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RESIDENTIAL WATER DEMAND MANAGEMENT: LESSONS FROM AURORA, COLORADO[1]

Douglas S. Kenney, Christopher Goemans, Roberta Klein, Jessica Lowrey, and Kevin Reidy[2]

ABSTRACT: Residential water demand is a function of several factors, some of which are within the control of water utilities (e.g., price, water restrictions, rebate programs) and some of which are not (e.g., climate and weather, demographic characteristics). In this study of Aurora, Colorado, factors influencing residential water demand are reviewed during a turbulent drought period (2000-2005). Findings expand the understanding of residential demand in at least three salient ways: first, by documenting that pricing and outdoor water restriction policies interact with each other ensuring that total water savings are not additive of each program operating independently; second, by showing that the effectiveness of pricing and restrictions policies varies among different classes of customers (i.e., low, middle, and high volume water users) and between predrought and drought periods; and third, in demonstrating that real-time information about consumptive use (via the Water Smart Reader) helps customers reach water-use targets.

(KEY TERMS: water conservation; drought; residential water demand; water pricing.)

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INTRODUCTION

A century ago, most western water issues focused on the pursuit of federally funded (and constructed) projects serving agricultural water demands through increased storage and conveyance facilities. Today, the landscape is dramatically different, as municipalities have emerged as the focal point of most water issues and decision-making, and as the scope of water management has come to focus on demands as well as supplies. In many cases, this municipal focus is on suburbs rather than core cities, as the suburbs often face the strongest growth pressures coupled with the least robust supply systems – a consequence of developing after core cities have already appropriated the most abundant and reliable local supplies. In these settings, the majority of water demands are typically for single-family homes; consequently, one of the strongest management needs is to better understand and predict how these household demands are likely to respond both to management interventions (such as price increases and outdoor water use restrictions) and exogenous factors (such as weather and demographic changes). This information is particularly valuable in the context of drought planning and mitigation.

In the following pages, a discussion of residential water demand in a rapidly growing western city is presented, focusing primarily on the levels of demand

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[2]Respectively, Deputy Director, Research Associates, and Professional Research Assistant (members of the NOAA-sponsored Western Water Assessment), University of Colorado, UCB 401, Boulder, Colorado 80309-0401; and Water Conservation Supervisor for Aurora Water, Aurora, Colorado 80012 (E-Mail/Kenney: douglas.kenney@colorado.edu).

management effectiveness associated with water pricing, outdoor water-use restrictions, and technology rebate programs. This discussion begins with background information about the case study setting, followed by a review of the relevant literature, a description of the data and methodology employed, and a discussion of results and conclusions. A brief appendix is also included to provide additional details about the study methodology.

Case Study: Drought in Aurora, Colorado

The investigation of residential water demand featured in this paper focuses on the city of Aurora, Colorado, a rapidly growing Denver suburb of approximately 309,000 residents served exclusively by a single municipal provider: Aurora Water. Based on our analysis of billing records provided by Aurora Water, approximately 70-80% of deliveries in the utility's service area are to residential customers, with single-family homes accounting for the bulk of these deliveries. Stretching supplies to meet demands in Aurora has been a growing challenge for several decades, as rapid population growth, combined with limited opportunities to expand supply, have placed a premium on demand management. In this respect, Aurora is similar to cities across Colorado's Front Range and much of the southwestern United States (Nichols and Kenney, 2003).

In 2002, water officials along the Front Range were confronted with one of the worst drought years on record (Pielke *et al.*, 2005), threatening the adequacy of Aurora's water supply. In response, Aurora Water implemented a variety of short and long-term demand management programs over the next few years. Programs included: drought restrictions (i.e., limits on outdoor water use), incentive programs, introductions of new technologies, and multiple changes in billing structures and rates, culminating in the adoption of an increasing block rate (IBR) pricing structure with individualized (household-specific) block widths (i.e., the volume of water priced at a given rate level) based on water budgets adjusted annually in response to consumption levels, water storage conditions, and revenue considerations. A timeline of the key management interventions – i.e., the pricing and water restrictions policies – is provided in Figure 1. Collectively, these water demand efforts were highly successful, reducing total annual deliveries in 2002 and 2003 by 8 and 26%, respectively, relative to average deliveries in the 2000-2001

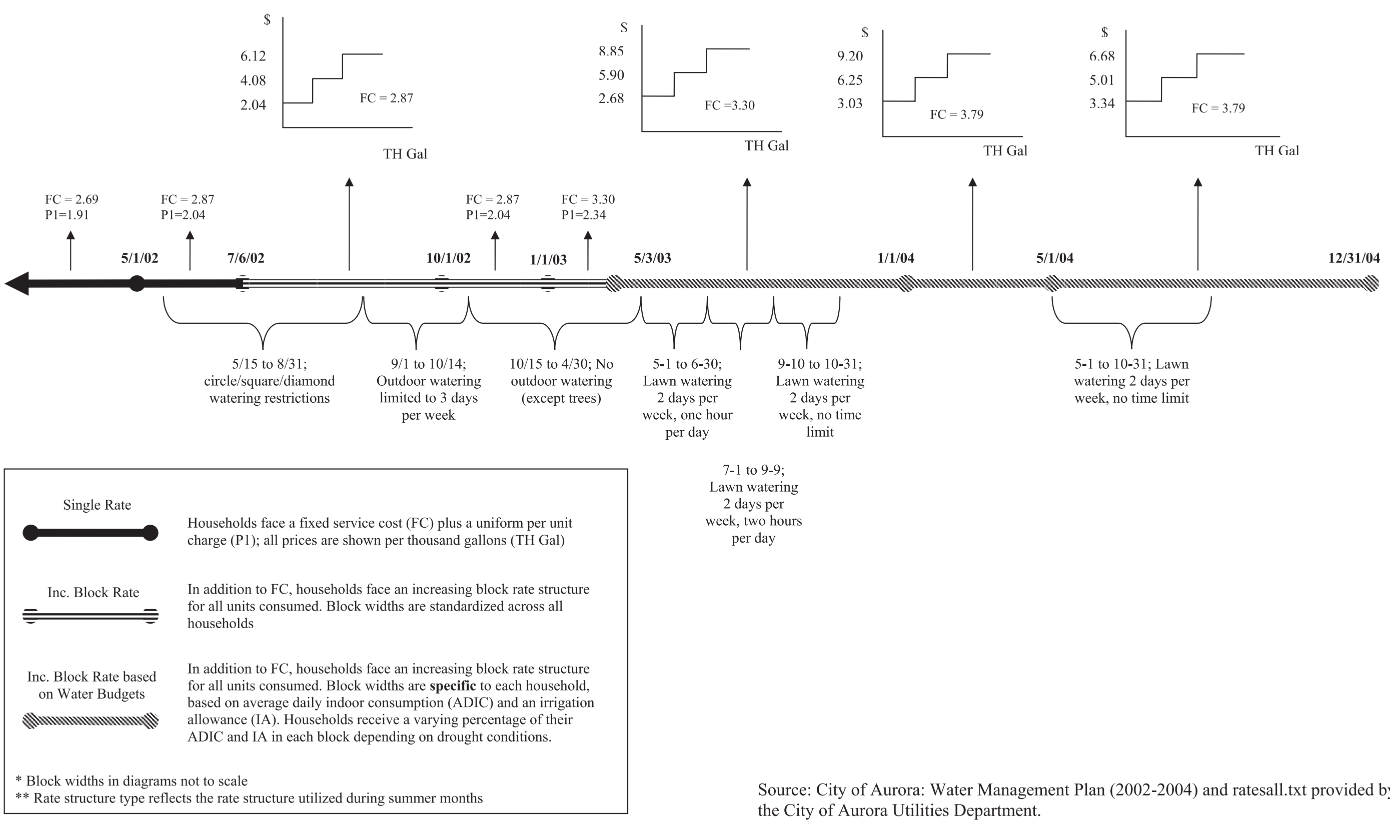

FIGURE 1. Timeline of Pricing and Restriction Policies.

period (Aurora Management Plan, 2005). The vast majority of these cutbacks came from the single-family home sector and occurred during the summer irrigation season.

Enthusiasm regarding the success of the demand management program was tempered somewhat by the inability to easily assess which of the simultaneously employed tools were responsible for the observed declines, and subsequently, which reductions could (and could not) be relied upon in the future. Answering these questions is necessary to improve both long-term and short-term planning. To investigate these questions, Aurora Water in the fall of 2005 entered into an ongoing research partnership with the Western Water Assessment (a NOAA-funded effort based at the University of Colorado's Cooperative Institute for Research in Environmental Sciences) to explore influences and recent trends in residential water demand. The timing for this research is ideal, as the extreme nature of the recent drought, combined with the aggressiveness and complexity of Aurora Water's drought response, provide an unusually broad spectrum of factors against which to track demand patterns. Aurora Water was able to provide a panel database of monthly consumption records over the study period tracking water demand at a household-by-household scale, which allowed us to investigate the impacts of different demand management programs enacted at different times and evaluate the behavior of different types of households. In contrast, most similar water demand studies rely on aggregated, citywide data (Hewitt and Hanemann, 1995; Arbués *et al.*, 2003). Recent exceptions to this include Pint (1999), Hewitt and Hanemann (1995), Renwick and Archibald (1998), and Renwick and Green (2000). Collectively, these qualities provide a largely unprecedented opportunity to explore several facets of residential water demand. Results from Phase 1 of research are presented herein; a Phase 2 is under development.

LITERATURE REVIEW

The literature on residential water demand has expanded significantly in recent years in terms of scope and sophistication, as quantitative, regression-based studies have illuminated many relationships while simultaneously identifying several new research questions (e.g., see Olmstead *et al.*, 2003 and Gaudin, 2006). Given our focus in this study on informing real-world demand management, our summary in this and subsequent sections explicitly distinguishes between factors under the control of water utilities and those that are not (a convention utilized by Gegax *et al.*, 1998). Most of our emphasis, accordingly, is on the former category; nonetheless, considering the full spectrum of influences on water demand is necessary for understanding and projecting demand, and for assessing opportunities for demand management.

Factors Under Utility Control

Pricing and Rate Structures. A consistent point of emphasis in the literature is the attempt to quantify price elasticity of water demand – i.e., the economic measure of how demand for water moves in response to price changes. This is a question of great practical importance, as pricing provides an obvious mechanism for water utilities to strategically manipulate customer behavior. The tremendous experimentation recently with new rate and pricing structures has provided many opportunities for this research, with dozens of studies confirming the intuitive notion that raising prices does in fact reduce demand, albeit only modestly (i.e., demand is largely price inelastic). Estimates of the price elasticity of residential water demand vary widely; one summary of this literature by Brookshire *et al.* (2002) suggests a fairly typical value to be −0.5 (meaning that a 10% increase in price nets a 5% decrease in consumption).

Nested within this general conclusion regarding price elasticity is a variety of subtle, but practically important, uncertainties and research questions. Chief among these is the notion that many individuals lack a clear understanding of their rate structure and water bill, raising difficult research issues about which price signals customers actually respond to (e.g., see Billings and Agthe, 1980; Shin, 1985; Jordan, 1999). In the modern era, more and more customers throughout the Southwest face an IBR structure which means that water gets progressively more expensive as their level of use moves them into and through pricing tiers designed to discourage excessive use (Western Resource Advocates, 2003). The rationale of this approach is based on the notion that consumers respond to marginal prices (i.e., the cost of the last unit purchased); however, there is reason to think that this viewpoint is too simplistic, as customers not only often lack an understanding of their rate structure, but rarely have anything resembling real-time information about their current level of consumption (Foster and Beattie, 1979; Arbués *et al.*, 2003; Carter and Milon, 2005). A further complication is identified by Olmstead *et al.* (2003), who provided evidence that the mere existence of an increasing block structure can reduce demand irrespective of the change in price. Still additional complications associated with calculating and utilizing price elasticities derive from the observation that price elasticity can vary significantly among seasons, uses, regions, and various social/economic conditions, and can be influenced by the existence of other demand management strategies (e.g., public education and water-use restrictions) (e.g., see Howe and Linaweaver, 1967; Renwick and Green, 2000; Cavanagh *et al.*, 2002). A more sophisticated understanding of these influences is key to translating a general understanding of price elasticity into effective demand management policies.

Nonprice Strategies. Due perhaps to political opposition, equity concerns, and legal limitations, water utilities are frequently reluctant to rely solely on price to allocate scarce supplies of water. Thus, in conjunction with price policies, utilities often implement a variety of nonprice programs designed to produce both temporary (drought-motivated) and permanent reductions in quantity demanded.

The range of nonprice strategies for managing water demand can generally be grouped into three categories: public education, technological improvements, and water restrictions. Research into the first category, public education programs, generally show them to be modestly beneficial, especially in the short-term (Michelsen *et al.*, 1999; Syme *et al.*, 2000). However, most water demand studies, including this one, offer little quantitative analysis on this variable as it remains a challenge to (1) separate the effect of education programs from other pricing and nonprice programs, (2) make meaningful distinctions between the nearly infinite variety of educational efforts, and (3) assess the long-term value of public education in promoting a conservation ethic. Research seems to suggest that a certain "critical mass" of educational programs is necessary to generate significant benefits, but that utilities soon reach a point of declining returns as additional efforts are implemented thereafter (Michelsen *et al.*, 1999).

Somewhat more attention has been given to understanding the effectiveness of technological changes, especially indoor retrofitting of water-using devices such as toilets, showerheads, and washing machines. Studies with this focus are frequently based on engineering assumptions of expected reductions (Michelsen *et al.*, 1999). One notable exception is provided by Renwick and Archibald (1998), whose empirical research of household water demand in Santa Barbara and Goleta, California, found that installing low flow toilets reduced consumption by 10% (per toilet), low flow showerheads by 8% (per fixture), and adoption of water efficient irrigation technologies by 11%.

Research into the effectiveness of outdoor watering restrictions generally focuses on the comparison of voluntary *vs*. mandatory programs. The literature is consistent in showing significant (sometimes 30% or more) savings from mandatory restrictions; findings regarding voluntary restrictions are much more variable, but with savings estimates generally lagging far behind the mandatory programs (e.g., see Lee, 1981; Lee and Warren, 1981; Shaw and Maidment, 1987, 1988; Renwick and Green, 2000; Kenney *et al.*, 2004).

Part of the challenge in assessing the impact of restrictions programs is that they are usually combined with other price and nonprice efforts. Few studies have included both types of policies in their analysis (e.g., Michelsen *et al.*, 1999; Renwick and Green, 2000), and even among those studies which include both sets of policies, two important factors are typically omitted. First, aggregate responsiveness to restrictions will depend heavily on the distribution of users (Goemans, 2006). For example, cities with a relatively small number of large water users are likely to experience less reductions in response to restrictions than those with a large number of these types of consumers. Second, as noted by Howe and Goemans (2002), the response of households to changes in price is likely to differ when restrictions are in place.

Factors Beyond the Control of the Water Utility

Weather. In addition to the various price and nonprice tools that utilities can utilize to manage demand are a host of independent factors known to influence residential water demand. Chief among these is weather. It is well documented that weather can impact short-term water demand decisions (particularly for landscape irrigation), and for this reason, weather variables are typically controlled for in regression-based studies focused on price and nonprice tools (e.g., see Gutzler and Nims, 2005). But beyond the intuitive conclusion that hot-dry weather generates higher demands than cool-wet conditions, the exact nature of the weather/water demand relationship has several areas of uncertainty. For example, researchers continue to search for the best combination of weather variables to explain consumption patterns, often finding precipitation to be the most useful predictive variable, but also finding value in measures of temperature, ET (evapotranspiration), and in some cases, indices designed to measure the unmet water needs of landscape plantings (e.g., see Maidment and Miaou, 1986; Woodard and Horn, 1988; Rhoades and Walski, 1991; Gutzler and Nims, 2005).

Exactly how to consider these variables is a challenging question; for example, what is more important: total precipitation over a month, the number of precipitation events, or the time between events? Questions of this nature are difficult to answer for a variety of reasons, including issues of microclimate (i.e., weather conditions in one neighborhood may not match another), the existence of major outdoor water uses other than for irrigation (e.g., the use of evaporative coolers), and distinguishing the impact of weather from the broad spectrum of pricing and nonprice management tools that are most frequently (and/or aggressively) employed during the hottest and driest seasons. The literature does not identify a preferred method for modeling weather variables. Furthermore, research is frequently constrained by the fact that household-level consumption data are only available at a monthly scale while weather variables change daily.

Demographic Considerations. Data limitations are a common impediment to assessing the impact of demographic characteristics on residential water demand. Researchers rarely have datasets that allow them to match household level consumption data with demographic data about the people and house associated with a residential water account. Nonetheless, research to date is sufficient to suggest that household water demand is influenced by heterogeneity associated with differences in wealth (income), family size and age distribution, and household preferences towards water use and conservation (Hanke and de Mare, 1982; Jones and Morris, 1984; Lyman, 1992; Renwick and Green, 2000; Syme *et al.*, 2000; Cavanagh *et al.*, 2002). Similarly, housing characteristics useful in explaining residential water demand can include the type of dwelling (e.g., single family home *vs*. apartment), age of house, size of house/lot, and the water-using technologies featured (Billings and Day, 1989; Lyman, 1992; Mayer *et al.*, 1999; Renwick and Green, 2000; Cavanagh *et al.*, 2002). Considering these influences is difficult not only due to the aforementioned lack of the relevant household/account level data, but also given that many features of a home (e.g., size) are likely to be correlated with household features, particularly income.

DATA AND METHODOLOGY

Data

As noted earlier, the dataset compiled for this investigation is unusually strong, in part due to the availability of household level data for many variables (namely price and consumption), the extreme drought conditions that characterized the study period, and the aggressiveness and diversity of the management interventions. Although the city of Aurora provided consumption records for every customer over the period 1997-2005, our analysis focuses on a subset of single family residential customers. Specifically, the results presented below correspond to the sample of households for which we had a complete, uninterrupted billing history between 1997 and 2005. This timeframe was utilized because it allowed us to categorize each household based on its water use habits during the relatively normal years 1997-1999, leaving observations occurring from 2000 to 2005 for inclusion in the regression analysis. As discussed later, this approach allowed us to examine important differences in behavior among subsets of the study population as well as during predrought and drought time periods.

After cleaning the data, we are left with roughly 680,000 unique billing period observations from over 10,000 household accounts. It is this subset of the city of Aurora population that constitutes our study population, and is referred to as “All Households” in subsequent discussions. Two important points are worth noting regarding this population. First, the consumption patterns for those households included in the study were not significantly different from those excluded due to the absence of a complete record. Second, and more important, the coefficient estimates obtained using the study sample (Column 1, Table 3) were not significantly different from those obtained when using household data for all city residents. Variable definitions and source information are provided in Table 1.

Price, Pricing Structures, and Consumption. At the heart of the research database are monthly billing records from Aurora Water keyed by a customer number and customer location which allowed us to track individual behavior while still preserving the anonymity of specific customers. Billing records provide two critically important types of information: consumption levels and the pricing structures (i.e., the delineation of tiers and their associated rates) associated with the observed levels of consumption. As shown earlier in Figure 1, these pricing structures have changed significantly in recent years. In summer of 2002, Aurora transitioned from a flat rate to an IBR pricing structure, with all households subject to the same rates and block widths (i.e., quantity of water sold at each price). Soon thereafter, Aurora began to refine its IBR structure by tailoring the size of each block width on a household by household basis, an approach known as individual water

TABLE 1. Variable Definitions.

Variable	Definition	Units	Source
Consum	Household consumption per billing period	TH Gallons	Aurora
Factors Under Utility Control			
cpilagap	CPI adjusted average price paid per thousand gallons during the previous bill period	1999 Dollars	Aurora
restrict	Indicator variable, equal to one if restrictions where in place at some point during the current bill period	0-1	Aurora
blprddays	Length of current bill period	Days	Aurora
outdoorrebate	Indicator variable, equal to one if household participated in outdoor rebate program	0-1	Aurora
indoorrebate	Indicator variable, equal to one if household participated in indoor rebate program	0-1	Aurora
wsr	Indicator variable, equal to one if household purchased a water smart reader	0-1	Aurora
Factors Outside of Utility Control			
Seasonal/Weather related			
Irrigation	Indicator variable, equal to one if any portion of the bill period occurred during the irrigation season (May-October)	0-1	
Holiday	Indicator variable, equal to one if Christmas or Thanksgiving occurred during some portion of the current bill period	0-1	
avemaxt	Average daily maximum temperature over the course of the current bill period	Fahrenheit	NOAA
totprecip	Total precipitation over the course of the current bill period	Inches	NOAA
Economic-Demographic (block-level)			
hhinc	Median household income	1999 Dollars	2000 Census
medage	Median age of homeowner	Years	2000 Census
pph	Median size of household	Persons	2000 Census
houseowned	Percentage of homes owner occupied	Percentage	2000 Census
newhome	Percentage of homes built after 1991	Percentage	2000 Census
oldhome	Percentage of homes built prior to 1970	Percentage	2000 Census
numbedrooms	Median number of bedrooms	# of bedrooms	2000 Census

budgets. This was initially done (in 2003) by focusing only on the width of the first block, based largely on the customer's historic average winter consumption. Since 2004, the size of each account's second block has also been determined on a household by household basis.

Over the course of the study period, nominal rates ranged from a low of $1.91 per thousand gallons (under the uniform rate structure in place prior to 2002) to $9.20 (in the highest (third) block in 2004). Thus, the effective marginal price for a consumer using a large volume of water has increased by more than $7 per thousand gallons (almost a factor of five), by far the largest swing we have observed in the literature.

In this analysis, we chose to use the average cost of water as the price signal in the statistical analysis, a conclusion reached after reviewing the extensive literature on the subject (e.g., see Michelsen *et al.*, 1999; Gaudin, 2006), and after an informal experiment among our university colleagues confirmed our suspicion that most customers likely have difficulty interpreting their bill and billing structure beyond the general conclusion that charges increase with usage. In our experiment, we provided several colleagues with copies of sample Aurora water bills, asking them, among other things, to identify the marginal price of water in the next month given a particular level of use. None were able to do this correctly.

We followed common convention by lagging this price variable a month; i.e., water use in a given month is assumed to be influenced by the magnitude of the water bill in the preceding month. Average price from the previous bill is used because this is the only pricing information available to consumers when making their current month's water use decisions. The database also includes a variable for number of billing days in each cycle.

Restrictions. The dataset also tracks periods featuring drought-inspired restrictions on outdoor water use, primarily focusing on the frequency and duration of lawn watering. Aurora Water, like most Colorado utilities, has recently employed restrictions as part of efforts to curb summer water demand (Kenney *et al.*, 2004). In Aurora, mandatory outdoor water-use restrictions of various degrees of severity were in place between May 15, 2002 and October 31, 2003, then again between May 1 and October 31, 2004 (see Figure 1). (Note in the following discussion of methodology and results that the interaction of restrictions and price is given particular attention in this study.)

Rebates and Water Smart Readers. Another unusual quality of our dataset is our ability to identify and track households that have taken part in city-sponsored rebate programs for water efficient technologies. Our analysis focuses on three different classes of programs: (1) those for indoor appliances, such as toilet retrofits; (2) those for outdoor technologies, such as sprinkler system upgrades; and (3) the Water Smart Reader (WSR) program. A WSR is an in-home device (similar in appearance to a pager) that intercepts radio signals from an individual's water meter, displaying real-time information about levels of water consumption. Use of a WSR allows individuals to track their water usage in relationship to their monthly water budget.

Rebates offered for water efficient indoor appliances range from \$100 for one low-flow toilet to \$400 for one water-efficient washer and two dual-flush toilets. Aurora also offered rebates of 50% of total cost up to a maximum of \$200 for irrigation efficiency upgrades. Aurora Water customers wanting a WSR are assessed a charge of \$30 (roughly half the cost of providing the product).

Weather and Climate. The research dataset utilizes daily weather data from the National Oceanic and Atmospheric Administration to construct average maximum daily temperature and total precipitation over the course of each billing period. As noted before, this dataset is unusual in its variability, as the study period contains several years of drought, particularly 2002 which has been estimated by some climate researchers as having a return period of roughly 400 years for some parts of Colorado's Front Range (the urban corridor running between the Wyoming border to the north and Pueblo to the south, along the eastern edge of the Rocky Mountains) (Pielke *et al.*, 2005). This is highly significant, as previous studies of residential water demand typically use climate variables from relatively normal periods to estimate responses in drought conditions; in contrast, we have the data necessary to measure this response directly. Additionally, some of those studies that have had extreme conditions as part of the study period have been limited by not having individual household data (e.g., Renwick and Green, 2000; Kenney *et al.*, 2004).

The climate in the study region is also considered by coding all billing period observations based on whether they occurred during the irrigation season, defined with respect to the start and end dates at which most households are believed to begin and end lawn watering (May-October). (Including dummy variables for each individual month was also originally done, but was found not to offer any benefits beyond the irrigation season approach.) After reviewing daily (system-wide) water delivery records, it was also decided to utilize a "holiday" parameter to account for the noticeable spikes observed in the daily water deliveries seen in the late November (Thanksgiving) and late December (Christmas) billing periods.

Demographic Data. The billing data are supplemented with a variety of household-level demographic data which are potentially useful in exploring how water demand varies among different types of families and houses. The U.S. Census data are reported at the block level, so average or median neighborhood values were assigned to the corresponding individual records. Data included are: median household income (1999 dollars), median age of homeowner, median size of household, percentage of homes owner-occupied, percentage of homes built after 1991, percentage of homes built prior to 1970, and median number of bedrooms. As noted below and in Appendix 1, while our model of demand includes these demographic factors, our choice of statistical technique cannot utilize data that are static over the study period, so our presentation of demographic data is limited to descriptive statistics.

Methodology

Model of Demand. Our model of household-level water demand is conceptually similar to those found in previous studies that assume water demand is primarily a function of price, weather, house and household characteristics, and any other notable (and observed) policy interventions taken during the study period (e.g., restrictions) (e.g., see Hewitt and Hanemann, 1995; Olmstead *et al.*, 2003; Gaudin, 2006). Specifically, we assume that total demand for water by household i during billing period t is defined as follows:

$$
\begin{aligned}
ln(w_{i,t}) &= \begin{pmatrix}
\beta_0 + \beta_1 ln(aveprice_{i,t-1}) + \\
\beta_2 (ln(aveprice_{i,t-1}) * restrict_t) + \\
\beta_3 restrict_t + \beta_4 blockrate + \\
\beta_5 ln(blprddays_{i,t}) + \beta_6 outdoorreb_{i,t} + \\
\beta_7 indoorreb_{i,t} + \beta_8 wsr_{i,t} + \beta_9 Irrigation_t + \\
\beta_{10} Holiday_t + \beta_{11} avemaxt_t + \beta_{12} totprecip_t + \\
\phi_1 ln(hhinc_i) + \phi_2 medage_i + \phi_2 pph_i + \\
\phi_3 houseowned_i + \phi_4 newhome_i + \\
\phi_5 oldhome_i + \phi_6 numbedrooms_i + \varepsilon_{it}
\end{pmatrix} \\
\varepsilon_{it} &= \eta_i + \mu_{it}
\end{aligned}
\tag{1}
$$

ϵ_{it} represents unobserved factors that influence demand. This term is composed of two parts: μ_{it} reflects random unobserved influences, where the mean of μ_{it} is assumed to be zero; η_i reflects differences between households which are unobserved from the analyst's perspective (e.g., lot size, irrigation technology, etc.).

In addition to the factors defined earlier (and shown in Table 1), our demand model includes two additional terms. First, standard microeconomic theory predicts that households will be less responsive to changes in price when constrained by restrictions (Howe and Goemans, 2002). To account for this we included a price-restriction interaction term ($ln(aveprice_{i,t-1})*restrict_t$), which explicitly accounts for any differences in responsiveness to price when restrictions are in place. When restrictions are *not* in place, the term $ln(aveprice_{i,t-1})*restrict_t$ equals zero and the price elasticity of demand is equal to β_1. Alternatively, when restrictions are in place, $ln(aveprice_{i,\ t-1})*restrict_t$ does not equal zero. During these periods, the price elasticity of demand is equal to $\beta_1 + \beta_2$. β_2 from Equation (1) is a measure of the change in price elasticity when restrictions are in place. This approach was originally suggested, albeit for different reasons, by Moncur (1987) and later by Michelsen *et al.* (1999); however, both of these studies omitted this variable from their final analysis (due largely to a lack of variation in the dataset resulting in high collinearity between the interaction term and other variables). To our knowledge, our study is the first to test for the difference in price elasticity when restrictions are in place. Second, we include a block rate dummy variable (blockrate) to allow for the possibility that, for reasons other than the direct price effect, household consumption patterns differ under IBR structures (Olmstead *et al.*, 2003).

Many studies of water demand utilize the regression technique known as ordinary least squares (OLS) to estimate demand for water. However, use of OLS to estimate Equation (1) is likely to produce biased results due to both the likely endogeneity of $ln(aveprice_{i,t-1})$ and $ln(aveprice_{i,t-1}) * restrict_t$, and the omission of unobserved individual effects (Arbués and Barberan, 2004). To account for this, we utilize fixed effects, instrumental variables (FE-IV) approach. This approach addresses both the potential endogeneity associated with price and the omission of unobserved individual effects, guaranteeing unbiased, efficient parameter estimates. Appendix 1 contains a more detailed discussion of this approach.

Comparison of Water Use Between Groups and Across Time Periods. As part of our efforts to generate findings that can be useful to managers in the design and implementation of demand management programs, and to take full advantage of the richness of the dataset, the study team chose to expand our analysis of water demand in two additional ways. The first compares households with respect to their relative levels of water consumption; the second compares consumption during the predrought and drought periods. Our rationale for doing so is largely evident in Figure 2, which plots system-wide residential water demand over the study period.

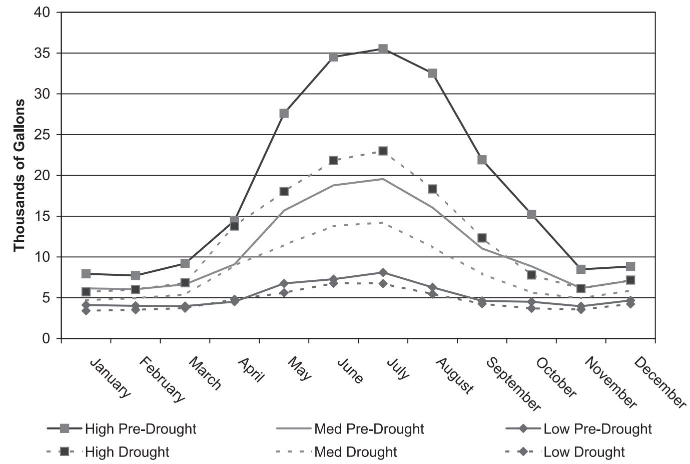

FIGURE 2. Average Consumption per Billing Period by User Type and Drought Condition.

The data presented in Figure 2 are organized in two ways which we find highly illuminating. First, it is disaggregated into predrought (2000-01-01 to 2002-04-30) and drought (2002-05-01 to 2005-04-30) periods to test the changing influence of price in these two periods. (Other variables, such as restrictions and rebates, are impossible to analyze in this way as they did not exist in both time periods.) Second, we divided our population into three groups based on each household's average summer consumption between 1997 and 1999, a period that experienced relatively normal summer weather conditions. Households whose average summer use was in the bottom 25% of all households are classified as "Low" volume users, while those in the highest 25% comprise "High" volume users; the rest of the households are designated as "Med" (medium). This was done so that we could investigate how the influence of price, restrictions, and price-restriction interactions varied among each of the three groups. In both cases, these subsets of data are analyzed using the same model of demand and statistical methodology that were applied to the full population, and are supplemental to that analysis.

Select descriptive statistics associated with these three subgroups are presented in Table 2. While it is worth noting that income is highly correlated with household type, our delineation of household types is

TABLE 2. Summary Statistics by Type of Household (averages).

Variable	All Households	Household Type		
		Low	Middle	High
Factors Under Utility Control				
consum	10.25	4.90	9.34	14.80
cpilagap	2.20	2.19	2.20	2.22
Factors Outside of Utility Control				
Economic-Demographic (block-level)				
hhinc	54,874	50,680	53,967	58,928
medage	34.77	33.66	34.33	36.35
pph	2.85	2.81	2.87	2.82
houseowned	0.79	0.75	0.78	0.81
newhome	0.02	0.01	0.02	0.03
oldhome	0.32	0.36	0.34	0.22
numbedrooms	1.44	1.40	1.44	1.46
# of households	10143	1015	6594	2534

not done to identify how income differences influence responsiveness to utility policies, nor are we attempting to estimate different portions of a representative consumer's demand curve. Rather, we wish to distinguish among customers based on the quantity of water they use for outdoor purposes; high-volume water users are large outdoor water users. The magnitude of the effect that restrictions (and price changes made when restrictions are in place) have on any given household is dependent on what its water use would have been absent the restrictions (i.e., its unconstrained demand). Stated differently, when restrictions are in place, a representative consumer does not exist. Rather, for every level of restriction there are two different types of households: those impacted by the restrictions and those that are not (i.e., households that either do not water outside or whose outdoor watering is already less than that allowed by the outdoor watering restrictions). Unfortunately we cannot directly observe who is, and who is not, bound by the restrictions. Splitting households into the three groups based on their predrought consumption levels represents our attempt to identify those households that are more (or less) likely to be constrained by the outdoor water use restrictions.

RESULTS AND DISCUSSION

The demand model used in this analysis performs well, as evidenced by the fact that all but one coefficient exhibits the expected sign and is significant at 1%. Moreover, the adjusted r^2-value of 0.40 is on the high end of the range presented in past studies that have utilized household level data (e.g., Hewitt and Hanemann, 1995; Renwick and Archibald, 1998; Pint, 1999). The results of the data analysis are presented below in Tables 3, 4, and 5, which disaggregate between those factors that are (Tables 3 and 4) and are not (Table 5) under the control of the utility and thus subject to management intervention.

Items Under Utility Control

Table 3 provides results (including coefficient estimates, z-test statistics, and significance levels for Equation (1) utilizing the FE-IV technique) for those items under utility control, namely price, restrictions, rate structures, and rebates.

Table 4 provides a summary of these findings as they relate to the influence of price and restrictions on water demand.

Influence of Price. Under the assumed log-log relationship between consumption and price

TABLE 3. Results for Utility Controlled Variables.

Dependent Variable: In(consum)	All Households	By Type of Household			Before *vs.* During Drought	
		Low	Middle	High	Before	During
Factors Under Utility Control						
In(cpilagap)	−0.60 (156.57)***	−0.34 (28.68)***	−0.57 (126.99)***	−0.75 (98.84)***	−0.56 (12.22)***	−1.11 (96.11)***
ln(cpilagap)*restrict	0.23 (34.54)***	−0.11 (6.03)***	0.19 (24.56)***	0.51 (36.64)***	NA	0.85 (62.31)***
restrict	−0.31 (57.9)***	0.03 (1.84)*	−0.28 (44.45)***	−0.57 (49.7)***	NA	−0.85 (−67.25)***
blockrate	−0.05 (31.22)***	−0.01 (2.22)**	−0.04 (23.55)***	−0.08 (25.64)***	NA	−0.09 (49.38)***
ln(blprddays)	0.61 (114.8)***	0.58 (34.69)***	0.62 (97.38)***	0.61 (57.02)***	0.57 (95.09)***	0.76 (73.26)***
outdoorrebate	0.01 (0.69)	−0.05 (1.27)	0.02 (1.43)	0.03 (2.08)***	NA	−0.11 (7.26)***
indoorrebate	−0.10 (15.54)***	−0.16 (5.7)***	−0.10 (12.54)***	−0.07 (6.65)***	NA	−0.14 (15.93)***
wsr	0.16 (9.38)***	0.17 (2.35)***	0.15 (6.82)***	0.13 (4.7)***	NA	−0.25 (4.61)***
Number of observations	679,134	68,059	441,833	169,242	274,671	364,237
Number of households	10,143	1,015	6,594	2,534	10,143	10,143
Overall R^2	0.4	0.18	0.45	0.59	0.42	0.36

Note: Absolute value of z statistics in parentheses.
*Significant at 10%; **significant at 5%; *** significant at 1%.

TABLE 4. Effectiveness of Price and Restrictions by Type of User.

	Price Elasticity	Price Elasticity During Restrictions	% Change in Demand Due to Restrictions Only*
All	−0.60	−0.37	−12.12
Low users	−0.34	−0.46	−6.49
Middle users	−0.57	−0.39	−12.11
High users	−0.75	−0.24	−13.82

*Assuming average prices during periods with restrictions.

presented in Equation (1), the coefficient on price, β_1, provides a direct estimate of price elasticity of demand when restrictions are *not* in place. Consistent with prior research we find price elasticity of demand to be significant and inelastic (−0.60) throughout the year. That is, given a 10% increase in price, demand can be expected to decrease by 6%. This result is well within the range of past estimates: e.g., in 15 studies reviewed by Brookshire *et al.* (2002), price elasticity ranged from −0.11 to −1.59 (average of −0.49), while Espey *et al.*'s (1997) review of 24 studies found 75% of price elasticity estimates fell between −0.02 and −0.75. Note that while our estimates reflect the high demands associated with Colorado's summer irrigation season, they represent a "year-round" estimate of price elasticity. This estimate likely would have been higher had we confined our focus to the irrigation season.

The analysis by type of user confirms the hypothesis that price elasticities vary considerably among user groups (perhaps explaining some of the range in price elasticity estimates in previous studies), with high water users generally more responsive to price (elasticity of −0.75) than low water users (−0.34). This observation can be important for planning purposes in many ways, such as in estimating how existing user populations are likely to respond to price interventions, and also in assessing how long-term changes in demographics and housing/land-use may alter opportunities for price-based demand management (see Martinez-Espineira, 2002; Goemans, 2006).

Also having significant management implications is the comparison of predrought price elasticities (−0.56) to those during drought (−1.11). We are unable to conclusively determine why customers were more than twice as sensitive to price during drought than before, but two possible explanations are worth considering. First, these differences in elasticity may derive, at least in part, from the wealth of media coverage and public education programs that accompany drought (Moncur, 1987; Nieswiadomy, 1992). Second, these differences might indicate that the price elasticity of demand is highly nonlinear outside of the range of prices experienced prior to drought (Pint, 1999). As noted earlier, the magnitude of price increases observed over the study period was significant, with the price per thousand gallons for water purchased in the highest block increasing by more than $7 during the drought. These are very different explanations suggesting very different demand management approaches; thus, this result is a subject worthy of further research. One key element of that research agenda is presented in the following section, and concerns the interaction of pricing policies with drought-inspired water restrictions.

Restrictions and Price-Restrictions Interactions. The coefficient on *restrict*, β_3, provides an estimate of the percentage change in demand, *absent the influence of price*, associated with imposing restrictions. In other words, it identifies how effective restrictions would be if the price of water were zero, which is shown in Table 3 as −0.31 (31% reduction). While this conceptualization is certainly unrealistic, it is theoretically useful when you consider that as the price of water increases from zero, the effectiveness of restrictions will be reduced as more and more users will find price, rather than restrictions, to be the more significant controlling factor on their water-using behavior. It is impractical, therefore, to think about the effectiveness of restrictions without

TABLE 5. Results for Variables Outside Utility Control.

Dependent Variable: In(consum)	All Households	By Type of Household			Before *vs.* During Drought	
		Low	Middle	High	Before	During
Factors Outside of Utility Control						
Irrigation	0.30 (133.19)***	0.15 (21.19)***	0.29 (108.02)***	0.38 (86.33)***	0.33 (88.03)***	0.30 (102.22)***
Holiday	0.07 (39.66)***	0.08 (13.96)***	0.08 (34.81)***	0.06 (17.33)***	0.08 (30.02)***	0.06 (24.22)***
avemaxt	0.02 (341.39)***	0.01 (58.77)***	0.02 (278.47)***	0.03 (216.09)***	0.02 (223.35)***	0.02 (222.2)***
totprecip	−0.04 (67.07)***	−0.03 (15.34)***	−0.04 (57.66)***	−0.04 (35.41)***	−0.03 (28.1)***	−0.05 (72.65)***
constant	−1.18 (63.31)***	−1.18 (20.09)***	−1.20 (54.33)***	−1.11 (29.69)***	−1.02 (30.01)***	−1.11 (30.04)***

Note: Absolute value of z statistics in parentheses.
*Significant at 10%; **significant at 5%; *** significant at 1%.

explicitly considering their relationship to price, which we have primarily done herein with the price-restrictions interaction term (discussed below). Nonetheless, it is worth noting that if we use the average price conditions observed when restrictions were in place in our model of water demand, the water savings that can be attributed solely to restrictions would be estimated at roughly 12% (which is generally consistent with other studies considering the relatively moderate restrictions utilized in Aurora). We caution against applying this result in other settings, as the effectiveness of restrictions is closely linked to case-specific factors including price, the distribution of customer types (also discussed below), weather conditions, and customer familiarity with (and support for) the restrictions.

Rather than considering how prices influence the effectiveness of restrictions, it is perhaps more useful to consider the problem in reverse: how does the adoption of restrictions modify the influence of price on demand (as measured by changes in price elasticity)? Consistent with economic theory, the interactions term in our model of water demand is positive and significant (+0.23), meaning that as restrictions are implemented, consumers are less responsive to price. Again, the explanation is clear: for any given customer, either price or restrictions (but not both) will be controlling, depending on which provides the lowest (i.e., first-encountered) threshold. Summing the price elasticity (−0.60) with the interactions term (+0.23) yields an effective price elasticity of demand during restrictions periods of −0.37.

The policy ramifications of this observation are particularly evident by looking at the results for each user group, which show the adjusted price elasticity during restrictions to range from −0.24 for high users to −0.46 for low users. Managers wishing to reign in the high users during drought, therefore, may be wise to focus on restrictions; whereas low water users are perhaps better targeted (if at all) with price modifications – although these users, by definition, have less opportunity to reduce consumption than others, and these price increases may therefore be more punitive than pragmatic. In any case, it is important to appreciate that the theoretical savings from pricing policies and drought restrictions are not additive, the impact of each policy can vary significantly among user groups, and the choice of policy has ramifications that go beyond water savings to include issues of equity and revenue generation. Similarly, it is important to note that price elasticities among the three groups go in opposite directions depending on whether drought-inspired restrictions are in place, suggesting that the appropriate tool for drought management is not necessarily the appropriate tool for long-term (baseline) water conservation. Stated differently, if the goal of demand management is to control the high users, pricing policies may provide the best long-term option whereas restrictions may provide the most logical drought-coping strategy.

Rate Structures. Also of note is that the coefficient on *blockrate* is significant and negative (−0.05), indicating that when faced with an IBR pricing structure, households consumed 5 percent less than they would have under a uniform rate pricing structure. This is consistent with previous research (Olmstead *et al.*, 2003), and supports the common argument that, in addition to price levels, rate structures themselves can be valuable in promoting conservation (e.g., see Western Resource Advocates, 2003). One argument for why this might be the case is that although households do not often have detailed knowledge of the rate structure, they are generally aware that excessive consumption will result in excess costs. This awareness causes them to consume less in an attempt to limit this possibility.

Rebates and Water Smart Readers. Indoor and outdoor rebate programs and the use of WSR are admittedly a diverse category, but are grouped together for discussion as their datasets share two similar limitations. First, participating individuals self-selected themselves for the particular programs; thus, while we can track how participation influenced water demand among these individuals, it is problematic to assume that a similar response would occur among all members of the population. Second, while the indoor rebate programs (e.g., toilet rebates) are designed to cover retrofitting activities, the outdoor programs covering the installation of more efficient sprinkler technologies likely cover a mix of both retrofits and new construction, perhaps including significant system expansions. As we have no data on these other activities, assessing the effectiveness of the outdoor rebate programs is difficult. In fact, the coefficient calculated for the outdoor programs, β_6, is statistically insignificant (and slightly *positive*), and thus is not discussed further in our analysis.

The coefficient calculated for the indoor rebate programs, β_7, is significant, large, and shows the expected negative sign (−0.10), suggesting that, all else constant, participation in the indoor rebate program reduces household demand by approximately 10%. This finding is nearly identical in magnitude to those reported in other investigations, particularly Renwick and Green (2000) and Renwick and Archibald (1998), and provides further empirical justification for using indoor rebate programs as a demand management tool.

The calculated coefficient for the Water Smart Reader, *wsr*, is also highly significant (+0.16), although the positive sign of the result was initially confusing. As noted above, WSR households self selected into the rebate program. One can control for the potential endogeneity of the WSR variable using methods similar to those utilized for average price. However, the discrete nature of the WSR variable complicates the use of these techniques, both computationally and technically. Thus, while we have omitted this type of analysis from this paper, we have applied these techniques to a random subset of Aurora households in a subsequent paper (in production) in which the effect of WSR ownership is the focus. There we estimate a FE-IV model where, in the first stage, we instrument for both price and WSR using a fixed effects logit model to estimate the probability of owning a WSR. The fact that a random subset of households was sent an additional advertisement for the WSR is used as an instrument for WSR ownership. Preliminary results from that work support the finding presented here: namely that WSR ownership had a positive effect on demand for water.

Conventional wisdom is that providing customers with real-time information about water use increases their ability to track consumption and charges, and thus should help convey the deterrent effect on excessive use provided by the IBR structure. Why, then, did the water consumption of our population of WSR customers increase by 16%? The answer, we believe, lies in the observation that although total use went up among this group, the frequency with which these users entered into the most punitive pricing tier (the third block) diminished. It appears that prior to obtaining a WSR, users fearful of entering the third block would err on the side of caution by consuming less than they would have otherwise preferred, but when armed with the ability to track consumption, these same users skillfully budgeted consumption to take full advantage of the lower priced blocks. The result is more extensive use of water in Blocks 1 and 2 (and thus higher net consumption), and less consumption in Block 3. This observation should be heartening to water managers, as it suggests that informed consumers will adjust their behavior in accordance with the water budget provided by the utility, adjusting use to fully utilize their apportionment in the low priced blocks (or tiers) that presumably reflect some notion of reasonableness while avoiding those blocks associated with excessive use.

Items Outside of Utility Control

Table 5 provides results for those influences on water demand that are beyond the control of water managers, namely the seasonality of water demand and weather.

Seasonality of Water Demand. As is intuitively obvious, demand for water is shown to be highly seasonal and dependent on climate and weather conditions. Water use in the irrigation season is fundamentally and significantly higher than the rest of the year (as shown earlier in Figure 2), a fact that makes demand management in summer a particular point of management emphasis. The coefficient on *irrigation* is significant and positive (+0.30), indicating that, irrespective of the influence of temperature and precipitation, household water use increases by 30% just by virtue of being in the irrigation season. As expected, this effect is most pronounced among high-volume users (+0.38). Also as expected, the coefficient on *holiday* is significant and positive (+0.07). Although this effect is clearly outside the scope of management, including this factor in models of water demand is worthwhile in improving the accuracy of all estimated variables.

Weather. Also intuitive is the observation that, all else being equal, demand for water increases as temperatures rise, and decreases as precipitation increases. Specifically, the model predicts that for every one degree Fahrenheit increase in average daily maximum temperature over the course of the billing period, water use increases about 2%. Similarly, for every inch of precipitation, water use decreases by roughly 4%. Understanding this relationship awaits additional research on household-level decision-making (particularly associated with lawn watering) and the types of irrigation technologies employed. (These questions are central to the emerging Phase 2 of research).

Findings that relate climate and weather conditions to residential demand can be useful in several facets of planning and management, especially in light of research suggesting that climate change will likely mean fundamental changes in average temperatures (clearly increasing), precipitation, and the frequency of extreme events such as droughts and floods (Wagner, 2003). Considering climate change issues is particularly challenging for water managers along Colorado's Front Range, where water source and demand areas are often separated by great distances and elevations. But regardless of what climatic changes are in store for Aurora and other Front Range cities, a growing reliance on demand management to cope with extreme conditions and stresses (including those associated with population growth) only underscores the need to understand all facets of residential water demand.

Demographic Considerations. Table 5 does not provide any statistics regarding the influence of household and house characteristics (i.e., demographic considerations) on residential water demand, a consequence (as noted earlier) of our method of data analysis that relies on fixed effects. Fixed effects models estimate household demand for water in each period as deviations from the household's average use over the period of record. This approach effectively "averages-out" time-invariant unobserved effects such as η_i, allowing the researcher to obtain unbiased parameter estimates for the remaining variables (i.e., the β^s). One obvious downside to this approach is that we are unable to recover parameter estimates for *any* time-invariant variables (i.e., the φ^s).

As discussed in Appendix 1, this is a small price to pay for insuring that we produce unbiased parameter estimates for the remaining variables. The central objective of this paper is to develop a better understanding of how utility policies introduced by Aurora influenced demand for water. Changes in income, age of homeowner, etc. are outside of the control of utilities. Although interesting, it is of greater importance to us to be sure that we have controlled for these variables, something the fixed effects approach offers. Note that we are not omitting the effect of income from the analysis; rather, we are controlling for it along with numerous unobserved individual characteristics.

Nonetheless, we would be remiss if we did not reiterate that some literature already exists to document demographic effects, and similarly, if we failed to acknowledge that our division of customers into three user groups suggests that high-volume water users tend to be wealthier, older, and live in newer and larger homes than other customers (see Table 2). We believe that a better understanding of demographic factors may be useful in designing and targeting demand management programs and in projecting future demand patterns as cities age and evolve.

CONCLUDING THOUGHTS

Overall, our findings are consistent with the literature in demonstrating that residential water demand is largely a function of price, the impact of nonprice demand management programs, and weather and climate. Our unique contributions derive from the depth of the household-level dataset, the presence of the extreme drought event in the study period, and the diversity of associated management interventions. Substantively, this study increases the knowledge of residential demand in at least three salient ways: first, by documenting that pricing and outdoor water restriction policies interact with each other ensuring that total water savings are not additive of each program operating independently; second, by showing that the effectiveness of pricing and restrictions policies varies among different classes of customers (i.e., low, middle, and high volume water users) and between predrought and drought periods; and third, in demonstrating that real-time information about consumptive use (via the WSR) helps customers reach water-use targets. At each point in the analysis, we have identified relevant management implications of these findings.

To the extent that future water demand research is pursued with the aim of further informing and empowering water managers to better predict and manipulate residential water demand, investigators will need to make additional progress illuminating the interplay among the many factors now known to influence demand. This suggests a need to better understand water-use decision-making processes at the household level, which in turn will necessitate the assembly of improved datasets. This seems particularly important as water utilities (like Aurora Water) adopt dynamic, customer-specific water budgets, with the competing aims of managing water demand (and water revenues) in both normal and emergency settings, all within a framework that customers can readily understand and endorse as equitable. To simultaneously achieve these goals is a formidable challenge, and is deserving of the same level of intellectual effort as has traditionally been devoted to understanding and managing water supplies.

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APPENDIX 1: METHODOLOGICAL CONSIDERATIONS

No model includes every relevant factor. Hence our inclusion of an error term (ϵ_{it}), which is intended to capture the net influence of everything omitted from the model. Under the assumption that ϵ_{it} is independently and identically distributed (across both time and individuals) with mean zero and constant variance, Ordinary Least Squares (OLS) is the best linear unbiased estimator (Johnston and DiNardo, 1997). However, as defined in Equation (1), ϵ_{it} is not likely to satisfy this assumption. Potential problems associated with the inclusion of lagged average price and the omission of unobserved individual effects will cause OLS to produce parameters estimates that are biased and/or inefficient. Therefore, we utilize a mixed fixed effects (FE), instrumental variables (IV) approach to account for these likely problems. In doing this we address both the potential endogeneity associated with price and the omission of unobserved individual effects, resulting in unbiased, efficient parameter estimates (Wooldridge, 2002).

We address the need for and appropriateness of this approach in subsequent subsections within this appendix. We first discuss problems associated with omitting unobserved individual effects and the motivation behind modeling these unobserved effects as FE. This is followed by a discussion of the problems associated with demand estimation under block rate pricing and the motivation behind instrumenting for price.

Unobserved Individual Effects

Our dataset undoubtedly omits numerous factors unique to each household that are relevant to determining water demand. Likely omissions include data about the presence/absence of evaporative coolers (Hewitt and Hanemann, 1995), and data about irrigable acreage and the type of sprinkler systems employed in their maintenance. In comparison to issues dealing with price, accounting for the potential presence of unobserved individual effects has received less attention within the water demand literature.

Consistent with standard panel data models developed in Johnston and DiNardo (1997), Baltagi (2005), Hsiao (2003) and Wooldridge (2002), these omissions can be represented in Equation (1) by decomposing ϵ_{it} into two parts so that $\epsilon_{it} = \eta_i + \mu_{it}$, where η_i corresponds to the unobserved individual effects mentioned above and μ_{it} is the standard error term satisfying the typical assumptions corresponding to the classic linear model. Ignoring η_i can lead to meaningless parameter estimates that are inconsistent and/or inefficient (Hsiao, 2003). Luckily, techniques to account for η_i in the panel setting are well developed. Under the assumption that η_i is uncorrelated with the right hand side regressors, random effects models may be used to generate parameter estimates that are consistent and efficient (note that this is not the same as saying that η_i is random). Alternatively, if η_i is correlated with any of the right hand side regressors FE models must be used (Johnston and DiNardo, 1997; Wooldridge, 2002; Hsiao, 2003; Baltagi, 2005). In short, which model is appropriate depends on the assumptions one is willing to make about η_i.

We choose to address η_i within the FE framework. FE models estimate household demand for water in each period as deviations from the household's average use over the period of record. This approach effectively "averages-out" time-invariant unobserved effects such as η_i, allowing the researcher to obtain unbiased parameter estimates for the remaining variables. Thus, we can recover parameter estimates for those variables which change over time (i.e., the β^s) by comparing individual households with themselves over time. The downside to this approach is that we are unable to obtain parameter estimates for any variables that remain constant across time, even if they vary across households. As a result, our demographic terms drop out of the analysis and we are unable to estimate the parameters for these variables (i.e., the φ's). However, as noted earlier, this is a small price to pay and in some ways advantageous given our reliance on Census data for these variables. It is unclear the extent to which census blocks are homogenous; as such, use of Census data might introduce additional error or bias into the model depending on the distribution of characteristics across any given block.

It is tempting to utilize random effects so that one can recover parameter estimates for time invariant variables (e.g., Gaudin *et al.*, 2001). However, use of random effects models would only be appropriate if η_i was uncorrelated with all of the regressors in Equation (1). We believe that this is highly unlikely, in which case modeling η_i as random effects would result in inconsistent parameter estimates. Omitted variables such as lot size, type of irrigation system, and type of cooling system are likely correlated with income, age of home, and the other right hand side variables include in Equation (1). A Hausman-Wu test, comparing random and FE estimates (after instrumenting for price) on all households and for each of the subgroups supported this belief. This is not surprising. Referring to the preference of many economists for FE estimates, Johnston and DiNardo (1997: 403) note: "This preference seems to be a consequence of the reasonable belief that, apart from purely experimental or quasi-experimental situations, it is unlikely that the FE are uncorrelated with the regressors of interest."

Our choice of FE is also motivated by the potential consequence of being incorrect. When the random effects model is valid, the FE models will still produce consistent parameter estimates. Alternatively, when a FE approach is appropriate, use of random effects techniques will NOT produce consistent parameter estimates.

Average Price

Under block rate pricing, the relationship between price and consumption is unusually complicated, as price (either average or marginal) not only influences consumption, but the level of consumption influences price. After more than 50 years of research, this issue is well documented; however, little consensus exists as to how to estimate consumer demand under such rate structures (e.g., see Pint, 1999; Arbués *et al.*, 2003).

Given the relationship between price and quantity, price is likely to be endogenous and OLS will produce biased estimates (Nieswiadomy and Molina, 1988). In our case, concern arises over the fact that both $ln(aveprice_{i,t-1})$ and $ln(aveprice_{i,t-1})^{*}restrict_t$ are likely to be correlated with $\epsilon_{i,t}$. This correlation may exist both through η_{i} when not using the FE model and μ_{it-1} when using the FE model framework (Arbués and Barberan, 2004). To account for this, we follow a common practice of using IV techniques. (For a more detailed discussion of this approach in the panel setting, see Wooldridge 2002.)

Consistent with Nieswiadomy and Molina (1988) and others, we use the parameters of the rate structure as instruments for $ln(aveprice_{i,t-1})$ and $ln(aveprice_{i,t-1})^{*}restrict_t$. Specifically, in the first stage the price of each block, by itself and interacted with $restrict_t$, are used to generate estimates of $ln(aveprice_{i,t-1})$ and $ln(aveprice_{i,t-1})^{*}restrict_t$ that are uncorrelated with $\epsilon_{i,t}$. These estimates are then used in the estimation of Equation (1).

Valid instruments for $ln(aveprice_{i,t-1})$ and $ln(aveprice_{i,t-1})^{*}restrict_t$ must possess two qualities: they must be correlated with average price and uncorrelated with the error term. The instruments described above satisfy both of these requirements. Our decision not to include the variables corresponding to the width of each block is worth noting. In this case the use of block width as an instrument for average price would be inappropriate, as the width of each block is likely to be correlated with $\epsilon_{i,t}$ during periods when water budgets are used.