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Conservation policies: Who responds to price and who responds to prescription?[☆]

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The efficiency properties of price and nonprice instruments for conservation in environmental policy are well understood. However, there is little evidence comparing the effectiveness of these instruments, especially when considering water resource management. We exploit a rich panel of residential water consumption data to examine heterogeneous responses to both price and nonprice conservation policies during times of drought while controlling for unobservable household characteristics. Our empirical models suggest that among owners of detached, single-family homes in six North Carolina municipalities, relatively low-income households are more sensitive to price and relatively high-consumption households are less sensitive to price. However, prescriptive policies such as restrictions on outdoor water use result in uniform responses across income levels, while simultaneously targeting reductions from households with irrigation systems and historically high consumption.

Introduction

Although prescriptive policies are commonly employed by resource managers to encourage conservation, economists tend to advocate for pricing mechanisms on efficiency grounds. However, many environmental management contexts involve resources whose prices are regulated by utility commissions or federal oversight. As such, the use of pricing tools to encourage conservation is politically challenging. This is particularly true with water resource management. Efficiency would dictate that price should reflect long-run marginal cost of provision, including scarcity rents, which is typically greater than regulated market prices (Mansur and Olmstead, 2012). As such, nonprice strategies, also referred to as prescriptive policies, have become popular demand management tools for water conservation during periods of drought when the short-run reliability of water resource systems is at risk. These strategies can take the form of restrictions on outdoor

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water use (Castledine et al., 2014; Renwick and Green, 2000), information campaigns (Coleman, 2009), social comparisons (Ferraro and Price, 2013; Brent et al., 2015), or financial incentives for technology adoption (Bennear et al., 2013; Renwick and Archibald, 1998).[1] A noteworthy case where nonprice (and to a lesser degree, price) policies have been adopted to reduce water consumption is that of California, where Governor Jerry Brown recently issued an executive order that mandates a 25 percent reduction in urban potable water use to combat the ongoing statewide drought.[2]

Despite growing use of nonprice policies in environmental contexts, and a corresponding literature measuring their effectiveness, there is little evidence of the relative merits of pricing versus prescriptive restrictions using household-level data that allow consideration of both policy types simultaneously. Moreover, there is even less evidence about the heterogeneity in responsiveness to these conservation tools across households. This research aims to fill these gaps with an application to residential water demand management. These responses are important to understand because water utility managers and policymakers are concerned with the incidence of pricing policies on lower-income households. Further, an important goal of water utilities is to manage the use of high-consumption households to minimize the need to invest in additional water infrastructure. While efficient pricing—such as dynamic increasing block rates or lump-sum rebates to low-income households—could address some of these concerns, they are rarely used in practice.

In this research, we provide evidence on important observable household and housing characteristics that influence responsiveness to demand-side management policies while econometrically controlling for unobservable household attributes. Olmstead and Stavins (2009) lay out an exhaustive comparison of price and nonprice policies and conclude that neither prices nor prescriptive policies are superior in their distributional bona fides, despite prices being a more cost-effective management tool. Although we do not directly consider the incidence of price and nonprice policies in this research, we provide strong empirical evidence that prescriptive conservation interventions have more palatable impacts across socioeconomic groups (compared with pricing policies) and lead to reductions among high resource users.

Our analysis exploits a rich dataset of monthly water consumption for 1727 households residing in detached, single-family homes located in six North Carolina municipalities. The data cover a two-and-a-half-year period that includes one of the most severe droughts in North Carolina history, as well as normal weather conditions. Our data include variation in drought conditions, price, and nonprice policies across municipalities both spatially and temporally. Further, for each household we observe socioeconomic and housing characteristics, including the household's income, lot size, and whether an irrigation system is present. Our rich panel data allow us to improve on the econometric strategies of recent research on water conservation that uses either aggregate data (Renwick and Green, 2000; Klaiber et al., 2014; Halich and Stephenson, 2009), relatively short panel data (Olmstead, 2009; Mansur and Olmstead, 2012) or data without simultaneous variation in pricing and prescriptive policies (Nataraj and Hanemann, 2011; Ferraro and Price, 2013; Castledine et al., 2014; Wichman, 2014; Brent et al., 2015). Given the long panel and rich variation in key variables, we are able to identify price and nonprice policy responses that reflect short-run responses within a household while controlling for time-invariant unobservable household characteristics that might confound results.

Our results suggest that voluntary and mandatory prescriptive policies focused on outdoor watering restrictions achieve approximately an 8.5 and 13 percent reduction in aggregate consumption, respectively. Interestingly, there is a notable lack of heterogeneity among households in their responsiveness to voluntary and mandatory prescriptive policies, with the very important exception of households with irrigation systems or those that are large-volume consumers. Households with irrigation systems and households in the upper 20th percentile of average consumption in their municipality are found to be almost twice as responsive to mandatory policies relative to other households. These results are robust to alternative model specifications, controls for the irrigation season, and definitions of key variables.

With respect to price responsiveness, we find short-run price elasticities ranging from -0.15 to -0.30 in our preferred models, which is consistent with the existing literature. Moreover, results from our empirical models suggest that there is important heterogeneity in how households respond to price: relatively low-income households are more responsive to price, whereas households with irrigation systems are essentially unresponsive to the price changes that occurred during our sample period. However, our estimated price coefficients are sensitive to whether we include the average or marginal price of water in the model, where the former generates robust and plausible demand responses but the latter does not. As we describe in the empirical strategy and results section, there are behavioral reasons why households may respond to average, rather than marginal, prices (e.g., Ito, 2014; Wichman, 2014). Alternatively, the sensitivity of our marginal price coefficients may be driven by limited price variation. We find this explanation somewhat less likely since our robust and plausible average price results are identified with *less* price variation than the inconsistent marginal price results (see the empirical strategy and results section). Regardless, it is interesting to note that our elasticity estimates suggest that an average price increase of more than 50 percent would be required to achieve the same 13 percent reduction in water use that the prescriptive policies achieved. This price increase would raise annual expenditures on water by $330 for the average household in our sample.[3] Of course, this calculation is only suggestive since it is based on a large, non-marginal change in price that is outside the range of our observed data.

[1] Select examples of these tools being used in the energy sector to manage household demand include social comparisons (Allcott, 2011) and financial incentives for technology adoption (Alberini et al., 2013).

[2] https://www.gov.ca.gov/docs/4.1.15_Executive_Order.pdf, (accessed 08.10.15).

[3] All dollar values reported are real and have been deflated to 2006$.

The remainder of the paper proceeds as follows. In the next section, we motivate our empirics by highlighting the unique data used in the analysis. The third section provides empirical models of residential water demand that incorporate household heterogeneity explicitly and presents key empirical results and sensitivity analyses. In the final section, we discuss the policy implications of our results and offer concluding remarks.

Data

Our empirical analysis couples 30 consecutive months of household-level billing data with survey responses for a sample of households in six municipalities across North Carolina. Our data have rich spatial and temporal variation in weather conditions, water rate structures, household water consumption, and demand-side management programs. We describe each of these features below.

We observe monthly water use for 1727 households residing in detached, single-family homes from July 2006 through December 2008, which spans two summers with persistent drought conditions (2007 and 2008) and one summer with normal conditions (2006). The six municipalities that provided water utility billing data are listed in Table 1, along with summary statistics for the households surveyed in each community. The municipalities span the three geographic regions of North Carolina, and the average weather and growing conditions vary across these municipalities as a result. Fayetteville and Greenville are in the coastal plain region of the state and are the warmest, with average July maximum temperatures of 90 degrees. Hendersonville is in the mountainous, western part of the state and is the coolest municipality, with average July maximum temperatures of 84 degrees. Charlotte, High Point, and Chapel Hill are in the central piedmont region of the state and have weather closer to that of the coastal plain, with average July maximum temperatures between 88 and 90 degrees.

Monthly water billing data including water and sewer usage were obtained in each of these municipalities. A stratified, random sample of households residing in detached, single-family houses with complete billing data was selected for a

Table 1
Summary statistics.

	Chapel Hill	**Charlotte**	**Fayetteville**	**Greenville**	**Hendersonville**	**High Point**	***Total***
Households (N)	234	363	388	226	245	271	1727
Panel A. Demographic characteristics							
Mean HH income	183,987	135,520	88,622	107,931	124,692	114,697	123,034
(std. dev.)	(115,693)	(97,469)	(56,627)	(66,176)	(88,834)	(59,002)	(87,140)
[Median]	[162,500]	[112,500]	[85,000]	[112,500]	[112,500]	[112,500]	[112,500]
Mean home value	355,203	244,868	141,645	188,328	290,638	188,220	226,214
(std. dev.)	(133,218)	(124,512)	(54,530)	(79,609)	(142,735)	(70,960)	(124,512)
[Median]	[325,000]	[225,000]	[137,500]	[187,500]	[275,000]	[187,500]	[187,500]
Mean lot acreage	0.553	0.532	0.633	0.526	1.122	0.513	0.634
(std. dev.)	(0.676)	(1.378)	(1.614)	(0.607)	(3.008)	(1.020)	(1.603)
[Median]	[0.420]	[0.295]	[0.420]	[0.420]	[0.630]	[0.420]	[0.420]
Mean home sq. ft.	2725	2711	2790	2633	2793	2636	2718
(std. dev.)	(808.1)	(939.2)	(1188.5)	(980.0)	(1085.6)	(908.9)	(1003.7)
[Median]	[2750]	[2250]	[2250]	[2250]	[2250]	[2250]	[2250]
Mean HH size	2.858	2.573	2.473	2.378	2.335	2.618	2.540
(std. dev.)	(1.314)	(1.183)	(1.217)	(1.086)	(1.041)	(1.231)	(1.198)
[Median]	[2.0]	[2.0]	[2.0]	[2.0]	[2.0]	[2.0]	[2.0]
Panel B. Monthly household water consumption: 30-month average (1000 gallons)							
Mean	5.232	6.235	5.099	5.560	4.717	4.668	5.289
(std. dev.)	(3.825)	(4.795)	(3.649)	(4.104)	(3.649)	(3.031)	(3.947)
[Median]	[4.000]	[5.236]	[4.000]	[4.480]	[3.800]	[3.740]	[4.480]
[10th–90th percentile]	[2.0–9.0]	[2.2–11.2]	[2.0–9.0]	[2.2–9.7]	[1.9–8.5]	[1.5–8.2]	[2.0–9.0]
Panel C. Monthly average effective water charges by municipality (30-month average, per 1000 gallons)[a]							
Mean AP	12.44	6.78	8.79	9.10	13.06	11.90	10.00
Mean MP	8.95	7.02	7.62	6.70	10.03	8.23	7.99
Mean base charge	17.95	3.49	7.70	12.59	13.39	15.26	10.90

[a] Effective prices are calculated as monthly prices paid by consumers adjusted for inflation to 2006$.

telephone interview that collected information on household demographics and irrigation habits. Interviews took place during August and September 2009 and were conducted by the Agricultural Statistics Division of the North Carolina Department of Agriculture and Consumer Services.[4] Between 225 and 388 surveys were completed in each municipality.[5]

Household characteristics

As indicated in Panel A of Table 1, our sample's mean income and median income are $123,034 and $112,500, respectively.[6] Given that our sample is composed entirely of owners of detached, single-family homes in relatively urbanized areas, it is not surprising that their incomes are significantly higher than that of the median North Carolina household in 2010 ($45,570). Mean income varies by municipality, ranging from $88,622 in Fayetteville to $183,987 in Chapel Hill. To gauge the representativeness of our sample to the municipalities from which the homes are sampled, we compare home values to the median home values within each municipality's boundary as reported by census. As shown in Table 1, median home values in our sample vary from $137,500 in Fayetteville to $325,000 in Chapel Hill. For five of the six municipalities, the median home value for the sample is approximately 30 percent higher than the census-reported median home value for the entire municipality. The exception is Chapel Hill, in which the median value for our sample of homes is 9 percent lower than the median home value for all of Chapel Hill.

Mean home size is approximately 2700 square feet across each of our municipalities, and the mean lot size is 0.6 acre, with the exception of Hendersonville in the mountainous western part of the state, which has an average of 1.1 acres per household. The average household size in the sample varies from 2.34 to 2.86 individuals per home, while the average for North Carolina during this time period was 2.47 individuals per dwelling unit of any type.

Water consumption and pricing

Panel B of Table 1 presents summary statistics for household water use. The mean monthly household consumption is 5289 gallons per month for the full sample, which is very close to the North Carolina average consumption of 5259 gallons per month per household.[7] The distribution of water use among households is right-skewed, as indicated by medians being less than means for all municipalities. As shown in the last row of Panel B, the 90th percentile of monthly water use among our sample is nearly double the magnitude of mean monthly use.[8] Across municipalities, residents in Charlotte consume the most water on average, and High Point residents the least.

Panel C in Table 1 reports the real prices paid by utility customers per 1000 gallons consumed, adjusted to 2006$. Each utility bills customers on a monthly basis and combines water and sewer charges into one bill.[9] We construct average and marginal volumetric charges for combined water and sewer use for each household in each month based on its ex post water consumption and published utility rate sheets. Four municipalities have an increasing block-rate structure during at least part of the study period, and two have a flat-rate structure throughout. Because all municipalities charge a base (fixed) service fee for water and sewer use, the average and marginal prices for water consumed diverge in all communities, not just those with increasing block rates.[10]

As indicated in Panel C, there is considerable heterogeneity in water prices across the municipalities. Mean average price across municipalities varies from $6.78 to $13.06 per thousand gallons, with Charlotte customers paying the lowest average prices and those in Hendersonville paying the highest. The differences in average prices are primarily driven by the wide variety in the fixed base service fee across municipalities ($3.49 to $17.95; see the third row of Panel C). Fixed fees are not reflected in marginal prices, and thus the variation in the mean marginal price paid is less than that of average price, varying from $6.70 to $10.03 across municipalities.

Panel A of Fig. 1 indicates the variability in water consumption over the study period. As shown, Charlotte has visibly higher average per capita consumption than the rest of the municipalities, with large peaks in the summers of both 2006 and 2007. Peak summer consumption in Chapel Hill is somewhat smaller than in Charlotte in 2006 and 2007, and it is the lowest among all municipalities in 2008. During summer 2008, Greenville exhibits the largest summer peak. Fayetteville tracks Greenville in early summer but then reduces average consumption by midsummer and is among the lowest for the sample during late summer 2008. Overall, there is a clear reduction in the peak for the summer of 2008 for most of the

[4] Phone numbers were purchased from InfoUSA, a private vendor, since the participating water utilities generally did not maintain phone numbers for their customers.

[5] Note that the billing and survey data are drawn from each water utility service area and thus encompass a broader population than just residents living within the city limits.

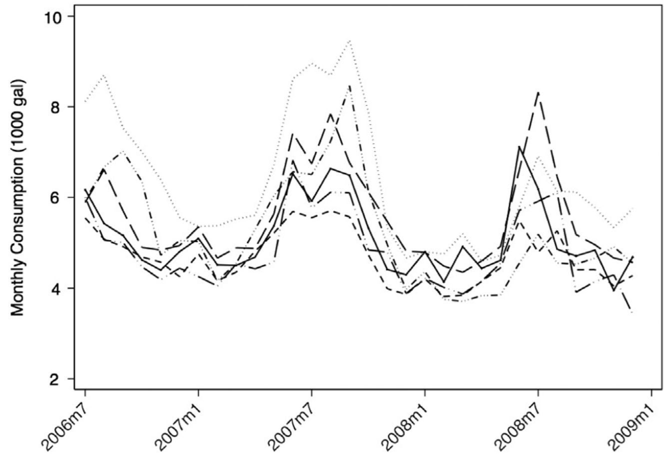
[6] Due to item nonresponse, household income data are taken from InfoUSA, the vendor providing household phone numbers. These income data are more disaggregated than survey-reported income.

[7] Average consumption for North Carolina is constructed using an estimated per capita consumption of 70 gallons per day in 2005 (Kenny et al., 2009).

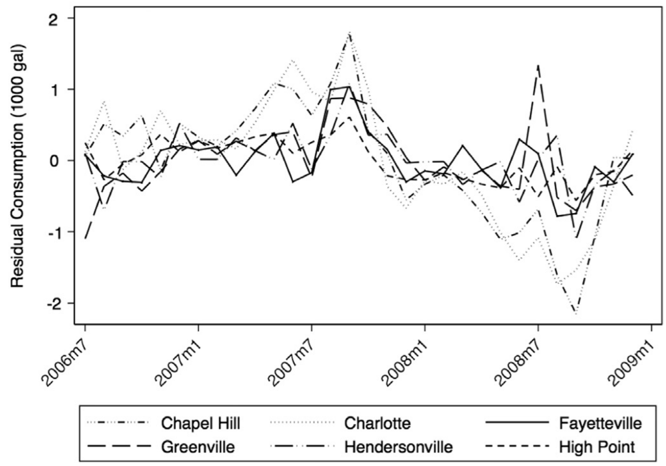
[8] Several municipalities in our study round consumption to the nearest thousand gallons each month for billing purposes. This factor explains the prevalence of 2000 gallons as the 10th percentile of consumption for the sample.

[9] For all utilities in our sample, sewer use is billed at the volume of metered water consumption, which is common practice in North Carolina.

[10] The two municipalities with flat rates actually had in place a declining rate structure for at least part of the study period. However, the first block was so large (e.g., up to 40,000 gallons per month) that nearly 100 percent of their customers fell well within the first block. Thus we treat these two communities as having a flat-rate structure.



Panel A. Mean monthly household consumption over time (1,000 gallons)



Panel B. Plot of sample mean residuals by municipality from a simple regression of consumption on monthly fixed effects (1,000 gallons)

Fig. 1. Water consumption by municipality over time.

utilities, with the exception of Fayetteville and Greenville. In the winter months, average consumption in Charlotte is consistently higher than the remaining five municipalities, which all have similar consumption levels.

In Panel B of Fig. 1, we plot the sample mean residuals by municipality for the 30-month period from a simple regression of household water use on monthly fixed effects. The figure highlights consumption differences across municipalities relative to normal seasonal consumption. Notably, consumption for Chapel Hill and Charlotte deviates positively from monthly averages in the summer of 2007 (prior to the drought and policy interventions) but tends negative from early 2008 onward. Most other municipalities display a positive deviation in 2007, with slightly lower residuals toward the end of the sample. The residual in Greenville, however, peaks in July 2008, which is when drought subsided for that municipality.

Fig. 2 presents the variation in real prices paid by water customers over the study period. As shown in Panel A, Charlotte customers paid the lowest average prices, while Chapel Hill, High Point, and Hendersonville customers paid the highest. A slightly increasing trend in average prices across all municipalities is evident, particularly toward the end of the sample. This increasing trend is driven by changes in rate structures implemented by each utility over the study period. All of the municipalities increased their prices in some way over the study period. In particular, Chapel Hill customers faced a uniform water rate until July 2007, after which an increasing block rate structure was adopted. In addition, Chapel Hill implemented seasonal and drought-induced surcharges in its rate schedule.

Panel B in Fig. 2 presents mean marginal prices over time and indicates that Hendersonville exhibits the consistently highest marginal price, with little variation over time, while Chapel Hill is the most variable, with mean marginal prices peaking higher than those of any other municipality because of an aggressive drought pricing mechanism. Greenville and Charlotte display the lowest marginal prices, reflecting similar trends to average prices, though Charlotte's introduction of

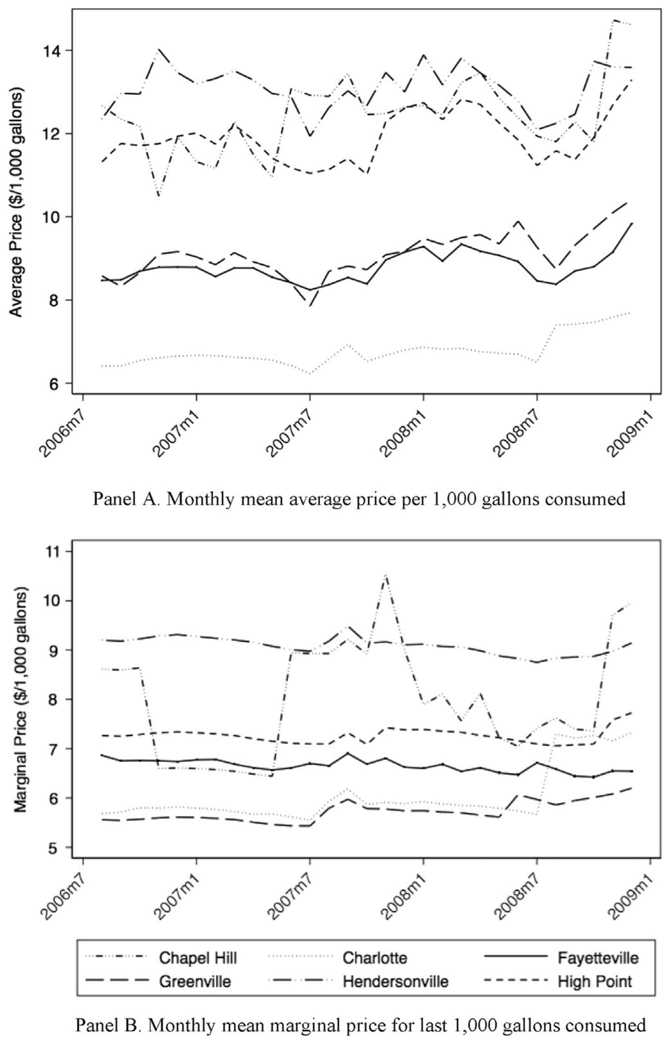


Fig. 2. Mean monthly average and marginal prices.

increasing block rates in the summer of 2008 raises the observed marginal price in the later months. Overall, by comparing Panels A and B, we see that average prices are more time-variant than marginal prices within a municipality.

Drought and policy parameters

An integral part of our research is the presence of significant water scarcity throughout North Carolina beginning in summer 2007. Table 2 presents a summary index of monthly drought conditions in each municipality throughout the study period, along with an indicator of whether voluntary (V) or mandatory (M) watering restrictions were in place for the majority of that month. We average over weekly drought conditions to compute the average status for each month. Weekly drought conditions are described by one of six categories ranging from "normal conditions" (=0) to "exceptional drought" (=5), the most severe category possible.[11] Thus, if in all weeks of a month a municipality is recorded as having "exceptional drought," the index for that month would be 5.0. Average conditions over the month are represented by shades of gray in Table 2, where the darkest shade with dots indicates a month with at least half of the weeks categorized as "extreme" or "exceptional drought," and diagonal lines indicate a month with all weeks classified as having "exceptional drought." The absence of color indicates a month in which the average drought condition across weeks in that month is less than 1.0 (see Table 2 for more details).

[11] Specifically, the categories are 0=normal conditions, 1=abnormally dry, 2=moderate drought, 3=severe drought, 4=extreme drought, and 5=exceptional drought. The definition of each drought category is from the US Drought Monitor, http://droughtmonitor.unl.edu/ (accessed February 19, 2016).

Table 2
Drought conditions and policy responses by municipality.

Year	Month	Chapel Hill	Charlotte	Fayetteville	Greenville	Henderson-ville	High Point
2006	Jul			M			
	Aug			M			
	Sep			M			
	Oct						
	Nov						
	Dec						
2007	Jan						
	Feb						
	Mar						
	Apr						
	May			M			
	Jun		V	M			
	Jul		V	M			
	Aug		V	M			
	Sep		M	M		V	V
	Oct	V	M	M		V	M
	Nov	M	M	M		V	V
	Dec	M	M	M	V	V	V
2008	Jan	M	M	M	V	V	V
	Feb	M	M	M	V	V	V
	Mar	M	M	M	V	V	
	Apr	V	M	M	V	V	
	May	V	M	M	V	V	
	Jun		M	M		V	
	Jul		M	M		V	
	Aug		M	M		M	
	Sep		M	M		M	
	Oct		M	M		V	
	Nov		M	M		V	
	Dec		M	M		V	

Notes: Drought conditions are reported weekly by the U.S. Drought Monitor using a scale in which 0 equals normal conditions and 5 equals "exceptional drought" (see the drought and policy parameters section for a detailed description). Average conditions over the month are represented by shades of gray. The darkest shade with diagonal lines indicates a month in which all weeks were classified as having "exceptional drought," and no color indicates a month in which the average drought condition across weeks in that month is less than 1.0. The lightest gray indicates an average of 1 to 1.99, and each successively darker shade of gray indicates monthly averages that range from 2 to 2.99, 3 to 3.99, and (with dots) 4 to 4.99. If a voluntary or mandatory watering restriction was in place for at least half the month, the cell is labeled with a V or M, respectively.

As indicated in Table 2, by September 2007 all regions were in severe drought. All regions were subsequently elevated to "exceptional drought" status—the most severe classification—by December 2007. These drought conditions persisted until April 2008 and gradually returned to normal levels afterward.

Water utilities in North Carolina responded to the 2007 drought by encouraging residential conservation through voluntary and mandatory outdoor watering restrictions. Among municipalities, voluntary restrictions typically took the form of asking customers to limit outdoor lawn and garden watering to two to three days a week or to water only during off-peak hours. In addition, customers were encouraged to limit other nonessential uses of water, such as washing cars, houses, or driveways. Mandatory restrictions were generally of the same form as the voluntary restrictions, but the austerity of the actions were increased, as described below.

Table 2 presents the months when voluntary and mandatory restrictions were in place, and Table 3 summarizes the restrictions broadly for each municipality.[12] As indicated in Table 2, all municipalities in our sample employed either voluntary or mandatory restrictions (or both) during the study period; however, Greenville (Fayetteville) never implemented a voluntary (mandatory)

[12] The characterization of the drought restrictions in Table 3 as either voluntary or mandatory is admittedly a coarse definition that was driven by data limitations. The policies considered, however, are comprehensive. No other policies were implemented to reduce consumption during our study period. North Carolina utilities are required to have a water shortage response plan that dictates what types of conservation initiatives they will implement when specific hydrological triggers are met.

Table 3
Components of voluntary and mandatory restrictions implemented.

	Voluntary restrictions		Mandatory restrictions		
	Turf irrigation	Other outdoor use	Turf irrigation	Nonturf irrigation	Other outdoor use
Chapel Hill	Odd–even	Limited	X	Limited[a]	X
Hendersonville	Limited	Limited	X	X[b]	X
Greenville	Limited	X			
High Point	Odd–even	X	X	X[b]	X
Fayetteville			Odd–even		X[c]
Charlotte	Limited		X: Sep07–Mar08 *Limited*: Apr–Sep08 *Odd–even*: Sep–Dec08		X: Sep07–Apr08 *Limited*: May–Dec08

Notes: An X indicates a complete restriction (ban) is suggested during voluntary restrictions or required during mandatory restrictions; "Odd–even" denotes an alternating watering schedule based on a household's street address; and "Limited" denotes that there are time-of-day or other miscellaneous water-use restrictions.
[a] Nonturf irrigation was completely prohibited in the last month in which mandatory restrictions were in place.
[b] Limited watering of vegetable gardens only is allowed.
[c] Complete restriction on other outdoor uses added to mandatory restrictions in November 2007.

policy. Two of the six municipalities (Fayetteville and Charlotte) implemented mandatory restrictions as early as May 2007 and September 2007, respectively, and kept them in place through the rest of our study period.[13]

During 2007, Charlotte and Fayetteville implemented similar mandatory restrictions. In summer 2007, both of these municipalities limited outdoor lawn watering to two days per week. In summer 2008, Charlotte strengthened this restriction to one day per week, while Fayetteville continued to allow two days per week. High Point and Chapel Hill implemented mandatory restrictions on outdoor water use, but not during the primary growing season in the case of Chapel Hill or for only one month in the case of High Point. Hendersonville implemented mandatory restrictions that banned lawn watering during the last two months of summer 2008. Greenville never moved from voluntary into mandatory restrictions. Overall, there is some degree of heterogeneity in the austerity of watering restrictions and enforcement across municipalities, an issue we explore in the next section.

Empirical strategy and results

The goal of our empirical analysis is to estimate the impacts of price and nonprice policies across sociodemographic and housing characteristics. To begin, however, we empirically investigate a number of modeling issues that help frame our subsequent analysis. First, an important empirical question centers on the specification of price—marginal or average—used in estimation. Economic theory strongly suggests that marginal price drives consumer decisions, but recent research indicates that average price may be more behaviorally relevant (Ito, 2014; Wichman, 2014). Second, how households respond to voluntary and mandatory policy interventions may depend on current drought conditions. In other words, policies may generate one set of behavioral responses when water scarcity is extreme and a different set otherwise. Third, as described in the previous section, we constructed relatively coarse dummy variables for the presence of voluntary and mandatory policies in the six municipalities. These variables, however, may mask heterogeneity across municipalities in terms of the particular policies adopted and how they were enforced.

To shed light on these issues, we estimate variations of the following log-linear water demand model:

$$\ln(q_{ikt}) = \beta_1 \ln(p_{ikt-1}) + \beta_2 \text{Voluntary}_{kt} + \beta_3 \text{Mandatory}_{kt} + \text{W}_{kt}\gamma + \theta_t + \alpha_i + \varepsilon_{ikt}, \tag{1}$$

where q_{ikt} is the monthly water demand for household i in municipality k in period t, $p_{ikt\text{-}1}$ is the corresponding (marginal or average) price of water lagged one period, Voluntary_{kt} and Mandatory_{kt} are dummy variables for whether voluntary or mandatory water restriction policies are in place in municipality k and period t, W_{kt} contains a second order Taylor series approximation of a nonlinear function of two weather variables (mean maximum daily temperature and total rainfall) and a drought control described below, α_i is a household fixed or random effect, θ_t is a month fixed effect, and ε_{ikt} is the model error term.

Table 4 reports summary statistics for variables included in our model. To account for the simultaneity of price and quantity arising from nonlinear pricing schedules, we follow common practice in the water demand literature and instrument $\ln(p_{ikt\text{-}1})$ with base service fees and marginal price (both in log form) evaluated at eight different levels of monthly consumption (Olmstead, 2009).[14] The rationale for these instruments is that the full structure of the block-rate schedule is correlated with the price a

[13] Since the 2002 drought, Fayetteville's default drought policy has been to implement mandatory restrictions corresponding to the irrigation months (May–September).

[14] Base service fees include both water and sewer fixed charges. Marginal prices are calculated at the following consumption levels: 1000, 3000, 5000, 7000, 9000, 12,000, 15,000 and 20,000 gallons. As a sensitivity analysis, models are also estimated with marginal price constructed at several other consumption levels, and the results reported here are robust to these perturbations.

Table 4
Variable definitions and summary statistics.

Variable name	**Definition**	**Mean (std. dev.) {N=48,166}**
Panel A. Consumption and fees		
q_{ikt}	Monthly water consumption for household i in municipality k in month t (1000 gallons)	5.29 (3.95)
AP_{ikt}	Average price per 1000 gallons consumed by household i in municipality k in month t, computed as total service fee divided by quantity of water consumed during the billing cycle	\$10.00 (3.24)
MP^{j}_{kt}	Marginal price per 1000 gallons in price block j in municipality k in month t	\$7.99 (1.55)
$Base_{kt}$	Base service fee for water and sewer use charged in municipality k in month t	\$11.25 (5.25)
Panel B. Policy and weather		
$Voluntary_{kt}$	=1 if a voluntary water restriction was in place for any part of a month; =0 otherwise	0.15 (0.36)
$Mandatory_{kt}$	=1 if a mandatory water restriction was in place for any part of a month; =0 otherwise	0.32 (0.47)
$Rain_{kt}$	Monthly rainfall, in inches[a]	3.69 (2.21)
$Temp_{kt}$	Mean of daily mean maximum temperatures during the month[a]	72.28 (13.07)
$Drought_{kt}$	=1 if the US drought monitor exceeds moderate (severe) drought in a given municipality; =0 otherwise	Moderate: 0.44 (Severe: 0.33)
Panel C. Household characteristics		
$Income_i$	Annual household income in \$10,000	12.28 (8.71)
$Irrsys_i$	=1 if household has installed an in-ground irrigation system; =0 otherwise	0.07 [HH=127]
Small lot_i	=1 if lot size $\le$0.25 acre; =0 otherwise	0.19 [HH=323]
Med lot_i	=1 if lot size is $>$0.25 acre but $\le$0.50; =0 otherwise	0.39 [HH=678]
Big lot_i	=1 if lot size is greater than 0.50 acre; =0 otherwise	0.42 [HH=726]
$>$80th $Cons_i$	=1 if mean household consumption before nonprice policies were implemented (July 2006–Aug 2007) is above the 80th percentile; =0 otherwise[b]	0.20 [HH=343]

[a] Monthly rainfall and mean maximum temperature measurements were obtained from the North Carolina State Climate Office and were measured at a representative weather station for each municipality.
[b] The consumption range is July 2006–May 2007 for Charlotte because of the earlier adoption of voluntary restrictions.

household pays for water but does not influence its water demand through other, more direct channels. Finally, to account for potential misspecification and serial correlation across periods, we report robust standard errors clustered at the household level.[15]

Alternative price specifications

In Table 5, we present coefficients from alternative specifications of our price variable. In column (1), we report key parameter estimates for Eq. (1) using marginal price, as neoclassical theory and recent empirical research by Szabo (2015) and Nataraj and Hanemann (2011) would suggest.[16] Surprisingly, there is a positive and significant price coefficient for the IV fixed effects model (Panel A) and a positive but insignificant coefficient for the IV random effects model (Panel B). In column (2), we add base charges to the specification, which are relatively large at about 20 percent of the average monthly bill and vary over time and across municipalities (see Table 4). Although base charges appear to be a significant predictor of household consumption the price estimates remain largely unchanged (see also column (3) where marginal price is excluded from the model). Finally, in Panel C we present models in which municipal fixed effects are replaced with household fixed or random effects. Although dropping the household controls dramatically reduces overall goodness of fit, the results in Panel C document that when we use within municipality variation (both across households and time) to

[15] All models were estimated using the xtivreg2 routine in Stata 14.1 (Schaffer, 2005).
[16] For marginal price models, we do not include the Taylor–Nordin difference variable (Taylor, 1975), which is commonly used to adjust for infra-marginal changes in price that affect virtual income. The coefficient estimate for the Taylor–Nordin difference variable is consistently a precisely estimated zero and does not improve the fit of the model in this context. As such, we include only marginal prices.

Table 5
Regression results for alternative reduced form price specifications.

Variable	Coefficient (std. err.)			
	(1)	**(2)**	**(3)**	**(4)**
Panel A. Household fixed effects				
ln MP	0.111***	0.094***		
	(0.031)	(0.031)		
ln Base		−0.142***	−0.148***	
		(0.022)	(0.038)	
ln AP				−0.277***
				(0.045)
Voluntary	−0.036***	−0.031***	−0.031***	−0.032***
	(0.005)	(0.005)	(0.007)	(0.005)
Mandatory	−0.103***	−0.091***	−0.088***	−0.092***
	(0.005)	(0.006)	(0.009)	(0.005)
Adj. R^2	0.060	0.061	0.092	0.081
Panel B. Household random effects				
ln MP	0.017	0.047		
	(0.042)	(0.043)		
ln Base		−0.149***	−0.147***	
		(0.021)	(0.021)	
ln AP				−0.331***
				(0.041)
Voluntary	−0.037***	−0.031***	−0.031***	−0.031***
	(0.007)	(0.007)	(0.007)	(0.007)
Mandatory	−0.098***	−0.089***	−0.088***	−0.090***
	(0.008)	(0.008)	(0.008)	(0.008)
Adj. R^2	0.034	0.053	0.051	0.199
Panel C. Municipal fixed effects				
ln MP	−0.175***	−0.112***		
	(0.033)	(0.035)		
ln Base		−0.157***	−0.190***	
		(0.030)	(0.028)	
ln AP				−0.333***
				(0.106)
Voluntary	−0.037***	−0.030***	−0.029***	−0.031***
	(0.009)	(0.009)	(0.009)	(0.007)
Mandatory	−0.098***	−0.086***	−0.087***	−0.093***
	(0.008)	(0.009)	(0.009)	(0.009)
Adj. R^2	0.045	0.050	0.056	0.163

Notes: All models include 48,166 observations (1727 households) and include weather covariates and month fixed effects as described for Eq. (1). Household fixed (random) effects are presented in Panel A (B); municipal fixed effects are presented in Panel C. Significance at the 10, 5 and 1 percent levels is indicated by *, **, and ***, respectively. All models report standard errors that are robust to an unknown form of heteroskedasticity and clustered at the household level.

identify price effects, we find a negative and significant price coefficient across all models. One interpretation of this finding is that there is insufficient within household variation in marginal price to identify its effect on demand within a fixed effects framework. In fact, there is limited variation—a regression of marginal price on household fixed effects and monthly dummies yields an overall R^2 of 0.69. However, a similar regression using average price as the dependent variable generates an R^2 of 0.83, implying there is even less residual variation in average price. Because we find significant, robust, and intuitively signed effects in our average price specifications, it seems doubtful that insufficient variation in marginal price is the main driver of our somewhat surprising results.[17]

Another explanation of our findings is that households respond to *average* price, not marginal price. The modest size of most water bills relative to income, information costs, and bounded rationality may lead households to be rationally unaware of their marginal water price. To simplify decision-making, households might use an average price heuristic to guide behavior, proxied by their most recent monthly water bill divided by total consumption. Empirically, Wichman (2014) and Ito (2014) use quasi-experimental methods and provide empirical evidence that average price better predicts household behavior than does marginal price in water and energy demand applications, respectively. Shin (1985) lays out a conceptual argument for why base charges should be included in average price for electricity consumption, as they shift a consumer's

[17] Another interpretation might be that there are important unobserved characteristics at the household level that are correlated with marginal price that may not be fully controlled for in our fixed and random effects specifications and thus lead to a biased price effect. However, these unobservables are apparently not correlated with average price, which is robust across all specifications in Table 5.

Table 6
The effect of drought severity on water consumption.

Variable	**Coefficient (std. err.)**				
	Baseline	**Moderate Drought**		**Severe Drought**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
AP	−0.277***	−0.279***	−0.283***	−0.268***	−0.267***
	(0.045)	(0.045)	(0.047)	(0.046)	(0.046)
Drought		0.027***	0.026***		
		(0.006)	(0.009)		
Severe Drought				0.050***	0.053***
				(0.005)	(0.011)
Voluntary	−0.032***	−0.046***	−0.052***	−0.060***	−0.056***
	(0.005)	(0.006)	(0.009)	(0.006)	(0.009)
Voluntary × Drought			0.010		
			(0.013)		
Voluntary × Severe Drought					−0.009
					(0.014)
Mandatory	−0.092***	−0.115***	−0.112***	−0.125***	−0.125***
	(0.005)	(0.007)	(0.010)	(0.007)	(0.007)
Mandatory × Drought			−0.003		
			(0.012)		
Mandatory × Severe Drought					−0.001
					(0.013)
Observations	48,166	48,166	48,166	48,166	48,166
Within R^2	0.114	0.114	0.115	0.115	0.115
Number of households	1727	1727	1727	1727	1727

Notes: All models include 48,166 observations (1727 households) and include weather covariates and month and household fixed effects as described for Eq. (1). In columns (2) and (3), the variable "Drought" equals 1 if our drought index is greater or equal to one for the entire month, and 0 otherwise. In columns (4) and (5), the variable "Severe Drought" equals 1 if our drought index is greater than or equal to 2.0 for the entire month, and 0 otherwise. Significance at the 10, 5 and 1 percent levels is indicated by *, **, and ***, respectively. All models report standard errors that are robust to an unknown form of heteroskedasticity and clustered at the household level.

perceived budget constraint. For water, his arguments are more salient because base charges are generally a more substantial share of the total bill.

Although the issue of whether marginal or average price is a better predictor of water consumption is unsettled, and therefore an important topic for future research, the current state of knowledge suggests that exploring both average and marginal prices in applied demand analyses is justified. Toward this end, column (4) reports parameter estimates with average price replacing marginal price. Across all specifications of fixed effects reported in Panels A, B or C, there is a negative, robust, and strongly significant price effects that aligns well with the existing literature (Espey et al., 1997; Dalhuisen et al., 2003). In addition, the adjusted R^2s for the average price specifications are consistently larger than those for the marginal price specifications, suggesting that average price fits our data better. Finally, it is worth noting that regardless of how price is specified and how unobservables are controlled for, the estimated effects of voluntary and mandatory watering restriction policies are very robust.

Based on these findings, our subsequent analyses employ average price as the relevant price variable throughout. We should be clear, however, that we do not take a stand on the external validity of our findings with regard to the appropriateness of using average versus marginal price in future water demand analyses, and we encourage future research into this important issue. Further, acknowledging that our marginal price results are perhaps surprising and a source of concern, we encourage readers to interpret our average price results with care. Finally, across all specifications reported in Table 5, a battery of Hausman and *F*-tests strongly suggests that IV fixed effects models fit our data better than IV random effects models and IV municipal fixed effects models. We therefore include household fixed effects in all subsequent models.

Controlling for drought

In the regressions reported in Table 5, we do not include controls for drought, which plausibly could affect household water consumption through channels other than the voluntary and mandatory policies designed to address it. In this section, we introduce these controls and investigate the degree to which the effects of voluntary and mandatory policies vary with drought conditions.

Our quantitative measures of drought take on six distinct levels based on the U.S. Drought Monitor index of weekly drought conditions in each municipality (see the drought and policy parameters section). Estimating models with each of these levels included as a separate variable is challenging because of the infrequency of some levels and their high degree of

Table 7
The effect of municipal-specific prescriptive policies.

Variable	Coefficient (std. err.)	
	(1)	**(2)**
ln AP	−0.268***	−0.147***
	(0.046)	(0.048)
Voluntary	−0.060***	−0.080***
	(0.006)	(0.011)
Voluntary × Chapel Hill		−0.060***
		(0.020)
Voluntary × Greenville		0.006
		(0.015)
Voluntary × High Point		−0.009
		(0.014)
Voluntary × Charlotte		0.128***
		(0.020)
Mandatory	−0.125***	−0.142***
	(0.007)	(0.022)
Mandatory × Chapel Hill		−0.015
		(0.026)
Mandatory × High Point		0.017
		(0.033)
Mandatory × Fayetteville		0.085***
		(0.024)
Mandatory × Charlotte		−0.010
		(0.025)
Severe Drought	0.050***	0.048***
	(0.005)	(0.006)
Observations	48,166	48,166
Within R^2	0.115	0.110
Number of households	1727	1727

Notes: All models include weather covariates and month and household fixed effects as described for Eq. (2). Significance at the 10, 5 and 1 percent level indicated by *, **, and ***, respectively. All models report standard errors that are robust to an unknown form of heteroskedasticity and clustered at the household level. Fayetteville is not interacted with the voluntary policy dummy variable because it had no voluntary policies during the study period. Similarly, Greenville had no mandatory policies during the study period and thus is not interacted with the mandatory policy dummy variable. Hendersonville is the left-out category for both voluntary and mandatory policies.

collinearity with drought policies. We therefore transform these levels into two dummy variables indicating different drought severity. The first, *Drought*, equals one if our drought index is greater than or equal to 1.0 for a given month. The second, *Severe Drought*, equals one if our drought index is greater than or equal to 2.0 for a given month.

Table 6 reports estimates for key parameters. The first column carries forward estimates from the preferred IV household fixed effects model in Table 5. Column (2) introduces a moderate drought main effect variable, which has a positive and significant coefficient. Moreover, adding this drought control increases the voluntary (mandatory) policy effect to 4.6 (11.5) percent. In column (3), we add drought-policy interactions and find that both interactions are quantitatively small and statistically insignificant. We then repeat the analysis with our severe drought variable in columns (4) and (5) and find similar results. Introduction of the severe drought variable implies slightly larger policy impacts relative to previous columns (6.0 and 12.5 percent, respectively), but we find no evidence of significantly different policy effects across periods with and without severe drought.

Based on these findings, our subsequent analyses do not consider interaction effects between policy and drought. We do, however, include the severe drought main effect variable in our regressions and for robustness report similar results in an online appendix using the moderate drought variable (Table A.3).

Municipal-specific prescriptive policies

Finally, we investigate the degree to which behavioral responses to policy interventions vary across municipalities. Because aggregating different policies into voluntary and mandatory categories masks some heterogeneity in the policies adopted in each municipality, it is possible that identical policies in different municipalities might generate different demand responses depending on enforcement.

Table 7 presents our key findings. As reported in Table 2, Fayetteville never implemented a voluntary policy, and Greenville never implemented a mandatory policy, so estimating municipal policy-specific interactions in these cases was not possible. Focusing on the voluntary policy effects first, we find no evidence of differential responses in Greenville and High Point relative to Hendersonville (the omitted municipality), but significantly stronger effects in Chapel Hill and significantly weaker effects in Charlotte.[18] In fact, our estimates imply significantly *positive* overall effects of 4.8 percent in Charlotte. The stronger policy effects in Chapel Hill may be driven by a stronger conservation ethic in the relatively liberal college town, but the perverse effects in Charlotte is more difficult to rationalize.

One explanation could be that Charlotte's voluntary policies ran for only three consecutive months starting in June 2007. These months fell at the beginning of the drought, when water scarcity was not yet severe or widespread (see Table 2). Thus household awareness of the drought and voluntary policies may have been limited. Moreover, the Charlotte water authority announced late in summer 2007 that mandatory policies were likely to be adopted if drought conditions persisted, so residents might have rationally consumed more water when only voluntary policies were in place (Charlotte-Mecklenburg Utility, 2007). Another explanation for a positive coefficient is the differential behavior of households with irrigation systems. If we drop these households from our analysis, our results suggest no effect of the voluntary policy (coef.=0.007, std. error=0.017). This implies that households with irrigation systems increased their usage during the three months the voluntary policy was in place, but non-irrigators did not. This could occur if either: (1) irrigation systems' moisture sensors automatically increased irrigation intensity without an offsetting behavioral response by households, or (2) households altered their irrigation settings to allow for prolonged periods of watering prior to mandatory restrictions being enacted.

For mandatory policies, the effects are generally larger than those for voluntary policies, although not significantly so for Chapel Hill. Table 7 reports similar mandatory policy effects for Chapel Hill, High Point, Charlotte, and Hendersonville (again the omitted municipality), but a significantly smaller effect for Fayetteville. This differential response could be explained by the lack of policy variation in Fayetteville (all but 7 of 30 months had mandatory policies in place and they are winter months). Moreover, the changes in mandatory policies in Fayetteville occurred in October 2006 and May 2007, months that generally have minimal outdoor water demand and preceded the onset of the 2007 drought. Thus the limited variation in and timing of Fayetteville's policies might confound our ability to cleanly identify its policy effect.

Based on these empirical findings, we include municipal-policy interactions in our subsequent work, although these additional controls do not change our findings significantly. For compactness, we do not report these interaction effects for future models but note that they vary little from those reported in Table 7.

Primary results

We now turn to our primary research question: Do household responses to prices and voluntary and mandatory policies vary differentially across sociodemographic and housing characteristics? We estimate IV fixed effects models consistent with the following specification:

$$\ln(q_{ikt}) = \beta_1^* \ln(\widehat{AP}_{ikt-1}) + \beta_2^* \mathrm{Voluntary}_{kt} + \beta_3^* \mathrm{Mandatory}_{kt} + \mathrm{W}_{kt}\gamma + \mathrm{D}_{kt}\delta + \theta_t + \alpha_i + \varepsilon_{ikt}, \tag{2}$$

where D_{kt} is a severe drought dummy variable, as defined above, and the other variables are as defined for Eq. (1). The heterogeneous parameters $\{\beta_1^*, \beta_2^*, \beta_3^*\}$ are specified as

$$\beta_1^* = \overline{\beta}_1 + \sum\nolimits_j \beta_{1j} HH_{ij},$$

$$\beta_h^* = \overline{\beta}_h + \sum\nolimits_k \beta_{hk}^M Muni_{ik} + \sum\nolimits_j \beta_{hj} HH_{ij}, h = 2, 3,$$

where $Muni_{ik}$ and HH_{ij} are municipality identifiers and household/housing characteristics, respectively. HH_{ij} includes the following: (1) income (divided by 10,000) and its square; (2) lot size indicators; (3) an indicator for the presence of an in-ground irrigation system; and (4) indicator variables for whether the household's consumption levels are in the top quintile of its municipal subsample.[19] Households in this highest quintile generally have more discretion with their water demand, and moreover, water utilities often wish to reduce consumption of this group to better manage peak demand periods and avoid overcapitalization of the delivery system. Although previous research has used similar variables to explore the impacts of high-consumption households (Nataraj and Hanemann, 2011; Klaiber et al., 2014; Wichman, 2014, 2015), we recognize that this variable is likely endogenous, even when we control for household heterogeneity with fixed effects. To minimize these concerns, we use average household consumption *before* watering restrictions were implemented to construct this variable. Specifically, as noted in Table 4, we define "pretreatment" consumption for the period of July 2006 through August 2007 (except for Charlotte, where "pretreatment" is July 2006 through May 2007). Our results are robust to different choices of pretreatment months, including limiting the pre-treatment definition to consumption in 2006, as well as dropping Fayetteville, which had a mandatory policy in place in 2006 (see Online Appendix Table A.4).

In Table 8, we report select results for six variations of Eq. (2). In Panel A, we present average weighted price and non-price effects, evaluated at mean values, to account for the stratified sampling procedure and to make them representative of

[18] Recall from Table 2 that Fayetteville never implemented a voluntary policy and Greenville never implemented a mandatory policy, so estimating municipal-policy specific interactions in these cases was not possible.

[19] When estimating Eq. (2), the housing/household characteristic interactions with price are endogenous. Thus we construct additional instruments by interacting the set of marginal prices and base charges with each household characteristic, and we include these as regressors in the first stage.

the target population (Solon et al., 2015). In Panel B, we present regression coefficients for the same set of models.[20] The first column carries forward estimates from column (2) of Table 7 that do not account for household/housing heterogeneity and thus serves as a benchmark for our specifications with heterogeneity. Columns (2) and (3) vary by whether or not a dummy variable is included that identifies households with an in-ground irrigation system, while column (4) excludes households with an in-ground irrigation system from the sample for reasons that we explain below. Finally, columns (5) and (6) present results that focus on high-volume water users and the two models vary by whether or not households with in-ground irrigation systems are included in the sample.

To begin, we focus on the weighted average price effects in Panel A. For the specifications employing the full dataset, these estimates are clustered between −0.15 and −0.3 and are statistically significant. Comparing price coefficients for specifications using the full dataset against those using only nonirrigators indicates modestly larger price elasticities when irrigators are excluded (i.e., comparing (3) versus (4) and (5) versus (6)).[21] Overall, the elasticity estimates fall on the lower end of those reported in the existing literature. For example, Espey et al. (1997) find an overall mean of –0.51 with a short-run median of −0.38 in a meta-analysis of US water price elasticity estimates.[22] More recent estimates that control for seasonality and household heterogeneity range from −0.12 and −1.93, although most of these estimates lie between −0.3 and −0.5 (e.g., Baerenklau et al., 2014; Wichman, 2014; Klaiber et al., 2014; Mansur and Olmstead, 2012; Nataraj and Hanemann, 2011; Halich and Stephenson, 2009; Olmstead, 2009; Olmstead et al., 2007). Our somewhat smaller elasticity estimates are probably best explained by the fact that we include household fixed effects in all our specifications and thus are identifying short-run demand responses from month-to-month fluctuations in average price.

For the average effect of nonprice policies (Panel A), we find statistically significant average responses that are tightly clustered around −8.5 percent for voluntary policies and −13 percent for mandatory policies.[23] When we drop irrigators, we find somewhat smaller policy effects, which again provides empirical evidence that irrigators respond differently to demand-side management policies. Overall, our estimates are generally consistent with recent research. For example, Halich and Stephenson (2009) explore changes in municipal-level average water use when voluntary and mandatory conservation policies were implemented in 21 Virginia municipalities. Their results indicate that voluntary restrictions reduced consumption by as much as 7 percent, but they also find no response to voluntary restrictions in some communities. Mandatory restrictions were found to reduce consumption by 4–22 percent. The authors attribute the variation in policy effectiveness to heterogeneity in information dissemination and enforcement across municipalities.

Several studies have explored nonprice policy effectiveness in the western United States using aggregate municipal (or utility-level) water consumption data. For example, Michelsen et al. (1999) analyze water use in seven southwestern municipalities and find that nonprice programs reduced water demand by 1–4 percent. However, Michelsen et al. do not distinguish between voluntary and mandatory programs, even though both were likely implemented at some point over their study period. By contrast, Renwick and Green (2000) find quite large impacts of nonprice programs on average water demand in eight California municipalities, ranging from an 8 percent reduction in average water use when information campaigns are used to a 29 percent reduction when watering restrictions are in place.[24] Similar to Brent et al. (2015) but in contrast to Halich and Stephenson (2009), Renwick and Green (2000), and Renwick and Archibald (1998), our relatively smaller estimates capture the effect of monthly variation of policies within a household, which again suggests that unobserved heterogeneity may have biased earlier estimates of policy impacts on water consumption away from zero. In addition, there are significant differences in the study areas. It may not be appropriate to compare conservation policies in the humid Southeast with that of the arid Southwest or coastal California.[25]

In Panel B of Table 8, we present heterogeneity with regard to household/housing characteristics in columns (2) through (4). Focusing initially on the heterogeneous price effects, perhaps the most striking result is the large positive effect of having an in-ground irrigation system in column (2). It seems plausible that irrigators would be less responsive to price given most systems are

[20] All parameter estimates for specifications reported in Table 8 are reported in Online Appendix Table A.1. Evaluated at August levels, these estimates imply warmer temperatures and lower rainfall lead to higher household water demand. In addition, Online Appendix Table A.2 reports first-stage estimates for the specification in column (1), with the remaining specifications' first-stage results suppressed due to space constraints. Across all specifications, F-tests for instrument relevance imply that our instruments are highly correlated with average price (p-values < 0.001) (Kleibergen and Paap, 2006).

[21] We do note that using average price as our primary price variable does not represent a true elasticity estimate in a structural sense of consumer behavior. However, we follow Ito (2014) and Wichman (2014) and refer to marginal effects of changes in average price as perceived price elasticities.

[22] Dalhuisen et al. (2003) reexamine the Espey et al. findings with a larger set of data and find that 90 percent of price elasticity estimates fall between 0 and −0.75.

[23] We should be clear that our average voluntary policy effects exclude Charlotte, where, as we argued in the previous section, data limitations likely explain our surprising positive estimate. We note that our interpretation of coefficients on dummy variables as semielasticities from our semilogarithmic econometric specification requires a slight adjustment, as suggested by Halvorsen and Palmquist (1980) and Kennedy (1981). The resulting adjustment, however, is small in magnitude, since our estimated parameters are relatively small, and thus we report only nominal coefficients in our analysis. As an example, the voluntary (mandatory) coefficient in column (1) of Table 8 changes from −0.080 to −0.077 (−0.142 to −0.132) after applying the adjustment, and statistical inference remains unchanged.

[24] Similarly, Renwick and Archibald (1998) estimate that mandatory restrictions in coastal California resulted in a 16–28 percent reduction in average municipal water use that varied by the average housing density within the service area, which the authors take to be a proxy for irrigation preferences.

[25] In related work, Castledine et al. (2014) exploit daily household-level water consumption in Reno, Nevada, and find that day-of-the-week mandatory watering restrictions result in "rigidity penalties" of 20 to 25 percent of weekly water use. In other words, households choose to irrigate on their assigned days, regardless of prevailing weather conditions, and irrigate suboptimally as a result. The authors conclude that rigid day-of-the-week irrigation restrictions result in higher water use peaks and less efficient average water use than what would occur under a more flexible policy regime.

Table 8
Main model results.

Variable	Coefficient (std. err.)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A. Weighted average effects[c]						
ln AP	−0.147***	−0.292***	−0.270***	−0.370***	−0.154***	−0.241***
	[0.048]	[0.049]	[0.047]	[0.052]	[0.047]	[0.046]
Voluntary	−0.086***	−0.084***	−0.084***	−0.080***	−0.085***	−0.082***
	[0.007]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Mandatory	−0.129***	−0.131***	−0.126***	−0.108***	−0.130***	−0.112***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Panel B. Price and policy coefficients[d]						
ln AP	−0.147***	−1.070***	−1.058***	−1.078***	−0.184***	−0.187***
	(0.048)	(0.160)	(0.161)	(0.164)	(0.052)	(0.053)
ln AP × Irrsys		0.816***				
		(0.197)				
ln AP × Income		0.069***	0.083***	0.071***		
		(0.012)	(0.012)	(0.012)		
ln AP × Income^2		−0.001***	−0.001***	−0.001***		
		(0.000)	(0.000)	(0.000)		
ln AP × Med lot		0.062	0.041	0.133		
		(0.128)	(0.128)	(0.132)		
ln AP × Big lot		0.202	0.142	0.254*		
		(0.131)	(0.131)	(0.134)		
ln AP × > 80th Cons					0.121	−0.279***
					(0.101)	(0.102)
Voluntary	−0.080***	−0.071***	−0.071***	−0.063***	−0.071***	−0.068***
	(0.011)	(0.020)	(0.020)	(0.021)	(0.011)	(0.011)
Voluntary × Irrsys		0.029				
		(0.036)				
Voluntary × Income		−0.001	−0.001	−0.002		
		(0.002)	(0.002)	(0.002)		
Voluntary × Income^2		0.000	0.000	0.000		
		(0.000)	(0.000)	(0.000)		
Voluntary × Med lot		0.004	0.006	0.006		
		(0.016)	(0.015)	(0.016)		
Voluntary × Big lot		−0.012	−0.011	−0.012		
		(0.016)	(0.016)	(0.015)		
Voluntary × > 80th Cons					−0.054***	−0.053***
					(0.015)	(0.014)
Mandatory	−0.142***	−0.120***	−0.112***	−0.131***	−0.124***	−0.123***
	(0.022)	(0.028)	(0.028)	(0.028)	(0.022)	(0.022)
Mandatory × Irrsys		−0.146***				
		(0.030)				
Mandatory × Income		−0.000	−0.002	0.001		
		(0.002)	(0.002)	(0.002)		
Mandatory × Income^2		−0.000	−0.000	−0.000		
		(0.000)	(0.000)	(0.000)		
Mandatory × Med lot		−0.022	−0.019	−0.018		
		(0.015)	(0.015)	(0.015)		
Mandatory × Big lot		−0.003	0.004	0.005		
		(0.015)	(0.015)	(0.015)		
Mandatory × > 80th Cons					−0.115***	−0.067***
					(0.015)	(0.015)
Observations	48,166	48,166	48,166	44,659	48,166	44,659

Table 8 (*continued*)

Variable	Coefficient (std. err.)					
	(1)	(2)	(3)	(4)	(5)	(6)
Within R^2	0.110	0.098	0.107	0.106	0.111	0.107
Number of households	1727	1727	1727	1600	1727	1600

Notes: All models include weather and drought covariates and month and household fixed effects as described for Eq. (2). Also included, but not reported here for succinctness, are municipal-specific interaction terms with the dummy variables indicating whether or not a voluntary or mandatory policy was in place during the month (these covariates are reported in Table 7 and change little across models in Table 8). Significance at the 10, 5 and 1 percent level indicated by *, **, and ***, respectively. All models report standard errors that are robust to an unknown form of heteroskedasticity and clustered at the household level. Standard errors in brackets are calculated from a parametric bootstrap with 200 draws.

[c] Weighted average effects, evaluated at sample mean values, are adjusted to account for the stratified sampling procedure and make them representative of the target population. Standard errors in brackets are calculated from a parametric bootstrap with 200 draws (Krinsky and Robb, 1986).

[d] Fayetteville is not interacted with the voluntary policy dummy variable because it had no voluntary policies during the study period. Similarly, Greenville had no mandatory policies during the study period and thus is not interacted with the mandatory policy dummy variable. Hendersonville is the left-out category for both voluntary and mandatory policies.

fully automatic and simply run at pre-programmed times throughout an entire watering season. However, the quantitative magnitude of our estimates also seems implausibly large. In particular, we find that for a household with a small lot size and average income (mean = 12.3; see Table 4), the estimated price elasticity is positive, statistically significant, and economically large (0.42). We speculate that our instruments may not have purged all endogeneity from our specification or, alternatively, that the behavior of irrigators is fundamentally different than that of nonirrigators. In other words, the decision to run an irrigation system is mostly at the extensive margin – turn the system on or not – that households make at the beginning of the summer and rarely reconsider. We therefore consider two alternative specifications: dropping the potentially endogenous *irrsys* variable (column (3)) and dropping households with irrigation systems from the sample (column (4)). Across columns (2) through (4), there is strong evidence that price sensitivity correlates with income. In particular, the estimates in columns (3) and (4) imply price elasticities of -0.23 and -0.4, respectively, for households with small lots and average incomes. As household incomes rise, these elasticities decline at a decreasing rate.[26] Moreover, the lot size variables generally indicate a positive but insignificant relationship between water demand and lot size. There is some evidence that households with big lots (>0.5 acre) have a significantly larger demand response (see column (4)), but this evidence applies only to the subpopulation of nonirrigators. Overall, our results cast some doubt on using lot size as a proxy for outdoor water consumption as is commonly done in the literature (Baerenklau et al., 2014; Renwick and Green, 2000; Mansur and Olmstead, 2012; Wichman, 2015).

Results in column (5) indicate that households in the highest consumptive quintile (>80th percentile) are less price elastic than those in the lower portion of the distribution. Although this finding is consistent with past research by Klaiber et al. (2014) and Baerenklau et al. (2014), it is not statistically significant. If we drop irrigators (see column (6)), we find a significantly more elastic demand response for high-consumption households. Since high-demand households are more than five times as likely to be irrigators, this result aligns with our earlier finding in column (2) that irrigators are less price responsive. This result also suggests a clear (and perhaps obvious) mechanism for why high-consumption households are less sensitive to price—the presence of in-ground irrigation systems.

Coefficient estimates for the voluntary and mandatory policy effects and how they vary with household/housing characteristics are also reported in Panel B. Overall, our results indicate there is little observable heterogeneity in household response to voluntary and mandatory watering restrictions—a result that contrasts with the observed heterogeneity in price responsiveness. One exception is that for voluntary and mandatory policies, we find that households in the highest consumptive quintile reduce their demand by roughly 5 and 7 percent, respectively (see column (6)). Additionally, the results in column (2) imply that mandatory policies generate a demand reduction for irrigators that is twice the magnitude of that of nonirrigators. Although the endogeneity concerns we raised earlier likely apply here as well, this finding suggests that irrigators are *more* responsive to mandatory policy restrictions but *less* responsive to price changes. Together, these results seem to validate one of the primary justifications water utility managers put forward in defense of nonprice conservation policies—unlike price policies, they generate larger reductions in water use among households that use large quantities of water in part to irrigate their lawns.

Sensitivity analysis and robustness checks

To investigate the robustness of our results, we present additional specifications that employ potential confounding factors or alternative definitions of household/housing characteristics in Table 9. In column (1), we replicate column (1) from

[26] For incomes more than one standard deviation above the mean, the estimates in columns (2) and (3) sometimes imply positive price elasticities, although the estimates in column (4) never do, at least for households with small lots. Our view is that the positive elasticity predictions reflect limitations with our quadratic specification. Although we tried specifications with higher-order terms, we consistently found these additional variables to be statistically insignificant predictors. Therefore, we interpret our results as providing qualitative evidence about the relationship between price elasticities and income, although the quantitative magnitudes should be interpreted cautiously.

Table 9
Results using alternative measures of key covariates.

Variable	**Coefficient (std. err.)**								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Panel A. Weighted average effects[c]									
ln AP	−0.142***	−0.308***	−0.275***	−0.384***	−0.271***	−0.247***	−0.347***	−0.174***	−0.252***
	[0.046]	[0.051]	[0.046]	[0.049]	[0.048]	[0.047]	[0.047]	[0.049]	[0.049]
Voluntary	−0.085***	−0.085***	−0.086***	−0.081***	−0.086***	−0.086***	−0.082***	−0.086***	−0.082***
	[0.008]	[0.008]	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.008]	[0.007]
Mandatory	−0.130***	−0.131***	−0.127	−0.109***	−0.132***	−0.127***	−0.110***	−0.129***	−0.112***
	[0.006]	[0.008]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Panel B. Price heterogeneity									
ln AP	−0.128***	−0.858***	−0.798***	−0.873***	−0.924***	−0.920***	−0.846***	−0.178***	−0.203***
	(0.047)	(0.148)	(0.148)	(0.152)	(0.120)	(0.121)	(0.122)	(0.049)	(0.049)
ln AP × Irr. Season (Jun–Aug)	−0.077***								
	(0.021)								
ln AP × Irrsys		0.757***			0.793***				
		(0.194)			(0.196)				
ln AP × Inc Q2		0.324**	0.414***	0.390***					
		(0.145)	(0.145)	(0.146)					
ln AP × Inc Q3		0.313**	0.380***	0.350***					
		(0.131)	(0.131)	(0.133)					
ln AP × Inc Q4		0.785***	0.948***	0.680***					
		(0.126)	(0.127)	(0.128)					
ln AP × Income					0.067***	0.080***	0.067***		
					(0.012)	(0.012)	(0.012)		
ln AP × Income^2					−0.001***	−0.001***	−0.001***		
					(0.000)	(0.000)	(0.000)		
ln AP × Med lot		0.034	0.010	0.109					
		(0.128)	(0.128)	(0.132)					
ln AP × Big lot		0.170	0.111	0.222*					
		(0.131)	(0.131)	(0.134)					
ln AP × Lot > 3/4 acre					−0.031	−0.113	−0.126		
					(0.119)	(0.119)	(0.121)		
ln AP × > 10th Cons								0.035	−0.723***
								(0.139)	(0.157)
Panel C. Voluntary policy heterogeneity									
Voluntary	−0.097***	−0.064***	−0.064***	−0.058***	−0.070***	−0.070***	−0.064***	−0.074***	−0.071***
	(0.011)	(0.019)	(0.019)	(0.019)	(0.016)	(0.016)	(0.016)	(0.011)	(0.011)
Voluntary × Irr. Season (Jun–Aug)	0.057***								
	(0.014)								
Voluntary × Irrsys		0.034			0.029				
		(0.034)			(0.035)				
Voluntary × Inc Q2		−0.027*	−0.028*	−0.025					
		(0.015)	(0.015)	(0.015)					
Voluntary × Inc Q3		−0.016	−0.015	−0.019					
		(0.015)	(0.015)	(0.015)					
Voluntary × Inc Q4		0.005	0.007	0.002					
		(0.015)	(0.015)	(0.015)					
Voluntary × Income					−0.001	−0.001	−0.002		
					(0.002)	(0.002)	(0.002)		
Voluntary × Income^2					0.000	0.000	0.000		
					(0.000)	(0.000)	(0.000)		
Voluntary × Med lot		0.004	0.005	0.006					
		(0.016)	(0.016)	(0.016)					
Voluntary × Big lot		−0.012	−0.011	−0.011					
		(0.016)	(0.016)	(0.016)					
Voluntary × Lot > 3/4 acre					−0.032**	−0.032**	−0.026*		
					(0.015)	(0.015)	(0.014)		

Table 9 (*continued*)

Variable	Coefficient (std. err.)								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Voluntary × > 10th Cons								−0.074*** (0.021)	−0.088*** (0.022)
Panel D. Mandatory policy heterogeneity									
Mandatory	−0.153*** (0.024)	−0.124*** (0.027)	−0.120*** (0.027)	−0.120*** (0.027)	−0.133*** (0.026)	−0.122*** (0.026)	−0.140*** (0.026)	−0.131*** (0.022)	−0.125*** (0.022)
Mandatory × Irr. Season (Jun–Aug)	0.028*** (0.010)								
Mandatory × Irrsys		−0.154*** (0.030)			−0.144*** (0.030)				
Mandatory × Inc Q2		−0.003 (0.015)	−0.008 (0.015)	−0.014 (0.015)					
Mandatory × Inc Q3		0.014 (0.015)	0.001 (0.015)	0.005 (0.015)					
Mandatory × Inc Q4		−0.015 (0.016)	−0.040** (0.016)	−0.007 (0.016)					
Mandatory × Income					−0.000 (0.002)	−0.002 (0.002)	0.001 (0.002)		
Mandatory × Income^2					−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)		
Mandatory × Med lot		−0.022 (0.015)	−0.018 (0.015)	−0.018 (0.015)					
Mandatory × Big lot		−0.004 (0.015)	0.002 (0.015)	0.002 (0.015)					
Mandatory × Lot > 3/4 acre					0.021 (0.013)	0.028** (0.013)	0.027** (0.013)		
Mandatory × > 10th Cons								−0.176*** (0.024)	−0.115*** (0.026)
Observations	48,166	48,166	48,166	44,659	48,166	48,166	44,659	48,166	44,659
Within R^2	0.117	0.097	0.104	0.105	0.106	0.098	0.106	0.114	0.109
Number of households	1727	1727	1727	1600	1727	1727	1600	1727	1600

Notes: All models include weather and drought covariates and month and household fixed effects as described for Eq. (2). Also included, but not reported here for succinctness, are municipal-specific interaction terms with the dummy variables indicating whether or not a voluntary or mandatory policy was in place during the month (these covariates are reported in Table 7 and change little across models in Tables 8 and 9). Irr. Season equals 1 for June, July, and August. Significance at the 10, 5 and 1 percent level indicated by *, **, and ***, respectively. All models report standard errors that are robust to an unknown form of heteroskedasticity and clustered at the household level.

[c] Weighted average effects, evaluated at sample mean values, are adjusted to account for the stratified sampling procedure and make them representative of the target population. Standard errors in brackets are calculated from a parametric bootstrap with 200 draws (Krinsky and Robb, 1986).

Table 8, but include an irrigation season dummy variable—equal to one for the months of June, July, and August—to control for potential nonlinear thresholds in households' irrigation behavior. Unsurprisingly, we find that households are more price elastic during the summer months. Voluntary and mandatory policies are slightly less effective during summer months, but both effects remain negative and statistically significant. The weighted average effects of voluntary and mandatory policies are, reassuringly, virtually identical to those presented in column (1) in Table 8. These results are also robust to variants of this specification, including alternative definitions of the irrigation season and limiting the sample to irrigation months (see Table A.5 in the Online Appendix).

Columns (2)–(4) replicate the specifications in columns (2)–(4) in Table 8 but replace the linear and quadratic household income variables with dummy variables for income quartiles in our sample. The cutoff points for these quartiles are $55,000, $95,000, and $150,000, and we exclude the lowest quartile dummy variable. Generally speaking, these estimates match those presented in Table 8. Focusing on the price heterogeneity in Panel B, results are that: the irrigation system dummy remains large and significant; all income quartile interactions are positive and significant; the highest income quartile exhibits the least price sensitivity; and the lot size interactions remain insignificant. With regard to voluntary policy heterogeneity (Panel C), the second quartile parameter is marginally significant but economically small in two of the three specifications, and all other observable heterogeneity variables are insignificant. And with regard to mandatory policy heterogeneity (Panel D), only the irrigation system interaction is statistically significant, which is similar to what we report in Table 7.[27]

[27] Although not reported here, we also estimated specifications employing income terciles (with cutoff points of $65,000 and $112,500) that imply similar results: households in the highest income bracket are the least price responsive, and there are no qualitative differences in response to voluntary or mandatory policies across income groups.

In columns (5)–(7), we replicate columns (2)–(4) in Table 8 to explore an alternative characterization of lot size heterogeneity. Instead of using the small, medium, and large categorical variables, we create a new dummy variable indicating whether the household's lot is larger than three-quarters of an acre (Lot $> 3/4$ acre). Under this definition, there is no significant heterogeneity in the price responsiveness of households to lot size, which aligns well with our results in Table 8. However, the estimates in columns (5)–(7) now indicate that households on the largest lots are somewhat more responsive to voluntary policies and relatively less responsive to mandatory policies. This result suggests that utility managers who target large consumption reductions from households on large lots during drought might not realize those reductions with mandatory policies.

Finally, we consider an alternative definition of high-consumption households in the last two columns of Table 9—the top decile instead of the top quintile that was considered in columns (5)–(6) in Table 8. This more narrow definition correlates more strongly with our irrigator variable (i.e., households in the top consumption decile are 6.5 times more likely to have in-ground irrigation systems compared with others) and produces results that are similar in sign but larger in magnitude compared with those reported in Table 8. One notable result is that there is no differential price response for high-consumption households for the full sample (see column (8)), but if we limit our analysis to nonirrigators, high-consumption households are significantly more price responsive (column (9)). This result buttresses our general finding that irrigators are less price sensitive than nonirrigators.

Conclusions

In this research, we employ household-level panel data to explore responses to both pricing and prescriptive policies that are employed by utilities to manage water demand in times of scarcity. Monthly water consumption is observed over two and a half years for 1727 detached, owner-occupied, single-family homes in six municipalities geographically dispersed across North Carolina. Both voluntary and mandatory water use restrictions are employed at various times by the municipalities in our sample, and water rates vary across municipalities and within municipalities over time. This unique data set allows us to improve on the econometric strategies of recent research that rely on less rich data. Our results are identified by observed short-run, within-household changes in water use in response to changes in price and prescriptive policies implemented during drought periods, while controlling for unobserved household characteristics.

Overall, we find that voluntary and mandatory restrictions are effective demand management tools, reducing household consumption by an average of approximately 8.5 and 13 percent, respectively, across the municipalities that employ these restrictions. We extend our understanding of how households respond to these prescriptive policies by exploring heterogeneity with respect to income levels, lot sizes, historical consumption levels, and the presence of irrigation systems. Of note are the results concerning household income and responses to both price and prescriptive mechanisms. Our results corroborate the findings of previous research that higher-income households are less sensitive to changes in price (e.g., Mansur and Olmstead, 2012; Renwick and Archibald, 1998). However, we find little evidence of differential responsiveness to nonprice policies such as outdoor irrigation restrictions among income classes. Taken as a whole, our results imply that price increases will fall more heavily on relatively poorer households, while both voluntary and mandatory drought irrigation restrictions induce similar responses among income groups and thus might be more politically attractive to implement.

Further, we isolate behavior from households with in-ground irrigation systems and find that households with irrigation systems do not respond to voluntary water restrictions. However, they exhibit more than double the response to mandatory watering restrictions compared with that of households without irrigation systems, reducing total consumption by 20 percent or more. While nonprice policies are a heavily used policy tool by utilities and it is important to emphasize the policy-relevant difference in response to voluntary and mandatory conservation initiatives.

Understanding how high-use households respond to watering restrictions is also of particular interest. In addition to reducing average use, utilities are interested in reducing use by those in the upper tail of the distribution to help avoid overcapitalization of the water delivery infrastructure. Similar to previous empirical research, we find that water customers with high historical usage tend to be more sensitive to price than the average household (e.g., Klaiber et al., 2014; Baerenklau et al., 2014). This result mirrors the motivation for the adoption of increasing block-rate pricing structures on the merits of maintaining affordability for low-use households and incentivizing conservation among high-use households. Additionally, high-use households exhibit a similar response to mandatory restrictions as that of households with irrigation systems. However, unlike households with irrigation systems, those with high historic consumption are also more responsive to voluntary policies than those with more moderate consumption, reducing consumption by a total of 12 percent.

To put the responsiveness to prescriptive policies into metrics that can be more directly compared with responsiveness to pricing policies, we compute the equivalent price increase that achieves the same reduction in water use as both voluntary and mandatory policies. A voluntary policy that reduces average consumption by 8.5 percent within our study reflects a price increase of \$3.40 relative to a \$10 average price per thousand gallons, which is greater than a standard deviation increase in our sample.[28] This increase corresponds to a 34 percent increase in the average consumer's monthly

[28] The change in price is calculated as $\Delta P = (\overline{P}/\varepsilon_P)\left(\Delta Q/\overline{Q}\right)$ where $\overline{P}$ is the average price in the sample, ε_P is a central estimated price elasticity (assumed to be -0.25), ΔQ is the change in quantity demanded induced by the policy, and $\overline{Q}$ is the sample average water use (all averages used can be obtained from summary statistics in Table 1 and estimation results from Table 8).

bill. For mandatory policies resulting in a 13 percent average reduction in quantity consumed, a $5.20 increase in average price per thousand gallons is necessary to achieve the same reduction. This price increase represents a substantial 52 percent increase in the average monthly bill, and if applied evenly, it would imply an approximately $6.9 million increase in aggregate monthly expenditures on water for the estimated 250,000 residential customers served by the six utilities in our sample.[29] Of course, these back-of-the-envelope calculations are illustrative only as they imply large, non-marginal changes in price that are outside the observed variation in the data. Further, we assume a price elasticity of 0.25.

In our view, price increases of the magnitude suggested above to achieve substantial short-run reductions in water consumption are unrealistic policy choices for most US municipalities. More practically, our results imply that price increases are likely to be ineffective at reducing outdoor irrigation among high-income households and households with irrigation systems. If efficient pricing of water is to gain public support, it is important for utility managers, policymakers, and researchers to examine and promote pricing structures that balance the competing objectives of incentivizing conservation, maintaining revenue stability, and remaining equitable.

As an alternative to prices, we show that mandatory restrictions on outdoor use can be effective conservation tools that achieve uniform responses among income classes while simultaneously achieving significant consumption reductions among households with high historical consumption or with in-ground irrigation systems. Although we do not directly consider the relative efficiency properties or incidence of prices and prescriptive policies in this research, our results do suggest that nonprice policies may have more homogenous impacts along sociodemographic dimensions that align with intended policy goals. This result, combined with political concerns, suggests that carefully constructed mandatory restrictions can be an important component of the policymaker's tool kit.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jeem.2016.07.001.

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[29] There are 374,216 total customer accounts in the municipalities in our study according to 2008 rate summary tables compiled by the Environmental Finance Center at the University of North Carolina at Chapel Hill. http://www.efc.sog.unc.edu/reslib/item/tables-water-and-wastewater-rates-and-rate-structures-north-carolina-january-2008 (accessed 15.07.14). Assuming, conservatively, that one-third of these accounts are non-residential, we multiply the policy-equivalent increase in customer bills by the assumed number of residential customers (249,477) for both voluntary and mandatory policies.

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