{Constant} - \text{Avg. Constant}) \\ & \qquad + \beta_1(\text{House Size} - \text{Avg. House Size}) \\ & \qquad + \beta_2(\text{Lot Size} - \text{Avg. Lot Size}) \\ & \qquad + \beta_3(\text{Precipitation} - \text{Avg. Precipitation}) \\ & \qquad + \beta_4(\text{Lagged Precipitation} \\ & \qquad\qquad - \text{Avg. Lagged Precipitation}) \\ & \qquad + \beta_5(\text{Temperature} - \text{Avg. Temperature}) \\ & \qquad + \beta_6(\text{Lagged Temperature} \\ & \qquad\qquad - \text{Avg. Lagged Temperature}) \\ & \qquad + \beta_7(\text{Price} - \text{Avg. Price}) \\ & \qquad + \beta_8(\text{Price}^2 - \text{Avg. Price}^2).\end{aligned}$$

Since the constant, house size, and lot size do not change over the sample period, the first three terms in this equation equal zero. Thus, rearranging terms, we have:

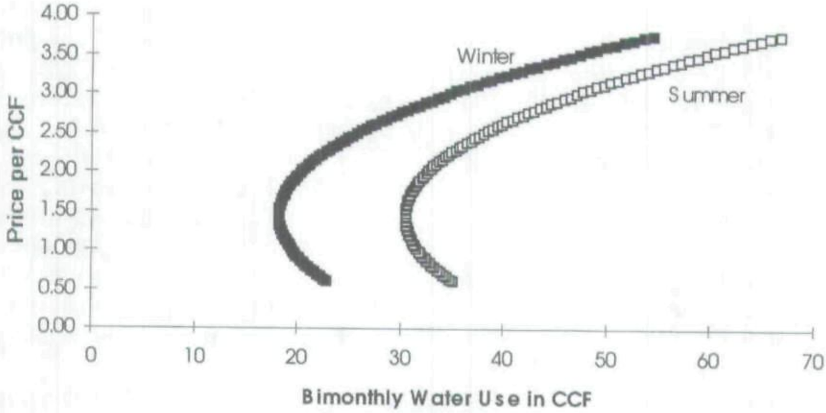

FIGURE 1
OLS MODEL

$$\begin{aligned}\text{Water Use} = {} & \text{Avg. Water Use} + \beta_3(\text{Precipitation} - \text{Avg. Precipitation})\\ & + \beta_4(\text{Lagged Precipitation} - \text{Avg. Lagged Precipitation})\\ & + \beta_5(\text{Temperature} - \text{Avg. Temperature})\\ & + \beta_6(\text{Lagged Temperature} - \text{Avg. Lagged Temperature})\\ & + \beta_7(\text{Price} - \text{Avg. Price}) + \beta_8(\text{Price}^2 - \text{Avg. Price}^2).\end{aligned}$$

This technique therefore allows each household's demand curve to have its own constant term, based on average household water use over the sample period.[15] The estimated coefficients represent the impact of changes in weather or price on household water use. So, for example, if the coefficient β_5 is positive, household water use is predicted to be above average when the temperature is above average.

This approach could solve the slope problem observed in the OLS estimates if the high-use households who paid the highest block rates during the drought were cutting back relative to their normal use in non-drought periods. Thus, each household could actually have a downward-sloping demand for water, but higher-use households would have a higher constant term. However, this hypothesis was not borne out in the fixed-effects estimates, shown in Table 5. Although the household-specific constants approximately double the adjusted R^2 of the equation from roughly 25% to 52%, the fixed-effects model still results in upward-sloping demand at high prices because of thecorrelation between high use and high price.A graph of the fixed-effects model evaluated at mean household water use and average summer and winter temperatures and precipitation is shown for illustration in Figure 2.

The problem of upward-sloping demand may be persisting in the fixed-effects model because the temperature and precipitation variables do not adequately control for seasonal fluctuations in water use, which appear to be more important predictors than price. Figure 3 shows an example of water use, temperature, and precipitation patterns for a single household that occasionally had high water use during the drought. Since fluctua-

[15] This constant term represents observable or unobservable characteristics that do not change over time. Thus, the household constant term includes effects due to observable variables, such as house size and lot size, as well as unobservable variables, such as whether the household has a swimming pool or a sprinkler system.

TABLE 5
FIXED EFFECTS DEMAND CURVE ESTIMATES

Variable	Household Fixed Effects	Monthly Dummies	Monthly Price Interactions	Monthly Dummies & Interactions
Precipitation	−0.3984	−0.4503	−0.4935	−0.3594
(*t* statistic)	(−7.22)	(−7.30)	(−7.99)	(−5.66)
Lagged Precipitation	−1.0445	−0.3994	−0.4167	−0.3413
	(−21.58)	(−7.38)	(−7.70)	(−6.10)
Average Temperature	0.2924	0.3328	0.3743	0.2900
	(18.93)	(10.93)	(12.35)	(9.35)
Lagged Average Temperature	0.6424	0.6880	0.7288	0.7028
	(43.02)	(23.83)	(25.44)	(23.95)
Price	−23.840	−22.703	−21.124	−22.889
	(−21.81)	(−21.15)	(−15.89)	(−4.21)
Price^2	6.8577	6.5221	7.2012	7.6596
	(24.05)	(23.37)	(13.29)	(5.28)
Monthly Dummies (*F* statistic)		(69.74)		(5.19)
Monthly Price Interactions			(46.27)	(3.54)
Monthly Price^2 Interactions			(7.89)	(2.44)
Adjusted R^2	.5156	.5431	.5438	.5459

Notes: The constant term, house size, and lot size are absorbed into the household's individual intercept.

The *F* statistic tests for the joint significance of the 11 monthly dummies or price interactions. (December is the omitted month.) Significant values are $F_{0.05,11,\infty} = 1.79$ and $F_{0.01,11,\infty} = 2.25$.

tions in water use are often greater than fluctuations in the weather variables, the fixed-effects model may not be able to capture reductions in peak use in response to higher prices.

To test the hypothesis that monthly intercept and price interaction terms could help explain household water use, I added these terms to the household fixed-effects model. Although the monthly terms were jointly significant, and improved the R^2 slightly (see Table 5), they were not able to correct the

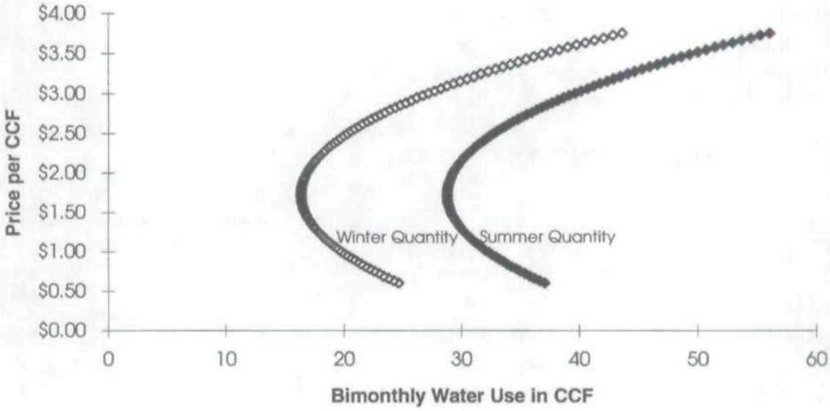

FIGURE 2
HOUSEHOLD FIXED EFFECTS MODEL

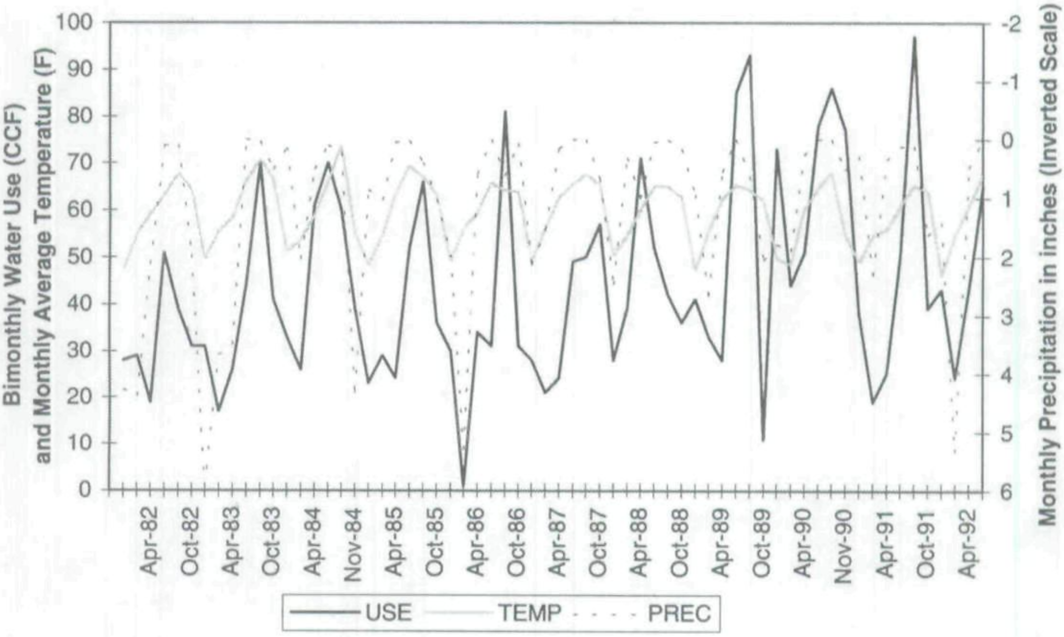

FIGURE 3
Seasonal Water Use by a High-Use Household

price endogeneity problem. The monthly dummy variables tended to result in lower predicted water use in the spring and fall months and higher predicted water use in the summer months relative to the water use predicted by weather variables alone. The price interaction terms tended to result in less elastic water demand during the winter months and more elastic water demand during the summer and fall months. However, demand still became upward-sloping at high prices.

V. MAXIMUM-LIKELIHOOD MODELS

The second approach used to correct for the price endogeneity problem was the use of maximum-likelihood models. These models are based on likelihood functions that reflect the probability that a household chose a particular block in the block rate structure, combined with the probability of its particular level of use, given the block that was chosen. Estimates of three different maximum-likelihood models are presented, based on previous work by Hewitt (1993): the heterogeneous-preferences model, the error perception model, and the two-error model. The structure of each model is based on the assumed source of the error in estimating household demand, such as errors in the data, missing variables, or errors in the household's actual consumption relative to its intended consumption.[16]

In the ''heterogeneous preferences'' model, the household's observed consump-

[16] The maximum-likelihood models presented in this section are described in greater detail in the Appendix. Estimating the maximum-likelihood models was very computer intensive. Each model required approximately 500 hours of offpeak computer time (over a one-month period) to converge using GAUSS software on a Sun Sparc10. The models took so long to estimate both because of the large number of observations and the complex nonlinear functions that were maximized. Because of limited computer resources, I was unable to estimate multiple specifications of the models using additional variables.

TABLE 6
MAXIMUM-LIKELIHOOD MODEL SPECIFICATIONS

Model	Source(s) of Error
Heterogeneous-Preferences	Unobserved Household Characteristics
Error Perception	Actual Water Use Differs from Intended Water Use
Two-Error	Unobserved Household Characteristics Actual Water Use Differs from Intended Water Use

tion is assumed to be equal to its intended consumption, but errors in estimation of demand arise because the researcher cannot observe all the relevant characteristics of the household. In the "error perception" model, the researcher is assumed to observe relevant household characteristics, but errors arise because the household's observed consumption is not necessarily equal to its intended consumption. For example, the household may make errors in consumption because it is difficult to monitor and control water use by all household members during the billing period. The "two-error" model combines both sources of error, and is therefore more general than the other two, but also more complex to estimate. These three model specifications are summarized in Table 6.

The structure of the likelihood function in the heterogeneous preferences and two-error models constrains the demand curve to be downward-sloping in the relevant price range.[17] Therefore, we are assured of obtaining demand curves that can be used to estimate consumer surplus losses. However, if demand is downward-sloping only because the constraint is binding, one might question whether the structure of the model accurately represents consumer behavior.

Results of the maximum likelihood estimation are shown in Table 7. The OLS estimate is shown for comparison purposes. Graphs of the underlying demand curves are shown in Figures 4–6. As the figures show, both the heterogeneous-preferences model and the two-error model yield downward-sloping demand curves. In the heterogeneous-preferences model, the slope constraint is not binding. The change in the specification of the model by itself yields downward-sloping demand in the relevant price range. However, the constraint is binding for the two-error model. The error perception model, which is not constrained to be downward-sloping, yields results similar to the OLS and fixed-effects models.

Since these models yield two downward-sloping demand estimates that could be used to predict household responses to increasing block rates, one must consider which is a more accurate reflection of household water demand. Note that the heterogeneous-preferences model results in a much less elastic demand curve than the two-error model.[18] Elasticity estimates from the two models (evaluated at median house size, lot size, and average summer and winter precipitation and temperatures) are shown in Table 8. They range from −.04 (at a price of \$.60 per CCF) to −.14 (at a price of \$3.75 per CCF) in the summer and from −.07 (at a price of \$.60 per CCF) to −.29 (at a price of \$3.75 per CCF) in the winter in the heterogeneous-preferences model, compared with −.20 (at a price of \$.60 per CCF) to −.47 (at a price of \$2.00 per CCF) in the summer and −.33 (at a price of \$.60 per CCF) to −1.24 (at a price of \$2.20 per CCF) in the winter in the

[17] See the Appendix for a more detailed discussion of the nature of this constraint. In any particular case the constraint may or may not be binding.

[18] This occurs because the heterogeneous-preferences model assumes that observed consumption is equal to intended consumption. Therefore, use in the high blocks must result from unobserved characteristics of households. Since the two-error model also allows households to make "mistakes" in consumption, the estimate of "true" demand can be more elastic, because there are two potential sources of error. In other words, the probability of a high draw from each error term in the two-error model is not as low as the probability of a very high draw from one error term in the heterogeneous preferences model.

TABLE 7
MAXIMUM-LIKELIHOOD DEMAND CURVE ESTIMATES

Variable	OLS	Heterogeneous-Preferences	Error Perception	Two-Error
Constant	−32.353	−51.453	−41.227	−40.939
(Estimate/std. err.)	(−22.19)	(−40.50)	(−19.07)	(−28.33)
House size	0.0064	0.0063	0.0065	0.0064
	(28.56)	(26.97)	(26.31)	(27.04)
Lot size	0.0011	0.0012	0.0013	0.0012
	(19.62)	(20.30)	(20.41)	(20.33)
Precipitation	−0.3524	−0.6306	−0.7692	−0.7419
	(−5.14)	(−9.59)	(−10.79)	(−11.07)
Lagged Precipitation	−1.0039	−1.0044	−1.1203	−1.1372
	(−16.72)	(−15.25)	(−15.59)	(−16.80)
Average Temperature	0.2865	0.6797	0.6818	0.6836
	(14.94)	(47.31)	(44.56)	(46.84)
Lagged Average Temperature	0.6483	0.4134	0.4114	0.3967
	(34.95)	(28.82)	(27.20)	(27.23)
Price	−19.244	−4.0131	−19.014	−15.204
	(−13.81)	(−6.42)	(−8.91)	(−17.67)
$Price^2$	6.7308	0.2012	5.4117	2.3555
	(18.34)	(2.29)	(9.22)	(17.67)
Variance	209.26			
	(135.18)			
Variance (Het. Pref.)		224.81		121.69
		(134.82)		(27.96)
Variance (Error Per.)			227.76	104.40
			(131.73)	(25.01)
Mean Log Likelihood	−4.0907	−4.0863	−3.9724	−4.0791

Note: Constraint that demand is downward sloping in the relevant price range is binding in the two-error model, but not in the heterogeneous preferences model.

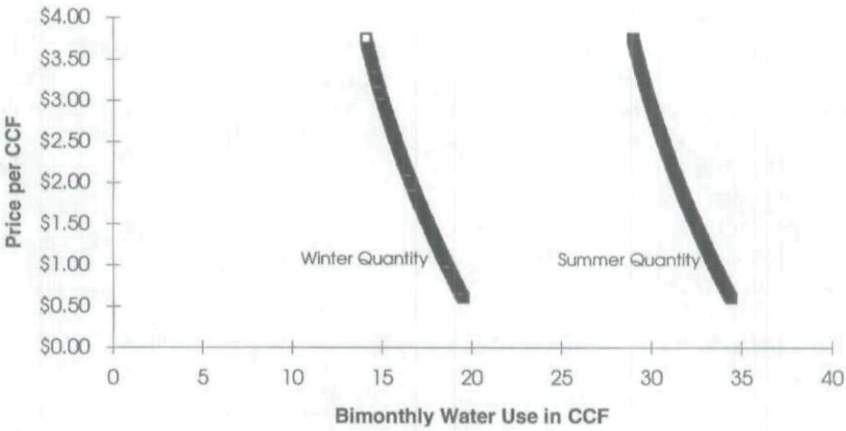

FIGURE 4
HETEROGENEOUS-PREFERENCES MODEL

TABLE 8
ELASTICITY ESTIMATES FROM MAXIMUM-LIKELIHOOD MODELS

	Elasticity Estimates			
Model	Minimum	At Price	Maximum	At Price
Heterogeneous-Preferences				
Summer	−0.04	\$0.60	−0.14	\$3.75
Winter	−0.07	0.60	−0.29	3.75
Two-Error				
Summer	−0.20	0.60	−0.47	2.00
Winter	−0.33	0.60	−1.24	2.20

Note: Elasticity is estimated at a point on the demand curve using the formula $(\partial Q/\partial p) \cdot (p/Q)$.

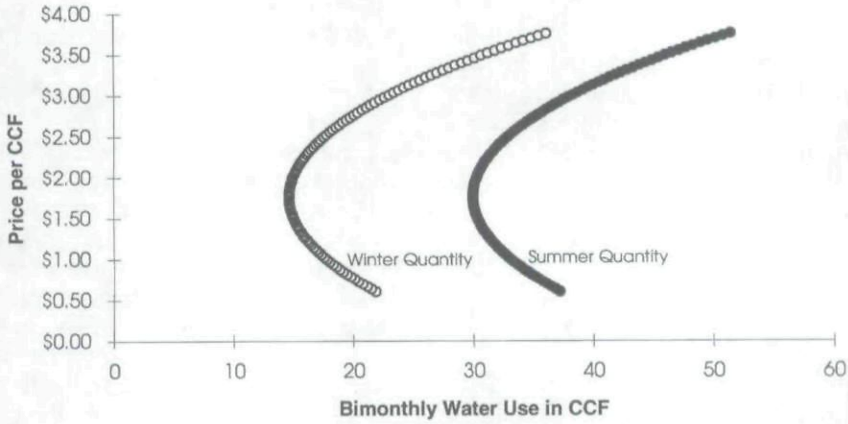

FIGURE 5
ERROR PERCEPTION MODEL

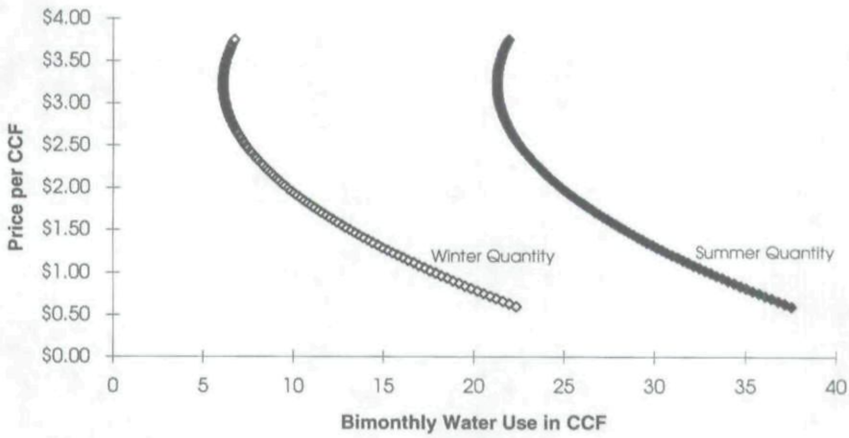

FIGURE 6
TWO-ERROR MODEL

two-error model.[19] Thus, the heterogeneous-preferences model predicts relatively small cutbacks in response to price increases, whereas the two-error model predicts larger cutbacks.

Because the slope constraint is not binding in the heterogeneous-preferences model, one can feel more confident about the specification of the model. However, the two-error model specification seems intuitively more plausible, since it is probably true both that researchers cannot observe all relevant characteristics of the household, and also that households cannot always accurately control their water use. Furthermore, a likelihood ratio test of the two models is significant at the .01 confidence level, indicating that the second error term significantly improves the log likelihood.[20] Another potential piece of evidence involves the predicted effects of the two models on total water use and total water agency revenues from single-family households. These predictions can be compared with aggregate data collected from Alameda County Water District as part of the water agency survey reported in Dixon, Moore, and Pint (1996).

Predicting water use by households with the maximum-likelihood models depends on the household's demand at each of the block rate prices. For example, during the period from July to December 1991, if the household's predicted demand at $0.90 per CCF is less than 28 CCF, that would be its predicted water use. If the household's predicted demand at $.90 per CCF is greater than 28 CCF, its demand must be recomputed at $1.80 per CCF. Three outcomes are possible. First, if demand at $1.80 per CCF is less than 28 CCF, the household's predicted water use is 28 CCF. Second, if it is between 28 and 38 CCF, it is the household's predicted use. Third, if it is above 38 CCF, demand must be computed at the next higher block rate. This process continues until the household's predicted water use is determined, and is summarized in Table 9. Similar calculations can be made for January–June 1992, and July–December 1992, using the block rate price structures and block sizes that were in effect during those periods.

Table 10 shows total single-family residential use and revenues from the ACWD survey response and predicted values derived from the maximum-likelihood models by calculating predicted water use for the 54,488 single-family residences in the Alameda County tax assessor data file.[21,22] The heterogeneous-preferences model prediction is very close to actual single-family household water use, whereas the two-error model underpredicts by about 10%. Both models tend to underpredict revenue, which probably reflects underprediction of water use in the highest blocks. However, it appears that the less elastic, heterogeneous-preferences model is better than the two-error model as a predictor of both water use and revenues.

VI. CONCLUSION

The example of Alameda County Water District illustrates that an increasing block rate structure can be an effective part of a drought management strategy. Although the estimated demand elasticities were small, the relatively large price increases across blocks contributed to a 16% reduction in residential water use from 13,408,421 CCF in 1990 to 11,251,328 CCF in 1991 (including both single-family and multiple-family residences). At the same time, residential water revenues

[19] Arc elasticities from a price of $.60 to a price of $3.75 for the heterogeneous preference are −.12 in the summer and −.22 in the winter. Arc elasticities for the two-error model are −.38 in the summer (from $.60 to $2.00) and −.78 in the winter (from $.60 to $2.20). Demand elasticity begins to decline at higher price levels in the two-error model because the curvature of demand increases.

[20] The value of the likelihood ratio is 535.34, compared with a significant value of 6.635.

[21] It is not clear whether the discrepancy between the 54,000 observations in the tax assessor data and the 63,000 single-family accounts reported by ACWD is due to multiple accounts at the same household, incorrect categorization of accounts by customer type, or incorrect codes in the tax assessor file. Predictions of district-wide water demand are based on the 54,000 households in the tax assessor file, because the extrapolation depends on the house size and lot size of each household.

[22] ACWD's total residential accounts as of 1991 were 63,069 single-family, and 2,251 multiple-family, so approximately 97% were single-family accounts. However, multiple-family accounts have higher water use and revenue, so the proportion was adjusted to 90%.

TABLE 9
PREDICTING WATER USE USING MAXIMUM-LIKELIHOOD MODELS

If . . .	Then . . .
Predicted Use at \$.90 ≤ 28 CCF	Predicted Use = Predicted Use at \$.90
Predicted Use at \$.90 > 28 CCF	Estimate Use at \$1.80
Predicted Use at \$1.80 ≤ 28 CCF	Predicted Use = 28 CCF
28 CCF ≤ Predicted Use at \$1.80 ≤ 38 CCF	Predicted Use = Predicted Use at \$1.80
Predicted Use at \$1.80 > 38 CCF	Estimate Use at \$2.70
Predicted Use at \$2.70 ≤ 38 CCF	Predicted Use = 38 CCF
38 CCF ≤ Predicted Use at \$2.70 ≤ 48 CCF	Predicted Use = Predicted Use at \$2.70
Predicted Use at \$2.70 > 48 CCF	Estimate Use at \$3.60
Predicted Use at \$3.60 ≤ 48 CCF	Predicted Use = 48 CCF
Predicted Use at \$3.60 > 48 CCF	Predicted Use = Predicted Use at \$3.60

Note: Predicted use at higher block rates only needs to be calculated if predicted use at lower rates exceeds the maximum block water use at that price.

actually rose, from $12.9 million in 1990 to $13.6 million in 1991. Many California water agencies that relied on quantity restrictions to reduce water use suffered severe drops in revenue, and were forced to raise water prices after the drought to recover their losses.

Water agencies in California were reluctant to use price increases to manage water demand during the drought, in part because past estimates of price elasticity have been low, but also because past estimates have been based on relatively small variations in water price. The estimates presented in this paper are unique in the sense that they are based on household responses to a steeply increasing block rate price structure. However, this rate structure creates an econometric challenge because of the positive correlation between price and observed household water use. This paper explores the use of fixed effects and maximum-likelihood models to correct for the endogeneity of price and water use.

I find that adding household fixed effects improves predictive power relative to OLS, but cannot correct for price endogeneity. The addition of monthly dummy variables and price interaction terms also improves the fit of the equations, but still results in upward-sloping demand. However, the use of maximum-likelihood techniques that model household responses to the increasing block rate structure are successful in producing downward-sloping demand estimates.

The two successful maximum-likelihood models are based on different error structures. One, the heterogeneous-preferences

TABLE 10
ACTUAL VS. PREDICTED WATER USE AND REVENUES

Single-Family Residential:	Time Period	Actual	Het.-Pref. Predicted	Two-Error Predicted
Water Use in CCF	7/91–9/91	3,057,640	3,171,553	2,799,475
	10/91–12/91	2,481,357	2,254,802	2,145,462
	7/91–12/91	5,538,997	5,426,355	4,944,937
Revenue	7/91–6/92	\$12,855,600	\$11,557,711	\$9,997,248

Note: Time periods are chosen to correspond with ACWD's survey responses regarding quarterly water use and fiscal year revenues. Actual water use and revenues are adjusted downward by 10% to account for the inclusion of multiple-family use and revenues in the total residential figures reported by ACWD. Predicted water use is adjusted upward by approximately 16% to account for the discrepancy between 63,069 reported single-family residential accounts and 54,488 single-family households in the tax assessor data.

model, assumes that errors arise because the econometrician cannot observe all of the relevant characteristics of the household that determine water demand. The two-error model combines this source of error with errors that result when the household's actual water use differs from its intended water use. Although the two-error model has a significantly higher likelihood and results in higher predicted price elasticity than the heterogeneous-preferences model, its predicted district-wide water use is less accurate than the heterogeneous preferences model. In addition, the constraint that demand be downward sloping in the relevant price range is binding in the two-error model, but not in the heterogeneous-preferences model. Thus, it is not clear which is the more accurate model of household water use. However, one could also regard the two models as upper and lower bounds on the estimates of elasticity of demand for water.

It would be difficult to generalize these results to other urban areas in California or in the United States, because of the dependence of the models on local weather conditions and because other water utilities may not use similar block rate price structures. Further modeling and statistical estimation of water demand in response to increasing block rate price structures is needed to build confidence in our understanding of customer responses. Better knowledge of water demand would allow us to make better assessments of the effectiveness of water management policies in dealing with droughts and water shortages, and to design better water management policies for the future.

APPENDIX

The maximum likelihood models discussed in this paper are based on Hewitt (1993) and Hewitt and Hanemann (1995), which provide more detail on the theoretical development of the models. The original models were developed to analyze a rate structure with two blocks, so they had to be generalized to fit the Alameda County Water District (ACWD) rate structures in effect over the period from 1982 to 1992. From 1982 through June 1991, a single block rate structure was in effect, so the maximum-likelihood model used during this period is equivalent to an OLS model. From June 1991 through June 1992, a four-block rate structure was in effect. As discussed above, the maximum-likelihood models for this period differ depending on the assumptions made about the source of the estimating error. I will discuss the specification of each of the maximum-likelihood models in turn.

Heterogeneous-Preferences Model

In the heterogeneous-preferences model, the household's observed water use is assumed to be equal to its intended water use, but the econometrician cannot observe all of the household's characteristics that influence its water use. Thus, when water use is estimated based on observable variables (such as house size, lot size, weather, etc.), an estimating error arises due to the effects of the unobservable variables.

Since it is assumed that observed water use is equal to intended water use, the household must have intended to consume in the observed block, and is responding to the price associated with that block. Therefore, within any block, the error is equal to the difference between observed water use and predicted water use (based on observable characteristics) at the price associated with that block. However, if observed water use is at the borderline between two blocks (i.e., at the "kink"), a range of error terms is possible. One possibility is that intended water use at the lower block price is exactly equal to the kink. The other possibility is that preferred water use at the lower block price is higher than the kink, but the household is not willing to pay the higher block price in order to increase its water use. Therefore, the error term could be one of a range of values based on the difference between intended use (equal to the kink) and predicted water use at either block price.

Equation [A1] below shows the log likelihood function for the heterogeneous-preferences model, assuming that the error term is normally distributed.[23] The first term in equation [A1] applies to periods when a single-block rate structure was in effect (1982 through June 1991) and the remaining terms apply to periods when a four-block rate structure was in effect (July 1991 through June 1992). The subscripts 1 through 4 in the remaining terms indicate that the price variables correspond with the block rate structure. For example, during the period July–December 1991,

[23] The normal distribution is an approximation to the actual error distribution, since water use cannot be negative.

the price in block 1 was \$.90, the price in block 2 was \$1.80, the price in block 3 was \$2.70, and the price in block 4 was \$3.60.

$$
\begin{aligned}
\ln L = & \sum_{\substack{\text{Obs. before}\\ \text{July 1991}}} -\frac{1}{2}\ln(2\pi\sigma_\varepsilon^2) - \frac{(y - X\beta)'(y - X\beta)}{2\sigma_\varepsilon^2} \\
& + \sum_{\substack{\text{Obs. in}\\ \text{Block 1}}} -\frac{1}{2}\ln(2\pi\sigma_\varepsilon^2) - \frac{(y - X_1\beta)'(y - X_1\beta)}{2\sigma_\varepsilon^2} + \sum_{\substack{\text{Obs. at}\\ \text{Kink 1}}} \ln\left[\int_{\text{Kink }1-X_1\beta}^{\text{Kink }1-X_2\beta} (2\pi\sigma_\varepsilon^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\varepsilon^2}} dz\right] \\
& + \sum_{\substack{\text{Obs. in}\\ \text{Block 2}}} -\frac{1}{2}\ln(2\pi\sigma_\varepsilon^2) - \frac{(y - X_2\beta)'(y - X_2\beta)}{2\sigma_\varepsilon^2} + \sum_{\substack{\text{Obs. at}\\ \text{Kink 2}}} \ln\left[\int_{\text{Kink }2-X_2\beta}^{\text{Kink }2-X_3\beta} (2\pi\sigma_\varepsilon^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\varepsilon^2}} dz\right] \\
& + \sum_{\substack{\text{Obs. in}\\ \text{Block 3}}} -\frac{1}{2}\ln(2\pi\sigma_\varepsilon^2) - \frac{(y - X_3\beta)'(y - X_3\beta)}{2\sigma_\varepsilon^2} + \sum_{\substack{\text{Obs. at}\\ \text{Kink 3}}} \ln\left[\int_{\text{Kink }3-X_3\beta}^{\text{Kink }3-X_4\beta} (2\pi\sigma_\varepsilon^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\varepsilon^2}} dz\right] \\
& + \sum_{\substack{\text{Obs. in}\\ \text{Block 4}}} -\frac{1}{2}\ln(2\pi\sigma_\varepsilon^2) - \frac{(y - X_4\beta)'(y - X_4\beta)}{2\sigma_\varepsilon^2}. \qquad \text{[A1]}
\end{aligned}
$$

Since observed consumption is assumed to be equal to intended consumption, each observation y is assigned to one block or kink point. Note that the integral terms in equation [A1] must be positive, which requires $X_1\beta > X_2\beta > X_3\beta > X_4\beta$, that is, demand must be decreasing in price over the observed range of prices in the block rate structure. This constrains the estimated demand curve to be downward-sloping. However, as discussed above, this constraint was not binding for the estimated coefficients of the heterogeneous-preferences model.

Error Perception Model

In the error perception model, it is assumed that the econometrician observes all of the characteristics relevant to the household's water use, but the household's observed use may differ from its intended use. This discrepancy may arise for a number of reasons, for example, because the household finds it difficult to monitor total use over the bimonthly billing period, or because it cannot control the behavior of individual household members.

Since observed use is not necessarily equal to intended use, we cannot associate observed use with any particular block price (in periods when there is more than one block). For each observation, the likelihood function must incorporate the possibility that intended use could have been in any block or at any kink in the rate structure, and that the error term could take on any value between $-\infty$ and $+\infty$, assuming that the error term is normally distributed. Equation [A2] shows the resulting likelihood function, where the first term represents periods when a single-block rate structure was in effect, and the remaining terms represent periods when a four-block rate structure was in effect.

The first term inside the brackets (for periods when the increasing block rate structure was in effect) shows the probability that intended use was in the first block times the probability that the error term was in the appropriate range to generate observed water use.[24] The second term shows the probability that intended use was at the first kink, in which case there is only one possible error term, equal to the difference between the first kink and observed water use. The remaining terms show the probabilities that intended use was in the remaining blocks or kinks. Since the limits of the integrals depend only on observed use and the location of the kinks (which are in increasing

[24] Given observed water use y and intended water use $X_i\beta$, the error term η must be in the appropriate range to get from the intended block to observed water use. The likelihood function assumes that this range of error terms will be symmetric around zero, depending on whether observed water use is higher or lower than intended water use. The normal distribution is symmetric around zero, but it is an approximation of the actual error distribution, because water use cannot be negative.

order), the estimated demand curve is not constrained to be downward-sloping.

$$
\begin{aligned}
\ln L = {} & \sum_{\substack{\text{Obs. before}\\ \text{July 1991}}} -\frac{1}{2}\ln(2\pi\sigma_\eta^2) - \frac{(y - X\beta)'(y - X\beta)}{2\sigma_\eta^2} \\
& + \sum_{\substack{\text{Obs. after}\\ \text{June 1991}}} \ln\left\{\left[(2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(y-X_1\beta)'(y-X_1\beta)}{2\sigma_\eta^2}}\right]\cdot\left[\int_{-\infty}^{\text{Kink 1}-y} (2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\eta^2}}\,dz\right]\right. \\
& + (2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(\text{Kink 1}-y)'(\text{Kink 1}-y)}{2\sigma_\eta^2}} \\
& + \left[(2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(y-X_2\beta)'(y-X_2\beta)}{2\sigma_\eta^2}}\right]\cdot\left[\int_{\text{Kink 1}-y}^{\text{Kink 2}-y} (2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\eta^2}}\,dz\right] \\
& + (2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(\text{Kink 2}-y)'(\text{Kink 2}-y)}{2\sigma_\eta^2}} \\
& + \left[(2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(y-X_3\beta)'(y-X_3\beta)}{2\sigma_\eta^2}}\right]\cdot\left[\int_{\text{Kink 2}-y}^{\text{Kink 3}-y} (2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\eta^2}}\,dz\right] \\
& + (2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(\text{Kink 3}-y)'(\text{Kink 3}-y)}{2\sigma_\eta^2}} \\
& \left. + \left[(2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(y-X_4\beta)'(y-X_4\beta)}{2\sigma_\eta^2}}\right]\cdot\left[\int_{\text{Kink 3}-y}^{\infty} (2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\eta^2}}\,dz\right]\right\}. \qquad \text{[A2]}
\end{aligned}
$$

Two-Error Model

The two-error model combines the two sources of error that are addressed separately by the heterogeneous-preferences model and the error perception model. It assumes that the econometrician cannot observe all of the relevant characteristics that determine household water use, and that households' observed consumption may differ from intended consumption because of difficulties in monitoring and controlling use by household members over the bimonthly billing period. Therefore, intended water use $X_i\beta + \varepsilon$ (where ε is the econometrician's error term from the heterogeneous-preferences model) could be in any block of a multiple-block rate structure, given observed water use $X_i\beta + \varepsilon + \eta$ (where η is the household's error term from the error perception model). The likelihood function for the multiple-block rate structure therefore combines the probability that intended water use is at any block or kink in the rate structure with the probability that the household's error term is in the appropriate range to get from intended use to observed use.

The likelihood functions for the two-error model are given by equation [A3], assuming that the error terms ε and η are normally distributed and independent of each other.[25] The first term in

[25] Given these assumptions, the joint distribution of $\varepsilon + \eta$ and ε will also be normal, and it can be factored into a marginal pdf and a conditional pdf that are both normal. The conditional pdf will depend on the correlation coefficient, $\sigma_\varepsilon(\varepsilon_\varepsilon^2 + \sigma_\eta^2)^{1/2}$ (Hewitt 1993, 85). The normal distributions are approximations to the actual error distributions, because water use cannot be negative.

equation [A3] represents periods during which a single-block rate structure was in effect, and the remaining terms represent periods during which a four-block rate structure was in effect. The first term inside the brackets shows the probability that intended water use was in the first block, times the probability that the combined error terms were in the appropriate range to generate observed water use. The second term shows the probability that intended water use was at the first kink, given observed use. The remaining terms show the probabilities that intended use was at the remaining blocks and kinks in the rate structure. The integral bounds for the kink points require that $X_1\beta > X_2\beta > X_3\beta > X_4\beta$, that is, that demand be downward sloping over the observed price range, as was the case in the heterogeneous-preferences model. This constraint was binding for the estimated coefficients presented above.

$$
\begin{aligned}
\ln L = & \sum_{\substack{\text{Obs. before}\\ \text{July 1991}}} -\frac{1}{2}\ln[2\pi(\sigma_\varepsilon^2+\sigma_\eta^2)] - \frac{(y-X\beta)'(y-X\beta)}{2\pi(\sigma_\varepsilon^2+\sigma_\eta^2)} \\
& + \sum_{\substack{\text{Obs. after}\\ \text{June 1991}}} \ln\Bigg\{\Bigg[[2\pi(\sigma_\varepsilon^2+\sigma_\eta^2)]^{-\frac{1}{2}} e^{-\frac{(y-X_1\beta)'(y-X_1\beta)}{2(\sigma_\varepsilon^2+\sigma_\eta^2)}}\Bigg] \cdot \Bigg[\int_{-\infty}^{\text{Kink 1}-X_1\beta-\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}(y-X_1\beta)} \left(2\pi\frac{\sigma_\varepsilon^2\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\right)^{-\frac{1}{2}} e^{-\frac{z^2}{2\left(\frac{\sigma_\varepsilon^2\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\right)}} dz\Bigg] \\
& + \Bigg[(2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(y-\text{Kink 1})'(y-\text{Kink 1})}{2\sigma_\eta^2}}\Bigg] \cdot \Bigg[\int_{\text{Kink 1}-X_1\beta}^{\text{Kink 1}-X_2\beta} (2\pi\sigma_\varepsilon^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\varepsilon^2}} dz\Bigg] \\
& + \Bigg[[2\pi(\sigma_\varepsilon^2+\sigma_\eta^2)]^{-\frac{1}{2}} e^{-\frac{(y-X_2\beta)'(y-X_2\beta)}{2(\sigma_\varepsilon^2+\sigma_\eta^2)}}\Bigg] \cdot \Bigg[\int_{\text{Kink 1}-X_2\beta-\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}(y-X_2\beta)}^{\text{Kink 2}-X_2\beta-\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}(y-X_2\beta)} \left(2\pi\frac{\sigma_\varepsilon^2\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\right)^{-\frac{1}{2}} e^{-\frac{z^2}{2\left(\frac{\sigma_\varepsilon^2\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\right)}} dz\Bigg] \\
& + \Bigg[(2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(y-\text{Kink 2})'(y-\text{Kink 2})}{2\sigma_\eta^2}}\Bigg] \cdot \Bigg[\int_{\text{Kink 2}-X_2\beta}^{\text{Kink 2}-X_3\beta} (2\pi\sigma_\varepsilon^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\varepsilon^2}} dz\Bigg] \\
& + \Bigg[[2\pi(\sigma_\varepsilon^2+\sigma_\eta^2)]^{-\frac{1}{2}} e^{-\frac{(y-X_3\beta)'(y-X_3\beta)}{2(\sigma_\varepsilon^2+\sigma_\eta^2)}}\Bigg] \cdot \Bigg[\int_{\text{Kink 2}-X_3\beta-\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}(y-X_3\beta)}^{\text{Kink 3}-X_3\beta-\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}(y-X_3\beta)} \left(2\pi\frac{\sigma_\varepsilon^2\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\right)^{-\frac{1}{2}} e^{-\frac{z^2}{2\left(\frac{\sigma_\varepsilon^2\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\right)}} dz\Bigg] \\
& + \Bigg[(2\pi\sigma_\eta^2)^{-\frac{1}{2}} e^{-\frac{(y-\text{Kink 3})'(y-\text{Kink 3})}{2\sigma_\eta^2}}\Bigg] \cdot \Bigg[\int_{\text{Kink 3}-X_3\beta}^{\text{Kink 3}-X_4\beta} (2\pi\sigma_\varepsilon^2)^{-\frac{1}{2}} e^{-\frac{z^2}{2\sigma_\varepsilon^2}} dz\Bigg] \\
& + \Bigg[[2\pi(\sigma_\varepsilon^2+\sigma_\eta^2)]^{-\frac{1}{2}} e^{-\frac{(y-X_4\beta)'(y-X_4\beta)}{2(\sigma_\varepsilon^2+\sigma_\eta^2)}}\Bigg] \cdot \Bigg[\int_{\text{Kink 3}-X_4\beta-\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}(y-X_4\beta)}^{\infty} \left(2\pi\frac{\sigma_\varepsilon^2\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\right)^{-\frac{1}{2}} e^{-\frac{z^2}{2\left(\frac{\sigma_\varepsilon^2\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\right)}} dz\Bigg]\Bigg\}. \quad \text{[A3]}
\end{aligned}
$$

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