How Price and Non-Price Incentives Affect California Water Demand

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Over the past two decades, drought conditions in California have repeatedly threatened fresh water security in the state. Many policies have been enacted to promote water conservation measures in a variety of ways. Raising the price of residential water is illegal under proposition 218, leaving non-price policies such as restrictions, rebates and information campaigns to account for water reduction. Since Governor Brown declared a state of emergency in 2014, conservation measures have increased dramatically. This paper uses fixed effects and difference-in-difference models to estimate the impact of both price and non-price incentives on the demand of residential water in California, and how it may impact California's conservation goal of 25% statewide. This analysis finds that non-price policies in the San Francisco Bay area leads to anywhere from 16% to 27% reduction in demand, with a price elasticity of -0.133, less than that of previous studies. These results are statistically significant.

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Acknowledgements: Special thanks to Drs. Nolan Pope, Nick Montgomery and Courtney Paulson for all the help.

Introduction:

Since 2012 the ongoing drought in California has changed state resource governance. Increasing population growth, the effects of climate change and lack of innovation in public utilities are just a few reasons why the drought has proved particularly difficult to manage. Governor Jerry Brown declared a state of emergency in January 2014 to prepare the state to deal with the drought. Since then, many executive orders have followed, primarily giving each utility the responsibility to enact policies at their own discretion, ranging from conservation rebates to mandatory restrictions. Under Proposition 218, which has been affirmed many times in the courts, water prices cannot exceed the price of delivery. Price signaling, the mechanism preferred by economists, is therefore limited. This places a higher importance on non-price policies used by utilities. In April 2015, Governor Brown declared a 25% statewide reduction in potable urban water. Each water district would have to reduce their consumption from 2013 levels, anywhere from 4%-36%, depending on their current usage. Governor Brown further required utilities to enact a conservation framework to make water conservation a way of life. This includes severe penalties of $1,000 a day if annual water targets are not met, and $10,000 a day during emergency droughts. By 2022, consumption per person per day will be reduced to 55 gallons, and to 50 gallons per day by 2030. While these are long-term goals, this paper seeks to understand short term effects of residential demand through price and non-price policies.

The purpose of this paper is to by estimate a demand function for residential water and examine price elasticities using data from 26 water districts in California. These 26 utilities are primarily in the San Francisco Bay Area. I will also investigate whether quantity restrictions in 2015 through 2017 affected residential consumption, while controlling for price and climate conditions. I am also exploring how demand is affected by the conservation tier each utility was placed on in the 2015 State of Emergency initiatives. In addition to my conservation tier analysis, I measure the impact of specific rebate policies of high efficiency washing machines and toilets on the overall reduction in consumption. To accomplish this, I extend the data from Buck et. al (2015) from 1996-2009 through 2017. These estimates can hopefully help to provide insight into the following questions: How do the welfare effects of quantity restrictions compare with the welfare impacts of restricting usage by raising price? How much would prices have to be raised to achieve the mandated reductions in consumption? Are they politically feasible? While I don't intend to answer every question, it is important to consider the issue in the larger context of water conservation policy.

I use data from BAWSCA, the Bay Area Water Supply Conservation Agency, for price and quantity measures as well as the rate structure of each utility. Each utility rate structure indicated the price for each block of consumption on the structure, with quantity(ccf) indicating the threshold each individual block price operates under. 1 ccf is approximately 720 gallons. I used NOAA for my climatology data.

I run a year and utility fixed effects model to account for heterogeneity between water districts using conservation tier dummies to represent the non-price effects of utility policy on each conservation tier enacted in 2015. I also run an instrumental variable model, using the first lag of the first four prices on the rate schedule of each utility to estimate price elasticity. This model intends to show how sensitive consumers are to block prices. I run two difference-in-difference models for high efficiency toilet and washing machine rebates according to the year each program started in and the participating utilities.

The results of the fixed effects model yield a price elasticity of -0.133, whereas the instrumental variable price elasticity for lagged block prices is -0.159. These results are similar to previous studies which have price elasticities consistently ranging from -0.14 to -0.2. Price is more elastic in the IV model, indicating consumers respond to increasing block prices. Climate variables are significant, but have extremely small coefficients, indicating the drought alone did not reduce residential demand. The conservation tier dummies are all significant with coefficients suggesting a demand reduction of 16% to 27%. The largest tiered utilities, requiring a 32% and 36% reduction from 2013 levels, each had smaller coefficients than the middle-tiered utilities, indicating scalable policies have not yet achieved their desired targets. Summary statistics for each of these tiers shows their consumption is much larger than that of smaller tiers. A chi-square test shows that each of the individual coefficients were statistically different from one another. The difference-in-difference models show that high-efficiency toilet and washing machine rebates had up to 4.8% and 0.1% decrease in overall consumption when each was enacted in 2008 and 2005, respectively. These results show that generally, non-price policies may achieve their goal of water consumption, albeit minimally, and will continue to do so as they become more standardized in utility regulation.

The remainder of the paper is organized as follows. In section 2, I review the literature on residential water demand, including previous models used to measure the price elasticity of water demand. Section 3 outlines my contribution to the literature. In Section 4, I present my methods and discuss the data I will use, including data collected from the Bay Area Water Supply Conservation Agency (BAWSCA). In Section 5 I present my results, with commentary about where future work may be heading.

Literature Review

The goal of this paper is to estimate the effects of price and non-price policies on water conservation efforts in the state of California. The general question of what drives conservation is extremely important to policy makers and has been studied extensively since Renwick and Green (1999) first introduced non-price policies into a model of residential water demand.

One of the first studies to examine the effectiveness of policies of conserve water in California was Renwick and Green (1999). Renwick and Green study how residential water consumption responds to non-price incentives. Specifically, they use pooled cross-section time series data for 8 utilities covering the period 1989 to 1996 to estimate a demand curve for residential water consumption. They control for various policies to reduce consumption, whether it be an information campaign, a rebate or a quantity restriction using a series of dummy variables. Their pooled cross-sectional results find a price elasticity of around -0.2 during the summer months, which is 25% more than any other months, indicating that activities like outdoor watering are highly discretional and significantly affect usage. Restrictions, information campaigns, retrofit subsidies and water rationing all have negative coefficients and are statistically significant. They also find that including non-price factors reduced estimates of the price elasticity of demand compared with estimates from previous studies that failed to include non-price factors. The two non-price policies that changed the demand curve in a tangible way are rationings and restrictions, which decreased household demand by 2.1 and 3.3 ccf per month, respectively. Retrofit subsidies and information campaigns decreased consumption by about 1 CCF per month each (Renwick and Green 1999). Renwick and Green's study concludes that prescriptive policies were effective in reducing demand, but the level of reduction varied significantly depending on income, seasonality, and type of non-price policy.

Buck et al. (2016) build upon and extend the work of Renwick and Green (2000). Using data from 1996-2009 for 37 utilities in the state of California, the authors estimate the demand for water using utility fixed effects to account for time-invariant unobservable variables. They also control for weather conditions and time fixed effects. They use their estimates of water demand to evaluate price elasticity using OLS and instrumental variables. They follow procedures from Olmstead's 2009 study to account for simultaneity bias between current price and consumption, control for specific drought conditions to account for other conservation efforts and use an instrumental variable that accounts for increasing block prices. With just fixed effects, Buck et al. find a price elasticity of -0.100. When lagged prices are introduced as instruments, the price elasticity becomes -0.143. When price is interacted with household income, the price elasticity (calculated at mean household income is -0.149. Buck et al. noted that these elasticities are similar to previous studies, but slightly more inelastic.

Prescriptive policies to curtail residential water demand have been increasingly necessary with the prolonged drought in California. However, while resource managers tend to prefer non-price policies (restrictions on use) to curb demand, economists believe pricing mechanisms best achieve conservation targets. There has been extensive work on the topic, most notably by Olmstead and Stavins (2009) who concludes that neither price nor prescription are superior to one another. Many believe that price is reflective of long term marginal price, but Olmstead concludes that water prices are not indicative of marginal cost and do not send an adequate signal to consumers (Olmstead and Stavins 2009). The cost of this is evident in the fact that despite attempts to lower levels of water through voluntary restrictions, consumption is not curtailed, punishing local resources for agriculture and general sustainability.

Mansur and Olmstead (2007) study the potential welfare gains from moving from a non-market approach for conservation to a market, price-based approach. They claim that between-household heterogeneity in willingness to conserve water has severe welfare implications Theoretically, unless outdoor watering use restrictions, the most common non-price policy, is not perfectly inelastic, moving to a price-based approach would be much more effective in conserving water demand efforts. Using panel data, Mansur and Olmstead measure the price elasticity of indoor and outdoor water consumption across four groups based on income, lot size. They account for increasing block prices by creating a piece-wise linear demand model. They estimate random effects and fixed effects models and find that outdoor watering price elasticity is constant across households at a coefficient of -0.684 and that indoor watering price coefficients are not significant due to lack of variability at -0.072 (Mansur and Olmstead 2007). However, Mansur and Olmstead also estimate welfare implications if a price-based approach were introduced. They estimate the market clearing price based on the quantity of water the utilities would save from each non-price approach. They find that under this scenario the least elastic group, wealthy households with large lot sizes, would increase their consumption by 13% and the most elastic group, the poor, small lot households would decrease consumption from 23% to 16%. The welfare effect of pricing is important because “heterogeneity is often ignored in economic analyses, which proceed from the viewpoint of the “representative consumer.” (Mansur and Olmstead 2009). While reduction in demand could be ultimately achieved through different pricing strategies, the variation of conservation across households of scarce water during a drought presents a myriad of issues for utilities in terms of reduction feasibility, pricing thresholds and political backlash.

Contribution

My contribution to California water economics is to estimate a demand function for residential water consumption in the state of California by extending Buck et. al.'s (2016) study using Bay Area Water Supply and Conservation Agency data. 11 of the 37 utilities did not appear in the more recent annual surveys, which is why they were dropped from my analysis. This demand function can help answer or at least shed light on some key questions surrounding conservation goals enacted since Buck et al.'s paper and the effect of price and non-price policy.

Like Buck et al. (2016), I use the median price of each utilities' rate schedule, meaning dollars per hundred cubic feet of water(ccf), or 720 gallons. Like these authors as well, for utilities with increasing block prices, the median tier price is used. This doesn't necessarily equal the marginal price as perceived by customers but helps to "decouple price from consumer's choice of block" (Buck, Steven et al.). To better measure marginal prices as perceived by consumers, I use lagged price variables to instrument for current median block price.

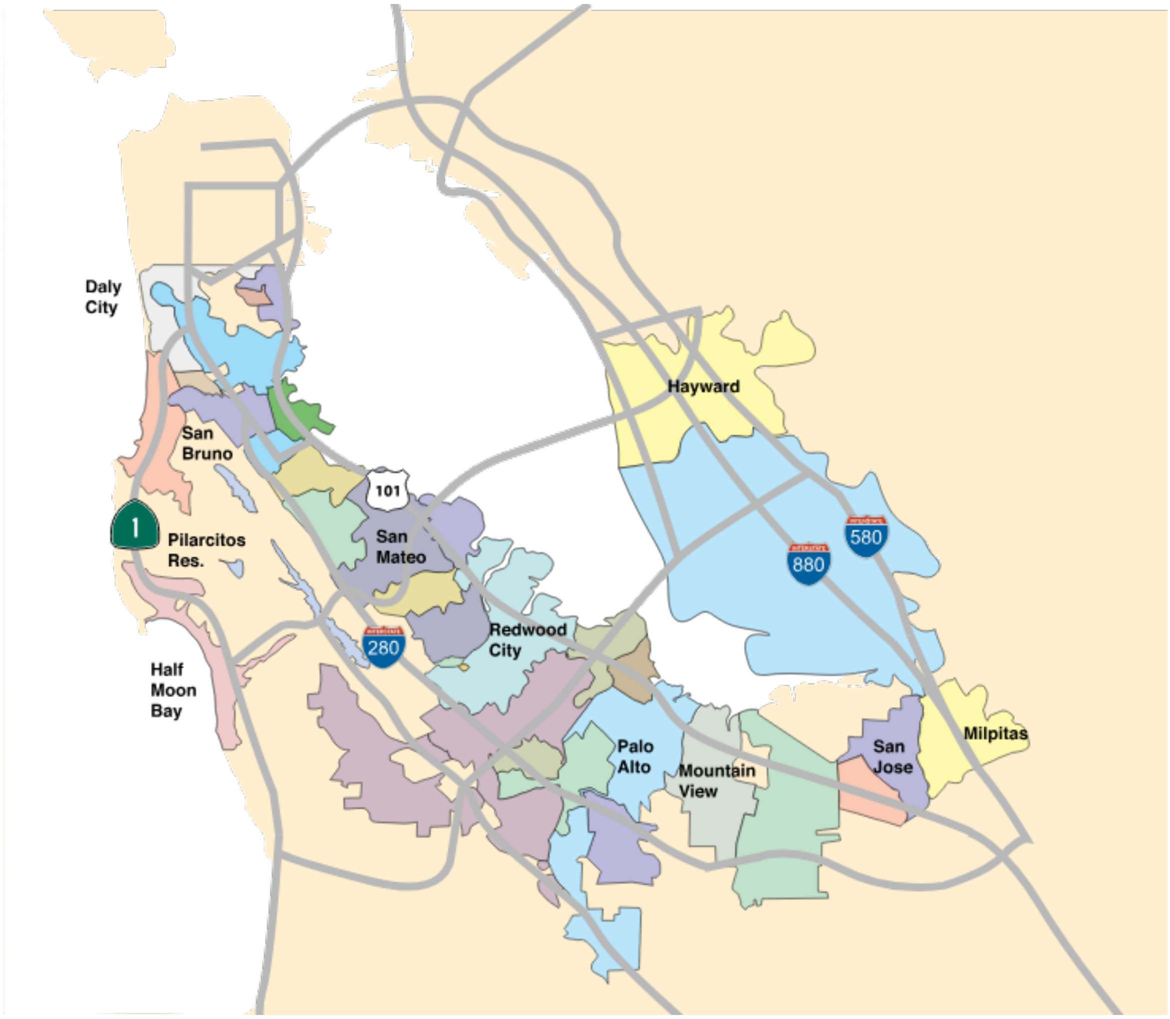
My econometric approach follows that of Buck et al. (2016) by estimating a utility fixed effects model. Like Buck et al. (2016), I control for factors such as weather, precipitation and year fixed effects. What I modify about this approach is the inclusion of other control factors that were used in Renwick and Green's work such as specific prescriptive policies, including specific conservation tiers set forth by the state of California. My results indicate a more inelastic price elasticity of -0.133 occurs with the inclusion of non-price policies, as the mandatory reduction tiers captures some of the effect of price in models without non-price policies.

My difference-in-difference models attempt to quantify the largest initiatives BAWSCA has undertaken to support water conservation: high efficiency washing machines and high efficiency toilet rebates. These rebates have been in effect since 2008 and 2006, respectively and are a part of a larger water conservation program which includes landscaping efficiency classes, public outreach, free sprinkler nozzles, rain barrel rebates, and grass replacement rebates. These programs were invigorated with the 2014 State of Emergency Declaration in which BAWSCA had to reduce their consumption 10% immediately and follow the tiered conservation approach once the drought subsided. Since 2014, BAWSCA has spent over $1 million on the two rebates I chose to study, administrating over 16,000 rebates since 2008 for the high efficiency toilets and over 50,000 rebates for high efficiency washing machines since 2006. Each appliance can save between $300 and $400 per acre-foot per year. My approach in my difference-in-difference model has the same control variables as the fixed effects model and will be run both with and without utility fixed effects to account for household characteristics like lawn size and people per household. Ultimately, these models measure the impact that the two largest rebate policies under BAWSCA by expenditure have on overall consumption for the utilities that offer the rebates compared to those who don't.

Data and Methodology

My study uses a panel dataset that consists of the data used by Buck et al. (2016), which received from the authors and then extended through 2017. Buck et al.'s original dataset contained data for 37 utilities in California that included variables such as average quantity(ccf) of monthly water use, the price schedule of each utility, and control variables such as temperature, precipitation, lot size and people per household. I collected data from the Bay Area Water Supply Conservation Agency (BAWSCA), which provides annual surveys of pricing policies and water consumption from utilities from the Bay area to Southern California. Figure 1 presents a map of the members of BAWSCA and their location in the Bay Area. I had to drop 11 of the Buck et al. utilities due to the fact they were not present in any of the BAWSCA Annual Surveys since 2010. As shown, most utilities have data dating back to 1995 or 1996, with only Brisbane, Hillsborough and Purisima Hills having later beginning dates to their data. The panel of utilities represents a broad area across the San Francisco Bay area, and each area was impacted in some way or another by drought conditions. From BAWSCA annual surveys, key metrics were found including the rate structure, average monthly household consumption and gallons per capita per day, which is used to specify the reduction tiers. For climatology data, NOAA provides annual precipitation levels and annual summer average precipitation. Buck et al. (2016) interact price with median household income for each utility based on the 2010 census to instrument price elasticity, which I intend to do.

Figure 1: BAWSCA Water District Map



Source: http://bawsca.org/members/map

Figures 2 and 3 below give a basic plot of the price and consumption of residential water between 1996 and 2017. These tables were constructed by computing an arithmetic average for each year of all utilities reporting in the year. Gallon per capita per day(GPCPD) decreases sharply in 2014 and 2015, showing that California's water restriction policies may have been effective, though one cannot conclude this just by looking at these graphs. Figure 3 shows an upward sloping increase in prices, though a log of the price would indicate prices were not affected by variables outside of inflation and regular cost of delivery increases. These two figures give an overarching sense of the data from easily understood metrics. It is important to note that when households are urged to reduce consumption, utilities need to raise prices to cover their fixed causes, which would indicate that utilities may not necessarily be raising price as a signal to conserve water. Consumption clearly decreases as price increases, which intuitively lays the groundwork for this paper.

Figure 2: Average Residential Gallons per Capita per Day (1996-2017)

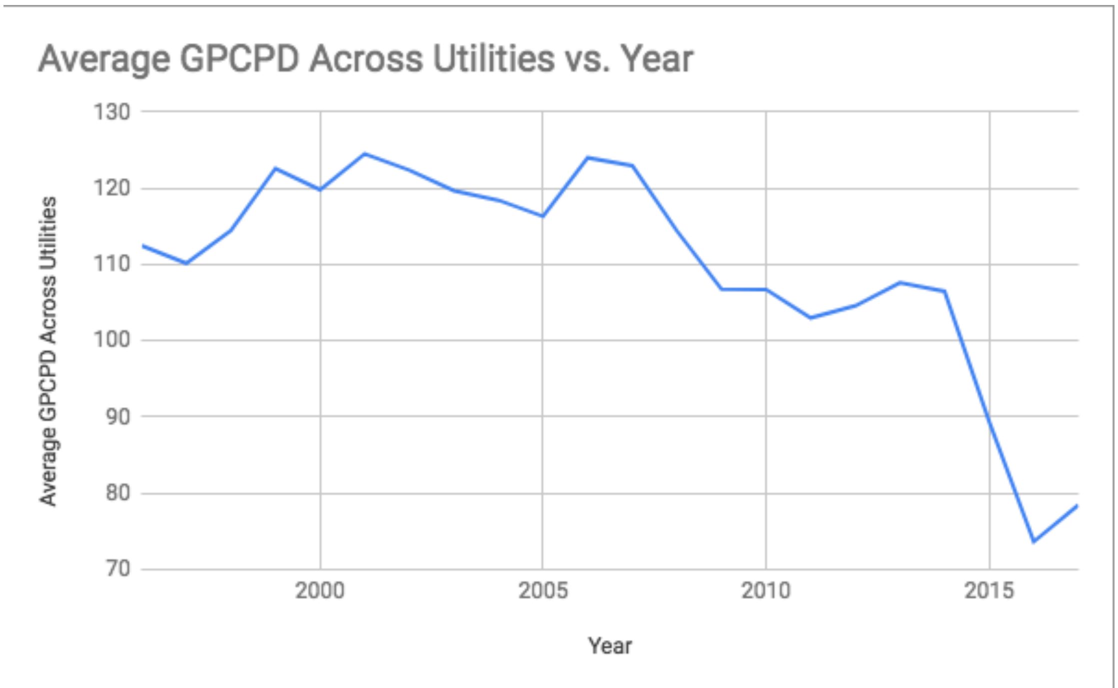
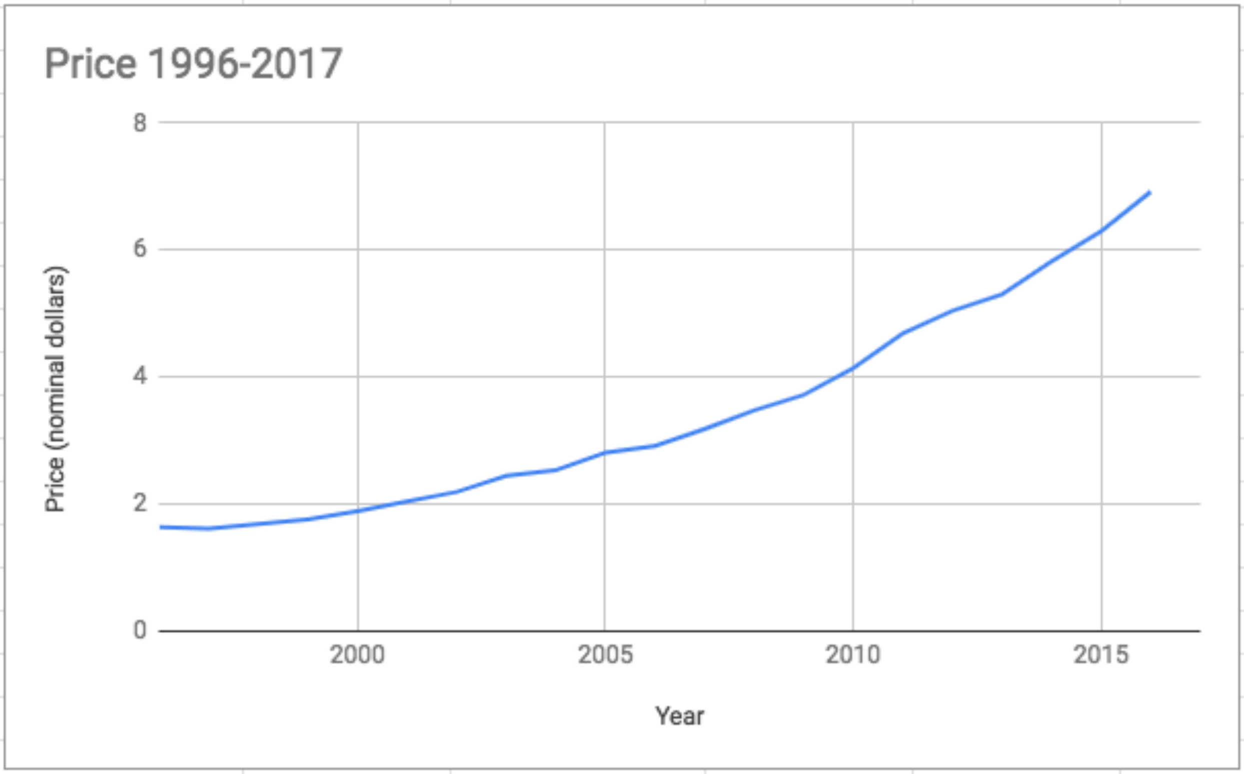


Figure 3: Average Median Tier Across Utilities (1996-2017)



Tables 7-12 show the individual summary statistics for the utilities in each conservation tier. While conservation tiers 8%-28% have similar consumption patterns, with average monthly household ccf measurements between 9 and 11 ccf, the 32% and 36% tiers have drastically higher consumption for the years 1996-2017, on average with consumption between 19 and 22.5 ccf. Median rates for the tiers in the data ranged between $2.91 and $4.74, with no discernable pattern or trend. However, for utilities implementing either the high-efficiency toilet or washing machine rebates, the median rate was larger than utilities not implementing the respective rebates. Rates for utilities implementing toilet rebates had average median rates of $3.62 per ccf while utilities not implementing the toiler rebates had an average rate of $3.12 per ccf. Utilities implementing washing machine rebates had an average median rate of $3.49 per ccf while utilities not implementing washing machine rebates had an average median rate of $3.19 per ccf.

While this may indicate utilities implementing additional conservation programs sponsored by BAWSCA charge more for the additional services they provide, this cannot be concluded in my analysis. However, this is an important distinction to note. Additionally, utilities implementing the rebates had lower average consumption with utilities implementing the toilet rebates and/or the washing machine rebates had an average of consumption of 10.95 ccf and 11.15 ccf, respectively. Meanwhile, utilities not implanting the toilet and/or washing machine rebates had an average consumption of 13.65 ccf and 13.5 ccf, respectively. While this pattern can't be connected to causation, it might suggest a more general assumption that utilities implementing these policies may intrinsically be making considerable efforts to curb consumption while utilities not implementing these rebates may lack the willpower or ability to conserve consumption overall.

The equations I will estimate will regress the log of quantity, which is ccf, on the log of price (price elasticity), average summer temperature, annual precipitation, the conservation tier variables indicating what tier a utility falls under with year and utility fixed effects. Temperature and precipitation are control variables, with the focus on measuring the impact the conservation tiers enacted in 2015 on overall water demand. The simple equation is as follows:

$$\text{(1)} \quad \ln(q_{it}) = \beta 0 + \beta_1 \ln(p_{it}) + \beta_2 temp_{it} + \beta_3 prec_{it} + \beta_4 tier*post_{it} + y_t + \eta_i + e_{it}$$

Where $\ln(q_{it})$ is log of ccf per household per month, $\ln(p_{it})$ is log of the median tier price, $temp_{it}$ is the average summer temperature, $prec_{it}$ is annual total precipitation, inc_{it} is average household income, $tier*post_{it}$ is a dummy variable indicating which conservation tier a water district was assigned to in 2015 as part of the 25% mandatory reduction, y_{it} being year fixed effects, η_{it} utility fixed effects and e_{it} being the error term.

The following subsections provide a detailed methodology of the intermediate steps, beginning with classifying median tiered rates and how I treated increasing block prices (IBP), and ending with a discussion about the instrumental variable procedure.

Price Measurement

To classify the median rate of each utility, I simply took the median block rate of each utility and as custom with even blocks, took the average of the middle two rates. The median rate is used to break the co-determination that might occur with price and consumption. The concept that consumers choose their consumption ahead of time based on observed block price would introduce bias within the econometric equation.

Buck et al. (2015) Replication

Buck paper's basic fixed effects equation is:

$$(2)\ \ln(q_{it}) = \beta_1 \ln(p_{it}) + \beta_2 W_{it} + \mu_i + \tau_t + e_{it}$$

where (qi_t) is single family residence monthly average, pit is the price per ccf on the median tier of the rate structure, W_{it} is precipitation and temperature measures, μ_i is a utility fixed effect and τ_t is a year fixed effect. In addition, to account for the fact that consumption decisions in period t may reflect prices in previous periods, Buck et al. (2016) use lagged prices to instrument for p_{it}. Including utility fixed effects controls for time invariant unobservable factors between utilities.

Replication Methodology

Following Buck et al, I will compute a number of different sets of results, an OLS buildup of the original equation and an IV panel data regression, one (of each) including utility fixed effects and one without. I will also extend Buck et al.'s (2016) equation to account for the 2015 mandatory 25% aggregate reduction by indicating in what conservation tier each utility falls. I will include year and water district fixed effects in these models to control for unobserved heterogeneity between districts and shocks to demand common to all utilities. The main concern here is that each water district has a unique approach to the combination of drought actions put in place to mitigate demand. Additionally, each utility bases its prices completely different. Some account for fixed charges using volumetric prices, while some account for variables costs using volumetric prices. Although under Proposition 218 the price of water must be limited to the cost of delivery, the calculations and rate-setting procedures used by each district are completely different. This might change how marginal price is interpreted in general demand and supply models. Additionally, I intend to utilize their two instrumented variables: interacting price and income variables to greater account for consumer choice, as well as using four lagged variables based on the first four prices on the increasing block schedule of each utility (Buck et al. 2015). The purpose of this instrument is to break the simultaneity bias that occurs for consumers that price may depend on one's own consumption as price increases. I include the full buildup of my model in the results.

My IV models will replace p_{it} by the instrument. The econometric equation is as follows:

$$(3)\quad \ln(q_{it}) = \beta_0 + \beta_1 \ln(\hat{p}_{it}) + \beta_2 temp_{it} + \beta_3 prec_{it} + \beta_4 tier{*}post_{it} + y_t + \eta_i + e_{it}$$

where every variable is the same as the OLS fixed effects regression, with $\hat{p}_{it}$ is indicating the instrumented price variable. This equation is also used for the instrumented variable model with

$\ln(p^4_{it-1})$ predicting price elasticity. In other words, the first four block prices in the year prior will instrument median tier, representing marginal price. There are two criteria for using an instrumented variable: the instrument must be correlated with the endogenous variable it is instrumenting and it must follow the exclusion restriction. The exclusion restriction entails that the instrument only affects the dependent variable through the variable it is replacing. The instrumented variable cannot directly affect the dependent variable. The lagged price variables in this case are directly correlated with current median price and the lagged prices for the first four tiers of the price schedule do not directly affect current consumption, thus this instrument meets both criteria.

The difference-in-difference models use the same control variables: temperature, precipitation, income and price and include the difference-in-difference measurement for both high efficiency washing machine rebates and high efficiency toilet rebates. I run both models with utility fixed effects and without to account for individual household characteristics that relate to water consumption such as lot size and people per household. Washing machine rebates have been offered since 2005 and the toilet rebates since 2008 as part of a larger effort to expand upon BAWSCA's core conservation program, which only included education and outreach programs. The difference-in-difference models is as follows:

$$\ln(q_{it}) = \beta_0 + \beta_1 \ln(p_{it}) + \beta_2 temp_{it} + \beta_3 prec_{it} + \beta_4 time_i + \beta_5 treat_t + \beta_6 time*treat_{it} + e_{it} \tag{4}$$

$$\ln(q_{it}) = \beta_0 + \beta_1 \ln(p_{it}) + \beta_2 temp_{it} + \beta_3 prec_{it} + \beta_4 time*treat_{it} + \mu_i + \tau_{t+}\, e_{it} \tag{5}$$

Where all the control variables are the same for each equation, but time denotes the time of the treatment, which is since 2005 for washing machine rebates and 2008 for toilet rebates, treat which is the utilities offering the rebates, which is 12 utilities for the toilet rebate and 14 utilities for the washing machine rebate. Time*treat is the difference-in-difference variable that measures the actual impact the rebates had on water consumption. The fixed effects equation is the second equation showed, where utility and fixed effects are present in lieu of the time and treatment variables. The summary statistics in Table 1 show a general overview of the data and can theoretically be used with the fixed effects results to show what the average demand curve would look like for each utility.

Increasing Block Prices (IBP)

Water prices are not determined by equilibrium, but through administrative techniques that should theoretically correspond to the marginal price. Proposition 218 in California limits the price of water to the cost of delivery, to ensure every person has access to affordable water. Several attempts to limit water prices have been shut down in several district disputes. The ongoing drought has renewed interest in increasing block prices, which are preferred by economists. Although increasing block pricing implies a different marginal cost for consumers, Buck et al. (2016) find that including an indicator of whether a utility has uniform or IBP is not statistically significant when measuring price elasticity. This consideration is used in my own econometric equation, which has the same proportion of uniform and IBP utilities. Different models used by Olmstead suggest that the demand function under IBP is piecewise linear, as consumption can stick between block prices if it doesn't have an effect on water consumption (Olmstead 2009). Thus, Olmstead conducts is discrete/continuous model(DCC) to account for price elasticities. A discrete/continuous model is not used in my econometric equation however because Olmstead found that the difference between the simple OLS and IV models' results compared to a complex DCC model's results are consistent, though DCC magnitudes are bigger, and each with their own biases (Olmstead 2009). The median tier of the price structure breaks the endogeneity issue with IBP without delving into the complicating and methodical approach Olmstead introduced of tracking each block price and fixed charges to diffuse simultaneous bias (Olmstead 2009).

The idea of drought management with the introduction of increasing block prices makes econometric modeling all the more difficult. As Buck et al. (2016) note, each additional tier on the price structure increases the degree of freedoms in how the utility can meet the supply constraint. The utility could nominally increase the price of one specific block, each block, or a combination of different increases for each block. Each scenario has different welfare effects on consumers (Buck et al. 2016).

Results

Table 2 shows the results of the linear model with each control variable considered. Without any controls, the price elasticity measured is -0.255. Once temperature and precipitation variables are factored in, the price elasticity falls to -0.22. Once all control factors were included, the price elasticity dropped to -0.133. This follows closely with that of previous studies, most notably of Buck et al. who calculated a price elasticity of -0.145, which is no surprise since this data are the same. It is less than that of Renwick and Green who measured a price elasticity of -0.2 during summer months. The reason the price elasticity was less than that of Buck et al. and Renwick and Green is because of the inclusion of tiered conservation variables. They are all significant and negative coefficients, indicating they decrease demand. In BAWSCA initiatives specifically, large rebates on low-flush toilets and high efficiency washing machines were favorable incentives that reduce water consumption. The tier coefficients on the fixed effects model range from -0.161 (8% tier) to -0.274 (20% tier).

What is notable about the results was that temperature was not significant in any of the regressions and had a small coefficient in relation to water quantity. This could be due to utility and year fixed effects capturing some of the effects of temperature. Precipitation was consistently negative, which intuitively makes sense as more precipitation would lead to less outdoor watering as well as utilities renewing their supply of water. As expected, each drought conservation tier had a negative and statistically significant coefficient, decreasing water consumption. It is unclear whether water districts used more price or non-price measures, but all were effective in curbing consumption. The policy extends through 2017, which may mean the results are simply due to the ongoing process of fully enacting drought policy.

Table 3 shows the instrumental variable results. In the regression with lagged prices predicting ln(price), the price elasticity increased to -0.159 and was highly significant. This may indicate that breaking the simultaneity bias of customers choosing quantity based on current prices increases the effect of prices, and indicates customers are sensitive to block prices in relation to consumption. Each of the conservation tier coefficients were all less than the coefficients in Table 2, again indicating that price has more of an effect on conservation when strategically priced historically.

One important aspect of my analysis is whether the coefficients for the conservation tier variables are statistically different from one another, a simple chi square test with a p-value of 2.4e^-11 allows me to reject the null hypothesis that all coefficients are equal. The individual fixed effects from equation (1) are presented in Figure 7. There is considerable unobserved heterogeneity across utilities, with CWS-Bear Gulch, Hillsborough and Purissima Hills constituting the utilities with fixed effects over three and Brisbane and Westborough having fixed effects below two.

Figure 7: Individual Utility Fixed Effects

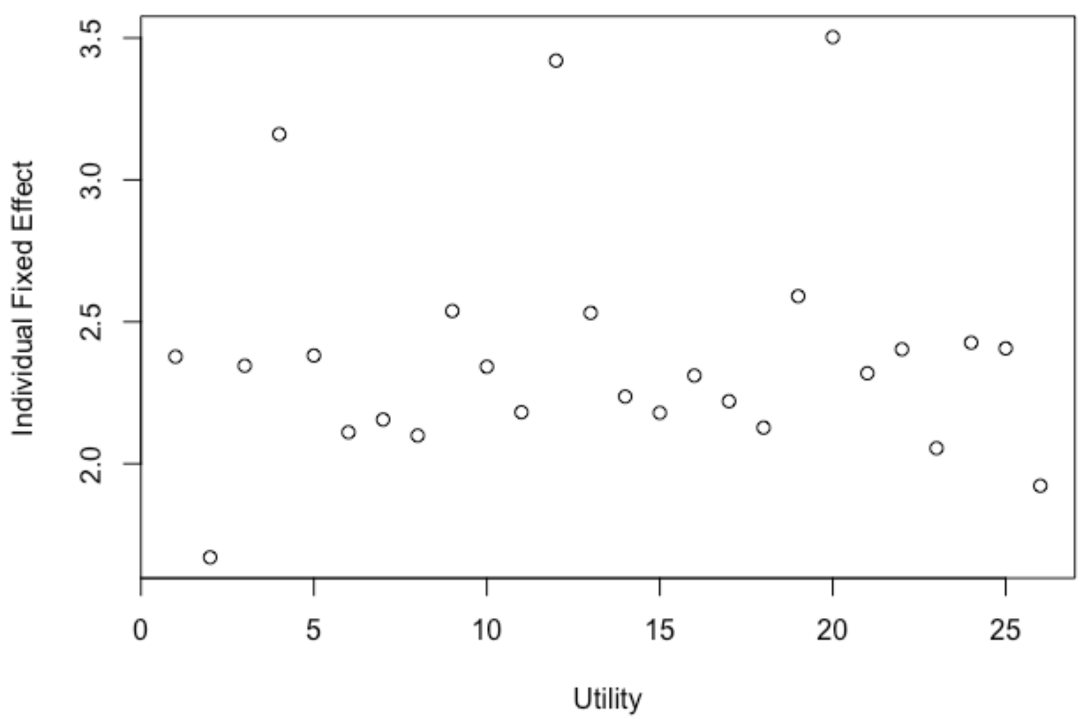


Table 4 below shows the results of the difference-in-difference models for the key rebates offered by BAWSCA. While not statistically significant, the difference-in-difference models without time and utility fixed effects show that utilities offering high efficient toilet rebates had a 4.8% decrease in consumption compared to those utilities that did not offer the rebates while utilities offering high efficiency washing machine rebates had a 0.1% reduction in consumption compared to those utilities that did not offer the rebate. This indicates the washing machine rebates did not have an impact on water consumption. The utility and time fixed effects models indicate the toilet rebates had a 2.8% reduction in consumption and is statistically significant at the 90% confidence level. The washing machine coefficient turned out to be slightly positive and not statistically significant, again indicating these rebates were not effective in their demonstrated aim. Each toilet rebate measure indicates that those rebate policies were effective in reducing consumption while washing machines rebates were not effective. Overall these policies can be treated as ancillary to Californian utility policies to reach the goal of having conservation be a way of life, the motto Governor Brown used when signing the State of Emergency statutes.

Conclusion

This paper studies how the demand function for residential water shifts when drought conditions are present and non-price policies are put in place to reduce consumption. This paper finds that the price elasticity of water demand decreases with the introduction of mandatory conservation tiers put forth by Governor Brown in 2015. More importantly, the demand curve for water has shifted to the left. The first five conservation tiers all exceeded their percentage reduction target, while the three highest tiers achieved less than their required percentage just through non-price measures.

Although the impact of the conservation tiers has yet to fully manifest, the findings in this paper can help shed some light on how California can best achieve their goal of 55 GPCPD by 2022. Utilities must include this conservation standard into their calculations but are ultimately judged only by one measure by the state: whether they are under budget or not. Rates are calculated differently for each utility, so it will be up to the state public commission during ratemaking cases as to whether water conservation standards are prudent and keep the cost of water to the cost of delivery. Block prices were proven to reduce consumption more than uniform rates, though it is important to note block prices may be set in ratemaking procedures in accordance to the additional strain more consumption puts on the utility system. Non-price policies such as rebates for high efficiency toilets or washing machines were proven in the difference-in-difference models to have mixed effectiveness in long-term conservation and may be a crucial tool for utilities to manage water supply in times of extreme drought if household activities are more properly accounted for. The washing machine rebates were not effective and show that other activities such as lawn watering may be more prudent to spend money on. It is important to note that BAWSCA's conservation program budget, including core and subscription programs, was $687,063 in 2008 and $1,369,456 as recently as 2016. This increasing inertia to fund prescriptive policies will only amplify the impact of non-price incentives on water consumption. These findings are consistent with economic theory and previous work. This study can be improved with access to better data, most notably more information regarding specific non-price policy and household characteristics. It is important to note that utilities have a plethora of tools at their disposal to incentivize reduced consumption, and identifying each individual method is key when examining an issue like the one in this study. The conservation tiers will most likely be very useful moving forward as a baseline for utilities, and each utility should have similar and coordinated reduction tactics. Policymakers need to align their actions to serve the best interest of their citizens, regardless of political backlash, and the question regarding price increases to precious commodities like water will only continue to grow in the 21st century as climate change exacerbates our current natural landscape.

Works Cited

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Tables

Table 1: Summary Statistics

Summary Statistics 1996-2017

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	572	12.25	6.42	4.10	8.80	13.05	40.00
Median Rate	572	3.35	1.97	0.69	1.81	4.53	11.74
Average Household Income (Thousands of Dollars)	572	108.57	43.09	49.11	71.64	147.78	216.58
Annual Total Precipitation(feet)	572	2.04	0.85	0.42	1.44	2.63	5.50
Average Summer Temperature	572	73.09	6.75	61.90	66.76	79.99	85.14

Table 2: Full Sample Linear Model

OLS Results

	Dependent variable: ln(quantity)			
	OLS Buildup 1	OLS Buildup 2 *panel linear*	Full Model	Full Model no FE *OLS*
	(1)	(2)	(3)	(4)
log(price)	-0.256*** (0.009)	-0.221*** (0.030)	-0.133*** (0.011)	0.138*** (0.041)
Precipitation		-0.007 (0.020)	-0.021*** (0.004)	0.005 (0.019)
Temperature		0.002 (0.003)	0.003*** (0.001)	0.025*** (0.003)
8% Tier			-0.162*** (0.025)	-0.430*** (0.111)
12% Tier			-0.208*** (0.034)	-0.431*** (0.154)
16% Tier			-0.272*** (0.025)	-0.454*** (0.110)
20% Tier			-0.274*** (0.023)	-0.434*** (0.099)
24% Tier			-0.261*** (0.029)	-0.482*** (0.126)
28% Tier			-0.205*** (0.029)	-0.498*** (0.126)
32% Tier			-0.215*** (0.035)	0.250 (0.152)
36% Tier			-0.190*** (0.028)	0.271** (0.127)
Constant				0.459 (0.281)
Observations	572	572	572	572
R^2	0.606	0.188	0.789	0.248
Adjusted R^2	0.587	0.150	0.774	0.233
F Statistic	837.217*** (df = 1; 545)	42.005*** (df = 3; 546)	181.555*** (df = 11; 535)	16.754*** (df = 11; 560)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3: Lagged Prices IV Model

IV Results

	Dependent variable: ln(quantity)		
	IV Buildup 1	IV Buildup 2	Full IV Model
	(1)	(2)	(3)
log(price)	-0.296*** (0.014)	-0.313*** (0.024)	-0.159*** (0.026)
Precipitation		-0.003 (0.002)	0.002 (0.001)
Temperature			-0.147*** (0.028)
8% Tier			-0.196*** (0.036)
12% Tier			-0.260*** (0.027)
16% Tier			-0.258*** (0.027)
20% Tier			-0.240*** (0.035)
24% Tier			-0.190*** (0.031)
28% Tier			-0.205*** (0.036)
32% Tier			-0.177*** (0.031)
36% Tier			-0.024*** (0.005)
Observations	571	571	571
R^2	0.605	0.629	0.787
Adjusted R^2	0.586	0.610	0.772
F Statistic	783.617*** (df = 1; 544)	293.655*** (df = 3; 542)	178.777*** (df = 11; 534)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: Rebate Difference-in-Difference Results

	Difference-in-Difference Results			
	Dependent variable: ln(quantity)			
	OLS		*Time and Utility Fixed Effects*	
	High Efficiency Toilets	High Efficiency Washing Machines	High Efficiency Toilets	High Efficiency Washing Machines
log(price)	0.059 (0.045)	0.042 (0.046)	-0.235*** (0.014)	-0.252*** (0.014)
Precipitation	-0.007 (0.020)	-0.001 (0.021)	-0.037*** (0.006)	-0.036*** (0.006)
Temperature	0.016*** (0.004)	0.022*** (0.004)	0.002 (0.001)	0.002 (0.001)
Treatment	-0.153*** (0.047)	-0.087* (0.052)	*NA*	*NA*
Time	-0.103* (0.059)	-0.049 (0.057)	*NA*	*NA*
Average Treatment Effect	-0.048 (0.065)	-0.001 (0.066)	-0.028* (0.015)	0.015 (0.014)
Constant	1.343*** (0.332)	0.869*** (0.309)		
Observations	572	572	572	572
R^2	0.176	0.148	0.641	0.640
Adjusted R^2	0.168	0.139	0.622	0.620
Residual Std. Error (df = 565)	0.380	0.386		
F Statistic	20.163*** (df = 6; 565)	16.355*** (df = 6; 565)	241.989*** (df = 4; 542)	240.440*** (df = 4; 542)
Note: Premium rebates were offered at $100 for higher efficiency toilets and standard rebates at $50. Both were considered in this model.			*p<0.1; **p<0.05; ***p<0.01	

Table 5: Water District Summary

Water District	Population	Increasing Block Prices
Alameda CWD	350,538	Uniform
Brisbane	4,156	6
Burlingame	31,109	Uniform
CWS - Bear Gulch	60,513	Uniform
CWS - Mid Peninsula	135,455	3
CWS - South San Francisco	257,737	3
Coastside CWD	16,704	4
Daly City	109,139	2
East Palo Alto WD	26,181	Uniform
Estero MID	37,518	2
Hayward	158,985	3
Hillsborough	10,869	5
Menlo Park	16,066	2
Mid-Peninsula	26,924	4
Millbrae	22,848	Uniform
Milpitas	77,528	Uniform
Mountain View	77,801	3
North Coast CWD	40,000	4
Palo Alto	66,930	2
Purissima Hills WD	6,150	5
Redwood City	87,023	4
San Bruno	44,409	3
San Jose	13,733	2
Santa Clara	123,752	Uniform
Sunnyvale	149,831	2
Westborough WD	14,050	Uniform
Total	1,965,949	

Table 6: 8% Tier Summary Statistics

8% Tier Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	90	9.75	2.97	5.60	7.60	11.11	17.83
Median Rate	90	3.33	1.78	1.52	1.81	4.37	9.02
Average Household Size (# of People)	90	3.32	0.64	2.40	2.63	3.39	4.19
Annual Total Precipitation(feet)	90	2.01	0.74	0.43	1.55	2.50	4.01

Table 7: 12% Tier Summary Statistics

12% Tier Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	44	9.46	1.99	5.00	8.29	10.96	12.49
Median Rate	44	4.74	2.05	1.81	2.73	6.73	8.83
Average Household Size (# of People)	44	2.69	0.02	2.67	2.67	2.71	2.71
Annual Total Precipitation(feet)	44	2.49	0.99	0.52	1.91	2.99	5.50

Table 8: 16% Tier Summary Statistics

16% Tier Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	91	10.05	1.83	5.70	8.80	11.18	13.28
Median Rate	91	3.23	1.62	1.45	1.98	4.40	7.54
Average Household Size (# of People)	91	2.70	0.27	2.44	2.56	2.89	3.15
Annual Total Precipitation(feet)	91	2.16	0.94	0.42	1.51	2.76	5.50

Table 9: 20% Tier Summary Statistics

20% Tier Statistics							
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	113	10.51	2.32	5.50	9.00	12.81	14.14
Median Rate	113	2.91	1.94	0.95	1.57	3.37	11.75
Average Household Size (# of People)	113	2.75	0.26	2.47	2.48	2.98	3.11
Annual Total Precipitation(feet)	113	2.00	0.82	0.42	1.43	2.54	5.07

Table 10: 24% Tier Summary Statistics

24% Tier Statistics							
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	66	10.59	1.76	5.90	9.82	11.92	13.16
Median Rate	66	2.97	1.95	0.69	1.73	4.01	8.91
Average Household Size (# of People)	66	2.64	0.56	2.24	2.24	3.43	3.43
Annual Total Precipitation(feet)	66	2.07	0.97	0.43	1.38	2.61	5.50

Table 11: 28% Tier Summary Statistics

28% Tier Statistics							
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	64	10.99	4.03	4.10	6.18	14.11	16.17
Median Rate	64	3.56	2.00	1	2.0	4.6	8
Average Household Size (# of People)	64	2.46	0.11	2.33	2.33	2.59	2.59
Annual Total Precipitation(feet)	64	1.81	0.65	0.43	1.36	2.31	3.22

Table 12: 32% Tier Summary Statistics

32% Tier Statistics							
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	44	19.34	6.05	8.60	14.77	25.47	28.87
Median Rate	44	2.72	1.50	1.10	1.66	3.26	7.15
Average Household Size (# of People)	44	2.79	0.06	2.73	2.73	2.85	2.85
Annual Total Precipitation(feet)	44	1.93	0.77	0.52	1.38	2.64	3.83

Table 12: 36% Tier Summary Statistics

36% Tier Statistics							
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	60	22.67	11.78	6.50	9.26	32.98	40.00
Median Rate	60	3.99	2.43	1.33	1.85	6.04	9.68
Average Household Size (# of People)	60	3.11	0.33	2.81	2.81	3.53	3.53
Annual Total Precipitation(feet)	60	1.98	0.85	0.43	1.37	2.52	4.56

Table 13: Toilet Rebate Participant Statistics

High-Efficiency Toilet Rebate Participants							
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	261	10.59	5.34	4.10	7.80	11.34	33.41
Median Rate	261	3.62	2.18	0.69	1.87	4.85	11.75
Average Household Size (# of People)	261	2.79	0.37	2.24	2.47	3.15	3.39
Annual Total Precipitation(feet)	261	2.22	0.92	0.42	1.62	2.76	5.50

Table 14: Toilet Rebate Non-Participant Statistics

High-Efficiency Toilet Rebate Non-Participants

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	311	13.65	6.91	5.00	9.53	14.34	40.00
Median Rate	311	3.12	1.75	1.07	1.79	4.18	8.70
Average Household Size (# of People)	311	2.85	0.52	2.25	2.48	2.98	4.19
Annual Total Precipitation(feet)	311	1.90	0.77	0.43	1.37	2.47	5.50

Table 15: Washing Machine Rebate Participant Statistics

High-Efficiency Washing Machine Rebate Participants

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	304	11.15	5.15	4.10	8.20	12.50	33.41
Median Rate	304	3.49	2.06	0.69	1.80	4.80	9.68
Average Household Size (# of People)	304	2.85	0.50	2.24	2.47	3.11	4.19
Annual Total Precipitation(feet)	304	2.20	0.92	0.42	1.57	2.76	5.50

Table 16: Washing Machine Rebate Non-Participant Statistics:

High-Efficiency Washing Machine Rebate Non-Participants

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Monthly Household Quantity(ccf)	268	13.50	7.43	5.50	9.12	13.66	40.00
Median Rate	268	3.19	1.87	1.07	1.83	4.24	11.75
Average Household Size (# of People)	268	2.79	0.40	2.25	2.47	3.15	3.53
Annual Total Precipitation(feet)	268	1.86	0.73	0.42	1.37	2.38	5.07