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.

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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; Newsham and Bowker, 2010; Kenney et al., 2011; Mayer, Hunter and Smith, 2018). Price increases can be used to reduce quantity demanded to meet (perhaps reduced) supply 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 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. These findings are in contrast with the previous literature. Explanations for these differences include the richness of our data as well as our treatment of consumer heterogeneity.

Understanding heterogeneity in demand for residential water is important for evaluating the impact of using prices to manage demand. 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 lawn and garden irrigation (Mayer et al., 1999; Balling, Gober and Jones, 2008; Swamee and Sharma, 2008). For price-based rationing strategies to successfully reduce water usage, price increases should have a significant impact on heavy-usage households who are likely to irrigate. Estimating heterogeneous responses to price changes is also a necessary precursor for the analysis of distributional effects.

The previous literature on water demand's price elasticity has explored heterogeneity

[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 are 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).

along two dimensions, independently of one another. First, studies have explored how price responses vary with wealth, usually proxied by home value or income. These studies suggest that wealthier households have less elastic demand for outdoor water usage as well as for water usage overall (Mansur and Olmstead, 2012; Wichman, Taylor and von Haefen, 2016). Second, studies have explored heterogeneous responses by usage. Wichman, Taylor and von Haefen (2016), for instance, find that higher-usage households with irrigation systems are generally less price sensitive.[2] Taken together, these previous results suggest that price-based policies may not be effective in reducing demand by heavy users, and may generate distributional effects by raising water expenditures by poor households.

We depart from previous work in several ways. First, our data have several advantages over those used in past studies. We observe a transition from year-round uniform pricing to seasonal pricing in which summer prices are about 40% above winter prices. To our knowledge, no other study has conducted a household-level longitudinal water demand analysis with similar degree of price variation.[3] 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 examine heterogeneous responses in terms of usage and wealth simultaneously instead of in isolation. This highlights the fact that both dimensions are necessary for understanding household responses, and neither is sufficient alone. Households with similar wealth levels may have different preferences for outdoor water usage and households with comparable levels of usage may respond differently to price changes given the resources at their disposal.

[2]Wichman, Taylor and von Haefen (2016) examine how price responses vary by wealth and usage characteristics but not the interaction of the two characteristics.

[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 (Renzetti, 1992; Lyman, 1992; Reynaud, 2010) have focused on aggregate demand rather than household-level demand.

[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.

Third, 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 interventions (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.

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 -0.5470, while wealthy low-usage households have a price elasticity of -0.1450.[6] By contrast, the previous literature typically finds that households with higher outdoor water usage are less price sensitive than other households (Mansur and Olmstead, 2012; Baerenklau, Schwabe and Dinar, 2014; Klaiber et al., 2014; Wichman, Taylor and von Haefen, 2016).[7] Why are our results different from the previous literature? One potential explanation is that the large price increases we observe provide a better opportunity to accurately estimate elasticities. Another possible explanation is 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 the price elasticity estimates.

[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. In addition, 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), and Wichman, Taylor and von Haefen (2016). Similar issues exist for residential energy demand; see Reiss and White (2005); Swan and Ugursal (2009); Borenstein (2012) and Auffhammer and Rubin (2018).

[6]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).

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

We complement our elasticity estimates with descriptive evidence of transitions in usage profiles over time. This provides insight into the extent to which households make substantial changes in water usage following the introduction of higher prices. These descriptions reveal that a large share of households reduced water usage significantly after the implementation of seasonal pricing.

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.[8] 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. We define monthly usage for each household in terms of these read periods. In recording households' usage data, OWASA truncates to the nearest thousand gallons the total quantity of water used during a read period.[9] 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.

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.[10] Next, we drop households with usage data that begins later than October 1st, 1999. This insures that we observe all house-

[8] In OWASA's service area there are 42 Block Groups which contain, on average, about 190 households each.

[9] 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.

[10] 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.

holds 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.[11] Our final sample contains 4,455 households, roughly 52% of the starting data.

1.2 Water Prices

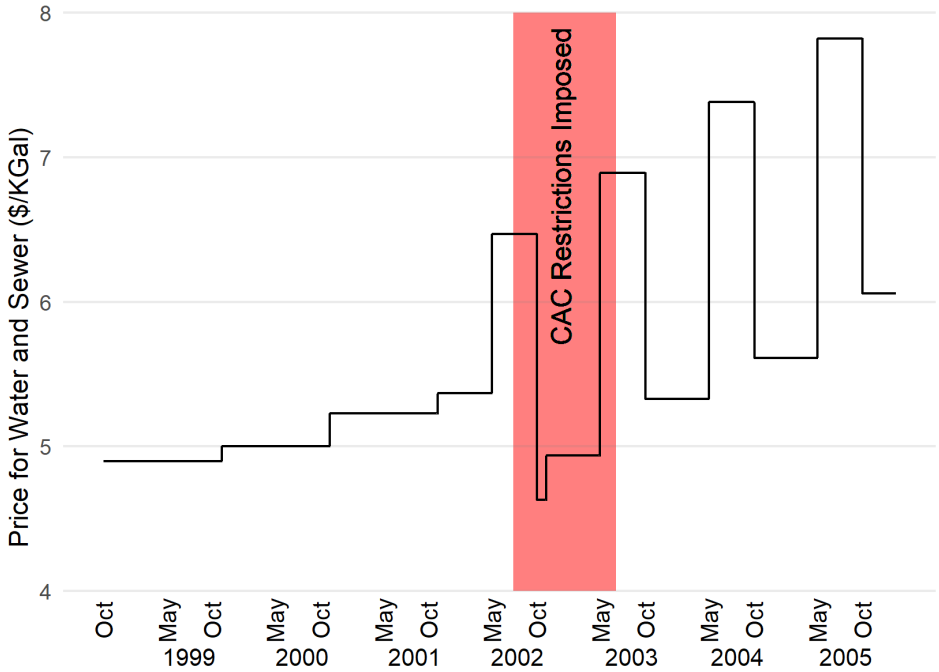
OWASA is among the first water utilities to use prices as part of a broader strategy to manage demand during non-drought periods. On May 1st 2002, OWASA replaced uniform year-round prices with seasonal prices that are higher in the summer.[12] The decision to adopt seasonal pricing was part of a longer-term plan to manage water resources and not in response to a particular event. OWASA sets the price schedule each year to cover their yearly expenses for the residential sector as a whole. Similar to many utilities, OWASA charges households a combination of volumetric and fixed fees. 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, we follow the literature in assuming that the effective marginal price is the combined price for water and sewer services.

We show the nominal marginal prices per thousand gallons (KGals) from October 1999 to October 2005 in Figure 1. 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 volumetric sewer charges remained constant throughout the year. In

[11] 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.

[12] In October 2007, OWASA transitioned to a different pricing schedule in which marginal prices depend on usage, referred to as increasing block pricing.

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.

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 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.[13] 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 D.

Following the 2002 drought, OWASA introduced new usage guidelines to encourage conservation. The 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 and were in effect while conservation concerns were less salient in the market.[14] We do not account for this policy shift in the analysis below, so it could influence our price elasticity estimates, which we obtain with temporal price variation that coincided with the new usage guidelines.

1.4 Usage Profiles and Wealth

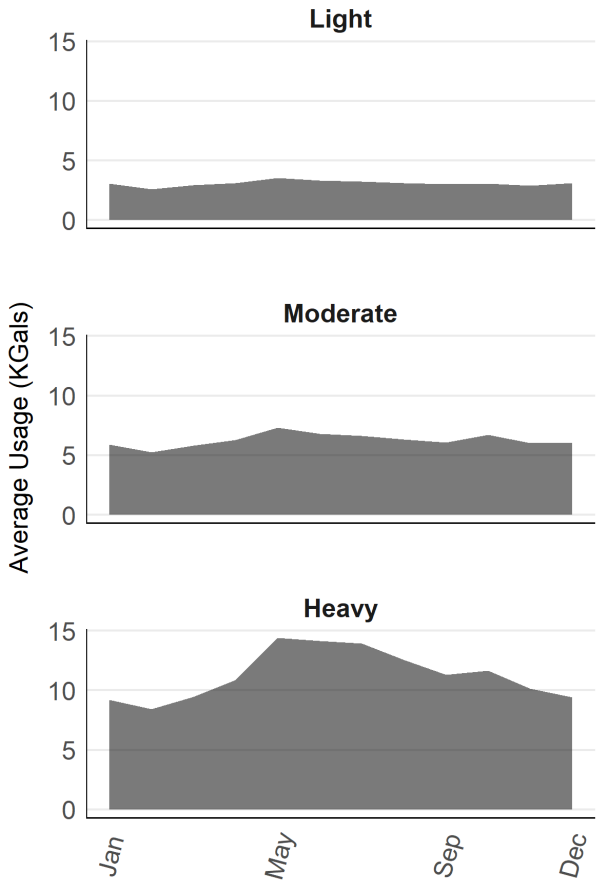
We use Ward's agglomerative hierachical clustering algorithm (Ward, 1963) to identify yearly usage patterns during October 1999-September 2001, the two pre-treatment years that feature constant within-year prices and small price changes between years. We define years to coincide with how OWASA implemented price changes. Combining the two pre-treatment years to create a representative year, we apply the clustering algorithm to identify yearly usage profiles based on the amount of water used in each respective month.[15] We allow the

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

[14] 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.

[15] To apply the machine learning clustering algorithm, we convert usage amounts from read periods to calendar months under the assumption that per-day usage is constant within a read period.

Figure 2: Usage Profiles from Clustering



algorithm to create three usage profiles; additional levels 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).[16] We illustrate the usage profiles – which we refer to as *Heavy*, *Moderate*, and *Light*– in Figure 2.[17]

The usage profiles are instructive in describing differences in how households use water over the course of the year. 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

[16]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.

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

significant amount 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 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.

These usage profiles are useful because they also capture household characteristics that we do not observe directly, such as the number of people in the household or preferences for outdoor water use. We assign each household to a profile based on its usage from October 2000 to September 2001, immediately before seasonal pricing's introduction. We use k-nearest neighbors, a supervised learning algorithm, to perform the match (Batista et al., 2014). 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 E.

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).[18] Specifically, we create an indicator for relative wealth based on the median assessed home value ($192,647) in the area of study in 2000.[19] 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 correlation between wealth and higher 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

[18]Studies that have explored how price responses interact with wealth measures have used homes' assessed 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).

[19]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.

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 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 gauges 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 heterogeneity. 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 or car washing) 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 F, 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. 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.[20] To account for demand heterogeneity, the

[20] Alternative assumptions, used elsewhere in the literature, include the assumption that households re-

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 i has usage profile u and wealth level w, and zero otherwise. We specify demand as:

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

The dependent variable, q_{it}, is the de-trended log of the total quantity of water demanded by household i during read period t. (We describe the de-trending approach below.) The variable p_t is the 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 vector X_{it} records CAC restrictions, $k \in \{$*Stage 1, Stage 2, Emergency*$\}$, that were implemented during the drought. The restrictions are mutually exclusive, and we record in X_{it} the share of days restriction k was in place during each read period. 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. We account for intra-year usage patterns with a sixth-order polynomial in a read period's average week number.

We leverage the panel nature of the data to control for time-invariant unobserved household characteristics that may be correlated with water demand. These characteristics are absorbed by the fixed effect η_i. Lastly, ϵ_{it} is an error term that captures unobservable

spond 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).

demand shocks that households experience during individual read periods. In estimating equation (1), we calculate standard errors using a bootstrapping procedure to account for sampling error in the detrending procedure described below.

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 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. However, we must account for the possibility that water usage trends contribute to changes in water usage after seasonal pricing began. Some factors that could contribute to usage trends include the gradual installation of modern low-usage appliances and changing practices in gardening and landscaping. Our data allow us to estimate a simple usage trend during the sample's pre-treatment years, and we use the trend estimates to project households' water usage in the absence of seasonal pricing.

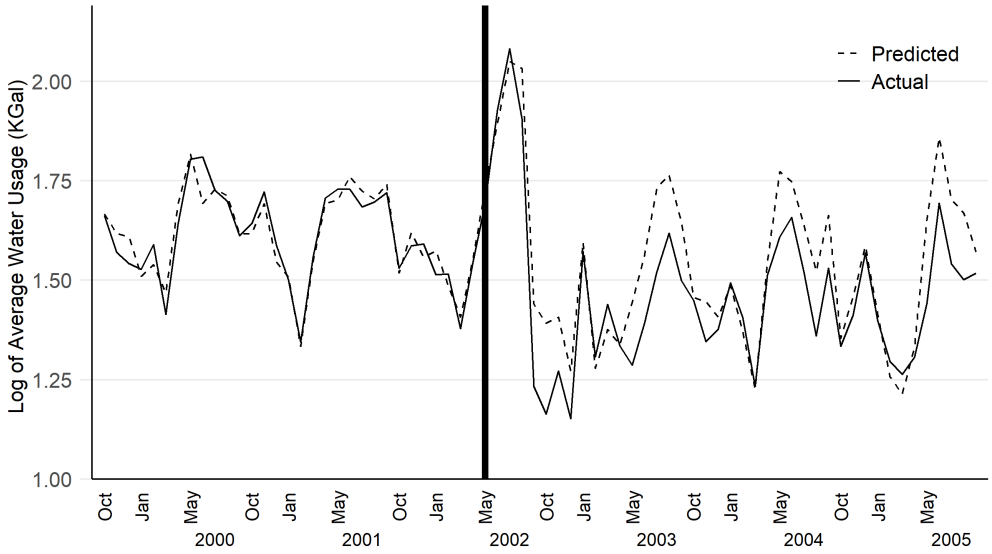
We de-trend the data using the following approach, which is described in greater detail in Appendix B. First, we estimate a parsimonious version of equation (1) with data from October 1999 until April 2002, the last month prior to seasonal pricing. This model includes household fixed effects, a year-round linear time trend, an additional summer-specific linear time trend, water stress and temperature, and a sixth-order polynomial in week number to account for intra-year usage patterns. We do not include price in this model because there is no significant price variation prior to seasonal pricing's introduction.[21] Next, we use the estimated trend coefficients to de-trend each household's usage during the full sample period. We perform our main estimation using this de-trended usage variable. We discuss below the robustness of our results to other approaches to account for usage trends.

In Figure 3 we display temporal variation in the raw data and the impact of our

[21] If we include price among the regressors, there are no significant changes to our results.

de-trending procedure. The vertical line marks seasonal pricing's introduction. The solid usage line is monthly household log usage, calculated directly from the data. Seasonal usage variation is apparent, as is the impact of the summer 2002 drought, which caused a large spike in usage. The usage data show a slight decline in usage between the panel's first two years, and then a stronger decline after OWASA introduced seasonal pricing. The dashed line is predicted usage based on a continuation of the estimated time trends and other variables included in the model we use to de-trend the data. The dashed line shows predicted usage in the absence of seasonal pricing and CAC restrictions. As expected, the estimated model generates usage predictions that follow the data well until May 2002. Once seasonal pricing begins, however, predicted and actual usage diverge. During the summer months, predicted usage (which assumes no change in prices) is often above actual usage. The magnitude of this difference, relative to the increase in summer prices, is essentially an aggregate demand elasticity for OWASA households. During the winter months, by contrast, predicted and average usage are much closer, reflecting the absence of a significant price change.

Figure 3: Actual and Predicted Water Usage



Note: The dashed line shows usage predicted in the absence of seasonal pricing and CAC restrictions. This is constructed using estimates of usage trends during the pre-treatment period. See Appendix Section B for details on the detrending procedure.

2.3 Elasticity Estimates

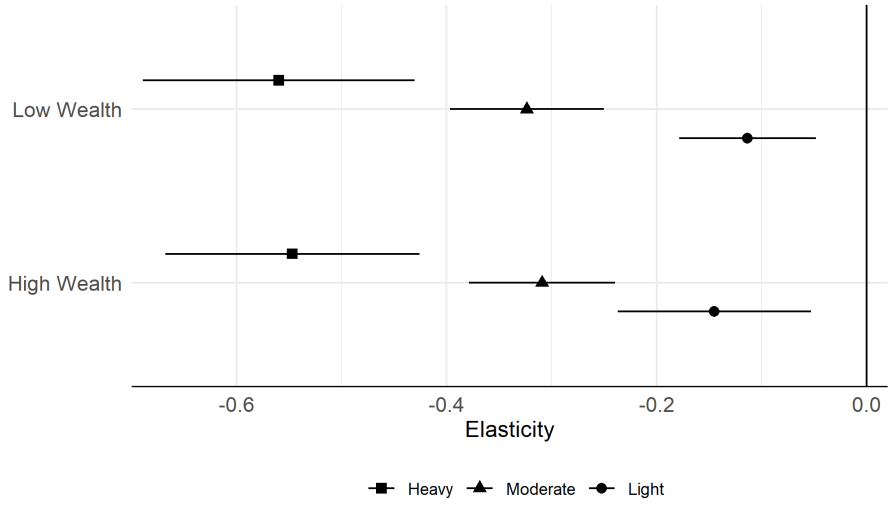
The results of estimating (1) are shown graphically in Figures 4 - 6 for various subsets of variables. The full set of coefficient estimates is in Table C1 in Appendix C. Starting with the price elasticity estimates shown in Figure 4, we find that there are significant differences across usage profiles. Among high-wealth households, those with *Heavy* usage profiles have price elasticity of -0.5470 while high-wealth households with *Moderate* and *Light* usage profiles have elasticities of -0.3091 and -0.1450 respectively. Conditional on usage profile, the price elasticities of low-wealth households are essentially the same as those of high-wealth households. This finding contrasts with 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 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 such as OWASA closely monitor overall peak-season usage in making choices about capacity needs and non-price usage-reduction strategies. By definition, high-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 high-usage households. The price elasticity heterogeneity we document compounds this effect, as high-usage households reduce usage by a greater percentage on top of a greater base.

In Appendix C, we review results from a collection of models that use alternative approaches to de-trending household water usage. In particular, we estimate models without a separate summer trend, without no de-trending at all, with separate summer and non-summer trends for high- and low-wealth households, and separate summer and non-summer trends by an interaction of wealth with an indicator for a greater-than-median lot size. Each model generates results that are qualitatively similar to the results in Figure 4. The price elasticities of high-usage households are significantly larger than price elasticities of medium-usage households, which in turn are larger than low-usage households.

In addition to documenting heterogeneity in price elasticities, we find that households vary in their responses to environmental factors; see Figure 5. Responses to water stress and

Figure 4: Water Price Elasticities



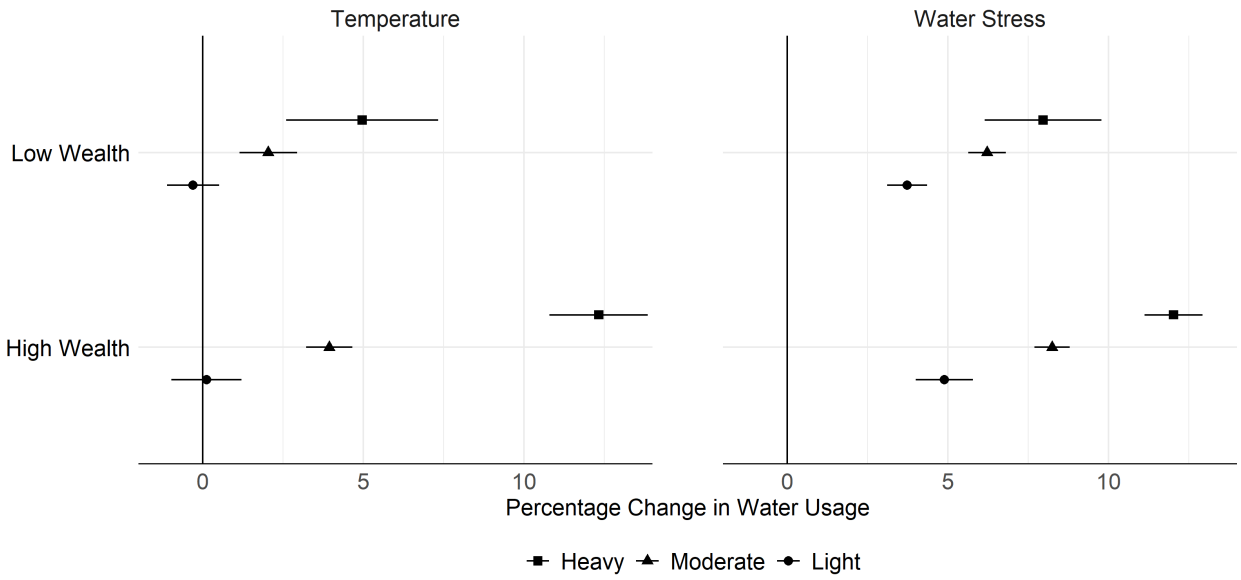
Note: Geometric shapes are point estimates and lines are 95% confidence intervals.

temperature increase in wealth and usage, with high-wealth high-usage households having significantly greater responses than all other usage and wealth types. Low-usage households, as expected, are relatively unresponsive to variation in environmental conditions. This heterogeneity provides an additional opportunity for our model to capture preference variation for outdoor water usage, and therefore appropriately capture households' responses to water prices.

To understand how our approach to environmental factors supports our estimation of price elasticities, consider the potential bias in price sensitivity that would follow from assuming homogenous responses to these factors across usage profiles. With this restriction, we would under-estimate high-usage households' responses to hot and dry weather while over-estimating low-usage households' responses. Environmental stress occurs at the same time of year as increased prices, so uncaptured variation in weather responses will spill over to estimates of price elasticities. In particular, if high-usage households' weather-related increased usage is not explained by their responses to summer weather conditions, then the model attempts to fit their behavior through biased price sensitivities that are too small. This source of bias could play a role in some previous studies' findings of relatively low price elasticities for households presumed to irrigate.[22] Likewise, homogeneous responses

[22]The same issues apply to settings with increasing-block pricing, a policy in which marginal prices rise

Figure 5: Effect of Environmental Factors on Water Usage



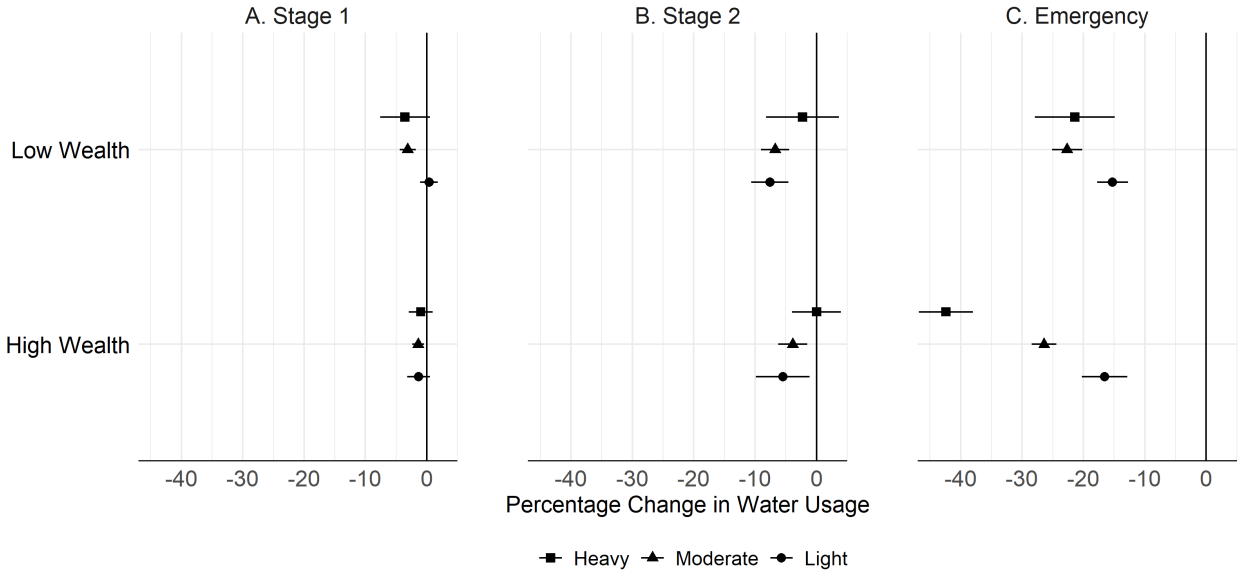
Note: Point estimates (geometric shapes) are percentage change in water usage per standard deviation increase in environmental factors. Lines are 95% confidence intervals.

to environmental factors will ascribe too-strong weather responses to low-usage households with little interest in outdoor water usage. When the restricted model predicts low-usage households should moderately increase usage in response to summer weather (when the true responses are closer to zero), the model will compensate by ascribing the absence of increased usage to strong price sensitivity. To demonstrate these effects in our setting, we re-estimate equation (1) while assuming homogeneous responses to water stress and weather. The results, which are in Appendix Table C3, show that low-usage households appear more price elastic than in our main specification, and high-usage households appear less elastic.

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. The *Stage 2* restriction appear to register fairly weak responses by high-usage households, who may have felt an 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.

with usage. When households on increasing-block pricing respond to hot and dry weather by increasing outdoor watering, their marginal prices rise.

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.

High-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. While the *Emergency* restrictions, like seasonal prices, induce high-usage households to reduce (likely) outdoor water usage, weaker restrictions appear less successful in generating responses among high-usage households.

3 Additional Evidence on Usage Profiles

For the elasticity estimation conducted in Section 2, we grouped households according to their ex-ante usage profiles. Though the results suggest that households with *Heavy* usage profiles were most sensitive to price, the way in which these households reduced usage is unclear. In this section, we examine how households move across usage profiles over the treatment period to provide 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). We use a k-nearest neighbors algorithm to match

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

each household's usage in each year to one of the three usage profiles previously identified (*Heavy* *Moderate* and *Light*).

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.

The two transition years are particularly interesting because they were affected by the introduction of seasonal prices, the onset of drought, and the implementation of CAC restrictions. Although we do not explicitly decompose these various effects on how households sort into usage profiles, it is important to note that there are two opposing forces at play during the summer months of seasonal pricing's first year (October 2001-September 2002). On one hand, the onset of drought conditions put upwards pressure on usage. From Section 2, we expect that this "drought effect" would primarily affect high-wealth households with outdoor usage, as drier conditions increase watering needs for landscaping. On the other hand, the implementation of higher seasonal prices and CAC restrictions put downward pressure on usage. For the full population (Panel A), we note a small, but noticeable, increase in the fraction of households with *Heavy* usage profiles during the transition years, and essentially no change in the fraction of households with *Light* usage profiles. These patterns suggest that the upward pressure exerted by the drought was generally greater than the downward pressure exerted by increased prices. Consistent with the results in Section 2, panels B and C show that the "drought effect" was particularly strong among high-wealth households.

In the following year (October 2002-September 2003), changes in usage profiles reveal large, observable decreases in usage. Since the drought officially ended in October 2002, these changes can be attributed to either seasonal prices or CAC restrictions. In particular, CAC restrictions were in place from October through the end of June, which would have affected the ability to irrigate during critical periods. We observe small increases in *Heavy* usage profiles between October 2002-September 2003 and October 2003-September 2004, suggesting a return to outdoor water usage following the lifting of the most stringent CAC restriction. Panels B and C indicate that wealthier households increased usage more strongly than 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

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

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* 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 higher usage profile. We provide a table of transitions by wealth in Online Appendix G.

The information in Table 3 corroborates the finding that there seems 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. Examining transitions also provides additional information on the effects of price that were not detectable in Table 2 during the onset of drought conditions. In particular, we observe some households increasing usage and others decreasing usage in the "Oct01-Sep02" row. This would suggest that increased prices may have been effective at mitigating the effect of drought on usage, although some of these decreases may have been attributable to CAC restrictions.

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. The richness of our data allows us to estimate elasticities that vary by both household wealth and usage profile. Our results indicate that households with higher usage profiles are more price-sensitive than low-usage households, for any wealth level. Relative to previous research, these results provide a more optimistic assessment of the utilities' ability to use prices to reduce water consumption by high-usage households.

We complement the analysis with an examination of how households are matched to usage profiles over time. Following the introduction of higher marginal prices during summer months, a large fraction of households with heavy usage transitioned to usage profiles with lower and flatter usage. Moreover, we observe similar transition patterns across wealth levels.

Our findings have implications for several areas of related research. First, from the perspective of a water utility, the effect of a price change on revenues 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 as 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.[23] Some recent demand estimation studies in western states 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.[24] 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.[25] We then model surface and subsurface water flowpaths over the watershed. Outputs of RHESSys relevant to this study includes catchment-scaled

[23]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.

[24]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).

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

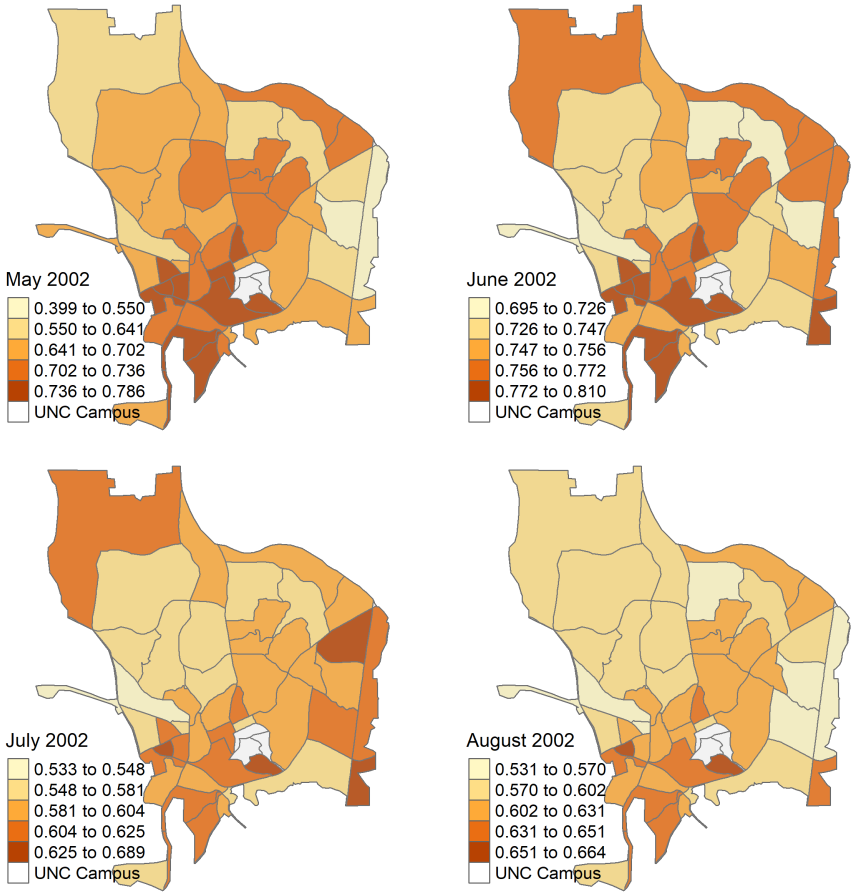
streamflow, patch-scaled (30 m) soil moisture, and patch-scaled vegetation water demand and evapotranspiration.

Using data from USGS gauges 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.[26] 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.[27] For each of these simulations, we summarize model outputs as an index, given by $WS_r = 1 - \xi^a/\xi^p$, that captures the lack of moisture available to lawns. In this equation, ξ^a represents actual evapotranspiration and ξ^p represents potential evapotranspiration. 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 watershed level. Figure A1 graphically represents the spatial and temporal variation in the water stress index in the study area during the onset of the 2002 drought.

[26] 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.

[27] 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 fitness for high flow events whereas the log transformed NSE coefficient provides information on model fitness for low flow events. High weekly and log-weekly NSE values are desired.

Figure A1: Water Stress During the 2002 Drought



B Accounting for Usage Trends

To isolate the impact of seasonal pricing on water usage, we de-trend household usage using the following procedure. First, we use data from October 1999 to April 2002 to estimate a simplified version of equation (2):

$$q_{it}^{*} = \gamma_1 z_t + \gamma_2 s_t z_t + Z_{it}\theta + \eta_i + \epsilon_{it}. \tag{2}$$

In equation (2), the dependent variable q_{it}^{*} is household i's log usage during read period t in thousands of gallons. The variable z_t is read period t's calendar year, with z_t normalized to zero for 1999. s_t is an indicator variable for whether t occurs during the "summer," i.e. between May 1 and September 30. The parameters γ_1 and γ_2, therefore, capture overall and summer-specific time trends during the pre-treatment period. The matrix Z_{it} contains the same variables as in equation (1): water stress, temperature, an intra-year time trend, and the number of days in read period t. Equation (2) does not include water prices, as real prices were largely unchanged prior to seasonal pricing. In addition, there is no role for CAC restrictions in equation (2) since none were in place during this portion of the sample period. In our main approach to de-trending, we estimate equation (2) under the assumption that households do not vary in their responses to Z_{it}, although in some extension models we allow parameters to vary with households' permanent characteristics.

Once we have estimated equation (2), we de-trend household usage by calculating for each i and t in the full sample period:

$$q_{it} = q_{it}^{*} - \hat{\gamma}_1 z_t - \hat{\gamma}_2 s_t z_t. \tag{3}$$

In our main empirical analysis, we estimate equation (1) with q_{it} as the dependent variable. We calculate standard errors by drawing bootstrap samples, clustered at the household level, and repeatedly re-estimating equation (2) and then equation (1). We also use the estimated point estimates in equation (3) to construct predicted usage values for each household, conditional on the price conditions that existed during the pre-treatment period. We take these predicted values, $\hat{q}_{it}^{*}$, and average them across households within read period to construct period-level averages. We display the averages in Figure 3, along with the raw data averages of q_{it}^{*} across households.

See Appendix C for estimates of γ_1 and γ_2, trend coefficients in alternative specifications of equation (3), and the price elasticity estimates that follow from the alternative approaches to de-trending.

One potential concern about our de-trending approach is that it could miss usage trends at the extremes of the usage distribution. In particular, if high-usage households were reducing their usage sharply prior to seasonal pricing (while other households reduced usage more modestly or not at all), our finding of large price elasticities for high-usage households could be driven by this missed trend rather than a response to increased prices. To explore this concern, we perform a quantile regression of equation (2)'s residuals on z_t, and $s_t z_t$, allowing for different trend coefficients at each decile. If the highest-volume households are sharply reducing usage prior to seasonal pricing, we should obtain negative and significant values of $\gamma_{d,1}$ and $\gamma_{d,2}$ for the upper deciles (d), especially during summer months. We do not. During the summer months, $\gamma_{d,1}$ and $\gamma_{d,2}$ for $d \leq 80$ imply residual trends very close to zero, as expected given that the residuals already include de-trending. The estimated values of $\gamma_{90,1}$ and $\gamma_{90,2}$ imply that residual usage variation misses some positive usage *growth* at the top end of the usage distribution. This suggests that the price elasticities we report for high-usage households are unlikely to be biased away from zero, and in fact may be too small in magnitude.

C Demand Estimation Results

Main Specification

The results from estimating (1) are in Panel A of Table C1. For comparison, we also analyze a model without any heterogeneous effects:

$$q_{it} = \beta_j p_t + \sum_k X_{it}\phi_{kj} + Z_{it}\theta_j + \eta_i + \epsilon_{it}. \tag{4}$$

The results from estimating (4) are in Panel B in Table C1.

Table C1: Estimation results

	Price	Stage 1	Stage 2	Emerg.	WS	Temp.
Panel A: Main Results						
Low wealth, light usage	-0.1134	0.0037	-0.0761	-0.1525	0.0374	-0.0030
	(0.0333)	(0.0073)	(0.0156)	(0.0128)	(0.0032)	(0.0042)
Low wealth, moderate usage	-0.3235	-0.0311	-0.0674	-0.2267	0.0622	0.0204
	(0.0374)	(0.0066)	(0.0118)	(0.0125)	(0.0030)	(0.0046)
Low wealth, heavy usage	-0.5599	-0.0356	-0.0229	-0.2139	0.0796	0.0497
	(0.0661)	(0.0207)	(0.0303)	(0.0333)	(0.0093)	(0.0121)
High wealth, light usage	-0.1450	-0.0136	-0.0548	-0.1655	0.0489	0.0012
	(0.0470)	(0.0094)	(0.0223)	(0.0190)	(0.0046)	(0.0056)
High wealth, moderate usage	-0.3091	-0.0140	-0.0387	-0.2642	0.0825	0.0394
	(0.0354)	(0.0050)	(0.0122)	(0.0103)	(0.0028)	(0.0037)
High wealth, heavy usage	-0.5470	-0.0100	0.0000	-0.4242	0.1203	0.1233
	(0.0618)	(0.0098)	(0.0203)	(0.0226)	(0.0046)	(0.0078)
Panel B: No Heterogeneity						
All	-0.2896	-0.0140	-0.0510	-0.2369	0.0697	0.0319
	(0.0299)	(0.0031)	(0.0070)	(0.0062)	(0.0017)	(0.0027)

Note: *Emerg.* is Emergency stage restriction, *WS* is water stress, and *Temp* is temperature. Regressors not shown: ln(read days), and intra-year time trend. Bootstrap standard errors are in parentheses.

In Table C2 we report trend coefficients from our main approach to de-trending usage plus several alternative approaches. Table C2 also provides the price elasticity estimates that correspond to each alternative approach to de-trending.

Table C2: Estimation results

	Baseline	No Trend	Alternative Specifications		
Panel A: Trend coefficients					
Year trend	-0.0326	.	-0.0296	-0.0393	-0.0210
	(0.0025)	.	(0.0025)	(0.0029)	(0.0049)
Summer trend	0.0146	.	.	0.0806	0.0071
	(0.0022)	.	.	(0.0027)	(0.0045)
Year trend, high wealth	.	.	.	-0.0127	-0.0268
	.	.	.	(0.0041)	(0.0072)
Summer trend, high wealth	.	.	.	0.0389	0.0201
	.	.	.	(0.0040)	(0.0070)
Year trend, large lot	.	.	.	.	-0.0045
	.	.	.	.	(0.0084)
Summer trend, large wealth	.	.	.	.	0.0181
	.	.	.	.	(0.0105)
Year trend, high wealth, large lot	.	.	.	.	0.0125
	.	.	.	.	(0.0076)
Summer trend, high wealth, large lot	.	.	.	.	-0.0274
	.	.	.	.	(0.0099)
Panel B: Price elasticities					
Low wealth, light usage	-0.1134	-0.1812	0.0111	-0.7210	-0.1557
	(0.0333)	(0.0217)	(0.0262)	(0.0464)	(0.0456)
Low wealth, moderate usage	-0.3235	-0.3993	-0.1943	-0.9558	-0.3698
	(0.0374)	(0.0309)	(0.0309)	(0.0569)	(0.0467)
Low wealth, heavy usage	-0.5599	-0.6371	-0.4324	-1.1841	-0.6093
	(0.0661)	(0.0617)	(0.0580)	(0.1072)	(0.0749)
High wealth, light usage	-0.1450	-0.2248	-0.0015	-1.1919	-0.1341
	(0.0470)	(0.0371)	(0.0393)	(0.0704)	(0.0563)
High wealth, moderate usage	-0.3091	-0.3915	-0.1691	-1.3318	-0.2958
	(0.0354)	(0.0199)	(0.0255)	(0.0558)	(0.0459)
High wealth, heavy usage	-0.5470	-0.6333	-0.4041	-1.5909	-0.5280
	(0.0618)	(0.0540)	(0.0544)	(0.0910)	(0.0694)

Notes: The regression models in Panel A include household fixed effects, a year-round linear time trend, water stress and temperature, and a sixth-order polynomial in week number to account for intra-year usage patterns as controls. For models that include interactions with household wealth and/or lot size, we interact these variables with each unreported control variable. In Panel B, models include the same controls described in Table C1's notes. Panel B's standard errors are calculated with a bootstrapping procedure.

Ignoring Heterogeneous Impact of Environmental Factors

We estimate a model in which the impact of environmental factors is not allowed to vary by either wealth or usage profiles:

$$q_{it} = \sum_u \sum_w \tau_{uw} \beta_{uw} p_t + \sum_u \sum_w \sum_k \tau_{uw} X_{it} \phi_{uwk} + \tau_u Z_{it} \theta + \eta_i + \epsilon_{it}. \tag{5}$$

The results from estimating (5) are in Table C3. Compared to Panel A in Table C1, elasticity estimates for high-wealth household are smaller while those for low-wealth households are larger for households with *Moderate* and *Heavy* usage profiles. We obtain positive elasticity estimates for high wealth households with *Heavy* usage profiles. Elasticity estimates under this specification are larger for both high- and low-wealth households with *Light* usage profiles.

Table C3: Main results not allowing environmental controls to vary by wealth or usage profile

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	-0.2027	0.0392	-0.0371	-0.1643
	(0.0325)	(0.0070)	(0.0150)	(0.0126)
Low wealth, moderate usage	-0.3477	-0.0220	-0.0577	-0.2320
	(0.0368)	(0.0066)	(0.0113)	(0.0121)
Low wealth, heavy usage	-0.5199	-0.0491	-0.0351	-0.2060
	(0.0588)	(0.0198)	(0.0291)	(0.0310)
High wealth, light usage	-0.2128	0.0114	-0.0256	-0.1793
	(0.0460)	(0.0090)	(0.0210)	(0.0191)
High wealth, moderate usage	-0.2823	-0.0273	-0.0568	-0.2614
	(0.0347)	(0.0048)	(0.0115)	(0.0100)
High wealth, heavy usage	-0.3602	-0.0764	-0.0728	-0.3795
	(0.0580)	(0.0098)	(0.0198)	(0.0206)

Note: *Emerg.* is Emergency stage restriction. Regressors not shown: ln(read days), and intra-year time trend. Regressors not shown: ln(read days), water stress, temperature, and intra-year time trend. Bootstrap standard errors are in parentheses.

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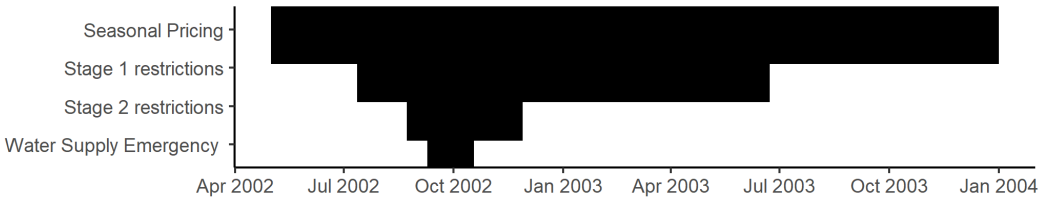
Online Appendix

D Command-and-Control (CAC) Restrictions

Figure D1: Timeline of CAC Restriction Implementation



Definitions of stage restrictions provided in April 2002

- **Stage 1:** Irrigation of lawns, gardens, trees, or shrubs with OWASA-supplied potable water applied through any system or device other than a hand-held hose or watering can shall be allowed only three days out of each week.
- **Stage 2:** Irrigation of lawns, gardens, trees, or shrubs with OWASA-supplied potable water applied through any system or device other than a hand-held hose or watering can shall be allowed only one day out of each week.
- **Emergency:** No OWASA-supplied potable water for any outdoor purposes other than emergency fire suppression or other activities necessary to maintain public health, safety, or welfare.

Modifications of CAC policies in June 2003

- **Year-Round Conservation Requirement:** Spray irrigation limited to 3 days/week. Use of reclaimed or harvested water strongly encouraged. Use of water saving fixtures strongly encouraged. Unless superceded by the declaration of a Water Supply Shortage or Emergency, this requirement did not apply to outdoor irrigation necessary for the establishment of newly sodded lawns and landscaping within the first 30 days of planting, or watering of newly seeded turf within the first six months of planting.

E Sensitivity Analysis: Usage Profile Assignment

In the main paper, we defined households in terms of their usage profile observed during the year prior to treatment, October 2000-September 2001. Here we consider an alternative specification in which the households are defined in terms of their usage profile observed during October 1999-September 2000.

Table E1 shows the results of estimating (1) using the usage profiles observed during October 1999-September 2000. We find that the main estimation results are robust to which pre-treatment year is used to assign usage profiles.

Table E1: Main Results, Different Reference Year

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	-0.0814	-0.0184	-0.0715	-0.1714
	(0.0350)	(0.0074)	(0.0156)	(0.0127)
Low wealth, moderate usage	-0.3173	-0.0544	-0.0816	-0.2166
	(0.0366)	(0.0070)	(0.0130)	(0.0119)
Low wealth, heavy usage	-0.5865	-0.0921	-0.0826	-0.3060
	(0.0680)	(0.0173)	(0.0299)	(0.0318)
High wealth, light usage	-0.0708	-0.0155	-0.0675	-0.1887
	(0.0434)	(0.0093)	(0.0219)	(0.0178)
High wealth, moderate usage	-0.3028	-0.0332	-0.0658	-0.2554
	(0.0372)	(0.0051)	(0.0128)	(0.0109)
High wealth, heavy usage	-0.5570	-0.0594	-0.0482	-0.4442
	(0.0598)	(0.0087)	(0.0204)	(0.0213)

Note: *Emerg.* is Emergency stage restriction, *WS* is water stress, and *Temp* is temperature. Regressors not shown: ln(read days), and intra-year time trend. Regressors not shown: ln(read days), and intra-year time trend. Bootstrap standard errors are in parentheses.

Table E2 shows the year-to-year transitions starting with October 1999-September 2000. The percentages are similar to those presented in Table 3.

Table E2: Transition in Usage Profiles, Different Reference Year

Panel A	All Households *(N=4455)*								
Oct99-Sep00	*Light (N=1508)*			*Moderate (N=2181)*			*Heavy (N=766)*		
	L	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
Oct00-Sep01	0.81	0.19	0.00	0.11	0.82	0.07	0.01	0.31	0.68
Oct01-Sep02	0.77	0.22	0.01	0.15	0.74	0.11	0.02	0.31	0.68
Oct02-Sep03	0.88	0.12	0.00	0.35	0.62	0.03	0.09	0.57	0.33
Oct03-Sep04	0.85	0.14	0.01	0.32	0.62	0.06	0.06	0.52	0.42
Oct04-Sep05	0.83	0.16	0.01	0.32	0.63	0.05	0.08	0.51	0.42
Panel B	Lower Wealth Households *(N=2080)*								
Oct99-Sep00	*Light (N=1005)*			*Moderate (N=886)*			*Heavy (N=189)*		
Oct00-Sep01	0.86	0.13	0.00	0.15	0.80	0.05	0.03	0.37	0.60
Oct01-Sep02	0.84	0.16	0.00	0.19	0.73	0.08	0.03	0.42	0.55
Oct02-Sep03	0.90	0.10	0.00	0.39	0.59	0.02	0.13	0.58	0.29
Oct03-Sep04	0.88	0.12	0.00	0.36	0.59	0.05	0.09	0.57	0.34
Oct04-Sep05	0.87	0.12	0.00	0.36	0.60	0.03	0.15	0.57	0.28
Panel C	Higher Wealth Households *(N=2375)*								
Oct99-Sep00	*Light (N=503)*			*Moderate (N=1295)*			*Heavy (N=577)*		
Oct00-Sep01	0.70	0.30	0.00	0.09	0.83	0.08	0.01	0.29	0.71
Oct01-Sep02	0.65	0.33	0.02	0.13	0.74	0.13	0.01	0.27	0.72
Oct02-Sep03	0.84	0.16	0.00	0.32	0.64	0.04	0.08	0.57	0.35
Oct03-Sep04	0.80	0.19	0.01	0.29	0.65	0.06	0.05	0.50	0.45
Oct04-Sep05	0.76	0.23	0.01	0.29	0.65	0.06	0.05	0.49	0.46

F Water Stress vs. Traditional Environmental Controls

In this section, we assess the goodness of fit for models using different sets of environmental controls. We compare the main set of results, using a Block Group-level water stress index, to models using collections of weather variables. We obtained data for weather variables from the NC Climate Office for the Chapel Hill-Williams Airport weather station. We estimate models using the following sets environmental of controls:

- Collection 1: Total precipitation and average temperature
- Collection 2: Total precipitation, lagged total precipitation, average temperature, lagged average temperature
- Collection 3: Total precipitation, total precipitation squared, number of days with no rain, average temperature
- Regional Water Stress and average temperature
- Census Block Group Water Stress and average temperature

We do not include NDVI in our comparison models, as the area of study is not well suited for use because the coarse resolution of the satellite images (30m x 30m) is not precise enough to discern landscapes on individual parcels in the study area. Aside from typically small parcel sizes, tree cover is prevalent, and the area is relatively wet, therefore cloud cover obstruction frequently results in unusable images.[28]

We assess model fit based on deviations in prediction accuracy using several model evaluation scores. We provide scores for root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) in Table F1. The errors provided in the table are based on differences between actual and predicted values and smaller errors reflect more accurate predictions. Scores differ in how large errors are treated. RMSE

[28]NDVI particular useful in areas such as the western United States, regions where parcel sizes are relatively large, climate is arid and hence experience few cloudy days, and tree cover sparse. https://earthexplorer.usgs.gov/

gives extra weight to large errors whereas MAPE and MAE give equal weight to all errors. MAPE differs from the other two metrics in that is scores are in terms of percentages and are therefore scale-independent. The results suggest that using water stress leads to minor improvements in model fit.

Table F1: Goodness of Fit Results

Environmental Model	RMSE	MAPE	MAE
Collection 1	39.452	27.641	28.702
Collection 2	39.322	26.205	28.584
Collection 3	39.145	28.265	28.492
Water Stress Regional	38.723	23.241	28.175
Water Stress Block Group	38.778	25.349	28.204

Notes: All models include average temperature. RMSE: Root mean square error, MAPE: Mean absolute percentage error, MAE: Mean absolute error

Estimation Results for Alternative Environmental Controls

Tables F2 through F5 contain results from models with alternative environmental controls. The results are qualitatively similar to the main estimation results, with a few small differences. Specifically, the alternative environmental controls produce lower price sensitivity among wealthier households with *Moderate* and *Light* usage profiles, although the differences are smaller in the models with more complex collections of weather variables. Our findings suggest that collections of weather variables in relatively wet climate areas similar to the area of study may be used in water demand estimation studies without the introduction of too much measurement error. Future research, however, is needed to test the robustness of this measure in the context of different climates.

The most common combination of weather variables used as environmental controls is *Collection 1*. Using these measures results in price elasticity estimates that are qualitatively similar though smaller in magnitude to those found when using water stress.

Table F2: Main Results with Collection 1 Instead of Block Group Water Stress

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	-0.1567	-0.0160	-0.0882	-0.1576
	(0.0319)	(0.0069)	(0.0146)	(0.0127)
Low wealth, moderate usage	-0.3477	-0.0688	-0.1000	-0.2347
	(0.0357)	(0.0065)	(0.0112)	(0.0126)
Low wealth, heavy usage	-0.5735	-0.0838	-0.0577	-0.2302
	(0.0596)	(0.0195)	(0.0298)	(0.0335)
High wealth, light usage	-0.1931	-0.0388	-0.0528	-0.1827
	(0.0457)	(0.0089)	(0.0217)	(0.0187)
High wealth, moderate usage	-0.3372	-0.0590	-0.0606	-0.2901
	(0.0344)	(0.0048)	(0.0117)	(0.0105)
High wealth, heavy usage	-0.5432	-0.0772	-0.0439	-0.4600
	(0.0613)	(0.0095)	(0.0195)	(0.0230)

Note: *Emerg.* is Emergency stage restriction. Regressors not shown: ln(read days), and intra-year time trend. Regressors not shown: ln(read days), precipitation, temperature, and intra-year time trend. Bootstrap standard errors are in parentheses.

When we include *collection 2* in the model, our price elasticity become more similar to those we obtain when using water stress.

Table F3: Main Results with Collection 2 Instead of Block Group Water Stress

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	-0.1713	-0.0078	-0.0948	-0.1620
	(0.0322)	(0.0073)	(0.0146)	(0.0128)
Low wealth, moderate usage	-0.3715	-0.0518	-0.1035	-0.2473
	(0.0365)	(0.0069)	(0.0112)	(0.0128)
Low wealth, heavy usage	-0.5997	-0.0645	-0.0628	-0.2452
	(0.0624)	(0.0213)	(0.0303)	(0.0339)
High wealth, light usage	-0.2109	-0.0287	-0.0593	-0.1884
	(0.0465)	(0.0096)	(0.0217)	(0.0189)
High wealth, moderate usage	-0.3721	-0.0349	-0.0770	-0.3028
	(0.0349)	(0.0050)	(0.0116)	(0.0107)
High wealth, heavy usage	-0.6001	-0.0386	-0.0742	-0.4792
	(0.0626)	(0.0096)	(0.0200)	(0.0235)

Note: *Emerg.* is Emergency stage restriction. Regressors not shown: ln(read days), and intra-year time trend. Regressors not shown: ln(read days), precipitation, lagged precipitation, temperature, lagged temperature, and intra-year time trend. Bootstrap standard errors are in parentheses.

Similarly, when we include *collection 3* in the model, our price elasticity estimates become more similar to those we obtain when using water stress.

Table F4: Main Results with Collection 3 Instead of Block Group Water Stress

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	-0.1632	-0.0227	-0.0665	-0.1775
	(0.0320)	(0.0070)	(0.0156)	(0.0128)
Low wealth, moderate usage	-0.3499	-0.0662	-0.0490	-0.2437
	(0.0363)	(0.0066)	(0.0121)	(0.0126)
Low wealth, heavy usage	-0.5712	-0.0764	0.0018	-0.2297
	(0.0611)	(0.0199)	(0.0301)	(0.0328)
High wealth, light usage	-0.1894	-0.0413	-0.0430	-0.1939
	(0.0452)	(0.0090)	(0.0225)	(0.0188)
High wealth, moderate usage	-0.3266	-0.0553	-0.0228	-0.2868
	(0.0342)	(0.0048)	(0.0121)	(0.0104)
High wealth, heavy usage	-0.5239	-0.0672	0.0218	-0.4422
	(0.0612)	(0.0096)	(0.0201)	(0.0227)

Note: *Emerg.* is Emergency stage restriction. Regressors not shown: ln(read days), and intra-year time trend. Regressors not shown: ln(read days), precipitation, precipitation squared, number of days with no rain, temperature, and intra-year time trend. Bootstrap standard errors are in parentheses.

We obtain similar price elasticity estimates when we use watershed-level water stress measures versus the Block-Group-level water stress measures of our main analysis.

Table F5: Main Results with Regional Water Stress Instead of Block Group Water Stress

	Price	Stage 1	Stage 2	Emerg.
Low wealth, light usage	-0.0990	0.0101	-0.0733	-0.1525
	(0.0334)	(0.0073)	(0.0156)	(0.0128)
Low wealth, moderate usage	-0.3075	-0.0216	-0.0586	-0.2270
	(0.0375)	(0.0067)	(0.0120)	(0.0125)
Low wealth, heavy usage	-0.5429	-0.0235	-0.0107	-0.2149
	(0.0658)	(0.0211)	(0.0303)	(0.0333)
High wealth, light usage	-0.1301	-0.0074	-0.0551	-0.1651
	(0.0470)	(0.0096)	(0.0226)	(0.0189)
High wealth, moderate usage	-0.2993	-0.0052	-0.0372	-0.2658
	(0.0356)	(0.0050)	(0.0121)	(0.0104)
High wealth, heavy usage	-0.5370	0.0036	0.0098	-0.4260
	(0.0618)	(0.0098)	(0.0200)	(0.0226)

Note: *Emerg.* is Emergency stage restriction. Regressors not shown: ln(read days), and intra-year time trend. Regressors not shown: ln(read days), watershed level water stress, temperature, and intra-year time trend. Bootstrap standard errors are in parentheses.

G Transitions in Usage Profiles By Wealth

In this section we provide information on the fraction of households that transition in usage profiles by household wealth. Transitions are qualitatively similar to that observed for the entire sample with the exception that significant decreases in usage in transitioning from *Heavy* to *Light* are more commonly observed among low wealth households than high wealth households.

Table G1: Transitions in Usage Profiles

Panel A	All Households *(N=4455)*								
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
Panel B	Lower Wealth Households *(N=2080)*								
Oct00-Sep01	*Light (N=1003)*			*Moderate (N=912)*			*Heavy (N=165)*		
Oct01-Sep02	0.87	0.13	0.00	0.15	0.77	0.07	0.02	0.35	0.63
Oct02-Sep03	0.90	0.10	0.00	0.40	0.57	0.02	0.06	0.60	0.34
Oct03-Sep04	0.88	0.12	0.00	0.36	0.59	0.05	0.04	0.56	0.39
Oct04-Sep05	0.88	0.12	0.00	0.36	0.61	0.03	0.10	0.57	0.33
Panel C	Higher Wealth Households *(N=2375)*								
Oct00-Sep01	*Light (N=478)*			*Moderate (N=1389)*			*Heavy (N=508)*		
Oct01-Sep02	0.74	0.26	0.01	0.10	0.76	0.14	0.00	0.20	0.79
Oct02-Sep03	0.87	0.12	0.00	0.32	0.65	0.03	0.05	0.55	0.40
Oct03-Sep04	0.82	0.17	0.01	0.28	0.65	0.07	0.05	0.47	0.48
Oct04-Sep05	0.79	0.19	0.01	0.27	0.65	0.07	0.05	0.47	0.48