Heterogeneous Responses to Price: Evidence from Residential Water Consumers *

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Abstract

Public utilities may respond to demand or supply fluctuations by adjusting prices to ration quantity. This approach's efficacy and distributional impacts depend on households' heterogeneous price sensitivity, which we estimate in a market for residential water usage. Our household-level panel data features a large change in marginal water prices and a novel measure of local hydrological stress. Contrary to prior research, we find that heavy-usage households are more price sensitive than other households, and price elasticity is largely invariant to household wealth. These findings suggest that price-based rationing can be an effective tool to reduce water usage.

Public or regulated utilities, such as water and electricity providers, often face demand or supply fluctuations that make it difficult to satisfy all demand with a single year-round price. Utilities may respond to these challenges with rationing, either through prices or explicit usage restrictions, or by increasing capacity. In recent years, price-based rationing has gained popularity as a demand management tool (Cuthbert and Lemoine, 1996; Renwick and Green, 2000; Newsham and Bowker, 2010; Kenney, 2011; Mayer, Hunter and Smith, 2018). Price increases can be used to reduce quantity demanded to meet (perhaps reduced) quantity available while allocating the utility's product to consumers with the greatest marginal benefit. The appeal of this approach may increase in the coming decades due to aging infrastructure, changes in climate and population, and the increasing cost of creating new capacity.[1] In residential water markets, the impact of price-based rationing strategies depends on how heterogeneous households respond to price changes. For these rationing strategies to be successful, price increases should have a significant impact on heavy-usage households that are likely to irrigate their lawns and gardens.[2] Estimating heterogeneous responses to price changes is also a necessary precursor for the analysis of distributional effects.

In this paper, we provide new insights into price-based rationing by analyzing a detailed panel of households' monthly water usage. The data allow us to describe how households of different wealth and water usage patterns respond, potentially differently, to variation in water prices, environmental conditions, and usage restrictions. Most notably, we find that heavy-usage households, regardless of wealth, are significantly more price-sensitive than other households, suggesting that prices may be an effective conservation tool in this context.

There are three salient characteristics to our work. First, the data has several useful features. We observe a transition from year-round uniform pricing to seasonal pricing in which summer prices are about 40% above winter prices, and all marginal prices are constant

[1]Most of the electrical grid and over 30% of water utilities already operate at or near maximum capacity. Experts have estimated that $1 trillion is required to maintain and expand service to meet demand over next 25 years (Fynn et al., 2007; American Society of Civil Engineers, 2017; American Water Works Association, 2019).

[2]Water supply networks are typically designed based on peak usage, which generally occurs during the summer when up to 50% of all usage is for irrigation (Mayer et al., 1999; Balling, Gober and Jones, 2008; Swamee and Sharma, 2008).

in a household's quantity consumed.[3] To our knowledge, previous studies of household-level water demand have not featured price shifts this large and as simple in structure. Additionally, severe drought conditions during part of the sample period triggered the use of command-and-control (CAC) policies that imposed restrictions on outdoor usage. This provides an opportunity to also examine the effects of CAC policies. Finally, we use a hydrological model, calibrated to the local area, to calculate a measure of local hydrological stress (i.e., moisture available to lawns). This enables us to employ a single variable to precisely measure conditions that stimulate outdoor water usage.[4]

Second, we characterize households' usage heterogeneity in terms of temporal patterns and levels over the course of a year. We use machine learning cluster analysis techniques to group households according to similarity in their usage. These groupings, which we call "usage profiles," identify households that likely irrigate, making use of available data without the need for costly monitoring of usage (DeOreo et al., 2011) or strong assumptions to explicitly distinguish between indoor and outdoor usage.[5] Furthermore, characterizing households in terms of usage profiles is intuitively meaningful and of practical relevance.

Third, and perhaps most important, we allow for considerable heterogeneity in household behavior.[6] In our estimation procedure, we partition households into six combinations of usage profiles and wealth. For each combination, we determine price elasticities and the effects of important control variables such as environmental conditions and usage restrictions. This formulation acknowledges that households with, say, similar wealth levels but different usage profiles, may have different preferences for outdoor water usage, may respond differently to environmental conditions and restrictions, and may exhibit different

[3]Seasonal pricing is also sometimes referred to as "peak-load" or "time-of-use" pricing. Previous studies of residential water demand under seasonal pricing have focused on aggregate demand rather than household-level demand (Renzetti, 1992; Lyman, 1992; Reynaud, 2010).

[4]Previous water demand studies vary in how they model environmental factors. See Arbués, García-Valiñas and Martínez-Espiñeira (2003) or House-Peters and Chang (2011) for reviews of the literature related to environmental controls.

[5]In water demand studies, it is often difficult to distinguish between outdoor and indoor usage. One common approach, pioneered by Howe and Linaweaver (1967), is to assume that a household's outdoor usage is equal to the difference between its usage during irrigation season and the "base usage" of winter months.

[6]Water demand studies generally have not addressed household-level heterogeneity; see reviews by House-Peters and Chang (2011) and Fuente (2019). Exceptions include Renwick and Archibald (1998); Mansur and Olmstead (2012); Klaiber et al. (2014); Wichman, Taylor and von Haefen (2016), and Buck et al. (2016). Similar issues exist for residential energy demand; see Reiss and White (2005); Swan and Ugursal (2009); Borenstein (2012) and Auffhammer and Rubin (2018).

price sensitivities given the financial resources at their disposal.

Our estimates of water demand shed new light on the efficacy and distributional consequences of price-based policies. In particular, we show that households that are most likely to irrigate (i.e. heavy-usage households) are more price sensitive than other households, and price sensitivity does not vary across wealth levels. For example, we find that wealthy heavy-usage households have a price elasticity of -0.356, while wealthy light-usage households have a price elasticity that is not statistically different from zero.[7] Our findings on usage-level heterogeneity are valuable because they suggest that price-based rationing can be an effective tool for utilities that need to substantially reduce total water usage. Water utilities closely monitor overall peak-season usage in making choices about capacity needs and non-price usage-reduction strategies. By definition, heavy-usage households consume a large amount of water, so a fixed percentage reduction in quantity, uniform across the population, would reduce usage gallons by the most for heavy-usage households. The heterogeneity in price elasticity that we document compounds this effect, as heavy-usage households reduce usage by a greater percentage on top of a greater base.[8]

We complement our elasticity estimates with descriptive evidence of how households' usage changes during the sample period. Of the households we match to the heaviest usage profile prior to seasonal pricing, more than half eventually reduce their usage enough to more closely resemble households in a lower usage profile. A much smaller share of households increase usage substantially during the sample period. This provides insight into the extent to which households make substantial changes in water usage following the introduction of higher prices.

The previous literature on water demand's price elasticity typically finds that households with higher outdoor water usage are less price sensitive than other households (Mansur and Olmstead, 2012; Klaiber et al., 2014; Wichman, Taylor and von Haefen, 2016).[9] Why

[7] These elasticity estimates are in the range of values that previous studies have found for areas with similar environmental conditions. Elasticity estimates tend to be greater in the western United States (Dalhuisen et al., 2003).

[8] One caveat to this argument is that water utility managers may be averse to implementing large price shifts in non-drought periods in part due to concerns over "demand hardening" as this would decrease potential amount of water reductions during periods of drought (Howe and Goemans, 2007).

[9] Although elasticity estimates for irrigating households vary, they are often statistically indistinguishable from zero and, in some cases, positive.

are our results different? One possible explanation is that our joint characterization of households in terms of both wealth and usage profiles more effectively identifies households' preferences for outdoor water usage and their price sensitivities. Indeed, we show that ignoring this heterogeneity can lead to differences in price elasticity estimates. Another possible explanation is that the pricing experiment that we observe features large price changes in an otherwise simple pricing environment in which the marginal price of water does not vary with quantity consumed. Prior studies generally have to account for marginal water prices that increase with quantity (i.e., "increasing block prices"). This leads to two challenges. First, households with greater demand face higher prices, which requires researchers to resolve endogeneity concerns that can bias estimates for heavy usage households in the direction of being less negative. Second, consumers may have difficulty understanding the schedule of increasing prices (Shaffer, 2019). The simplicity of the pricing schedule in our data allows us to largely avoid these issues.

1 Data

1.1 Water Usage Data

The Orange Water and Sewer Authority (OWASA) in Orange County, North Carolina provided us with monthly water usage and rate data from October 1999 through September 2005 for single-family residential properties. We match this data with each property's parcel-level characteristics using Orange County Land Records' geographic information system. These characteristics include lot size, square footage, year built, assessed value of the home in 2000, and the Census Block Group.[10] During the sample period, OWASA staff recorded usage from household water meters approximately monthly, with different households' usage recorded on different days of the month. While households' billing period lengths and time-of-month vary in practice, there is no systematic relationship between bill timing and water usage. We define monthly usage for each household in terms of biling "read periods." In recording households' usage data, OWASA truncates to the nearest thousand gallons the total quantity

[10] In OWASA's service area there are 45 Block Groups which contain, on average, about 190 households each.

of water used during a read period.[11] Usage above a truncation point carries-over to the next read period, which effectively delays payment rather than allowing some usage to be unbilled entirely.

In this study, we focus on single family customers who did not change premises during the study period. To prepare the sample we use for empirical analysis, we remove observations that may be incomplete or contain errors. First, we eliminate households that, despite OWASA's billing designation, may not be single-family households.[12] From the remaining sample of 8,501 customers, we drop households with usage data that begins later than October 1st, 1999 or ends earlier than October 1st, 2005, reducing our sample to 4825 customers. This insures that we observe all households for more than two years prior to OWASA implementing seasonal pricing in May 2002. We eliminate outliers by dropping households with monthly usage values that ever exceed the 99.9th percentile of usage; some of these extreme outliers are due to meter misreads or catastrophic leaks. We also drop households with zero-usage readings in 2+ consecutive periods or 12+ periods in total, in order to exclude households with frequent absences due to travel or intermittent rental activity.[13] Our final sample, summarized in Table 1, contains 4,455 households, which account for 70% of all household-month observations in the initial sample.

1.2 Water Prices

OWASA is among the first water utilities to use prices as part of a broader strategy to manage demand during non-drought periods. On May 1st 2002, OWASA replaced uniform year-round prices with seasonal prices that are higher in the summer.[14] The decision to adopt seasonal pricing was part of a longer-term plan to manage water resources and not in response to a particular event. OWASA sets the price schedule each year to cover its yearly expenses

[11] In our empirical analysis, we treat monthly usage as a continuous variable so that we are able to perform estimation using standard fixed effects methods.

[12] For example, we eliminate customers with multiple location identifiers as they may represent households that own multiple homes or properties managed by rental agencies. We also eliminate customers whose land record information is inconsistent with a single-family property.

[13] A zero-usage reading may also be due to meter rounding for very low usage amounts, or it could indicate a water shutoff due to non-payment. Our estimation results are robust to different sample construction rules related to missing readings, including dropping households with any zero-usage months.

[14] In October 2007, OWASA transitioned to a different pricing schedule in which marginal prices increase with usage.

for the residential sector as a whole. Similar to many utilities, OWASA charges households a combination of volumetric and fixed fees. In each month, the volumetric portion of the bill includes separate per-unit charges for both water and sewer services. Because households are billed for both services on the same bill and in the same quantity units, the effective marginal water price is the combined price for water and sewer services.

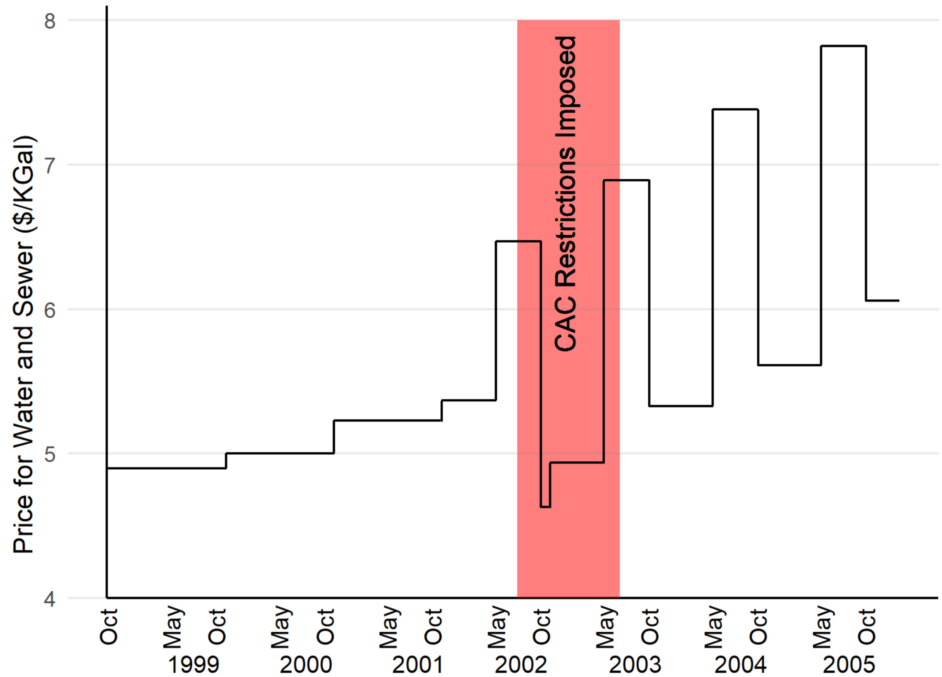
In Figure 1, we show the nominal marginal prices per thousand gallons (KGals) from October 1999 to October 2005. Prior to 2002, price changes were limited to small increases on October 1st of each year. The introduction of seasonal prices, which we refer to as the treatment, began in May 2002. This pricing scheme features marginal prices that are 40% greater during summer months (May-September) relative to the rest of the year. Water prices during non-summer months are largely unchanged with the introduction of seasonal prices. Fixed fees and per-gallon sewer charges remained constant throughout the year.[15] In our empirical analysis, we convert all prices to January 1999 dollars using the seasonally-adjusted U.S. city average monthly consumer price index (CPI) from the U.S. Bureau of Labor Statistics.

1.3 Command-and-Control Restrictions

Approximately two months after the implementation of seasonal pricing in 2002, drought conditions led to falling reservoir levels, triggering the use of CAC restrictions, indicated with shading in Figure 1. CAC restrictions target outdoor water usage to encourage conservation. These restrictions are determined by reservoir levels and are independent of OWASA's introduction of seasonal prices. Violations of CAC restrictions were considered misdemeanors and enforced through fines by the local townships and Orange County. OWASA implemented CAC restrictions in three stages, with stricter requirements imposed during each subsequent stage. On July 11th, 2002, the first restriction, *Stage 1*, was implemented, restricting irrigation of lawns, gardens, trees, or shrubs to three days out of each week. Approximately

[15]Marginal rates displayed in Figure 1 are applicable to 94% of customers. Of the 4,455 customers in the sample, two customers have dedicated irrigation equipment and are charged an additional monthly marginal charge of approximately \$2.08/KGal for irrigation use. Additionally, 245 customers are charged for water services but not sewer. The average monthly fixed fee during the sample period is approximately \$13, and the average monthly volumetric charge is about \$32.

Figure 1: Seasonal Prices and CAC Restrictions



Notes: Prices are nominal US dollars. CAC restrictions were imposed from July 11th 2002 through June 2003. The dip in the marginal price observed in October 2002 was due to a brief administrative error.

one month later, the second restriction, *Stage 2*, was implemented, further restricting irrigation to only one day a week. Two weeks after the implementation of *Stage 2*, OWASA implemented water supply *Emergency* restrictions as reservoir levels continued to fall.[16] This restriction prohibited the use of outdoor water for any purposes other than fire suppression or necessary emergency activities. OWASA began the process of lifting CAC restrictions after heavy rains in October 2002 ended the drought. Definitions of each CAC restriction and a timeline of their implementation are in Online Appendix C.

Following the 2002 drought, OWASA introduced new usage guidelines to encourage conservation. These guidelines encouraged the use of reclaimed or harvested water, the installation of water-saving fixtures, and reductions in some outdoor watering activity. The guidelines are similar to OWASA's *Stage 1* restrictions, but they were less widely publicized

[16]At the time, OWASA was concerned that households were responding to anticipated restrictions by increasing watering before the new restrictions went into effect.

and were in effect while conservation concerns were less salient in the market.[17]

1.4 Usage Profiles and Wealth

We use Ward's agglomerative hierarchical clustering algorithm (Ward, 1963) to identify yearly usage patterns during October 1999-September 2001, the two pre-treatment years that feature constant within-year prices and small price changes between years. We define a year's usage to start on October 1, when OWASA implemented price changes. For each household in our balanced panel, we have two October-to-September sequences of monthly pre-treatment usage.[18] We pool the sequences of all households and years, and then we allow the clustering algorithm to partition the sequences into three groups – our usage profiles – that satisfy the algorithm's standards for within-group similarly. Allowing additional profiles did not add clear value for our empirical approach. As a practical matter, we need the profiles to capture enough households so that they can be further divided by other household characteristics (i.e. wealth).[19] We illustrate the usage profiles – which we refer to as *Heavy*, *Moderate*, and *Light* – in Figure 2, where we show the average monthly usage for members of each profile.[20]

The usage profiles are instructive in describing differences in how households use water over the course of the year and capture household characteristics that we do not observe directly, such as the number of people in the household or preferences for outdoor water use. They intuitively describe annual usage patterns, conforming with informal classifications of residential water usage. The timing and magnitude of water usage of the *Heavy* profile, for example, is consistent with lawn care. In particular, the large quantities of water usage during peak summer months suggests outdoor irrigation, and the significant amount of usage late in the fall suggests watering of re-seeded lawns in preparation for the following summer. Conversely, the *Light* profile reflects consistently low water usage month-to-month, indicative

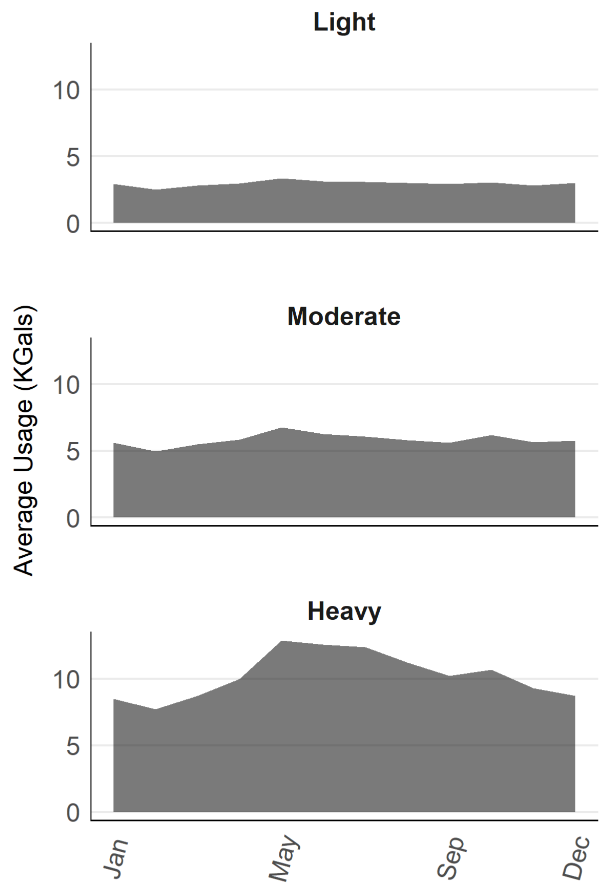
[17] The guidelines also included substantial allowances for outdoor watering of new grass and plantings, which would allow households to irrigate year-round without restriction if they put down grass seed in the spring and fall.

[18] We convert usage amounts from read periods to calendar months under the assumption that per-day usage is constant within a read period.

[19] When we experimented with adding a fourth usage profile, we found that it did not add information about the timing of water usage within the year, just its level.

[20] Ward's agglomerative hierarchical clustering method groups together time series that are closest to each other in multivariate Euclidean space. The method's agglomerative coefficient, a measure of the clustering structure, is 0.993 in our data, indicating a strong clustering structure.

Figure 2: Usage Profiles from Clustering



of no outdoor water usage. Finally, the *Moderate* profile reflects usage in between the two other profiles. Relative to the *Light* profile, the *Moderate* profile has higher usage during the winter and small but distinct peaks during the summer and fall, likely reflecting occasional outdoor water use. In the discussion below we emphasize differences in overall usage volume across profiles, but the ordering of profiles would be the same if we were to emphasize differences in usage seasonality, i.e. how much more water is used in summer relative to winter.

As part of the profile-creation process, each year of a household's October 1999-September 2001 activity is assigned to one of the usage profiles. For our main elasticity analysis, we assign each households a type – *Heavy*, *Moderate*, or *Light* usage – based on which profile contains the household's usage during October 2000 to September 2001, immediately before seasonal pricing's introduction. As a robustness check, we redo all analyses using

October 1999 to September 2000 usage to match households to profiles, and we find that our results are not sensitive to the choice of pre-treatment year. These results are provided in Online Appendix D.

We follow the convention in the literature and define household wealth using assessed value of the home (Jones and Morris, 1984; Dandy, Nguyen and Davies, 1997; Arbúes, Barberan and Villanua, 2004).[21] Specifically, we create an indicator for relative wealth based on the median assessed home value ($192,647) in the area of study in 2000.[22] We identify a household as $High$ wealth if the home value is above the median, and *Low* wealth otherwise. Columns 2 and 3 of Table 1 summarize parcel-level household characteristics by wealth level. As indicated by the average house value for lower-wealth households ($131,369), OWASA's service area is generally wealthier than the rest of North Carolina (median home value $108,300) and the United States ($119,600).

As shown in Table 1, there is a positive correlation between wealth and usage, consistent with the literature (Dalhuisen et al., 2003; Harlan et al., 2009). However, 25% of the households with *Heavy* usage profiles have lower-than-median home values. In addition, the set of households with higher-than-median home values and *Heavy* usage profiles represents only 21% of wealthier households.

1.5 Environmental Conditions

Environmental conditions are important factors that drive demand for outdoor water usage such as lawn irrigation. The standard approach has been to account for this with an *ad hoc* collection of weather variables. By contrast, we introduce a novel measure based on hydrological stress. This measure more directly captures the water needs of a household's lawn. We use a hydrology model to account for how water moves through the hydrological cycle, while also accounting for land use and vegetation cover patterns. Specifically, we introduce

[21] Studies that have explored how price responses interact with wealth measures have used assessed home values or income as a proxy. Wealth may be more appropriate than income in understanding a household's ability to pays its bills, due to former capturing savings, access to credit, and other financial resources (Meyer and Sullivan, 2003).

[22] This approach is consistent with previous work. For example, Olmstead and Mansur (2012) define households with incomes and lot sizes both above the sample medians as "rich, big lot" household and those with incomes and lot sizes both below the medians are categorized as "poor, small lot."

Table 1: Usage and Parcel Characteristics

	All	***Wealth Level***		***Usage Profile***		
		Low	***High***	***Light***	***Moderate***	***Heavy***
Usage (KGals)	5.63	4.65	6.49	3.25	5.93	9.78
	(4.31)	(3.30)	(4.87)	(2.22)	(3.45)	(6.40)
House size (sq. ft.)	2346	1700	2910	1923	2444	2923
	(878.20)	(494.57)	(740.38)	(748.10)	(792.35)	(983.17)
Number of bedrooms	3.56	3.14	3.93	3.24	3.64	3.97
	(0.96)	(0.85)	(0.91)	(0.91)	(0.92)	(1.02)
Number of bathrooms	2.55	2.04	3.00	2.19	2.64	3.01
	(0.85)	(0.66)	(0.75)	(0.80)	(0.76)	(0.95)
Yard size (acres)	0.44	0.35	0.51	0.39	0.45	0.50
	(0.34)	(0.26)	(0.39)	(0.33)	(0.35)	(0.34)
House value (1000 USD)	206.65	131.37	272.31	162.93	216.27	268.20
	(98.18)	(36.68)	(87.28)	(79.08)	(90.24)	(117.67)
Year built	1975	1969	1981	1972	1977	1979
	(18)	(17)	(17)	(18)	(18)	(17)
Total households (N)	4455	2080	2375	1481	2301	673
High wealth households (N)				478	1389	508

Note: Values are means and standard deviations in parenthesis.

an index derived from a spatially-explicit eco-hydrological model known as Regional Hydro-Ecologic Simulation (RHESSys) (Tague and Band, 2004; Gao et al., 2018; Lin et al., 2019) to summarize the exogenous factors that determine lawn and soil dryness. This approach builds on previous hydrological research that has found that calculations of soil water deficits are better than weather variables (which mostly capture atmospheric conditions) at identifying periods in which plants are likely to be water-stressed in agricultural settings (Yao, 1974; Torres, Lollato and Ochsner, 2013).

We construct the index in two steps. First, RHESSys produces estimates of actual evapotranspiration and potential evaporation, which are measurements of the amount of moisture transferred from lawns to the atmosphere. The two measurements differ in that actual evapotranspiration is a conditional measure, limited by the amount of soil moisture currently available, whereas potential evapotranspiration is an unconditional measure that reflects the maximum amount of moisture that could theoretically be transferred. To produce these estimates, the model combines a high-resolution landcover database (NLCD, 2001;

Pickard et al., 2015) with other model inputs (e.g. precipitation, soil water potential, air temperature, solar radiation) to model spatial and temporal dynamics of soil moisture. We calibrate and validate the model using United States Geological Survey gages to derive estimates of soil moisture specific to lawns. In the second step, we use the resulting estimates of actual and potential evapotranspiration to produce a "water stress" index, $WS \in [0, 1]$, that captures soil conditions for each Census Block Group in OWASA's service area. A value of $WS = 0$ indicates minimally stressed (i.e., wet) conditions, and $WS = 1$ indicates maximally stressed (dry) conditions. In Appendix A, we provide further details on water stress as well as an illustration of its temporal and spatial variation. In our estimation models, we also include a measure of average temperature to capture demand for seasonal recreational water uses (e.g. water used to fill swimming pools) that water stress does not capture.

The use of water stress presumes that households water their lawns when their plants are stressed. It is possible, however, that households respond to weather variables instead. We also collect weather data and construct environmental controls similar to those typically used in the literature. In Online Appendix E, we compare our results to estimates obtained when controlling for environmental factors using *ad hoc* collections of weather variables. We show that commonly used collections of weather variables generally produce smaller estimates of price sensitivity among wealthier households with *Heavy* and *Moderate* usage profiles. We also show that is possible for collections of several weather variables to approximate our results when we use water stress. The advantage of using water stress is that it summarizes environmental factors in a single variable. This allows us to estimate differential responses to environmental factors in a parsimonious way.

2 Water Demand Estimation

2.1 Empirical Specification

We estimate a demand function for water. In considering the demand model's components and parameterization, it is useful to consider a household's constrained optimization problem.

We assume that households are heterogeneous in two dimensions: their taste for landscaping and their budget constraints. In our empirical model, we allow usage profiles and house values, respectively, to proxy for these sources of heterogeneity. In addition to the utility from landscaping and the budget constraint, a household must consider the "technology" that produces healthy landscaping. This technology requires water as an input, and in general the need for watering or irrigation is greater during hot, dry weather. For a given water price, households with different landscaping utility and budget constraints will have different water usage throughout the year. As the price of water increases, households with different landscaping tastes and budget constraints may respond differently to this price variation. This motivates one characteristic of our empirical specification, which allows a different price elasticity term for each usage-wealth combination. Similar to the heterogeneous effect of prices, when changes in environmental conditions affect water's productivity in maintaining a lush lawn, households of different tastes or wealth may respond differently in their water choices. This motivates a second characteristic of our empirical specification, which allows a different response to water stress for each usage-wealth combination. Finally, households may vary in how they view CAC restrictions, which some may see as hard limits on the total amount of outdoor water to be used, while others interpret them as increasing water's price through possible fines or social pressures. Our demand model allows households with different wealth and usage profiles to have different responses to CAC restrictions.

We assume that household i's demand for water during read period t is a function of water's contemporaneous marginal price.[23] To account for demand heterogeneity, the model's parameters vary with a household's usage profile, $u \in \{Heavy, Moderate, Light\}$, and its wealth, $w \in \{High, Low\}$. For each household and combination of u and w, we define a set of indicator variables, τ_{iuw}, that are equal to one if household i has usage profile u and

[23] Alternative assumptions, used elsewhere in the literature, include the assumption that households respond to lagged prices (because they believe that prices printed in recently-received bills also apply to the current period) or they respond at the margin to an average of fixed and marginal prices (because the true marginal prices are difficult to decipher).

wealth level w, and zero otherwise. We specify demand as:

$$q_{it} = \sum_u \sum_w \tau_{iuw}\beta_{uw}p_t + \sum_u \sum_w \sum_k \tau_{iuw}\phi_{uwk}x_{itk} + \sum_u \sum_w \tau_{iuw}\theta_{uw}Z_{it} + \eta_i + \epsilon_{it}, \qquad (1)$$

The dependent variable, q_{it}, is the natural log of the total quantity of water demanded by household i during read period t. Our analysis drops observations with zero consumption; this affects about 0.87% of all observations, and therefore has only a minor impact on our estimates. The variable p_t is the natural log of the marginal price in effect during read period t. The coefficient β_{uw} therefore represents price elasticity for wealth level w and usage profile u.

The scalar x_{itk} records CAC restrictions, $k \in \{\textit{Stage 1, Stage 2, Emergency}\}$, that were implemented during the drought. The restrictions are mutually exclusive, and we record in x_{itk} the share of days restriction k was in place during read period t for household i. The coefficient ϕ_{uwk} captures the change in usage due to CAC restriction k for households with wealth level w and usage profile u. Responses to CAC policies are identified, in part, with variation across households in exposure to restrictions per read period, due to asynchronous meter-reading and billing.

The vector Z_{it} contains controls for other factors that influence water demand during each read period. These include Census Block Group level water stress, average temperature, and the natural log of number of days in each household's read period t. We standardize the values of both Census Block Group level water stress and average temperature, demeaning then normalizing them by their standard deviations, to put them on the same scale. Z_{it} also contains variables to account for intra- and interyear usage trends. We capture intrayear trends with a sixth-order polynomial of the week number (values 1 through 52) for the day halfway through a read period.[24] We estimate separate intrayear trend coefficients for each usage-wealth type. Estimating the trends separately allows different households to have different baseline seasonal usage trends, and therefore is an important component of our measurement of the different impacts of seasonal pricing across usage-wealth groups. We capture interyear trends with a linear trend variable and the interaction of this trend variable

[24] Asynchronous meter reading and billing across households implies that we see considerable cross-household variation in average week number.

with an indicator for summer months (May-September). Both types of trend variables are primarily identified by intra- and interyear changes in usage prior to seasonal pricing's introduction in May 2002.[25] The intrayear trend captures seasonal variation in water demand, while the interyear trend could be influenced by the gradual installation of modern low-usage appliances or changes in gardening and landscaping choices unrelated to water prices. Finally, we include an indicator variable that is equal to one beginning in May 2002 to account for differences in attitudes about water usage and conservation during the seasonal pricing regime.

We leverage the panel nature of the data to control for time-invariant unobserved household characteristics that may be correlated with water demand, such as the age of the home's water fixtures or appliances, its numbers of bedrooms and bathrooms, and its number of occupants and their average taste for water usage. These characteristics are absorbed by the fixed effect η_i. Lastly, ϵ_{it} is an error term that captures unobservable demand shocks that households experience during individual read periods. In estimating equation (1), we cluster standard errors at the household level.

2.2 Price and Usage Variation over Time

To estimate the price elasticity coefficients in equation (1), we rely on temporal price variation due to the introduction of seasonal pricing. During the first 2.5 years of our sample, households faced fairly stable water prices year-round, and for the sample's remaining 3.4 years households' summer water prices were considerably higher and winter prices declined modestly relative to the pre-treatment nominal price trend (see Figure 1). We observe household-level data in one water market only, so we do not have the opportunity to compare treated households (facing seasonal pricing) to untreated households at the same time.

We can, however, conduct a simple comparative analysis of per-capita usage between OWASA and the neighboring city of Durham NC to investigate whether OWASA's introduction of seasonal prices coincided with region-wide usage changes that might confound our elasticity estimates. The Durham service area is adjacent to OWASA, and moreover, Durham

[25] Because the interyear trend terms and household usage types are both identified by usage prior to seasonal pricing, we do not allow the trend coefficients to vary by household type.

did not have major pricing changes during the sample period. If there was a change in water usage practices in the region, we would expect to see it affect usage in both Durham's and OWASA's service areas.[26] In Figure 3, we display monthly per-capita residential water usage in both areas. For comparability to Durham, the displayed OWASA time series is not limited to single-family households, as in our estimation sample, but this does not qualitatively affect the OWASA data. Two-thirds of Durham residential water accounts are associated with single-family households, while about 80% of OWASA accounts are single-family homes. We normalize each data series using its respective average prior to OWASA's introduction of seasonal pricing. This equalizes mean usage, which is greater in OWASA's service area, yet reflects how the two usage series differ in terms of summer and winter usage.[27] Figure 3 shows that the normalized per-capita usage in OWASA and Durham are very similar in their seasonality and modest year-to-year changes up until May 2002. After OWASA introduced seasonal pricing, however, OWASA usage is consistently below Durham. For the first year of seasonal pricing, this difference includes OWASA's CAC restrictions in addition to increased summer water prices. Throughout the seasonal pricing regime, OWASA's water usage varies less between summer and winter, as we expect with seasonal prices. This suggests that our primary identification strategy – to examine within-household usage changes by OWASA customers – can provide credible estimates of demand elasticities.

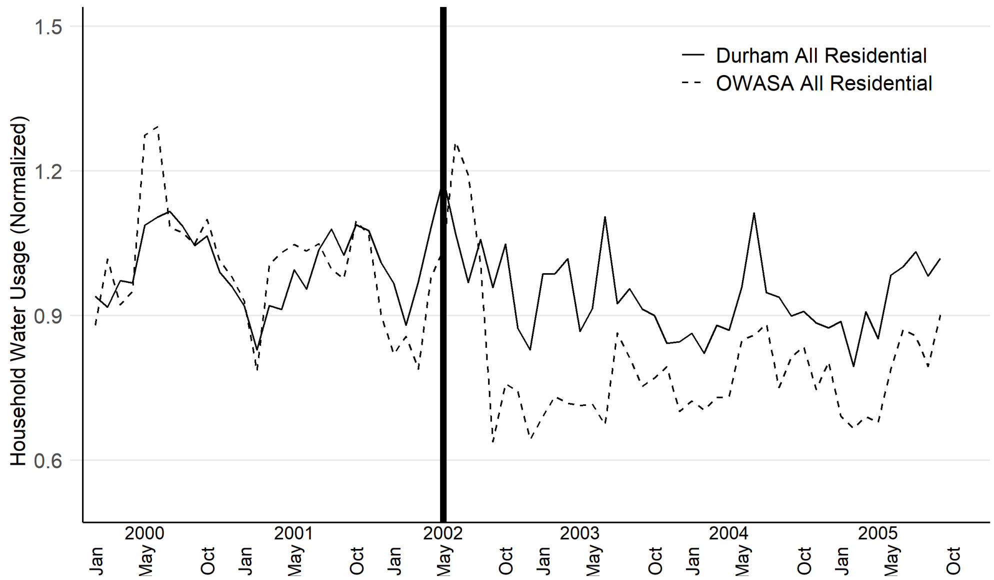
2.3 Elasticity Estimates

We show in Figures 4 - 6 collections of coefficients and confidence intervals from our estimated demand model. We report the full set of estimates in Appendix B's Table B1, Table B2, and Figure B1. Starting with the price elasticity estimates shown in Figure 4, we find that there are significant differences across usage profiles. Among high-wealth households, those with *Heavy* usage have a price elasticity of -0.356, while high-wealth households with *Moderate* usage have a price elasticity of -0.117, and *Light* usage households have a price

[26] While this comparison of locations with and without a policy change suggests an opportunity for a difference-in-differences analysis, we do not have data from Durham on household characteristics or their water usage, so we are unable to perform our estimation of water demand heterogeneity with a difference-in-differences research design.

[27] Usage differences reflect, in part, differences in income (55% greater in OWASA) and home value (76% greater in OWASA).

Figure 3: Water Usage in Chapel Hill and Durham



Note: The graph shows the per-capita monthly usage by all residential customers regardless of residence type in Durham (solid line) and OWASA (dashed line). Each data series is normalized using its respective average prior to OWASA's introduction of seasonal pricing.

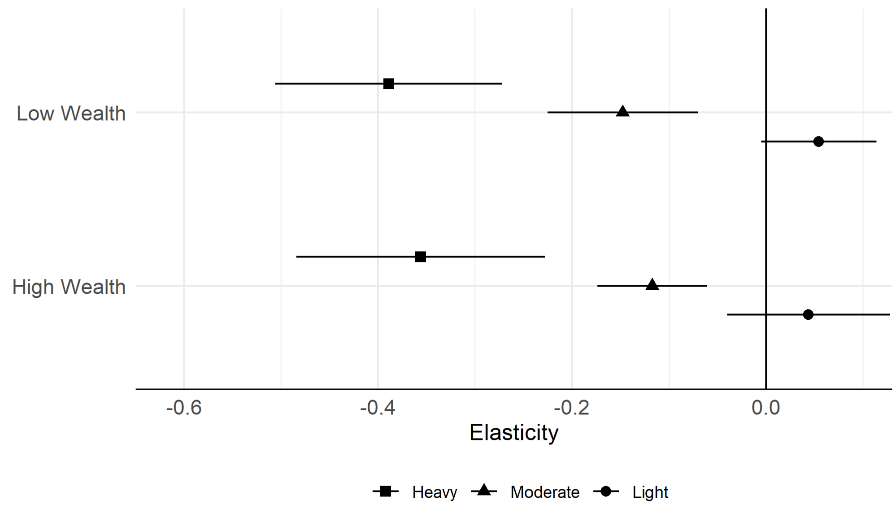
elasticity that is not statistically different from zero. Conditional on usage profile, the price elasticities of low-wealth households are essentially the same as those of high-wealth households.[28] In contrast, previous studies that have found that prices induce a larger reduction in demand among poorer households (Renwick and Archibald, 1998; Mansur and Olmstead, 2012; Wichman, Taylor and von Haefen, 2016).

Our findings offer support for using price-based rationing to reduce total water usage. Although it may initially seem counterintuitive that heavy-usage households can both consume more water and have a greater price elasticity, this can certainly be the case.[29] Furthermore, demand functions with this property are consistent with a theoretical model in which all households have an inelastic demand for indoor usage and some households have additional demand for outdoor use. Of course, our data only allows us to estimate a single elasticity. To further identify the indoor and outdoor elasticity separately, one would need

[28] We find the same qualitative pattern in elasticities if we limit the sample to the pairs of adjacent months (April and May, and September and October) when OWASA switches between winter and summer prices during the seasonal pricing regime.

[29] Consider demand functions $Q = a(1 - P^b)$ where a and b are positive constants. Let household A have $a = 1$ and $b = 1$ and let household B have $a = 3$ and $b = \frac{1}{2}$. Then household B has greater quantity demanded and greater price elasticity at any price $\in (0, 1)$.

Figure 4: Water Price Elasticities

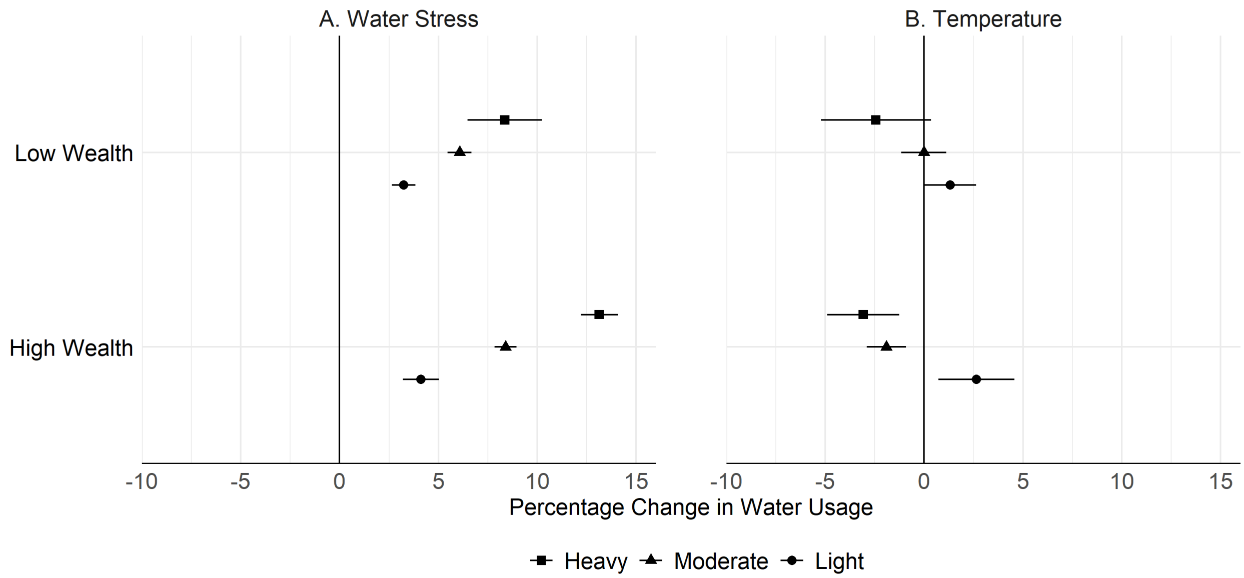


Note: Geometric shapes are point estimates and lines are 95% confidence intervals.

meaningful variation within both summer and winter prices, not simply in summer prices as we have in this study.

In Appendix B, we analyze the sensitivity of our price elasticity results under alternative approaches to the data. In Appendix Table B2 we consider different ways to account for interyear trends in water usage. In particular, we estimate a model where we estimate summer and non-summer trends in a separate step using only data prior to seasonal pricing, as well as additional models that allow summer and non-summer trends to vary by household wealth, by an indicator of relative lot size based on the median value, and by the interaction of wealth and lot size indicators. Each model generates results that are qualitatively similar to the results in Figure 4. The price elasticities of heavy-usage households are significantly larger in magnitude than price elasticities of moderate-usage households, which in turn have greater price sensitivity than light-usage households. In addition, we investigate the impact of replacing the clustering algorithm's grouping of households with simpler approaches that separate households into terciles according to different aspects of their pre-treatment usage. The results from these models, shown in Appendix Table B3, are very similar to our main results in Figure 4. In the same appendix table we show that our elasticity results are unaffected when we replace our water stress variable with the well-known Palmer Drought Severity Index (Palmer, 1965).

Figure 5: Effect of Environmental Factors on Water Usage



Note: Point estimates (geometric shapes) are percentage change in water usage per standard deviation increase in environmental factors. Lines are 95% confidence intervals.

An important feature of our estimation strategy is that we allow households to have heterogeneous responses to environmental conditions. In Figure 5 we display our estimates of how households of different usage-wealth types respond to variation in water stress and temperature. Responses to water stress increase in wealth and usage, with high-wealth heavy-usage households having significantly greater responses than all other usage and wealth types. *Light* households, as expected, are relatively unresponsive to variation in environmental conditions. Conditional on water stress, households' responses to air temperature are near zero for all usage and wealth types. This is consistent with our argument that our water stress variable is an appropriate way to capture how households' outdoor water demand responds to variation in environmental conditions. If we omit water stress from the demand model, we find that all household types increase water usage when air temperature increases.

To understand how our approach to heterogeneity supports our estimation of price elasticities, consider the potential bias in price sensitivity that would follow from assuming homogenous responses to environmental factors. With this restriction, we may under-estimate heavy-usage households' responses to hot and dry weather while over-estimating light-usage households' responses. Environmental stress occurs at the same time of year as increased prices, so uncaptured variation in weather responses may spill over to estimates of price elasticities. In particular, if heavy-usage households' weather-related increased usage is not explained by their responses to summer weather conditions, then the model may attempt to fit their behavior through biased price sensitivities that are too small in magnitude. This source of bias could play a role in some previous studies' findings of relatively inelastic demand for households presumed to irrigate.[30] Likewise, homogeneous responses to environmental factors may ascribe too-strong weather responses to light-usage households with little interest in outdoor water usage. When the restricted model predicts light-usage households should moderately increase usage in response to summer weather (when the true responses are closer to zero), the model may compensate by ascribing the absence of increased usage to strong price sensitivity.

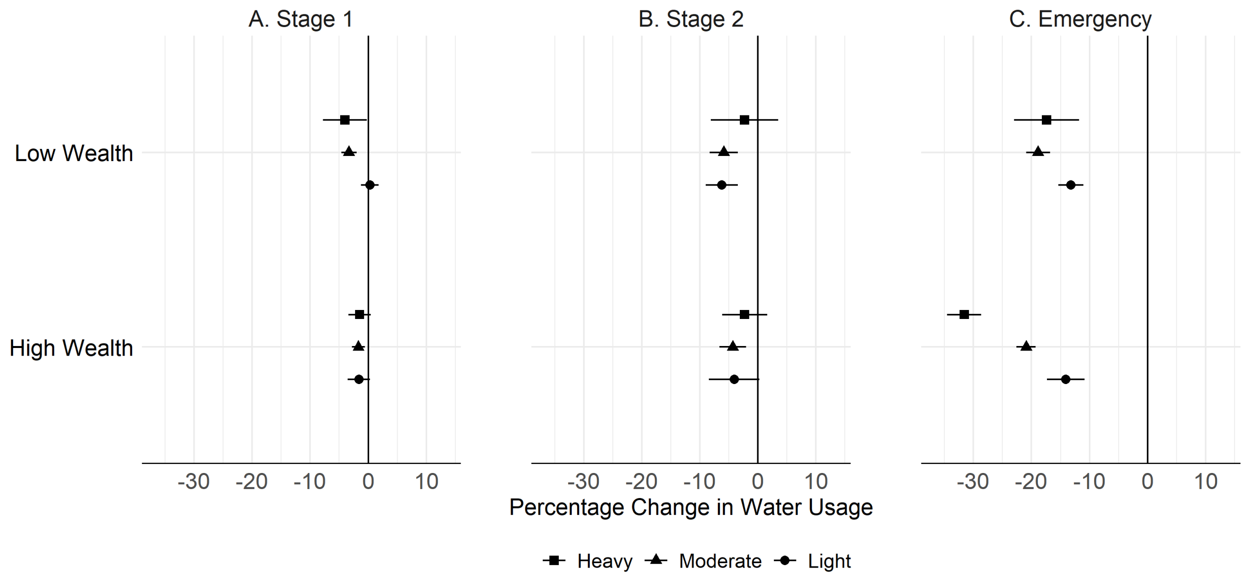
To test these conjectures, we turn off some of the sources of heterogeneity in equation (1) and re-estimate the model with simpler specifications. These results are shown in Appendix Table B4. In Column A, we assume that households have identical responses to water stress and air temperature, as well as identical intrayear usage patterns. We find that, as expected, high-wealth households' price elasticities are smaller in magnitude than in our main results. In fact, the ordering of high-wealth households' price elasticities is reversed relative to Figure 4, and low-wealth households' elasticities are roughly constant in usage. If we additionally restrict households to have identical price elasticities within wealth, or alternatively restrict households to have identical price elasticities within usage, we find that high wealth and high usage households are the least price sensitive. See Columns B and C of Appendix Table B4 for these results.

In Figure 6 we turn to the effects of CAC restrictions. The *Stage 1* and *Stage 2* restrictions had relatively modest impacts on water usage, and these effects are largely similar across usage profiles and wealth.[31] The *Stage 2* restriction also generated fairly weak responses by households in all groups; the weak response may have been influenced by an

[30]The same issues apply to settings with increasing-block pricing, a policy in which marginal prices rise with usage. When households on increasing-block pricing respond to hot and dry weather by increasing outdoor watering, their marginal prices rise.

[31]Percent changes are calculated from the OLS coefficients using the Halvorsen-Palmquist-Kennedy approach to interpreting indicator variable coefficients in semi-log specifications (Jan van Garderen and Shah, 2002).

Figure 6: Effect of Command and Control Policies on Water Usage



Note: Point estimates (geometric shapes) are the percent change in water usage due to command and control restrictions. Lines are 95% confidence intervals.

incentive to increase water usage in anticipation of the stricter *Emergency* restriction that followed. Households' responses to the *Emergency* restrictions were substantially larger than to the other CAC policies. Heavy-usage high-wealth households, which is the group most likely to engage in regular lawn irrigation, had the largest reductions in usage under *Emergency* restrictions. Differences in responses to this restriction across usage-wealth groups could be due to a variety factors, including pre-restriction water usage type and level, sensitivities to fines and neighbors' disapproval, and intrinsic motivations to obey guidelines. While the *Emergency* restrictions, like seasonal prices, induce heavy-usage households to reduce (likely) outdoor water usage, weaker restrictions appear less successful in generating responses among heavy-usage households.

3 Additional Evidence on Usage Profiles

For the elasticity estimation conducted in Section 2, we grouped households into usage profiles based on their activity prior to seasonal pricing. Though the results suggest that heavy-usage households were most sensitive to price, the way in which these households reduced usage is unclear. In this section, we examine how households' consumption may transition away from their initial classification and begin to resemble other usage profiles over the treatment period. This exercise provides supplementary information about the effects of seasonal pricing on usage. This information is relevant to water utilities, which are concerned with both price elasticities and peak-usage timing when setting policies for reservoir management (e.g. Zeff and Characklis, 2013; Zeff et al., 2016). To implement this analysis, we use the k-nearest neighbors algorithm to match a household's usage in each year to the *Heavy*, *Moderate*, or *Light* profile. For the year immediately before seasonal pricing, the matching algorithm almost always (greater than 97 percent of the time) assigns the household to the group of usage sequences to which it was assigned in the initial clustering procedure.

We start by providing in Table 2 the fractions of households in each usage profile over time. For example, Panel A shows that, in the first year of the sample, 34% of households had *Light* usage profiles. This fraction stayed relatively constant for two more years before increasing to about 45%. Overall, the fractions are generally stable in the sample's first couple of years, move around in the middle two "transition years" – October 2001-September 2002 and October 2002-September 2003 – and then are generally stable at a new level in the sample's final years. These patterns suggest a qualitative shift in usage following the introduction of seasonal pricing. Panels B and C show that a similar effect holds within both high- and low-wealth households.

To shed additional light on the reduction in usage after the implementation of seasonal pricing, we report in Table 3 changes in household-level usage profiles relative to usage profiles in the year prior to treatment (October 2000-September 2001). We describe how to understand the entries in this table using the transitions of households with *Heavy* usage profiles. As shown in the "Oct00-Sep01" row, 673 households were classified as having a *Heavy* profile during October 2000-September 2001. Of these households in the "Oct00-Sep01" row, 75% were in that same profile the following year ("Oct 01-Sep02"), while 24% moved to *Moderate*, and 1% moved to *Light*. The next row, labeled "Oct02-Sep03," shows that 56% of initially heavy-usage households in "Oct00-Sep01" row were in the *Moderate* profile during the second year of seasonal pricing. Among households identified as *Moderate*

Table 2: Usage Profile Shares

	Light	Moderate	Heavy
Panel A	*All Households (N=4455)*		
Oct99-Sep00	0.34	0.49	0.17
Oct00-Sep01	0.33	0.52	0.15
Oct01-Sep02	0.34	0.49	0.17
Oct02-Sep03	0.49	0.44	0.07
Oct03-Sep04	0.45	0.44	0.10
Oct04-Sep05	0.45	0.45	0.10
Panel B	*Lower Wealth Households (N=2080)*		
Oct99-Sep00	0.48	0.43	0.09
Oct00-Sep01	0.48	0.44	0.08
Oct01-Sep02	0.49	0.43	0.08
Oct02-Sep03	0.61	0.35	0.04
Oct03-Sep04	0.59	0.36	0.05
Oct04-Sep05	0.59	0.37	0.04
Panel C	*Higher Wealth Households (N=2375)*		
Oct99-Sep00	0.21	0.55	0.24
Oct00-Sep01	0.20	0.58	0.21
Oct01-Sep02	0.21	0.54	0.25
Oct02-Sep03	0.37	0.52	0.11
Oct03-Sep04	0.34	0.51	0.15
Oct04-Sep05	0.33	0.52	0.15

prior to seasonal pricing, many more reduced their usage to *Light* than increased to *Heavy*. Similarly, relatively few households initially identified as *Light* moved to a heavier usage profile. We provide a table of transitions by wealth in Online Appendix F.

When households move between adjacent usage categories, the magnitude of their usage changes might be large or small. In particular, small changes can induce transitions across a margin yet not represent substantial usage changes at all. We investigate this issue by examining the magnitudes of usage changes by households that have transitions across usage profiles. The average water usage by a *Heavy* usage household is 11.37 KGal per month immediately before seasonal pricing, with an interquartile range of 9.43-12.51 KGals. Households that switched from the *Heavy* to *Moderate* profile during consecutive years averaged 10.46 Kgals during the *Heavy* year and 3.06 KGals less after changing to

Table 3: Transitions in Usage Profiles

Oct00-Sep01	*Light (N=1481)*			*Moderate (N=2301)*			*Heavy (N=673)*		
	L	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
Oct01-Sep02	0.82	0.17	0.00	0.12	0.76	0.11	0.01	0.24	0.75
Oct02-Sep03	0.89	0.11	0.00	0.35	0.62	0.03	0.05	0.56	0.39
Oct03-Sep04	0.86	0.13	0.01	0.31	0.63	0.06	0.04	0.49	0.46
Oct04-Sep05	0.85	0.14	0.01	0.31	0.64	0.06	0.06	0.49	0.44

Note: The table above shows the proportion of users of in each initial usage profile whose consumption best matches each profile in the subsequent four years.

Moderate, a substantial reduction in water usage. Movement across non-adjacent profiles more obviously coincide with large reductions in water usage. In particular, households that switched from *Heavy* to *Light* used 10.8 KGals during the *Heavy* year and 7.16 KGals less once in the *Light* usage profile.

The information in Table 3 corroborates the finding that there appears to have been a permanent downward shift in usage for many households. It also provides further insight into the overall impact that seasonal pricing had on usage. In particular, the adoption of seasonal pricing was effective at reducing usage during peak summer months, resulting in observable decreases in *Heavy* usage profiles among both high- and low-wealth households.

4 Conclusion

Water utilities are increasingly using price-based demand management strategies as an alternative to infrastructure expansion. Evaluating these strategies requires an understanding of the consequences of price increases. In this study, we estimate demand for residential water using household-level panel data. Our data allows us to estimate elasticities that vary by both household wealth and usage profile. We find relatively large price sensitivity among households that are likely to irrigate their lawns, while much of the previous literature, which largely uses data from settings with increasing-block pricing (IBP), finds that households with heavy outdoor water usage are relatively price-inelastic.

There are several potential interpretations of this difference in results. One interpretation is that uncovering elasticity in IBP settings is difficult, and differences in results are due to imprecision or bias in previous elasticity estimates. If this is the case, then readers may view our elasticity estimates as recovering a better estimate of the underlying price sensitivity parameters that consumers bring into any water usage choice, regardless of the price structure. This suggests that raising prices for heavy usage in IBP may have a strong effect on outdoor usage, despite some previous evidence to the contrary. This interpretation is contingent on households paying sufficient attention to their marginal water price, for which there is conflicting evidence. This suggests a second interpretation of our results. Heavy-usage households may appear to be price-insensitive under IBP because they misinterpret their water price schedules, perhaps acting as if a lower price (e.g. the average of all marginal prices) applies to their usage. If households' difficulty in interpreting IBP is viewed as a constraint on real-world water pricing policy, then our results suggest that water utilities that seek to lower outdoor usage may consider using simpler seasonal pricing in place of IBP, or raising the prices of all steps in an IBP scheme rather than just the heavy-usage ones. A third interpretation, of course, is that the differences in results are simply due to differences in the populations studied. There are good reasons to support each of these interpretations (individually or in combination), and we leave it to future work to provide more evidence on which ones are appropriate.

Our findings have implications for several areas of related research. First, from the perspective of a water utility, the relationship between price and quantity is an important consideration because utilities tend to recoup a large percentage of their fixed costs from variable charges (Beecher, 2010). Second, water utilities may be concerned with the welfare impacts of higher prices on various customer classes. In contrast to previous findings, we show that poorer households have similar demand elasticities to wealthier households. This provides the basis for future research exploring welfare implications of price changes and the affordability of water services.

Appendices

A Deriving the Water Stress Index

Previous studies of water demand have taken a variety of approaches in modeling relevant environmental factors. The most common controls used are measures of precipitation (Moncur, 1987; Renwick and Archibald, 1998; Martínez-Espiñeira and Nauges, 2004; Roseta-Palma et al., 2013) or a combination of precipitation and temperature measures (e.g. Taylor, McKean and Young, 2004; Gaudin, 2006; Wichman, 2017). Some studies have instead relied on measures of evapotranspiration (e.g. Hewitt and Hanemann, 1995; Dandy, Nguyen and Davies, 1997; Olmstead, Hanemann and Stavins, 2005). Many additional measures – such as wind speed, minutes of sunshine, and temperature differences relative to some threshold – have also been used.[32] Some recent demand estimation studies in western U.S. have made use of satellite imagery data to calculate a Normalized Difference Vegetation Index (NDVI), a measure of landscape "greenness" to represent demand (e.g. Wolak, 2016; Brent, 2016; Clarke, Colby and Thompson, 2017).

In contrast to these approaches, we create a water stress index using the RHESSys model.[33] The advantage of this model is that it uses elements of ecosystem models (e.g. BIOME-BGC (Running and Hunt Jr, 1993) and CENTURY (Parton et al., 1987)) to model spatial and temporal dynamics of soil moisture available to lawns (the top 20 cm of soil). To do this, we first provide the RHESSys model with highly detailed spatial information to partition the landscape into forest, roads, rooftops, impervious surfaces, wetlands, pasture/agriculture lands, and lawns.[34] We then model surface and subsurface water flowpaths over the watershed. Outputs of RHESSys relevant to this study includes catchment-scaled

[32]Though typically weather variables are included as linear terms, Maidment and Miaou (1986) argue that the effects of weather may be nonlinear, as the effects of rainfall, for example, diminish over time. Martínez-Espiñeira (2002) argues that the number of rainy days can have a psychological impact therefore can have a greater impact on water demand.

[33]RHESSys has been widely used to model spatially distributed soil moisture, evapotranspiration, surface and subsurface runoff, carbon and nitrogen cycling in different biomes and under different climate and land-use change scenarios (Band et al., 1993; Hwang, Band and Hales, 2009; Miles and Band, 2015; Bart, Tague and Moritz, 2016; Hanan, Tague and Schimel, 2017; Gao et al., 2018; Lin et al., 2019).

[34]We use land use land cover information at a resolution of 1 meter from the Environmental Protection Agency's EnviroAtlas (Pickard et al., 2015).

streamflow, patch-scaled (30 m) soil moisture, and patch-scaled vegetation water demand and evapotranspiration.

Using data from USGS gages in the OWASA service area, we calibrate parameters related to hydrologic conductivity (water transport rate in soil columns) in our model using information for 2000-2004 and validate the model using information for 2007-2009.[35] We conduct Monte Carlo simulations to generate predictions of streamflow/catchment runoff using these parameters. These predictions are then compared to the observed streamflow in order to find the set of conductivity parameters that best represents the area under study. Model fit is evaluated using the weekly Nash–Sutcliffe model efficiency coefficient (NSE), both logged and in levels.[36] For each of these simulations, we summarize model outputs as an index, given by $WS = 1 - \xi^a/\xi^p$, that captures the lack of moisture available to lawns. In this equation, ξ^a represents actual evapotranspiration (ET) and ξ^p represents potential evapotranspiration (PET). We create two versions of the variable at different spatial scales: a Census Block Group specific measure (used in the main analysis) and another at the regional (watershed) level. Figure A1 graphically represents the spatial and temporal variation in the Census Block Group water stress variable.

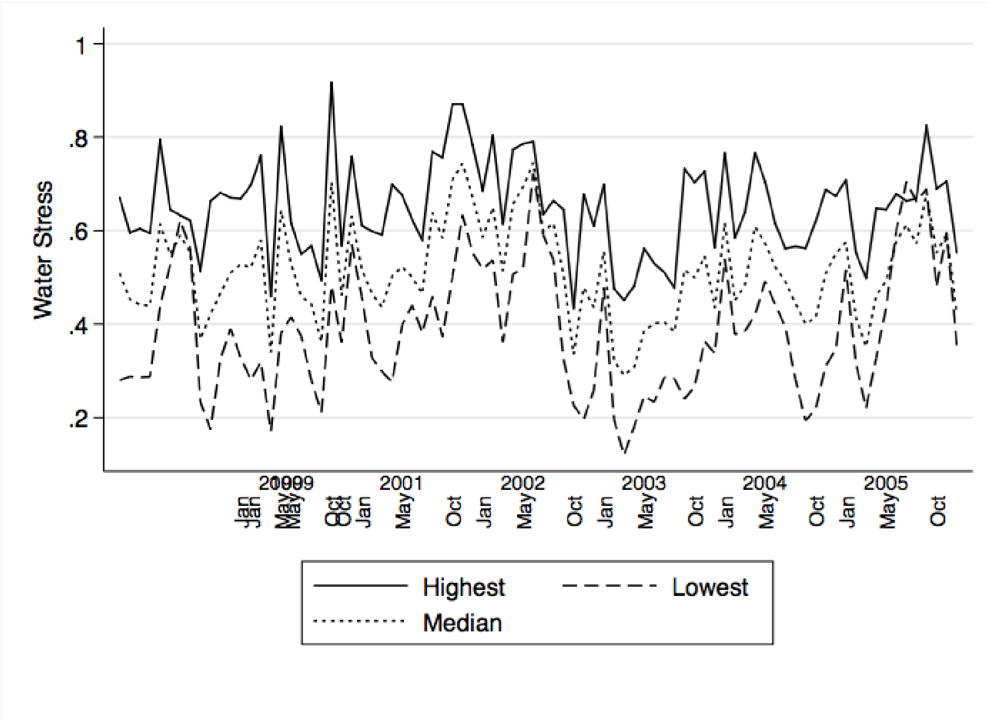
Previous work in the hydrology literature has documented high spatial variation in soil moisture even over small spatial scales (Tague et al., 2010; Rosenbaum et al., 2012). In the context of the area we study, there are two potential drivers. First, topography plays an important role. Specifically, differences in elevation has a direct impact on flow paths. Second, (sub)urbanized landscapes also alter flow paths. For instance, roads, sidewalks, buildings, and other impervious surfaces can block off infiltration. Fragmented forests and patchy lawns and gardens can affect vegetation water needs over the landscape.

[35] We calibrate the model using low streamflow conditions due to drought conditions during 2001-02 and high streamflow that resulted from the extreme wet event in the latter part of 2002. Other time periods provide information on "normal" streamflow conditions. We validate the hydrological model using 2007-2009, a time period in which another drought occurred.

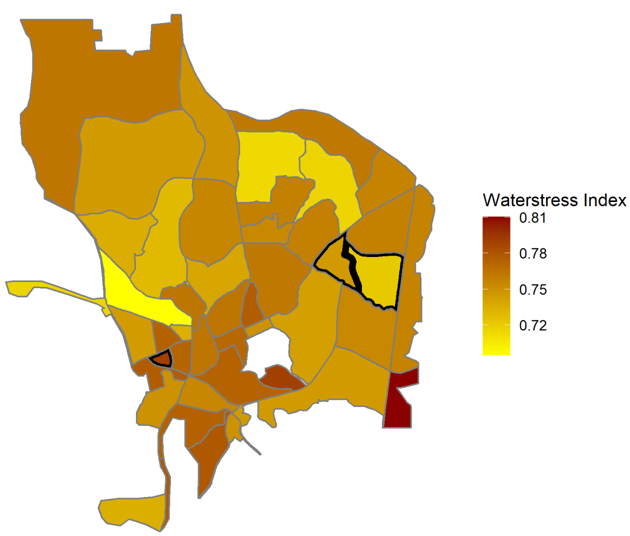
[36] Comparisons of predicted to observed streamflow require consideration of how predictions perform under various flow events (high vs. low). The NSE coefficient in levels provides information on model fit for high flow events whereas the log transformed NSE coefficient provides information on model fit for low flow events.

Figure A1: Water Stress

(a) Water Stress for Three Census Block Groups: 1999-2005



(b) Water Stress During June 2002 for all Census Block Groups



Notes: "Highest" refers to the block group with the highest average water stress during the period, "Median" the block group with the median average water stress and "Lowest" the block group with the lowest average water stress. The vertical line indicates the date for which water stress is shown for all block groups in Figure A1(b). The block groups with bold boundaries correspond to the three block groups in Figure A1(a).

B Demand Estimation Results

Main Specification

The results from estimating (1) are in Panel A of Table B1. For comparison, we also analyze a model without any heterogeneous effects:

$$q_{it} = \beta_j p_t + \sum_k x_{itk}\phi_{kj} + Z_{it}\theta_j + \eta_i + \epsilon_{it}. \tag{2}$$

The results from estimating (2) are in Panel B in Table B1.

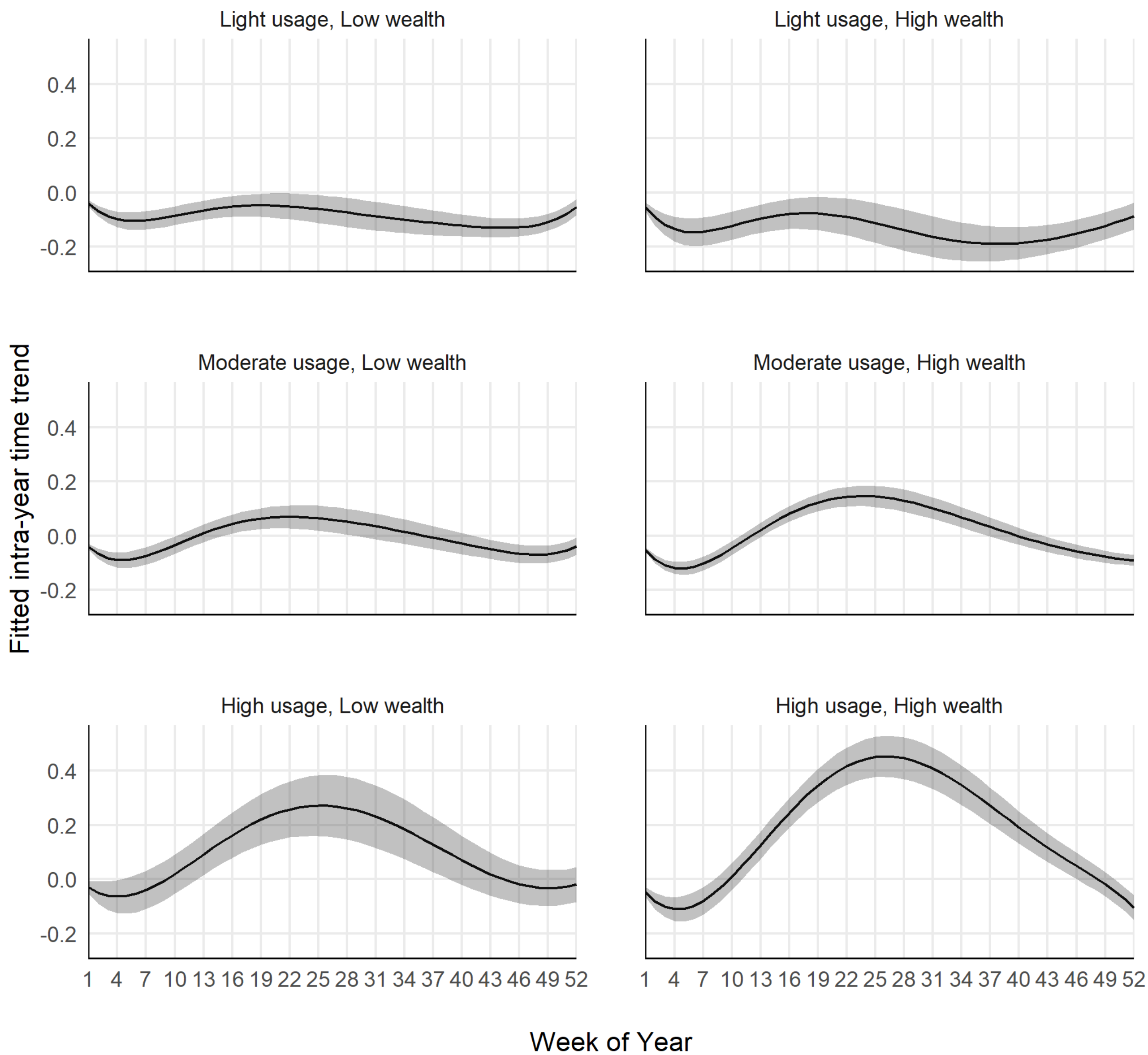
Table B1: Estimation results

	Price	Stage 1	Stage 2	Emerg.	WS	Temp.
Panel A: Main Results						
Low wealth, light usage	0.0544	0.0028	-0.0645	-0.1418	0.0324	0.0132
	(0.0304)	(0.0078)	(0.0149)	(0.0128)	(0.0030)	(0.0067)
Low wealth, moderate usage	-0.1476	-0.0339	-0.0605	-0.2089	0.0607	-0.0002
	(0.0396)	(0.0069)	(0.0130)	(0.0131)	(0.0031)	(0.0058)
Low wealth, heavy usage	-0.3889	-0.0410	-0.0230	-0.1907	0.0836	-0.0244
	(0.0597)	(0.0201)	(0.0304)	(0.0345)	(0.0096)	(0.0142)
High wealth, light usage	0.0441	-0.0163	-0.0417	-0.1520	0.0411	0.0265
	(0.0429)	(0.0100)	(0.0231)	(0.0192)	(0.0046)	(0.0098)
High wealth, moderate usage	-0.1172	-0.0171	-0.0444	-0.2348	0.0840	-0.0191
	(0.0287)	(0.0056)	(0.0121)	(0.0107)	(0.0028)	(0.0051)
High wealth, heavy usage	-0.3560	-0.0151	-0.0234	-0.3796	0.1314	-0.0308
	(0.0654)	(0.0099)	(0.0203)	(0.0219)	(0.0048)	(0.0093)
Panel B: No Heterogeneity						
All	-0.1037	-0.0136	-0.0448	-0.2106	0.0689	-0.0026
	(0.0260)	(0.0033)	(0.0067)	(0.0063)	(0.0016)	(0.0030)

Note: The "Price" column contains price elasticity estimates. The "Stage 1," "Stage 2," and "Emerg" columns contain responses to the three levels of CAC restrictions. The "WS" and "Temp" columns contain responses to water stress and average temperature, respectively. In addition to the variables displayed in this table, the model includes an indicator variable for the seasonal pricing regime and interactions of usage type and wealth indicators with log(read days), and a nonlinear intrayear time trend. The model also includes linear interyear time trends for summer and non-summer usage, for which results are reported in the "Baseline" column of Table B2. Standard errors, clustered at the household level, are in parentheses.

In Appendix Figure B1, we display the estimated type-specific intrayear trends, which we specify as a sixth-order polynomial for each type. As exected, the estimated intrayear trends largely follow the temporal usage patterns in Figure 2.

Figure B1: Estimated Intrayear Time Trends



Notes: Solid lines are the mean values for each of the type-specific fitted polynomial functions. The shading around the lines represent 95% confidence bands.

We next assess our results' sensitivity to different approaches to usage trends. In addition to our main specification, we estimate several alternative specifications and report the results in Table B2, where Panel A contains trend coefficients and Panel B contains price elasticities. The "Baseline" column reports the interyear trend estimates from our main specification and repeats the elasticity estimates from Table B1 Panel A. The "Two-Step" column reports trend coefficients from a model that uses data prior to seasonal pricing (May 2002) and homogeneous coefficients for all households, as in equation (2). We use these estimates to de-trend the usage data of the seasonal pricing regime, and we estimate an adapted version of equation (1) to obtain elasticity estimates. The intuition behind the two-step model is that the pre-seasonal pricing portion of the sample period should pin-down the interyear usage trends, and by restricting the data to this period we avoid confounding the trends with other sources of temporal variation during the seasonal pricing regime. In the remaining columns of Table B2, we explore specifications that allow usage trends to vary with permanent household characteristics that could be correlated with water demand. The "Wealth" column allows for separate interyear summer and non-summer trends for high- and low-wealth households within equation (1). The "Lot Size" column estimates separate trends for households above and below the OWASA median lot size. The "Wealth $\times$ Lot" column estimates separate trends for each combination of wealth and lot size indicators. In all cases, the elasticity estimates in Table B2 Panel B are qualitatively the same as our Baseline results. The "Two-Step" elasticities are more negative than the Baseline results but retain the same ordering across usage types while being invariant to wealth. The remaining elasticity results, using combinations of wealth and lot size, are quantitatively nearly identical to the Baseline results.

Table B2: Estimation results

	Baseline	Two-Step	Alternative Specifications		
Panel A: Trend coefficients					
Year trend	-0.0411	-0.0351	-0.0377	-0.0369	-0.0372
	(0.0015)	(0.0018)	(0.0020)	(0.0019)	(0.0024)
Summer trend	0.0002	0.0000	-0.0063	-0.0023	-0.0027
	(0.0021)	(0.0026)	(0.0023)	(0.0021)	(0.0028)
Year trend, high wealth	.	.	-0.0026	.	0.0009
	.	.	(0.0028)	.	(0.0032)
Summer trend, high wealth	.	.	0.0051	.	0.0004
	.	.	(0.0041)	.	(0.0042)
Year trend, large lot	.	.	.	-0.0086	-0.0015
	.	.	.	(0.0023)	(0.0035)
Summer trend, large lot	.	.	.	0.0060	-0.0112
	.	.	.	(0.0015)	(0.0046)
Year trend, high wealth, large lot	.	.	.	.	0.0021
	.	.	.	.	(0.0022)
Summer trend, high wealth, large lot	.	.	.	.	0.0058
	.	.	.	.	(0.0030)
Seasonal pricing regime	0.0081	-0.0119	0.0080	0.0085	0.0083
	(0.0048)	(0.0041)	(0.0048)	(0.0048)	(0.0048)
Panel B: Price elasticities					
Low wealth, light usage	0.0544	0.0521	0.0600	0.0449	0.0503
	(0.0304)	(0.0222)	(0.0348)	(0.0303)	(0.0351)
Low wealth, moderate usage	-0.1476	-0.1501	-0.1422	-0.1564	-0.1516
	(0.0396)	(0.0293)	(0.0457)	(0.0395)	(0.0461)
Low wealth, heavy usage	-0.3889	-0.3913	-0.3838	-0.3976	-0.3935
	(0.0597)	(0.0559)	(0.0616)	(0.0599)	(0.0621)
High wealth, light usage	0.0441	0.0414	0.0396	0.0368	0.0370
	(0.0429)	(0.0363)	(0.0490)	(0.0431)	(0.0492)
High wealth, moderate usage	-0.1172	-0.1201	-0.1213	-0.1243	-0.1233
	(0.0287)	(0.0188)	(0.0368)	(0.0292)	(0.0371)
High wealth, heavy usage	-0.3560	-0.3592	-0.3602	-0.3627	-0.3603
	(0.0654)	(0.0536)	(0.0768)	(0.0664)	(0.0773)

Notes: The "Baseline" column matches the specification in Table B1 Panel A. The "Wealth," "Lot Size," and "Wealth × Lot" specifications are identical to "Baseline" with the exception of the interyear trend variables with coefficients reported in Panel A. Standard errors, clustered at the household level, are in parentheses. The "Two Step" column's trend coefficients are estimated using data pre-dating seasonal pricing, and we use these estimates to de-trend the usage data and obtain the Panel B estimates in a model identical to the "Baseline" specification. Standard errors are calculated using a bootstrapping procedure to account for sampling error.

Additional Alternative Specifications

In this section, we analyze our data using other approaches to understand how our estimates may change if we do not exploit several of the salient characteristics of our methodology. First, we use water stress in our main specification to represent environmental factors. Alternatively, one could use the well-known Palmer Drought Severity Index (PDSI, Palmer (1965)) instead. Though the two indexes are correlated, there are two theoretical reasons to prefer water stress. First, water stress is constructed from a spatially distributed hydrological model that takes into account plant physiology and hydrological response to estimate the ET and PET at 30 m resolution in an urbanized region over time. The RHESSys model itself has already incorporated the climate inputs to simulate infiltration, soil water drainage, capillary rise, field capacity, soil water lateral water transport, and runoff in the urbanized catchment parameterized by the EPA 1m Enviroatlas (Pickard et al., 2015). Second, the purpose of our water stress index is not to explicitly model drought, where drought is defined as a prolonged and abnormal moisture deficiency. This type of moisture deficiency is not characteristic of North Carolina where rainfall levels are generally high and water moisture is higher relative to Kansas and other locations for which the PDSI was primarily designed. Dry conditions in our setting represent moisture deficiencies that can be interpreted as urban lawn and garden signals which may prompt irrigation. Our index, therefore, is meant as an irrigation signal and not a drought signal. Specifically, the value of our index is designed to capture the water deficiency (i.e. water stress) that vegetation in an area would experience in the absence of irrigation. Note also that the PDSI is defined spatially according to "climate divisions." There are 8 in the entire state of NC, and all of OWASA's service area is in one climate division. Thus water stress is much more spatially distinct. All of this notwithstanding, we estimate a model using PDSI instead of our measure of water stress as an additional robustness check. The results are presented in the "PDSI" column in Table B3 and are fairly similar in magnitude to our main results. Though the impact of using PDSI and our water stress measure are similar, water stress is the more appropriate measure as it is a direct attempt at modeling moisture available to lawns using highly detailed spatial information.

Second, we replace our machine learning algorithm with a simple procedure to assign usage groups. In particular, we separated households into terciles based on their total year-round usage prior to seasonal pricing. We refer to this classification approach as "TercilesA" in Table B3. We also separated households into terciles based on their total usage during summer months; this classification is "TercilesS." These alternative approaches have the advantage of being simpler than our machine learning approach, but they set ex-ante constraints on the shares of households that will be classified as having high, medium, and low usage. By comparison, using our preferred approach, we place only 15% of households in the heavy-usage category. We obtain results that are qualitatively similar to our main results. Heavy-usage households have the greatest price sensitivity, followed by medium-usage households, and low-usage households show little or no significant response to price variation.

Third, we estimate our main model using unbalanced panel data, where we ease the requirement that households are present in all years of the sample period. In this setup, we require customers to be present in the sample's first two years, but we place no restriction on whether customers remain until the end of the sample period. This increases the sample size to 5824 households. The results, which we display in Table B3's "Unbalanced" column, are very similar to those from our main specification.

Fourth, our main estimating equation allows for heterogeneous effects of controls across groups through the ϕ and θ parameters in (1). In Table B4 we consider various restrictions imposed on this model. The column labelled "Main" reproduces our main results from Table B1. In column A, we place restrictions on ϕ and θ so these coefficients do not vary across groups. The results are strikingly different. In particular, the elasticities for high wealth groups are essentially reversed. In columns B and C, we keep the same ϕ and θ restrictions of column A in place and estimate the wealth and usage effects separately of each other. Again we see quite different results from our main specification. These alternative specifications support our argument that a potential reason for the differences between our results and those in the previous literature may be due to our treatment of heterogeneity.

Table B3: Price Elasticities Under Alternative Specifications

	Main	PDSI	TercilesA	TercilesS	Unbalanced
Low wealth, light usage	0.0544	0.0505	0.0493	0.0765	0.0686
	(0.03040)	(0.02960)	(0.03040)	(0.03020)	(0.02950)
Low wealth, moderate usage	-0.1476	-0.1399	-0.1206	-0.0870	-0.1345
	(0.03960)	(0.03850)	(0.03740)	(0.04210)	(0.03160)
Low wealth, heavy usage	-0.3889	-0.3684	-0.2667	-0.3889	-0.3717
	(0.05970)	(0.05630)	(0.05800)	(0.04350)	(0.05180)
High wealth, light usage	0.0441	0.0471	0.0180	0.0701	0.0964
	(0.04290)	(0.04150)	(0.04350)	(0.04170)	(0.04590)
High wealth, moderate usage	-0.1172	-0.1032	-0.0584	-0.0280	-0.1585
	(0.02870)	(0.02780)	(0.03130)	(0.03000)	(0.02620)
High wealth, heavy usage	-0.3560	-0.3199	-0.2706	-0.3391	-0.3324
	(0.06540)	(0.06300)	(0.04360)	(0.04640)	(0.05250)

Note: Column contain price elasticity estimates. Models also include CAC restrictions, linear interyear time trends for summer and non-summer usage, an indicator variable for the seasonal pricing regime and interactions of usage type and wealth indicators with: water stress, temperature, log(read days), and a nonlinear intrayear time trend. Standard errors, clustered at the household level, are in parentheses.

Table B4: Price Elasticities Under Alternative Heterogeneity Approaches

	Main	A	B	C
Low Wealth	.	.	-0.1752	.
	.	.	(0.0287)	.
High Wealth	.	.	-0.0094	.
	.	.	(0.0296)	.
Light Usage	.	.	.	-0.1555
	.	.	.	(0.0287)
Moderate Usage	.	.	.	-0.1252
	.	.	.	(0.0283)
High Usage	.	.	.	0.1077
	.	.	.	(0.0487)
Low wealth, light usage	0.0544	-0.1425	.	.
	(0.0304)	(0.0298)	.	.
Low wealth, moderate usage	-0.1476	-0.2028	.	.
	(0.0396)	(0.0358)	.	.
Low wealth, heavy usage	-0.3889	-0.2207	.	.
	(0.0597)	(0.0599)	.	.
High wealth, light usage	0.0441	-0.1509	.	.
	(0.0429)	(0.0394)	.	.
High wealth, moderate usage	-0.1172	-0.0508	.	.
	(0.0287)	(0.0289)	.	.
High wealth, heavy usage	-0.3560	0.2431	.	.
	(0.0654)	(0.0579)	.	.

Note: Column contain price elasticity estimates. In column A, controls are not allowed to vary across groups. In columns B and C, we estimate the wealth and usage effects separately of each other. Models also include CAC restrictions, linear interyear time trends for summer and non-summer usage, an indicator variable for the seasonal pricing regime and interactions of usage type and wealth indicators with: water stress, temperature, log(read days), and a nonlinear intrayear time trend. Standard errors, clustered at the household level, are in parentheses.

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