Journal of Urban Economics 71 (2012) 332–346

Contents lists available at SciVerse ScienceDirect

Journal of Urban Economics

www.elsevier.com/locate/jue

The value of scarce water: Measuring the inefficiency of municipal regulations

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ARTICLE INFO

Article history:
Received 5 October 2010
Available online 8 December 2011

JEL classification:
L51
Q25
Q28
Q58
L5
Q2

Keywords:
Drought policy
Increasing-block price
Market-based regulation
Urban water demand
Water price
Water restriction

ABSTRACT

Rather than allowing urban water prices to reflect scarcity rents during periods of drought-induced excess demand, policy makers have mandated command-and-control approaches, primarily rationing the use of water outdoors. While such policies are ubiquitous and likely inefficient, economists have not had access to sufficient data to estimate their economic impact. Using unique panel data on residential end-uses of water in 11 North American cities, we examine the welfare implications of urban water rationing in response to drought. Using estimates of expected marginal prices that vary both across and within markets, we estimate price elasticities specific to indoor and outdoor water use. Our results suggest that current policies do target water uses that households, themselves, are most willing to forgo. Nevertheless, we find that rationing outdoor water in cities has costly welfare implications, primarily due to household heterogeneity in willingness-to-pay for scarce water. We find that replacing rationing policies with a market-clearing "drought price" would result in welfare gains of more than 29% of what households in the sample spend each year on water.

1. Introduction

Where markets are not employed to allocate scarce resources, the potential welfare gains from a market-based approach can be estimated. We assess the potential welfare gains and possible distributional outcomes from using prices rather than rationing to reduce urban water consumption. Between January 1997 and June 2007, moderate to extreme drought conditions affected, on average, 20% of the contiguous United States (National Climatic Data Center, 2007). During droughts, municipal water restrictions focus almost exclusively on the residential sector (which comprises one-half to two-thirds of urban consumption). Rather than allowing prices to reflect scarcity rents during periods of excess demand, policy makers have mandated the curtailment of certain uses, primarily outdoor watering, requiring the same limitations on consumption of all households. If indoor demand is not perfectly inelastic, or households have heterogeneous willingness-to-pay for scarce water, a price-based approach to drought policy has a theoretical welfare advantage over water rationing.

Using unique panel data on residential end-uses of water for 1082 households in 11 urban areas in the United States and Canada, we examine the implications of the current approach to urban drought. Most households in the sample face increasing-block prices for water, in which quantity demanded and marginal price are simultaneously determined. Rather than using endogenous, *ex post* prices, we use estimates of expected marginal prices that capture greater variation than typical instruments used in estimating water demand under increasing-block prices. Using these expected prices that vary by season and household, we identify price elasticities specific to indoor and outdoor water demand. We find that outdoor watering restrictions do mimic household reactions to price increases, on average, as outdoor demand is much more price elastic than indoor use. However, the real advantage of market-based approaches lies in their accommodation of heterogeneous marginal benefits. When regulators impose identical frequency of outdoor watering, shadow prices for the marginal unit of water may vary greatly among households. Our estimates of separate end-use elasticities for four heterogeneous household groups, based on income and lot size, suggest that households are heterogeneous in these markets. We estimate shadow prices for each consumer, and utility-level market-clearing prices under four drought policy scenarios of increasing stringency. We then

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doi:10.1016/j.jue.2011.11.003

simulate the effects of moving to a market-based approach, in comparison to a two-day-per-week outdoor watering restriction.

Our results have important implications for urban water policy. The welfare gains from a price-based approach are approximately \$96 per household during a lawn-watering season, about 29% of average annual household expenditures on water in our sample. These direct welfare gains would also come with potential savings in enforcement and monitoring costs – volumetric metering and billing systems are already in place for water consumption in most North American cities, while command-and-control approaches currently require direct observation of individual households' outdoor consumption.

Switching to a price-based policy would have allocative consequences. Drought prices enable customers who are the least price sensitive, wealthy consumers with large lots, to reduce consumption less than low-income households with small lots. The distributional consequences of these changes depend on the assignment of water rights. If utilities retain these rights, their profits would rise by an estimated \$152 per customer. Households would be worse off by \$58, on average. Rebates from water suppliers to consumers could make everyone better off.

This paper provides the most comprehensive estimates to date of the welfare loss from rationing urban water. Rationing approaches are ubiquitous in the water sector, especially in arid regions. For example, during a 1987–1992 drought in California, 65–80% of urban water utilities implemented outdoor watering restrictions (Dixon et al., 1996). In 2008, 75% of Australians lived in communities with some form of mandatory water use restrictions (Grafton and Ward, 2008). Our results suggest that the economic losses from such approaches may be substantial.

The paper proceeds as follows. In Section 2, we review the related literature. Section 3 presents a simple model of water demand and drought pricing. The data and estimation are discussed in Section 4. In Section 5, we present our price elasticity estimates for end uses and consumer groups. Section 6 discusses the economic consequences of current regulatory policies and distributional impacts of switching to a price-based allocation mechanism. In Section 7, we conclude.

2. Related literature

The questions addressed in this paper arise from the general theoretical literature on the conditions under which gains in social welfare are possible through the introduction of markets for managing scarcity (Weitzman, 1977; Suen, 1990). In urban settings, there are theoretical and empirical estimates of the gains from increasing the influence of markets on traffic congestion on roadways (Small and Yan, 2001; Parry and Bento, 2002; Parry and Timilsina, 2010) and at airports (Daniel, 2001; Pels and Verhof, 2004). The gains from price-based approaches to allocation in these cases, as in the case considered here, derive largely from heterogeneity in consumers' marginal benefits.

A related literature has compared market-based and command-and-control approaches to pollution control (Baumol and Oates, 1988; Tietenberg, 1995; Burtraw et al., 1998). In these applications, welfare gains are achievable through policies that take into account pollution abatement cost heterogeneity among regulated firms.

More closely related to our work, Collinge (1994) proposes a theoretical municipal water entitlement transfer system. An experimental study simulates water consumption from a common pool and predicts that customer heterogeneity will generate welfare losses from command-and-control urban water conservation policies (Krause et al., 2003). Neither of these analyses estimates the magnitude of potential welfare gains, nor do they explore distributional implications in any depth. Renwick and Archibald (1998) compare the distributional implications of price and non-price municipal water conservation policies, but do not consider welfare impacts. Two empirical studies estimate the welfare losses from rationing water during a drought in a single city. The estimated economic costs of a two-day-per-week sprinkling restriction in Perth, Australia are almost \$100 per household per season (Brennan et al., 2007). Water restrictions in Sydney in 2004–2005 led to estimated welfare losses of about \$150 per household (Grafton and Ward, 2008).[1]

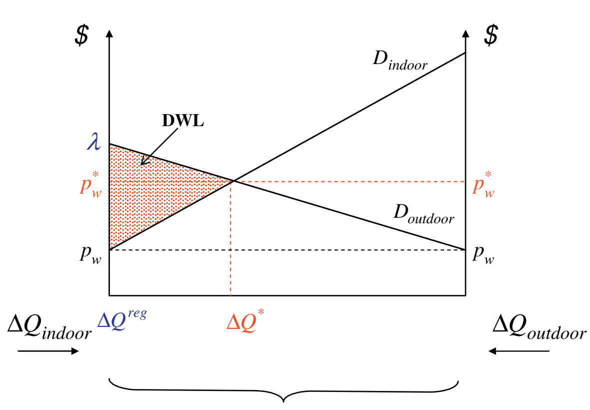


Fig. 1. Welfare loss from outdoor consumption restrictions.

3. A model of water demand and drought pricing

The current approach to drought management achieves a citywide required demand reduction by uniformly restricting outdoor uses. The theoretical welfare gains from price-based municipal water regulation come from possible substitution within and across households. Prices allow households to choose end-use consumption according to their preferences (*i.e.*, households could substitute some indoor for outdoor reductions). Thus, if indoor demand is anything but perfectly inelastic, the current approach creates a deadweight loss (DWL). Fig. 1 maps stylistic linear demand curves for indoor and outdoor water use against a required demand reduction (on the horizontal axis).[2] The outdoor reduction mandated under the current approach (ΔQ_{reg}) creates a shadow price for outdoor consumption (λ) that is higher than the current marginal price of water (p_w). Under a market-clearing price (p_w^*), some of the citywide required reduction would take place indoors, and the shaded DWL from rationing water outdoors would disappear.

Additional welfare losses from the current approach come from disallowing substitution across households. Fig. 2 describes households with the same indoor demand curve, but different preferences with respect to outdoor demand. Here we assume that indoor demand is the least elastic portion of demand (C), and that for outdoor demand, there is a group of relatively elastic households (A), and a group of somewhat less elastic households (B). If households are heterogeneous, outdoor regulations not only drive a wedge between outdoor shadow prices and current marginal prices, but, since they are the same for all households, they also

[1] In a related paper, Timmins (2003) compares a mandatory low-flow appliance regulation (a technology standard) with a modest water tax, using aggregate consumption data from 13 groundwater-dependent California cities. He finds the tax to be more cost-effective than the technology standard in reducing groundwater aquifer lift-height in the long run.

[2] We assume that supply, in the short-run situation of drought, is perfectly inelastic.

create variation in outdoor shadow prices across households. A market-clearing price would realize all potential gains from trade, eliminating the shaded DWL triangles. See Appendix A for a more formal theoretical modeling of these welfare effects.

We model water demand as Eq. (1), in which w_{total} is total daily water demand for household i on day t, p is the expected marginal water price, y is household income, Z is a vector of daily and seasonal weather variables, and H is a vector of household characteristics. The unobservable error structure comprises θ_i, a household heterogeneity parameter, and υ_{it}, the idiosyncratic shock.

$$\ln w_{total_{it}} = \alpha \ln p_{it} + \mu \ln y_i + \delta Z_{it} + \beta H_i + \theta_i + v_{it}. \quad (1)$$

Or, in matrix notation:

$$\ln \mathbf{w}_{total} = \mathbf{X}'\boldsymbol{\gamma}_{total} + \boldsymbol{v}_{total} \quad (2)$$

Estimation of the welfare losses from outdoor watering restrictions requires that we estimate separate demand models for indoor and outdoor water uses. Indoor demand is identical to (2) except for the dependent variable:

$$\ln \mathbf{w}_{in} = \mathbf{X}'\boldsymbol{\gamma}_{in} + \boldsymbol{v}_{in} \quad (3)$$

As noted in Section 4, most days households do not water outdoors. Thus, we model outdoor demand as censored:

$$\mathbf{w}^*_{out} = \mathbf{X}'\boldsymbol{\gamma}_{out} + \boldsymbol{v}_{out}$$
$$w_{out_{it}} = \begin{cases} w^*_{out_{it}} & \text{if } w^*_{out_{it}} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

4. Data and estimation

The data used in this study were collected by Mayer et al. (1998) for a study funded by the American Water Works Association Research Foundation. The data comprise 1082 households in 11 urban areas in the United States and Canada, served by 16 water utilities.[3] None of these utility service areas were experiencing drought or outdoor watering restrictions during the data collection period.

The study conducted a one-time household survey, mailed to a random sample of 1000 single-family residences in each city.[4] (Cities served by multiple utilities also had 1000 households surveyed, divided among the multiple utilities.) A random sample of 100 households was drawn from among the returned surveys in each city for end-use data collection.[5] The sample is appealing in its broad geographic scope, across variable climates, and its restriction to single-family homes; the type of drought restriction we simulate, an outdoor watering restriction, is targeted at precisely this consumer group (as opposed to apartment buildings, for example), since this is where most outdoor consumption takes place. Due to the nature of the sample and the policy question we analyze, our estimates and conclusions would not be readily transferable to settings in which multi-family housing predominates, especially where residents do not pay a water bill.

4.1. Water consumption data

Daily household water demand is observed over two periods of two weeks each, once in an arid season and once in a wet season. The data were collected between 1996 and 1998, but for each household, the two seasons of observation occurred within the same year. Daily demand data were gathered by automatic data loggers, attached to magnetic household water meters by utility staff and, thus, out of sight during water use. Total demand was disaggregated into its end uses using magnetic sensors attached to water meters. These sensors recorded water pulses through the meter, converting flow data into a flow trace, which detects the "flow signatures" of individual residential appliances and fixtures (Mayer et al., 1998). We add together consumption from all indoor fixtures (primarily toilets, clothes washers, showers, and faucets) to obtain indoor demand, and consumption from all outdoor uses (irrigation and pools) to obtain outdoor demand.[6] Leaks and unknown uses are included in total demand, but are not modeled explicitly as either indoor or outdoor consumption.[7]

Table 1 provides descriptive statistics. Water demand varies by season, but only for outdoor use. Outdoor water demand in an arid season is, on average, five times outdoor demand during a wet season. In addition, the fraction of observations using any water outdoors, at all, is 0.42. We use Tobit models for outdoor demand, due to this censoring at zero.

4.2. Water price data

The households in the sample face either uniform marginal prices (39%); or two-tier (44%) or four-tier (17%) increasing block prices.[8] Each household faces one price structure throughout each season of observation, but six sample utilities changed prices or price structures between the two periods.[9] Given cross-sectional and time series variation, there are 26 price structures in the data; eight two-tier increasing block structures, ten four-tier increasing block structures, and eight uniform marginal prices. Price variation in the sample is primarily in the cross-section. Regressing prices on city fixed effects results in an R-squared of 0.71, and on household fixed effects, 0.91. This suggests our price elasticity estimates will be closer to long-run than short-run estimates. To estimate the welfare effects of policies restricting water consumption during periodic droughts, ideally we would use short-run demand curves. Unfortunately, the within-household price variation over time in our sample is insufficient to estimate true short-run demand curves. We know of no other data that disaggregate consumption into its indoor and outdoor components that could be used for such a study.

Increasing-block prices create piecewise linear budget constraints, under which marginal price and the quantity consumed are positively correlated. Structural discrete-continuous choice

[3] The sample utilities are: Denver Water Department; Eugene Water and Electric Board; Seattle Public Utilities (and three other Seattle-area utilities: City of Bellevue Utilities, Northshore Utility District, Highline Water District); San Diego Water Department; City of Lompoc; Walnut Valley Water District; Las Virgenes Municipal Water District; Tampa Water Department; City of Phoenix; Tempe Public Works Department; City of Scottsdale Water Department; and Waterloo and Cambridge, Ontario.

[4] The survey achieved an average 45% response rate across cities, and in all cases but for Tempe, AZ, the resulting sample's water use characteristics were not statistically different from the utility's population of single-family water use accounts.

[5] An additional 25–50 accounts were sampled per city, in case some refused to participate. Out of the 1100 households chosen, 40 declined. Some were replaced with households randomly selected from the extra accounts. We drop two households from the total sample of 1084, since they did not report household characteristics.

[6] The listed indoor uses comprise 94% of indoor consumption. Remaining indoor uses include evaporative cooling, dishwashers, bathtubs, water treatment, hot tubs, and humidifiers. In outdoor use, we can distinguish between water for swimming pools and all other outdoor uses. We cannot distinguish among irrigation, car-washing, and washing of sidewalks and driveways, but these uses are all typically regulated or prohibited by drought policies.

[7] Leaks comprise approximately 6% of total consumption, and unknown uses approximately 1%.

[8] About one-third of households in the United States face increasing-block prices. Thus, these price structures are over-sampled in the data. This matters for elasticity estimates only if elasticity varies across price structures – an unresolved empirical question (Olmstead et al., 2007).

[9] The utilities with price changes across the two seasons were: San Diego, Scottsdale, and all four utilities in the Seattle area (City of Seattle, Bellevue, Highline, and Northshore).

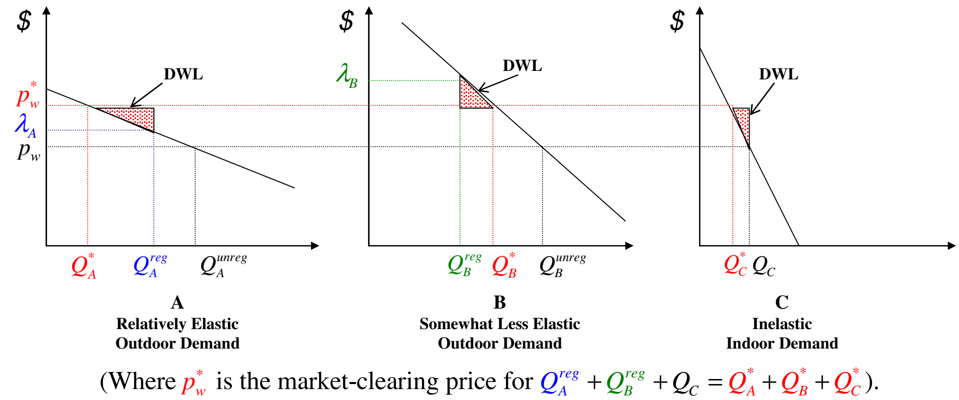


Fig. 2. Welfare losses from outdoor consumption restrictions with heterogeneous outdoor demand.

Table 1
Descriptive statistics.

Variable	Description	Units	Mean	Std. dev.	Min.	Max.
w	Daily household water demand	kgal/day	0.40	0.58	0	9.78
	Arid season	kgal/day	0.54	0.71	0	9.78
	Wet season	kgal/day	0.25	0.34	0	7.17
w_{out}	Daily water demand outdoors	kgal/day	0.22	0.55	0	9.50
	Arid season	kgal/day	0.36	0.69	0	9.50
	Wet season	kgal/day	0.07	0.30	0	6.79
w_{in}	Daily water demand indoors	kgal/day	0.17	0.13	0	1.91
	Arid season	kgal/day	0.17	0.13	0	1.04
	Wet season	kgal/day	0.17	0.13	0	1.91
$P(w_{out} > 0)$	Fraction obs. for which outdoor > 0		0.42	0.49	0	1
$P(w_{in} > 0)$	Fraction obs. for which indoor > 0		>0.99	0.02	0	1
Obs price	Observed marginal water price	\$/kgal/mo.	1.71	0.57	0.50	4.96
Price	Expected marginal water price	\$/kgal/mo.	1.71	0.53	0.76	4.73
Income	Gross annual household income	\$000/yr	69.72	67.66	5.00	388.64
Arid season	Irrigation season = 1/not = 0		0.51	0.50	0	1
Weath	Evapotransp. less effective rainfall	mm/day	5.06	8.41	−46.15	19.37
Maxtemp	Maximum daily temperature	°C	24.12	8.78	0	42.78
Famsize	Number of residents in household		2.78	1.34	1	9
Bathrooms	Number of bathrooms in household		2.58	1.30	1	7
sqft	Area of home	000 ft^2	2.02	0.82	0.40	4.37
Lotsize	Area of lot	000 ft^2	10.87	9.21	1	45.77
Home age	Age of home	yrs/10	2.89	1.62	0.07	5
Evap cooling	Evaporative cooling = 1/not = 0		0.09	0.28	0	1
Region 1	Southern California		0.37	0.48	0	1
Region 2	Arizona		0.19	0.39	0	1
Region 3	Pacific Northwest		0.17	0.38	0	1
Region 4	Florida		0.09	0.29	0	1
Region 5	Ontario		0.08	0.28	0	1
Region 6	Colorado		0.09	0.29	0	1

Notes: kgal is thousands of gallons. Water utilities in each region are as follows. Region 1: San Diego, Las Virgenes, Walnut Valley, and Lompoc (California). Region 2: Phoenix, Tempe, and Scottsdale (Arizona). Region 3: Seattle, Washington and Eugene, Oregon. Region 4: Tampa, Florida. Region 5: Waterloo and Cambridge (Ontario). Region 6: Denver, Colorado.

(DCC) models have been used to estimate water demand under increasing-block prices, accounting for price endogeneity (Hewitt and Hanemann, 1995; Pint, 1999; Olmstead, 2009; Olmstead et al., 2007). These models derive from studies of the wage elasticity of labor supply under progressive income taxation (Burtless and Hausman, 1978), and have benefited from the generalizations of Hanemann (1984) and Moffitt (1986, 1990).

Another common approach is to use the full price schedule, plus fixed monthly charges for water service, as instruments for observed prices in a two-stage least squares (2SLS) model. This, too, is a well-accepted method for dealing with endogenous marginal prices under non-linear price schedules, used in water and energy demand estimation (Olmstead, 2009; Hewitt and Hanemann, 1995; Wilder and Willenborg, 1975), and for estimating the elasticity of taxable income (Gruber and Saez, 2002). The full set of marginal prices in the price schedule is uncorrelated with the unexplained portion of current household demand, but correlated with the price a household does face. The same is true of fixed charges (they are correlated with volumetric prices because regulated utilities meet zero-profit constraints through marginal and infra-marginal rate-setting and the establishment of fixed fees; thus higher marginal prices should imply lower fixed fees, all else constant, and vice-versa). In the context of this paper, however, the IV method has a disadvantage; the price instruments derived from price schedules, alone, do not capture the seasonal variation in marginal prices paid by a household over time created by movement within a price schedule – this variation is precisely the source of endogeneity such IV approaches are designed to eliminate.

We develop an alternative approach here. From a structural model using the same data, we obtain the probability for each household of consuming at each possible marginal price on each day (Olmstead et al., 2007). Probabilities are functions of the structural parameter estimates, the data, and characteristics of each household's water price structure (number and magnitude of marginal and infra-marginal prices, as well as block cutoffs). We use these probabilities from earlier work to estimate an expected marginal price, the sum of the products of marginal prices, times the probabilities of facing those prices.[10] We then use the seasonal average, by household, of these daily probability-weighted prices, as expected prices in the water demand functions. Appendix B describes expected prices in greater detail.

This approach has several advantages.[11] First, it is consistent with the mounting evidence that consumers facing non-linear prices react to an expected or average price that is not necessarily equal to their observed marginal price (Borenstein, 2009, Ito, 2011). Second, our expected prices capture the effect of intra-annual variation in household consumption, primarily due to outdoor watering, that places households in on different tiers of an increasing block price structure in the arid than in the wet seasons. Third, the approach exploits this variation in prices within a household across seasons without introducing endogeneity bias. The source of this bias in a demand function with observed prices on the right-hand side is the fact that a household's marginal price is determined by how much water is consumed; thus, even though increasing-block water price schedules are set administratively, marginal price and quantity are simultaneously determined.

Marginal prices range from $0.00 per thousand gallons (kgal) for the first 4490 gallons per month in Phoenix, to $4.96 per kgal in the most expensive block in the Las Virgenes Municipal Water District, with an average marginal price of $1.71/kgal.[12] The mean expected price is equal to the mean observed marginal water price, and the standard deviation is slightly smaller (see Table 1). Average total expenditures on water in the sample, including fixed charges, are $326 per year, or about 0.47% of average annual household income.

4.3. Household characteristics and weather

We use Mayer et al. (1998) survey data to obtain gross annual household income, as well as household characteristics that proxy for consumer preferences (the vector H from Eq. (1)), including family size, home age and size, lot size, the number of bathrooms, and the presence of evaporative cooling.[13] Home age enters quadratically because we expect that old and new homes may use less water than "middle aged" homes. Old homes may have smaller connections to water systems and fewer water-using appliances, such as dishwashers and hot tubs, than newer homes. The newest homes in the sample may have been constructed with water-conserving toilets and showerheads.

The inclusion of income in H is complicated by the increasing-block prices in the data. Following Hall (1973) and many later applications in labor and environmental economics, we use "virtual income" as our income variable in the demand function to account for the fact that the marginal price is not the price paid for all units consumed, unless household demand lies in the first price block. We add to reported annual income the difference between total water expenditures if the household had purchased all units at the marginal price, and actual total water expenditures, treating the implicit subsidy of the infra-marginal prices as lump-sum income transfers. This introduces simultaneity bias, since virtual income is determined by a household's water consumption. We use two-stage least squares (2SLS) to estimate the water demand functions, instrumenting for virtual income with reported income. In the Tobit 2SLS framework, we must take one extra step to obtain unbiased estimates, including both fitted virtual income and the residuals from the first-stage income equation as independent variables in the second stage (Newey, 1987).

In Z from Eq. (1), we include season (arid vs. wet), maximum daily temperature, and daily evapotranspiration less effective rainfall (0.6 times total rainfall), with daily weather observations from local weather stations (we abbreviate this variable as *weath*). Finally, regional fixed effects control for long-run climate variation not absorbed by daily and seasonal weather variables.[14] The set of independent variables we choose have been shown to influence total household water demand in many other studies. From the Mayer et al. (1998) survey, we might have included many other possible explanatory variables, such as whether a household has a pool or a flower garden, but such variables would be endogenous.

The exogenous variables, vectors H and Z, reflect households' tastes for water consumption. Outdoor demand depends not only on weather, lot size, income, and family size, but also on unobservable tastes for a certain style of living: other variables like number of bathrooms and house size proxy for these tastes. Similarly, indoor demand may be a function not only of the number of bathrooms and other housing characteristics, but potentially lot size, again reflecting households' tastes. For these reasons, we include the full set of exogenous variables in estimating Eqs. (3) and (4).

In our tests of consumer heterogeneity, we divide the sample into four subgroups, based on income and lot size. Income is our best available proxy for ability to pay, and lot size is our best available proxy for preferences for the services that households derive from outdoor water consumption (such as lawns, gardens, pools, and looking better than the neighbors). We expect that wealthier consumers and those with larger lots will be less price-sensitive. Those with both incomes and lot sizes above the sample medians ($55,000 per year, and 9000 ft^2) are categorized as "rich, big lot" households; those with both incomes and lot sizes below the medians are categorized as "poor, small lot" households; and so on for the two groups in between. In the absence of any drought policy, households in these groups consume, on average: 785 gallons/day for rich, big lot; 417 gallons/day for rich, small lot; 488 gallons/day for poor, big lot; and 360 gallons/day for poor, small lot. Households may also be heterogeneous within groups; in this sense, we will underestimate the true DWL from rationing.

[10] Kink point probabilities are, on average, 5% for two-block price structures, and they range from 1% to 3%, on average, for four-block price structures. We divide the kink probabilities evenly (for each household day) between the marginal prices on either side of the kink. Our results are robust to two other assumptions: placing all of the kink probabilities on the prices below the kinks, and placing them all on the prices above the kinks.

[11] We use estimates from a DCC model (estimated for our sample) for this purpose. If we had a longer time series in the sample, we could, alternatively, have exploited prior demand, prices, and other observables to estimate expected prices (Borenstein, 2009).

[12] For some sample utilities, marginal wastewater charges are assessed on current water consumption. In addition, some sample utilities benchmark water use during the wet season as a basis for volumetric wastewater charges assessed the following year. For households observed during these periods (and there are some in the data), effective marginal water prices would include some function of the present value of expected future wastewater charges associated with current use. We do not do this here; marginal wastewater charges are excluded from the present analysis.

[13] Evaporative cooling, common in arid climates, substitutes water for electricity in the provision of air conditioning. Less than 10% of sample households have evaporative coolers, but 43% of sample households in Phoenix have them, and about one-third of households in Tempe and Scottsdale. Households with evaporative cooling use, on average, 35% more water than households without.

[14] Regions are: (1) Southern California (Las Virgenes MWD, City of San Diego, Walnut Valley Water District, City of Lompoc); (2) Arizona (Phoenix, Tempe, Scottsdale); (3) Pacific Northwest (City of Seattle Public Utilities, Highline Water District, City of Bellevue Utilities, Northshore Utility District, Eugene Water and Electric Board); (4) Florida (City of Tampa Utilities); (5) Ontario (Waterloo and Cambridge); and (6) Colorado (Denver).

5. Results

5.1. Comparison of end-use water demand models with endogenous prices

Table 2 compares alternative indoor and outdoor water demand models with different approaches to endogenous marginal prices. Panel A reports indoor demand models. Column (1) reports price and income elasticities from the estimation of equation (3) using a random effects, generalized least squares (GLS RE) model which does not address endogeneity. This naïve model, as expected, suggests upward-sloping demand, reflecting the upward-sloping increasing block price structures in the data. In column (2), we estimate the common 2SLS GLS model described in Section 4.2, instrumenting for marginal prices and virtual income with the full volumetric price schedule, fixed charges, and actual income. The full set of price instruments, including variation over time and across utilities, comprises 21 unique values of the fixed monthly water charge, and 23–24 unique values of each of twelve volumetric prices for consumption at various levels (as many as the price variation in the data will allow), ranging from 1000 gallons to 75,000 gallons per month.

In column (3), we report estimates from the new approach described in Section 4.2, in which we instrument for virtual income with actual income and use expected marginal prices in the demand function. Column (4) reports estimates from a 2SLS model where we check the validity of our expected marginal price estimates by instrumenting for them using the same instruments as in column (2), allowing us to test whether the expected prices are really exogenous.

Moving from column (1) to column (2), it is clear that the standard IV approach deals with the problem of endogenous prices. A Hausman test comparing columns (1) and (2) rejects that the GLS estimates are consistent with the instrumented results. In column (2), while the indoor price elasticity is not significantly different from zero, the sign is negative, and the income elasticity is positive and significant. For indoor demand, it is important to deal with endogenous prices, but the three models that do this have similar results. Finally, we run a Hausman test on columns (3) and (4) to test whether instrumenting for expected prices changes the coefficient estimates. This test fails to reject the hypothesis that the column (3) estimates are not different from column (4), suggesting that column (3) is both efficient and consistent. These results support our expected price approach in column (3).

Panel B of Table 2 reports results from the same set of four treatments of endogenous prices, but for Tobit models of outdoor demand (Eq. (4)). As with indoor demand, the naïve model in column (1) estimates significant upward-sloping demand, reflecting the increasing-block prices. A Hausman test confirms that the estimates in column (1) are inconsistent with those in column (2). In columns (2) through (4), demand is downward-sloping, and income elasticities are positive and significant. The price coefficient in our expected price approach (column (3)) is larger than the one from the traditional IV approach (column (2)). This suggests that the expected prices pick up the variation in marginal prices from households' seasonal movement within the price structure, while the instruments in column (2) do not. Note that the price coefficient in column (4) lies between those in columns (2) and (3). The final Hausman test in Table 2 ($\chi^2 = 9.1$) fails to reject the hypothesis that the full set of column (3) parameter estimates

Table 2
Tests of end-use water demand models with endogenous marginal prices.

	(1)	(2)	(3)	(4)
Panel A: Tests of indoor water demand models				
Results (price and income)				
lnprice	0.618***	−0.074	−0.093	−0.079
	(0.043)	(0.063)	(0.059)	(0.062)
lny	0.029	0.068**	0.069**	0.068**
	(0.029)	(0.027)	(0.028)	(0.027)
Model characteristics				
Method	GLS RE	2SLS RE	2SLS RE	2SLS RE
Instrumented variables	None	lnprice, lny	lny	lnprice, lny
Price variation	Actual	Actual	Expected marginal	Expected marginal
First stage price *F*-stat		564***		4402***
Hausman tests		(1) vs. (2)		(3) vs. (4)
Overall (χ^2)		217.9***		0.6
lnprice (diff. α)		−0.692***		0.014
(s.e.)		(0.047)		(0.021)
lny (diff. μ)		0.039***		−0.001
(s.e.)		(0.01)		(0.006)
Panel B: Tests of outdoor water demand models				
Results (price and income)				
lnprice	0.471***	−0.333***	−0.406***	−0.364***
	(0.045)	(0.05)	(0.052)	(0.054)
lny	0.046*	0.096***	0.108***	0.106***
	(0.024)	(0.02)	(0.022)	(0.022)
Model characteristics				
Method	Tobit RE	Tobit IV RE	Tobit IV RE	Tobit IV RE
Instrumented variables	None	lnprice, lny	lny	lnprice, lny
Price variation	Actual	Actual	Expected marginal	Expected marginal
First stage price *F*-stat		564***		4402***
Hausman tests		(1) vs. (2)		(3) vs. (4)
Overall (χ^2)		1036.9***		9.1
lnprice (diff. α)		−0.804***		0.041***
(s.e.)		(0.023)		(0.015)
lny (diff. μ)		0.050***		−0.001
(s.e.)		(0.015)		(0.003)

Table 3
Models of total, indoor and outdoor water demand.

Variable	Total demand (1)	Indoor demand (2)	Indoor demand, by season (3)	Outdoor demand (4)	Outdoor demand, by season (5)
lnprice	−0.326***	−0.093	−0.086	−0.406***	−0.341***
	(0.069)	(0.059)	(0.059)	(0.052)	(0.053)
lnprice * wet season			−0.034		−0.269***
			(0.028)		(0.038)
lnincome	0.147***	0.069***	0.070***	0.108***	0.108***
	(0.032)	(0.028)	(0.028)	(0.022)	(0.022)
Arid season	0.313***	−0.018	−0.035*	0.420***	0.287***
	(0.021)	(0.016)	(0.022)	(0.022)	(0.028)
Weath	0.008***	0.000	0.000	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maxtemp	0.020***	−0.001	−0.001	0.033***	0.033***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Famsize	0.194***	0.236***	0.236***	0.039***	0.040***
	(0.015)	(0.013)	(0.013)	(0.010)	(0.010)
Bathrooms	0.056**	0.001	0.001	0.057***	0.058***
	(0.025)	(0.022)	(0.022)	(0.017)	(0.017)
sqft	0.125***	0.013	0.014	0.131***	0.132***
	(0.038)	(0.033)	(0.033)	(0.027)	(0.027)
Lotsize	0.008***	0.003*	0.003*	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Home age	0.097*	0.055	0.055	0.061	0.060
	(0.059)	(0.052)	(0.052)	(0.041)	(0.041)
Home age^2	−0.018*	−0.013	−0.013	−0.010	−0.010
	(0.010)	(0.009)	(0.009)	(0.007)	(0.007)
Evap cooling	0.256***	0.197***	0.197***	0.111*	0.114**
	(0.082)	(0.072)	(0.072)	(0.056)	(0.056)
N (observations)	25668	25136	25136	25668	25668
I (households)	1082	1082	1082	1082	1082
R^2 within	0.110	0.001	0.001		
between	0.361	0.272	0.271		
overall	0.211	0.135	0.135		

Notes: For total and indoor models, dependent variable is natural log of daily household demand (total or indoor) and models are 2SLS random effects, instrumenting for virtual income. For outdoor models, the dependent variable is daily household outdoor demand and models are 2SLS Tobit random effects, instrumenting for virtual income. Actual income is the excluded instrument in all models. Regional fixed effects and a constant are included in all models. Columns 4 and 5 also include the residuals from the first stage (fitted income) equation, as in Newey (1987); the parameter estimates for each of these variables are significant at .01 in both models.
*** Significance at .01.
** Significance at .05.
* Significance at .10.

are not different from column (4). While the outdoor price elasticity estimates in columns (3) and (4) are within each other's 95 percent confidence interval, a separate Hausman test on the price coefficients, alone, suggests that the point estimates are significantly different.

Taken as a whole, the results in Table 2 support the choice of the column (3) models, using expected prices directly in the water demand equations, as the main models for the remainder of the paper. We include several robustness checks in Section 5.4, and we carry these through all the way to estimation of welfare impacts in Section 6.3. One such robustness check is the traditional IV model from column (2) of Table 2, which is the least elastic of all of the reasonable models in the table, providing a useful comparison to the main results.

5.2. End-use price elasticity estimates

Column 1 of Table 3 reports estimates of total water demand as in Eq. (2), with the full set of parameters. Expected prices are on the right-hand side, and we use 2SLS to instrument for virtual income. The price elasticity is −0.33, and income elasticity is 0.15.[15] In column (2), indoor use is influenced by income, family size, and evaporative cooling, and weakly by lot size. Outdoor demand parameters are all significant, with the exception of home age. Some significant outdoor demand parameters would seem to be drivers of indoor, rather than outdoor consumption (for example, the number of bathrooms). These variables may be correlated with omitted variables that represent preferences for outdoor water consumption.[16] In columns (3) and (5) of Table 3, we estimate separate price parameters for indoor and outdoor demand, by season.

Table 4 summarizes the results of these models with respect to price, the parameter of interest, and reports elasticities, rather than price coefficient estimates, for the outdoor models.[17] The demand models reveal variation in elasticity across uses and across seasons. Indoor demand is weakly responsive to price in the wet season, but the overall elasticity is not significantly different from zero, and magnitudes are small. Outdoor demand in the wet season is elastic (−1.20), and is still quite responsive to price (though inelastic) in the arid season (−0.67).[18]

Does targeting outdoor consumption, as command-and-control water conservation policies do, provide a good first approximation to a price-based approach? Outdoor uses are those that households,

[15] The median of published short-run price elasticity estimates over the past four decades is about −0.3, and of long-run estimates about −0.6 (Dalhuisen et al., 2003). The income elasticity, 0.14, is low relative to prior studies; the median in the literature is 0.24 (Dalhuisen et al., 2003). Most such estimates exclude many household characteristics which are strongly correlated with income. If we drop all household characteristics but income from the total demand equation in column 1, the income elasticity rises to 0.38.

[16] While these variables are significant in the outdoor models, they have a minimal effect on the price coefficient. If we drop *bthrm*, *sqft*, *age*, *age2*, and *evap* from the model in column 4, the outdoor price coefficient is −0.36.

[17] See the notes to Table 4 for the calculation of Tobit elasticities.

[18] If groundwater wells or public surface water sources are available in the sample for irrigation, our outdoor elasticity estimates are greater in magnitude than they would be in the absence of substitutes.

Table 4
Summary of elasticity estimates.

	Indoor demand elasticities	Outdoor demand elasticities
Overall	−0.093	−0.618***
	(0.059)	(0.080)
Arid season	−0.086	−0.669***
	(0.059)	(0.104)
Wet season	−0.120*	−1.197***
	(0.063)	(0.119)

Notes: See Table 3 for notation. Elasticities are calculated for models reported in Table 3. Indoor elasticities are constant-elasticity demand model coefficients. Outdoor elasticities are estimated as follows, where α_{Tobit} is the Tobit price coefficient, and $\bar{P}$ and $\bar{w}$ are sample averages: $\varepsilon_{out} = \frac{\alpha_{Tobit} * P(w_{out}>0)}{\bar{w}_{out}}$.

Table 5
Price elasticities of demand, by income/lot size group.

Household group	Indoor demand elasticities	Outdoor demand elasticities
Rich, big lot	−0.149*	−0.421***
	(0.083)	(0.117)
Poor, big lot	−0.102	−0.702***
	(0.100)	(0.140)
Rich, small lot	−0.086	−0.712***
	(0.074)	(0.109)
Poor, small lot	−0.060	−0.791***
	(0.078)	(0.112)

Notes: See Table 3 for notation. The number of observations is 7188 for rich, big lot; 4016 for poor, big lot; 7386 for rich, small lot; and 7117 for poor, small lot.

themselves, would choose to reduce most in response to a price increase. But an important cost of the prescriptive approach derives from household heterogeneity.

5.3. Household heterogeneity

To test whether households are, in fact, heterogeneous in their preferences for water consumption, we divide the sample into four sub-groups, based on income and lot size and estimate separate elasticities for the four groups.[19] Results are reported in Table 5. The price elasticity of indoor demand is weakly different from zero, but very small, for the rich, big-lot households, and zero for the other groups. Households presumed to have the strongest preferences for outdoor water consumption, the rich, big-lot group, exhibit the least elastic outdoor demand (−0.42). Those presumed to have the weakest preferences for outdoor consumption, the poor, small-lot group, exhibit the most elastic outdoor demand (−0.79). The two middle groups appear to be about equally price elastic outdoors.[20]

5.4. Robustness of elasticity estimates

We test the robustness of our elasticity estimates by exploring a number of other specifications. Column 1 of Table 6 reports results from 2SLS models using traditional instruments for marginal price, as discussed in Sections 4.2 and 5.1 (we refer to this as the "alternative IV" approach from here onward).[21] The alternative IV results are supportive of our main results, suggesting that households are heterogeneous in the price-responsiveness of outdoor demand, and that indoor demand elasticity is not significantly different from zero, but the relative magnitudes of outdoor elasticities differ from our main results. The two "rich" groups are more elastic than the two "poor" groups. The only (weakly) significantly different groups are the rich, small-lot and poor, small-lot. Clearly, discarding the variation in prices within households over time (as the instruments in the alternative IV approach do) affects our estimates.

The second robustness check in Table 6 (column 2) returns to our expected price model, but uses city fixed effects, rather than regional fixed effects, in the demand models. As discussed in Section 4.2, much of the price variation in the data is cross-sectional by city. Nonetheless, enough price variation within cities remains to estimate elasticities for the four household groups. Indoor elasticities are not significantly different from zero. Outdoor elasticities are all significant and heterogeneous in the same relative order as our main models, though they are somewhat less different from each other (rich, big-lot is weakly different from rich, small-lot and poor, small-lot, but not from poor, big-lot).

We estimate an additional model (column 3) that uses only two observations for each household, collapsing daily variation in household demand and regressing aggregate seasonal demand on the independent variables. In this model, the difference between rich, big-lot households and the other groups is more pronounced than the main model. These estimates are less elastic than the main results. The final robustness check (column 4) uses city-specific median income and lot size, rather than sample medians, to define household groups. In this case, none of the outdoor elasticities are significantly different from each other (though they are all significantly different from zero) and the poor are weakly price-responsive indoors.

These robustness checks are all consistent with the main model conclusions that: (1) indoor demand is much less price elastic (if at all) than outdoor demand; and (2) outdoor price responsiveness differs across households. However, some of the Table 6 models flatten out the differences between household groups in outdoor elasticity, and others exaggerate them relative to the main models. In two cases, robustness checks challenge our result that the rich, big-lot households are the least elastic outdoors. We return to these differences in the discussion of welfare estimates in Section 6.3.

6. Simulations and discussion

Traditional regulations limit the number of days in a week that households may use water outdoors (watering lawns, washing cars, or filling swimming pools). The stringency and enforcement of these type-of-use restrictions vary greatly (Dixon et al., 1996). A common policy is to limit outdoor watering to two days a week. We examine the implications of this policy, as well as limits of three, one, and zero days per week.

Households' willingness-to-pay for the marginal unit of water should increase with drought policy stringency. To calculate shadow prices, we estimate the constrained level of expected consumption for each household under each policy, and then back up along that household's outdoor demand curve – using Eq. (4) – to obtain their willingness-to-pay for the marginal unit of water.[22]

Some households are unconstrained by the policies; their probability of watering on a given day is less than or equal to the probability imposed by the watering restrictions. For constrained households, we calculate the difference in their expected quantity demanded in the unrestricted and restricted scenarios.

For example, for a twice-per-week watering policy, the restricted probability of watering is 2/7 (assuming full compliance).

[19] We define these heterogeneous groups based on sample median income and lot size, and test an alternative definition of city-specific medians as a robustness check.

[20] F-tests find "rich, big lot" to differ significantly from "rich small," "poor big," and "poor small" (p-values are 0.007, 0.055, and 0.005, respectively). The other categories do not differ significantly from each other.

[21] As before, we instrument for virtual income with reported income.

[22] We compute shadow prices using the model estimates underlying the elasticities in Table 5. This model provides predictions of the probability of watering, conditional usage, and the price sensitivity of demand, $\hat{\alpha}$.

Table 6
Robustness of heterogeneity estimates.

	Alternative IV		City FE		Aggregate data		City-specific group classification	
	(1)		(2)		(3)		(4)	
Household Sub-group	Indoor	Outdoor	Indoor	Outdoor	Indoor	Outdoor	Indoor	Outdoor
Rich, big lot	−0.059	−0.548***	0.049	−0.579***	−0.129	−0.191	−0.097	−0.728***
	(0.092)	(0.115)	(0.107)	(0.175)	(0.087)	(0.155)	(0.081)	(0.109)
Poor, big lot	0.046	−0.480***	0.079	−0.759***	−0.087	−0.704***	−0.147*	−0.553***
	(0.108)	(0.138)	(0.124)	(0.198)	(0.102)	(0.183)	(0.088)	(0.119)
Rich, small lot	−0.058	−0.644***	0.089	−0.770***	−0.085	−0.584***	−0.019	−0.611***
	(0.081)	(0.105)	(0.099)	(0.172)	(0.080)	(0.143)	(0.075)	(0.105)
Poor, small lot	−0.065	−0.430***	0.126	−0.818***	−0.121	−0.553***	−0.132*	−0.676***
	(0.084)	(0.108)	(0.105)	(0.180)	(0.081)	(0.146)	(0.077)	(0.106)

Notes: See Table 3 for notation. Results in Table 6 should be compared to the main results reported in Table 5.

Table 7
Shadow prices, market-clearing prices under various drought policies.

Drought policy	Current price mean ($/kgal) [Std. dev.]	Shadow price mean ($/kgal) [Std. dev.]	Market-clearing price mean ($/kgal) [Std. dev.]
(1) Status quo (no drought policy)	1.79		
	[0.61]		
(2) No outdoor watering		50.00	17.85
		[0.00]	[14.82]
(3) Outdoor watering once/week		7.52	7.37
		[11.13]	[9.27]
(4) Outdoor watering twice/week		5.36	4.04
		[8.24]	[3.72]
(5) Outdoor watering 3 times/week		3.68	2.79
		[5.28]	[1.83]

Notes: All prices are for arid season only. We assume willingness-to-pay is at most $50 per thousand gallons.

A household with a probability of watering greater than 2/7 is constrained and will have a resulting decrease in expected quantity demanded, $E(\Delta w_{out_{it}})$, as in (5). Let:

$$\begin{aligned} \mathbf{prob} &= \Pr(\mathbf{X}'\widehat{\boldsymbol{\gamma}}_{out} + \boldsymbol{\nu}_{out} > 0) \\ \mathbf{w}_{out}^{cond} &= E(\mathbf{X}'\widehat{\boldsymbol{\gamma}}_{out} + \boldsymbol{\nu}_{out} | \mathbf{X}'\widehat{\boldsymbol{\gamma}}_{out} + \boldsymbol{\nu}_{out} > 0) \end{aligned} \tag{5}$$

Then for each household day:

$$E(\Delta w_{out_{it}}) = \begin{cases} (prob_{it} - \frac{2}{7}) * w_{out_{it}}^{cond} & \text{if } prob_{it} > \frac{2}{7} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

We estimate $E(\Delta w_{out_{it}})$ for the arid season only, for the four drought policies described above.[23]

The simulation assumes full compliance with drought policies, and that conditional outdoor demand is unchanged under watering restrictions – households water less frequently, but the same amount per watering as they did in the absence of regulation. Most municipal drought ordinances forbid allowing water to run off of residential properties onto sidewalks and streets, making it unlikely that households would over-water in response to reduced allowable watering frequency. Nonetheless, if conditional demand were to increase under the drought policies we simulate, or if compliance were less than full, the aggregate demand reduction achieved under the rationing policy would be less than what we simulate. Adding non-compliance or inter-temporal substitution would, thus, be equivalent to simulating less stringent rationing policies (with smaller welfare impacts), as long as compliance and inter-temporal substitution are not correlated with willingness-to-pay for an additional unit of outdoor water, and short-run supply is not perfectly inelastic.[24] We return the possibilities of non-compliance and increased conditional demand in Section 6.3.[25]

Finally, we do not simulate the impact on demand and welfare of an actual drought – we make no changes to evapotranspiration, rainfall, or maximum daily temperature. Simulating an actual drought would increase the welfare impact of moving to a price-based approach, due to the reduced availability of a substitute (rain), but not by much. Even a 25 percent increase in our weather variable that describes outdoor watering needs (*weath*) would increase consumption by less than one percent.[26] In addition, the characteristics of a drought vary significantly across sample cities, depending not on weather variables, alone, but also reservoir capacity and other characteristics.

6.1. Shadow prices

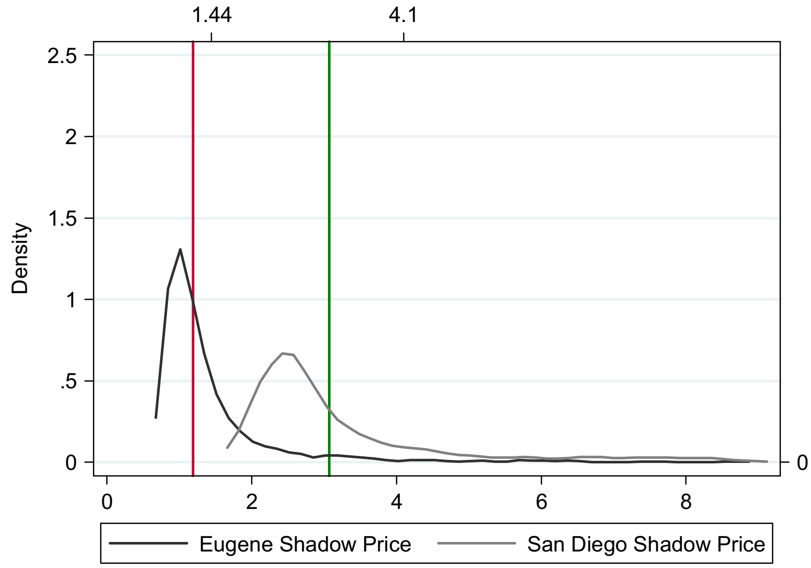
Based on the separate elasticity estimates for our household sub-groups, we calculate shadow prices (by household-day) and market-clearing prices (by utility) under drought policies of varying stringency. Table 7 reports shadow prices for the arid season. In the most extreme policy, when no watering is allowed, our nonlinear functional form implies an infinite shadow price for all

[23] For the two-day-a-week policy, about 86% of the sample is constrained, with rates greater for richer households, and for households with larger lot sizes. Note that with uncertainty, the probability of a policy binding would be nonzero even for households with an expected probability less than $x/7$. However, given the relatively small changes in expenditures, we assume households to be risk neutral over the range of policy simulations.

[24] If non-compliance is punished with a fine, some of the benefits of drought pricing may be realized under the rationing policy, depending on the magnitude of the fine.

[25] Were we to deal with both of these issues by simulating a set of percentage aggregate demand reductions, rather than allowable frequency of watering, we would lose an important benefit of our current approach. The apportionment of aggregate reductions across households would be arbitrary, whereas now it is based upon a household's probability of watering, calculated using the data and parameter estimates.

[26] Our calculation is based on the sample average and coefficient estimate for *weath* reported in Tables 1 and 3, respectively.



Notes: Kernel density estimate of shadow prices for Eugene, Oregon and San Diego, California, for a two day/week watering policy, assuming an epanechnikov kernel with Stata's optimal bandwidth. Numbers at the top of the figure identify average shadow prices for each city, and vertical lines represent the alternative policy of a market-clearing price, in dollars per thousand gallons.

Fig. 3. Distribution of shadow prices in Eugene, OR and San Diego, CA.

customers. We assume that willingness-to-pay is at most $50 per thousand gallons.[27] The most common policy (of allowing outdoor watering two days per week) has an average shadow price of $5.36 per thousand gallons (row 4). Note that this is almost three times the average marginal price consumers actually pay during the arid season ($1.79).

As we would expect, shadow prices increase with the stringency of the drought policy. Furthermore, the standard deviation of shadow prices across all customers is increasing in drought policy stringency. These standard deviations reflect the potential gains from trade achievable through a market. For example, Fig. 3 shows the distribution of shadow prices in two cities Eugene, OR and San Diego, CA.

6.2. Market-clearing prices

We estimate market-clearing prices under drought policies of varying stringency, assuming that each utility's goal is simply to conserve the aggregate quantity of water it would save by implementing each type of drought policy, no matter how that aggregate water consumption reduction is achieved. The aggregate water savings implied by each drought policy is the sum over the $E(\Delta w_{out_{it}})$ in Eq. (5), for all household-days within a utility. From the households' perspective, these savings could be achieved indoors, outdoors, or by purchasing "credits" from another household.[28,29] We then identify the market-clearing price for that aggregate reduction during the arid season, constraining households to non-negative consumption. The total implied seasonal water demand reduction for a two-day-per-week restriction in the full sample is about 32%.

The last column of Table 7 reports market-clearing prices by utility. Like the shadow prices, they increase monotonically with the stringency of watering restrictions. Within a utility, there is a common price. Prices vary substantially, though not as much as shadow prices, across utilities. For the two-day-per-week watering policy, the average market-clearing price is $4.04 per thousand gallons, more than twice the current mean marginal price.

6.3. Welfare implications

The management of water scarcity through residential outdoor watering restrictions results in substantial welfare losses, given the observed heterogeneity in willingness-to-pay. For each utility, we simulate the welfare losses from a two-day-per-week watering policy over a 180-day arid (irrigation) season, relative to the introduction of a market-clearing price. We estimate deadweight loss by integrating demand curves, as described in the Table 8 notes. A technically correct estimate of DWL requires the calculation of compensating or equivalent variation. Our Marshallian consumer surplus estimates should be considered an approximation of DWL.[30]

Table 8 reports the median estimate of average per-household DWL by utility, with 5th and 95th percentiles in parentheses, from 1500 replications of a nonparametric bootstrap. For the bootstrap sampling, we cluster by household, utility and season to account for the fact that observations for a household across seasons are not independent, and to preserve the price variation across utilities and seasons from the original sample. For each bootstrap sample, we re-estimate indoor and outdoor demand elasticities by household group, as well as shadow prices, market-clearing prices, and DWL by utility. The median of bootstrapped DWL estimates ranges

[27] Results are robust to assuming a higher maximum WTP of $100/kgal.

[28] An actual tradable credit system would likely be infeasible due to large transactions costs. However, with no uncertainty, a regulator could equivalently set a higher price so as to clear the market.

[29] While most indoor elasticity estimates in our models are not significantly different from zero, some indoor uses do respond to prices. In Tobit demand equations for individual indoor uses, we find that showers have a price elasticity of −0.15, and clothes-washing of −0.20 (both significant at .01). The other indoor uses have demand curves that are approximately vertical. Given evidence of some price-responsiveness indoors, and the small likelihood that utilities would or could regulate specific indoor uses, we use our overall indoor elasticity estimates in the welfare analysis.

[30] In some of our empirical models, we use constant-elasticity demand functions. In these cases, the difference between our Marshallian consumer surplus estimate and Hicksian equivalent variation is likely to be small (West and Williams, 2004).

Table 8
Estimated welfare impacts by utility.

Utility	Shadow price ($/kgal)		Market price ($/kgal)	DWL ($/household/summer) median [90% C.I.]
	Mean	Std. dev.		
Cambridge, ONT	1.75	0.53	1.69	2.1 [0.3, 6.9]
Waterloo, ONT	2.24	0.34	1.95	2.2 [0.7, 6.1]
Seattle, WA	2.94	0.42	2.91	2.6 [1.7, 5.4]
Tampa, FL	1.93	0.98	1.83	11.4 [6.9, 23.5]
Eugene, OR	1.44	1.05	1.19	16.2 [9.8, 30.2]
Lompoc, CA	3.05	1.23	2.78	20.7 [12.1, 39.4]
Highline, WA	3.96	1.99	3.45	26.2 [8.1, 83.3]
Tempe, AZ	2.66	1.75	2.06	40.9 [20.9, 104.1]
Northshore, WA	3.49	2.05	3.14	41.5 [20.2, 93.7]
Bellevue, WA	3.69	2.26	3.15	41.5 [19.2, 102.0]
San Diego, CA	4.10	3.72	3.07	55.1 [27.8, 125.9]
Denver, CO	3.99	4.41	2.74	67.2 [33.3, 151.6]
Scottsdale, AZ	5.39	4.21	3.79	92.1 [41.5, 265.5]
Phoenix, AZ	5.44	7.44	3.72	138.7 [68.6, 249.4]
Walnut Valley, CA	8.17	9.52	4.97	175.2 [79.2, 317.8]
Las Virgenes, CA	19.43	15.59	14.78	407.7 [199.9, 1299.2]
Sample-weighted Average	5.36	4.44	4.04	95.6 [50.2, 223.4]

Notes: Shadow prices and deadweight losses (DWL) are calculated for a two-day per week outdoor watering policy. Estimates and averages are for arid season only. DWL is estimated as the median area under demand curves from 1500 nonparametric bootstrap replications, with 95% confidence interval in parentheses. For indoor demand, $\hat{w}_{in} = e^{Z\hat{\delta}}e^{H\hat{\beta}}p^{\hat{\alpha}}\tilde{y}^{\hat{\mu}}$. Let $C_{in} = e^{Z\hat{\delta}}e^{H\hat{\beta}}\tilde{y}^{\hat{\mu}}$. Then, $\hat{w}_{in} = C_{in}p^{\hat{\alpha}}$ and the integral is: $C_{in}p(\frac{p^{\hat{\alpha}}}{(\hat{\alpha}+1)}) = \frac{\hat{w}_{in}p}{\hat{\alpha}+1}$. For outdoor demand, $\hat{w}_{out} = \hat{\alpha}\ln p + \hat{\mu}\ln\tilde{y} + \hat{\delta}Z + \hat{\beta}H$. Let $C_{out} = \hat{\mu}\ln\tilde{y} + \hat{\delta}Z + \hat{\beta}H$. Then, $\hat{w}_{out} = C_{out} + \hat{\alpha}\ln p$, and the integral is: $C_{out}p - \hat{\alpha}p + \hat{\alpha}p\ln p$.

from $2.09 per household in Cambridge, Ontario, to $407.66 per household in the service area of the Las Virgenes Municipal Water District.[31] The variation in DWL is correlated with the standard deviation of shadow prices, a strong indicator of potential gains from trade. In our sample, society would be better off by an average of $96 per household per summer through the introduction of drought pricing.[32] If households are modeled as having a common parameter on price, variation in other observables still results in substantial heterogeneity of shadow prices, accounting for about 62% of the DWL: $60 [39, 97]. We have defined heterogeneous household preferences in terms of four groups of households; in reality, preferences and elasticities likely vary by household, though our data are insufficient to estimate elasticities at this fine level. Our DWL estimates increase when we allow more heterogeneity in the sample.[33]

6.3.1. Robustness of welfare estimates

In Section 5.4, we discussed robustness checks (Table 6) for our elasticity estimates. Given the differences between some of these estimates and our main models, we examine the differences in welfare estimates implied by these alternative models, re-estimating shadow prices, market-clearing prices, and bootstrapped DWL. If we use the alternative elasticity estimates from columns 1–4 of Table 6, we obtain median DWL and 95% confidence intervals of: (1) $132.1 [75.1, 281.2]; (2) $78.0 [34.0, 236.1]; (3) $230.9 [169.1, 342.8]; and (4) $60.7 [39.2, 102.8]. Our average DWL estimate is within the 95% confidence interval of the DWL estimates for each of these models, with the exception of the aggregate data model in column 3 of Table 6, for which even the 5th percentile of the average DWL exceeds our median estimate.[34]

6.3.2. Non-compliance with drought policies

Recall from Section 6, our welfare estimates compare drought pricing to a two-day-per-week outdoor watering restriction with which households comply fully, and do not increase the amount of outdoor water used, conditional on watering. The impact of relaxing these assumptions on our DWL estimates varies, depending on what is assumed about the "hardness" of the water supply constraint, and the relationship between willingness-to-pay and compliance. If non-compliance and inter-temporal substitution are random – there is no correlation between a household's probability of compliance and its willingness-to-pay for an additional unit of outdoor water – and a utility's water supply is elastic in the short run, then relaxing either of these assumptions will decrease our DWL estimates. Less water will be saved, at a reduced cost to households. The implications are not as straightforward if water supply is inelastic in the short run, necessitating achievement of the aggregate demand reduction implied by the rationing policy, or if willingness-to-pay is correlated with the probability of compliance.

To quantify the potential impacts of relaxing these assumptions on the welfare estimates, we simulate three non-compliance scenarios (also interpretable as inter-temporal substitution scenarios, since both activities decrease aggregate water savings for a specified rationing policy). In scenario 1, we assume a positive, uniform rate of non-compliance, and inelastic short-run supply. Thus, the utilities must enact a more stringent policy, reducing allowable watering to one day per week. The uniform rate of non-compliance with the one-day policy for each water utility is exactly the rate that preserves the aggregate water savings achievable under full compliance with a two-day policy (the required aggregate water savings) for each utility. On average, this rate is 58%, close to the only estimate available in the literature for average compliance (50%) with mandatory quantity restrictions (Dixon et al. 1996).[35] The mean DWL under this scenario is 12% lower than our main estimate.

Next, we modify scenario 1 by introducing a negative correlation between willingness-to-pay for the marginal unit of outdoor

[31] If we included multi-family homes in a market-based policy, gains from trade might be larger. Their (currently unregulated) indoor use would be added to the "common pool." If sensitive to prices, this would be an additional source of reductions to support increases in higher-valued uses.

[32] Without bootstrapping, the average per-household DWL for the sample is about $107 per household; a small upward bias is introduced from attributing to household heterogeneity some variation in shadow prices that is actually sampling error.

[33] For example, if we divide households by terciles of income and lot size, creating nine heterogeneous groups, we estimate an average per-household DWL about 8 percent higher, $104 [53, 226].

[34] For the aggregate data model, the rich, big-lot outdoor elasticity is small (−.19) and not significantly different from zero. When we bootstrap the DWL estimates for this model, market-clearing prices are often above our imposed cap ($50), so equilibrium cannot be reached for these bootstrap samples – the reported median and 95% confidence interval are based on 1061 bootstrap replications, rather than 1500.

[35] In the same study, only 20% of utilities implementing outdoor watering restrictions assessed penalties for non-compliance. The small number that did levy penalties actually assessed penalties on 12% of household accounts, on average (Dixon et al., 1996). Non-compliance rates are likely much higher under no threat of penalty.

water and non-compliance. The household with the highest shadow price in each utility has a 100% probability of compliance, and the average shadow-price household has the same average probability of compliance as in scenario 1.[36] The average DWL from rationing increases by 10% in this scenario, relative to our main estimate, because to attain the required level of water savings, households with high willingness-to-pay for additional water reduce their outdoor usage more than households with low willingness-to-pay.

In scenario 3, we instead assume positive correlation between willingness-to-pay and non-compliance, assigning the average probability of compliance to the average shadow-price household, and zero probability to the highest shadow-price household. The average DWL from the policy decreases very significantly (by 49%) relative to our main model, because households with low willingness-to-pay contribute more of the burden of water use reduction than those with high willingness-to-pay.

No water rationing policies were in place during collection of the data for our sample, and the literature offers no guidance on the relationship between compliance and willingness-to-pay for outdoor water. Intuition suggests that such a correlation, if it exists, could go either way. High-income households with large lots are more likely than low-income households with small lots to have invested in sprinkler timers, automatic moisture sensors, and other technologies that facilitate compliance with outdoor watering restrictions, and may also be more aware of such restrictions, given their preferences for outdoor use and potentially higher readership of newspapers and other outlets for posting regulations. On the other hand, their economic incentive to cheat on the rationing regulations is higher, since they value the rationed good more than low-income, small-lot households.

6.3.3. Generalizability of results and remaining concerns

To what degree are the single-family households in our sample representative of all single-family households within the 11 cities in which they reside? Five of our 11 cities are represented in the American Housing Survey (AHS) between 1994 and 1998 (recall that our data were collected in 1996–1998): Denver, Phoenix, San Diego, Seattle and Tampa. Compared with occupied, standalone houses from the AHS, households in our data have 10% higher income, 24% smaller housing lots, 4% larger homes, and 13% older homes.[37] As a final check on our main results, we weight the DWL estimates for each of these cities based on the estimated probability that a household is representative of that city's AHS sample.[38] For these cities, weighting using the AHS raises our average per-household DWL estimate for these cities ($60.4) by about 2%, to $61.5 (the average DWL by utility ranges from 86% to 115% of our main estimates).

We face the standard worry about the welfare effects of a theoretical first-best policy in a second-best setting (Lipsey and Lancaster, 1956; Harberger, 1974). Ours is a partial equilibrium analysis, thus spillovers to other markets from changes in water expenditures as a result of a policy change may be a concern, as it is in the well-known theoretical and empirical studies of environmental taxation in a second-best setting (Sandmo, 1975; Goulder et al., 1999; Goulder and Williams, 2003).

In our case, the distortions of greatest concern are within water markets, themselves. In most cases, marginal water prices are well below the marginal social cost of water supply (Hanemann, 1997; Timmins, 2003). Drought pricing will result in higher marginal prices for all households (even if total expenditures fall for some households through lump-sum transfers). To the extent that drought pricing results in more households paying something closer to marginal social cost, the pre-existing distortion does not change the basic nature of our results. However, if marginal prices in the sample are well below marginal social cost, the welfare impacts of moving to drought pricing may pale in comparison to the impacts of moving to marginal cost pricing, period. This is an important issue, but it is beyond the scope of this analysis.

6.4. Distributional implications

While the shift from outdoor watering restrictions to a price-based municipal drought policy would be welfare-improving in all markets, the distributional implications depend on the allocation of property rights. Prices would re-distribute scarce water so that those with high willingness-to-pay for water consumption outdoors would consume more than they do under outdoor use restrictions, and those with low willingness-to-pay would consume less. Hence, drought pricing would result in a water allocation that would "soak the rich."

Under drought pricing, relative to the traditional approach, the consumption share of the least elastic group (at least for outdoor uses), the rich, big lot households, would rise from 34% to 47%; the consumption share for the most elastic group, the poor, small lot households, would fall from 23% to 17%, with smaller reductions in consumption shares by the remaining two groups. Absolute consumption falls among all groups under both types of drought policies.

Given these changes in consumption shares, the largest DWL under the current approach is experienced by the rich, big lot households (Table 9) – in fact, the ordering of DWL by household group follows the ordering of consumption shares under no regulation; those groups who use the most water experience the greatest losses from rationing. A more meaningful number to households is the change in surplus. We calculate the average changes in producers' surplus (PS) to water utilities, consumers' surplus (CS), and average change in CS by group that would result from the adoption of a price-based approach. On average, consumers in each group are worse off under drought pricing, primarily because current average marginal prices do not reflect scarcity, and are thus below current shadow prices. Consumers would not support this change without a rebate. The average PS, $152 per household, could be used for this purpose, as US utilities are usually restricted to zero (or small) profits. Households' minimum rebate to support the policy may equal their average change in CS. The change in CS includes the transfer to producers from introducing the higher market-clearing price, as well as the DWL. The ordering of CS changes by household group mirrors that of the DWL by group, except that poor households with large lots have a greater loss in CS than poor households with small lots. This is due to the fact that average per capita consumption under water rationing among the "poor, big lot" group is larger than among the "poor, small lot" group.

Conditional on lot size, drought pricing without a rebate would be regressive, though more so for households with large lots (column 3 in Table 9). A progressive price-based approach can be designed through the use of transfers. A pure lump-sum rebate, the same amount for each household, would be sufficient to make the overall distributional effects of the policy progressive. Utilities could go further, setting rebates based on whether households are enrolled in utility discount programs for low-income households,

[36] If the slope of the line connecting the highest with the average household suggests a probability of compliance less than zero for the lowest shadow-price household, we re-calculate the probabilities assuming that the lowest shadow-price household has no probability of compliance (but, again, pinning the average shadow-price household at the average probability of compliance).

[37] They are also 11% more likely to have a college degree (for the head-of household), though education is not a parameter in the water demand functions.

[38] Pooling the AHS and end use data, for each city, we run a probit of an indicator for being in the AHS on a third-order cubic spline of income, lot size, house size and house age. We weight using these predicted probabilities.

Table 9
Average deadweight loss and change in surplus by group.

Group	Average DWL ($/arid season)	Average change in surplus	Average change in surplus/ average annual income
Rich, big lot	$ 196 [97, 223]	−$ 97 [−33, −180]	−0.74 [−0.25, −1.37]
Rich, small lot	68 [33, 418]	− 57 [−35, −464]	−0.62 [−0.38, −5.05]
Poor, big lot	38 [21, 229]	− 44 [−29, −100]	−1.21 [−0.79, −2.74]
Poor, small lot	52 [27, 81]	− 25 [−3, −68]	−0.69 [−0.08, −1.93]
Average household	96 [50, 113]	− 58 [−32, −180]	−0.83 [−0.45, −2.57]
Suppliers (per household)	–	152 [88, 412]	

Notes: This table reports medians and [90% confidence intervals] from 1500 nonparametric bootstrap replications. DWL is welfare loss from the absence of a market, expressed here as the gain from implementing a market. Average changes in consumer and producer surplus result from introducing a constant, market-clearing price.

where such programs exist. Low-income households could receive sums greater than their loss in CS, since the average PS exceeds the average CS by the size of the average re-captured DWL. Market-based policies need not be regressive.

7. Conclusions

Using unique panel data on residential end-uses of water, we examine the welfare implications of outdoor water rationing as a demand reduction policy. To deal with endogenous marginal prices under increasing-block price structures, we use estimates of expected marginal prices that capture greater variation than typical instruments used in estimating water demand under non-linear prices. We identify price elasticities for indoor and outdoor consumption. Outdoor uses are more elastic than indoor uses, suggesting that current policies target those water uses households, themselves, are most willing to forgo, on the margin. Nevertheless, we find that use restrictions have substantial welfare implications, primarily due to household heterogeneity in willingness-to-pay for scarce water.

Heterogeneity is often ignored in economic analyses, which proceed from the viewpoint of the "representative consumer." For heavily regulated goods, estimating the welfare gains from introducing markets requires the opposite starting point—it is precisely the variation in marginal benefits that creates potential gains from trade within non-market allocations. We find some potential for substitution within households across end-uses, and some for substitution across households.

Of all the currently regulated markets in which alternative price-based policies have been proposed, municipal water markets may be the easiest in which to imagine actually introducing a price-based approach, even one that involves lump sum transfers to achieve equity goals. Household water use is metered, and monitored by utility staff for the purpose of billing and collection.[39] It is likely that compliance would be higher under a price-based policy than under the current approach. "Cheating" in the market context would require that households figure out how to consume piped water outdoors off-meter, and in the current context can be accomplished by watering at night, or in some other way that avoids observation by utility staff or vengeful neighbors. Were such a system to be implemented, a municipality would have the rare opportunity to affect an actual Pareto improvement, in which gains not only exceed losses, but no household is made worse off.

If concern about "everyone doing their part" during a drought is the reason for the current predominance of command-and-control, rather than market-based approaches to the management of scarce water resources, economists' discussion of potential lump sum transfers and Pareto improvements may fall on deaf ears. There is irony in this. In the long run, command-and-control regulations provide no incentive for the invention, innovation, and diffusion of water conserving technologies (outdoors or indoors). Water priced below marginal social cost also results in inefficient land-use patterns, like the establishment of large, lawn-covered lots and thirsty non-native plant species where water is scarce. Further investigation of the welfare gains from water marketing within and across sectors is an important area for additional research.

Acknowledgments

We are grateful for input from Patrick Bayer, Nathaniel Keohane, Sharon Oster, Robert Stavins, Christopher Timmins, and seminar participants at Yale, Harvard, Dartmouth, Columbia, Rutgers, Williams, Camp Resources, and the California Occasional Workshop on Environmental Economics. The comments of three anonymous referees improved the manuscript considerably. All remaining errors and omissions are our own.

Appendix A

A.1. Theoretical model of welfare effects from drought pricing

The implications for economic theory of rationing outdoor water during a drought are straightforward. Consider a market with two goods, water (w) and a numeraire good (x). Water consumption has two components, indoor use (w_{in}) and outdoor use (w_{out}), and for all households (i), $w_{in_i} + w_{out_i} = w_i$. Households maximize utility, subject to a budget constraint and a constraint on outdoor water consumption imposed by a rationing policy during a drought in consumer i's market (A.1), where φ_i and ψ_i are Lagrange multipliers on the budget constraint and the outdoor water consumption constraint, respectively. The rationing policy we model is a uniform constraint on the number of days households may legally water outdoors each week. However, the constraint on the amount of outdoor water consumed ($\bar{w}_{out_i}$) varies by household since, conditional on watering, each household may use a different quantity of water.

$$\begin{aligned} \max_{\{w_{in_i}, w_{out_i}, x_i\}} \quad & U_i(w_{in_i}, w_{out_i}, x_i) \\ \text{s.t.} \quad & p_w w_i + x_i \leqslant y_i : \phi_i \\ & w_{out_i} \leqslant \bar{w}_{out_i} : \psi_i \end{aligned} \tag{A.1}$$

Under the typical assumptions for an interior solution, the first-order conditions from the maximization problem are given in (A.2), (A.3), (A.4):

$$\frac{\partial U_i}{\partial x_i} - \phi_i = 0 \tag{A.2}$$

[39] This is quite unlike the case of market-based pollution regulation, which requires the installation of continuous emissions monitoring infrastructure (for tradable permits), or the case of congestion pricing, which requires a new system with which regulators can track consumers' use of priced roadways.

$$\frac{\partial U_i}{\partial w_{in_i}} - p_w \phi_i = 0 \tag{A.3}$$

$$\frac{\partial U_i}{\partial w_{out_i}} - p_w \phi_i - \psi_i = 0 \tag{A.4}$$

Let $\lambda_i = p_w + \psi_i$, so that λ is the shadow price of outdoor water consumption (as in Fig. 2). The utility maximization problem gives rise to an indirect utility function, $V_i(p_w, \lambda_i, y_i)$, which by Roy's identity gives the Marshallian demand functions $w_{in_i} = w_{in_i}(p_w, \lambda_i, y_i)$ and $w_{out_i} = w_{out_i}(p_w, \lambda_i, y_i)$.[40]

The DWL from the rationing of outdoor water is a function of the market clearing water price, p_w^*, needed to achieve each market's required aggregate demand reduction (A.5):

$$\sum_{i=1}^{N} w_{in_i}(p_w) + w_{out_i}(\lambda_i) = \sum_{i=1}^{N} w_{in_i}(p_w^*) + w_{out_i}(p_w^*), \tag{A.5}$$

where N is the number of households in the market. We approximate the DWL as the loss in Marshallian consumer surplus from imposing $\bar{w}_{out_i}$, rather than charging p_w^*. In Fig. 2, this is depicted as the sum of the DWL triangles for each household. We sum DWL over all consumers in a market (A.6). As noted in Section 6.3, our Marshallian change-in-surplus estimates should be considered an approximation of Hicksian DWL, though the two would be close for the models using constant-elasticity demand (West and Williams, 2004).

$$DWL = \sum_{i=1}^{N} \left\{ (p_w^* - p_w) w_{in_i}(p_w) + (p_w^* - \lambda_i) w_{out_i}(\lambda_i) - \int_{p_w}^{p_w^*} w_{in_i}(z)dz - \int_{\lambda_i}^{p_w^*} w_{out_i}(z)dz \right\} \tag{A.6}$$

Appendix B

B.1. Estimation of expected prices

The water demand function (B.1) is in exponential form, where w is total daily water demand, Z is a matrix of seasonal and daily weather conditions, X is a matrix of household characteristics, p is the marginal water price, $\tilde{y}$ is virtual income, η is a measure of household heterogeneity, ε is optimization or perception error; and δ, β, α, and μ are parameters.[41]

$$w = e^{Z\delta} e^{X\beta} p^{\alpha} \tilde{y}^{\mu} e^{\eta} e^{\varepsilon} \tag{B.1}$$

Let $\underline{w}_k^*(\cdot) = e^{Z\delta} e^{X\beta} p_k^{\alpha} \tilde{y}_k^{\mu}$, or optimal consumption in block k. Then, unconditional demand under a two-tier increasing-block price structure, in which w_1 is the kink point, can be represented as (B.2), and unconditional price as (B.3).

$$w = \begin{cases} \underline{w}_1^*(\cdot) e^{\eta} e^{\varepsilon} & \text{if} \quad 0 < e^{\eta} \leqslant \frac{w_1}{\underline{w}_1^*(\cdot)} \\ w_1 e^{\varepsilon} & \text{if} \quad \frac{w_1}{\underline{w}_1^*(\cdot)} < e^{\eta} \leqslant \frac{w_1}{\underline{w}_2^*(\cdot)} \\ \underline{w}_2^*(\cdot) e^{\eta} e^{\varepsilon} & \text{if} \quad \frac{w_1}{\underline{w}_2^*(\cdot)} < e^{\eta} \end{cases} \tag{B.2}$$

$$p = \begin{cases} p_1 & \text{if} \quad 0 < e^{\eta} \leqslant \frac{w_1}{\underline{w}_1^*(\cdot)} \\ \text{indet.} & \text{if} \quad \frac{w_1}{\underline{w}_1^*(\cdot)} < e^{\eta} \leqslant \frac{w_1}{\underline{w}_2^*(\cdot)} \\ p_2 & \text{if} \quad \frac{w_1}{\underline{w}_2^*(\cdot)} < e^{\eta} \end{cases} \tag{B.3}$$

Consumption only occurs at the kink point if the consumer maximizes utility for choices that are unavailable at all (p_k, y_k), so for kink observations, $\underline{w}_1^*(\cdot) > w_1$ and $\underline{w}_2^*(\cdot) < w_1$.

From the conditional price equation, we derive a daily probability-weighted price (B.4). Our expected marginal price is the seasonal average, by household, of $\hat{p}$ in Eq. (B.4). Errors are assumed to be independent and normally distributed. Thus, $e^{\eta} \sim LN(\mu_{e^{\eta}}, \sigma_{e^{\eta}})$, and integrations in (B.5) are over the probability density function of the lognormal distribution.

$$\hat{p} = \Pr A * p_1 + \Pr B * (.5p_1 + .5p_2) + \Pr C * p_2 \tag{B.4}$$

where

$$\begin{aligned} \Pr A &= \int_0^{\frac{w_1}{\underline{w}_1^*(\cdot)}} f(e^{\eta}) de^{\eta} \\ \Pr C &= \int_{\frac{w_1}{\underline{w}_2^*(\cdot)}}^{\infty} f(e^{\eta}) de^{\eta} \\ \text{and } \Pr B &= 1 - \Pr A - \Pr C \end{aligned} \tag{B.5}$$

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[40] $w_{in_i} = \frac{\partial V_i}{\partial p_w} / \frac{\partial V_i}{\partial y_i}$; $w_{out_i} = \frac{\partial V_i}{\partial \lambda_i} / \frac{\partial V_i}{\partial y_i}$.

[41] The structural model includes two additional parameters, σ_η and σ_ε. Our approach does not allow separate identification of the two error variances. We use the structural estimate of σ_η to calculate block and kink probabilities in (B.5).

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