How Price and Non-Price Incentives Affect California Water Demand

By Christopher Deranian*

Advised by Maureen L. Cropper

Over the past two decades, drought conditions in California have repeatedly threatened freshwater security in the state. Since Governor Jerry Brown declared a state of emergency in 2014, a variety of policies have been enacted to promote water conservation. However, raising the price of residential water is illegal under proposition 218, leaving non-price policies such as restrictions, rebates and information campaigns responsible for water reduction. This paper uses fixed effects and difference-in-differences models to estimate the impact of both price and non-price incentives on the demand for residential water in California, and how they may impact California's goal to reduce water usage by 25% statewide. This analysis finds that non-price policies in the San Francisco Bay Area result in a 16% to 27% reduction in demand, with a price elasticity of -0.133, less than that of previous studies. These results are statistically significant.

∗ University of Maryland - College Park
email: chris.deranian@gmail.com
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Introduction

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, and many executive orders have followed the declaration. These orders allow utilities to enact policies at their own discretion, ranging from conservation rebates to mandatory restrictions. Under Proposition 218, 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. In April 2015, Governor Brown declared a goal of a 25% statewide reduction in potable urban water use. Each water district had to reduce water consumption from 2013 levels, and utilities were required to enact a conservation framework making water conservation a way of life. This included penalties of $1,000 a day if annual water targets were not met, and $10,000 a day during emergency droughts. Water consumption per person per day should be reduced to 55 gallons by 2022, and to 50 gallons per day by 2030. While these are long-term goals, this paper seeks to understand the short-term effects on residential demand through price and non-price policies.

The purpose of this paper is to estimate a demand function and price elasticities for residential water demand using data from 26 water districts in the San Francisco Bay Area. To accomplish this, I first extend the 1996-2009 data from Buck et al. (2015) through 2017. I then investigate whether quantity restrictions from 2015 through 2017 affected residential consumption, while controlling for price and climate conditions. I also explore how demand is affected by the conservation tier each utility was placed in under the 2014 State of Emergency initiatives. Finally, I measure the impact of specific rebate policies for high-efficiency washing machines and toilets on the overall reduction in consumption.

I use data from the Bay Area Water Supply Conservation Agency (BAWSCA) for price and quantity measures as well as the rate structure of each utility. Each utility rate structure indicates the price for each block of consumption on the structure, with quantity indicating the threshold each individual block price operates under. I retrieved climatology data from the National Oceanic and Atmospheric Association (NOAA).

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 is intended to show how sensitive consumers are to block prices. I run two difference-in-differences models for high-efficiency toilet and washing machine rebates according to the year each program began 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 estimate price elasticities ranging from -0.14 to -0.2. Price is more elastic in the IV model, indicating that 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 highest-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 are statistically different from each other. The difference-in-differences analysis of appliance rebates do not find a statistically significant effect of high-efficiency toilet and washing machine rebates on water consumption. These results show that non-price policies may achieve their goal of water consumption, albeit minimally, and will continue to do so as they become more standard in utility regulation.

Literature Review

The factors driving water conservation are extremely important to policy makers and have been studied extensively since Renwick and Green (1999) first introduced non-price policies into a model of residential water demand.

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 from 1989 to 1996 to estimate a demand curve for residential water consumption. They control for policies to reduce consumption such as information campaigns, rebates, and quantity restrictions 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 other months, indicating that activities like outdoor watering are both 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 reduces estimates of the price elasticity of demand, compared to estimates from previous studies that did not include non-price factors. The two non-price policies that change the demand curve in a tangible way are rationings and restrictions, which decrease household demand by 2.1 and 3.3 centum cubic feet of water (ccf) per month, respectively. Retrofit subsidies and information campaigns each decrease consumption by about 1 ccf per month (Renwick and Green 1999). Renwick and Green conclude that prescriptive policies were effective in reducing demand, but the level of reduction varies with income, seasonality, and type of non-price policy.

Buck et al. (2016) build upon the work of Renwick and Green (1999). 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 unobservables. 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 (2009) 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 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 generally believe pricing mechanisms best achieve conservation targets. There has been extensive work on this topic, most notably by Olmstead and Stavins (2009) who conclude that neither price nor prescription are superior to the other. Olmstead and Stavins argue that water prices are not indicative of marginal cost and do not send an adequate signal to consumers (2009).

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 BAWSCA data. This demand function can shed light on key questions about recent conservation goals and the effects 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). 1 ccf is approximately 720 gallons. Like these authors as well, I use the median tier price for utilities with increasing block prices. This is not necessarily the marginal price as perceived by customers but it helps to "decouple price from consumer's choice of block" (Buck, Steven et al.). To better measure perceived marginal prices, I use lagged price variables to instrument for current median block price.

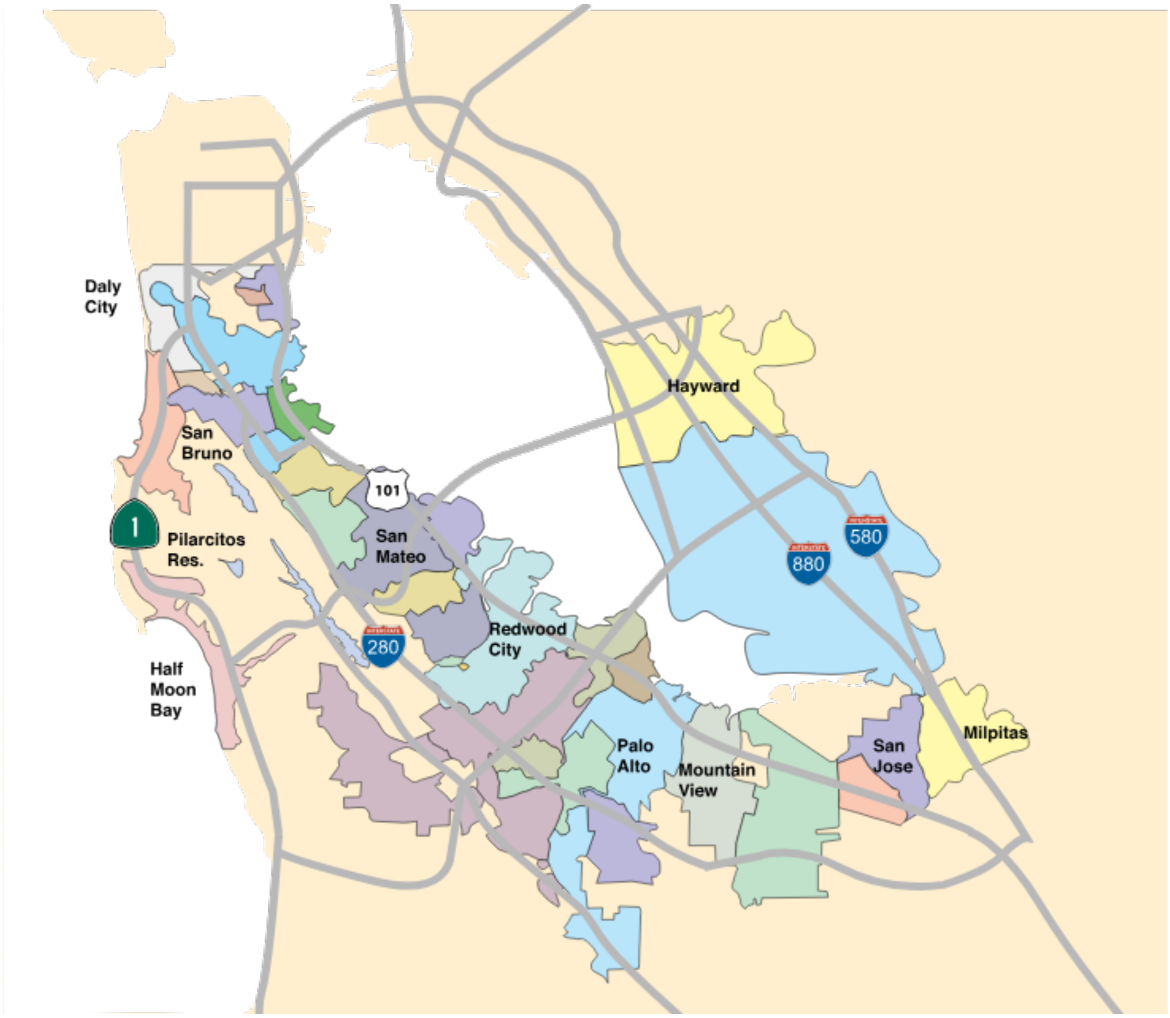
My econometric approach follows that of Buck et al. (2016) by estimating a utility fixed effects model. Like Buck et al. (2016), I control for weather, precipitation and year fixed effects. I extend this approach by controlling for prescriptive policies, including specific conservation tiers assigned by the state of California. My results indicate a more inelastic price elasticity of -0.133 with the inclusion of non-price policies, as the mandatory reduction tiers capture some of the effect of price in models without non-price policies.

My difference-in-differences models attempt to quantify the largest initiatives BAWSCA has undertaken to support water conservation: high-efficiency washing machine 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 initiated by the 2014 State of Emergency Declaration, under which BAWSCA had to immediately reduce water consumption by 10% and follow the tiered conservation approach once the drought subsided. BAWSCA has administered over 16,000 high-efficiency toilet rebates since 2008 and over 50,000 high-efficiency washing machine rebates since 2006. Each appliance can save between $300 and $400 per acre-foot per year. My difference-in-differences model has the same control variables as the fixed effects model and is run both with and without utility fixed effects to account for household characteristics such as lawn size and people per household. Ultimately, these models measure the impact that the two largest rebate policies have on overall consumption.

Data and Methodology

My study uses a panel dataset originally used by Buck et al. (2016), and I extend the dataset 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, utility price schedules, 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 in the Bay Area. Figure 1 presents a map of BAWSCA members. I dropped 11 of the original Buck et al. utilities which were not present in any BAWSCA annual surveys since 2010. The BAWSCA annual surveys provide rate structure, average monthly household consumption and gallons per capita per day, which is used to specify reduction tiers. The National Oceanic and Atmospheric Administration (NOAA) provides annual precipitation levels and average summer precipitation.

Figure 1: BAWSCA Water District Map



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

Figures 2 and 3 show prices and consumption levels for residential water between 1996 and 2017. Gallons per capita per day (GPCPD) decreases sharply in 2014 and 2015, indicating that California's water restriction policies may have been effective. Figure 3 shows an 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 encouraged to reduce consumption, utilities must raise prices to cover their fixed costs, which suggests utilities may not necessarily be raising price as a signal to conserve water. Still, consumption clearly decreases as price increases, which lays the intuitive groundwork for this paper.

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

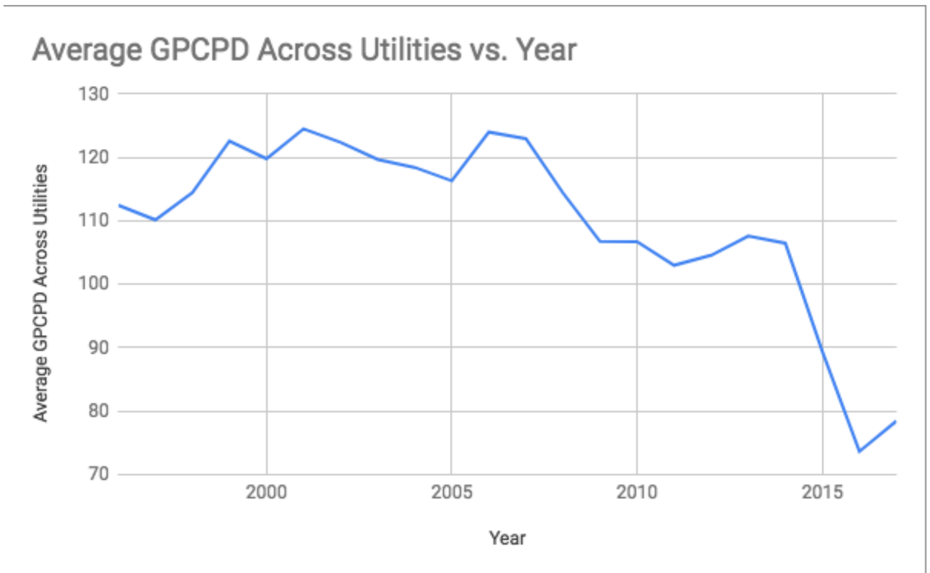
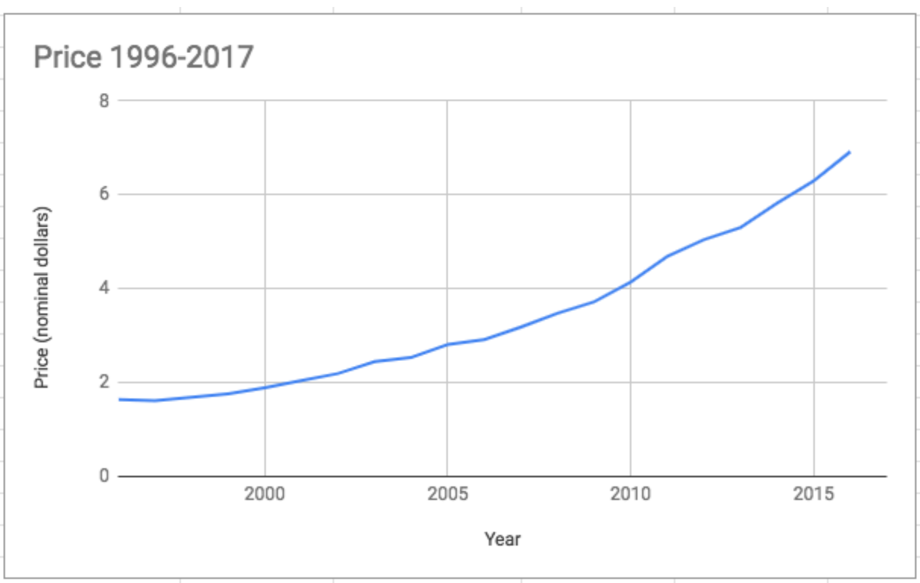


Figure 3: Average Median Tier Across Utilities (1996-2017)



Tables 7-12 show the individual summary statistics for the utilities in each conservation tier. While conservation tiers 8%-28% have similar consumption patterns, the 32% and 36% tiers have drastically higher consumption for the years 1996-2017. Median rates for the tiers in the data range between \$2.91 and \$4.74, with no discernible 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. Additionally, utilities implementing the rebates had lower average consumption. Utilities implementing the high-efficiency toilet rebates or high-efficiency washing machine rebates had average consumption levels of 10.95 ccf and 11.15 ccf, respectively. Meanwhile, utilities not implementing the toilet or washing machine rebates had average consumption levels of 13.65 ccf and 13.5 ccf, respectively. This pattern does not necessarily imply causation. Indeed, utilities implementing these policies may already be making considerable efforts to curb consumption, while utilities not implementing rebates may lack the willpower or ability to reduce consumption.

The equations I estimate regress the log of quantity (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:

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

Here, $\ln(q_{it})$ is the log of ccf per household per month, $\ln(p_{it})$ is the log of the median tier price, $temp_{it}$ is 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, y_{it} is year fixed effects, η_{it} is utility fixed effects and e_{it} is the error term. The following subsections describe my intermediate steps, beginning with my approach to median tiered rates and increasing block prices (IBP), and ending with a discussion of the instrumental variable procedure.

Price Measurement

To classify the median rate of each utility, I simply took the median block rate of each utility. For utilities with an even number of blocks, I took the average of the middle two rates, as is the custom. The median rate is used to break the co-determination that might occur between price and consumption. Using the block prices that individual consumers face could introduce bias within the econometric equation, as a consumer's choice of consumption level changes the price that they face.

Buck et al. (2016) Replication

The basic fixed effects equation from Buck et al. (2016) is:

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

where q_{it} is single family monthly average consumption (ccf), p_{it} 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, because consumption decisions in period t may reflect prices in previous periods, Buck et al. (2016) use lagged prices to instrument for p_{it}. I include utility fixed effects to control for time-invariant unobservable factors between utilities.

Replication Methodology

I compute an OLS buildup of the original equation and an IV panel data regression, where one of each includes utility fixed effects and one does not. I 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 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 sets its prices differently. Although under Proposition 218 the price of water must be limited to the cost of delivery, districts use distinct calculations and rate-setting procedures. This changes how marginal price is interpreted in general demand and supply models. Additionally, I utilize two types of instrumented variables. First, I interact price and income variables to better account for consumer choice. Second, I use four lagged variables based on the first four prices on the block schedule of each utility (Buck et al. 2015). The purpose of this instrument is to break the simultaneity bias among consumers when price depends on one's own consumption. I include the full buildup of my model in the results. My IV models will replace p_{it} by the instrument. The equation is as follows:

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

All variables except $\hat{p}_{it}$ are the same as in the OLS fixed effects regression, and $\hat{p}_{it}$ indicates 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 prior year will instrument median tier, representing marginal price. There are two criteria for using an instrumented variable. First, the instrument must be correlated with the endogenous variable it is instrumenting. Second, the instrument must satisfy the exclusion restriction, which stipulates that the instrument only affects the dependent variable through the variable it is replacing. 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-differences models use the same control variables (temperature, precipitation, income and price) and include the difference-in-differences measurement for both high-efficiency washing machine rebates and high-efficiency toilet rebates. I run both models with and without utility fixed effects to account for individual household characteristics, such as lot size and people per household, which may affect household water consumption. The difference-in-difference models are as follows:

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

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

The control variables are identical in each equation. Time denotes the time of the treatment, which is the number of years since 2005 for washing machine rebates and since 2008 for toilet rebates. Treat is the utility 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-differences variable that measures the actual impact the rebates had on water consumption. The fixed effects equation is the second equation shown, 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 determined through administrative techniques that should theoretically correspond to the marginal price. The ongoing drought has renewed interest in increasing block prices. Although increasing block pricing implies a different marginal cost for consumers, Buck et al. (2016) find that whether a utility has uniform or increasing block prices has no statistically significant effect on price elasticity. This consideration is used in my own equation, which has the same proportion of uniform and IBP utilities.

Modeling conservation with IBP is more difficult than with uniform block prices. As Buck et al. (2016) note, each additional tier on the price structure increases the degrees of freedom in how utilities can meet the supply constraint. The utility could increase the price of one specific block, each block, or a combination of 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 in turn. 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. This is no surprise, since the two studies are based on the same data. It is less than that of Renwick and Green, who measured a price elasticity of -0.2 during summer months. The price elasticity is less than that of Buck et al. and Renwick and Green due to the inclusion of tiered conservation variables. Each conservation tier has 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).

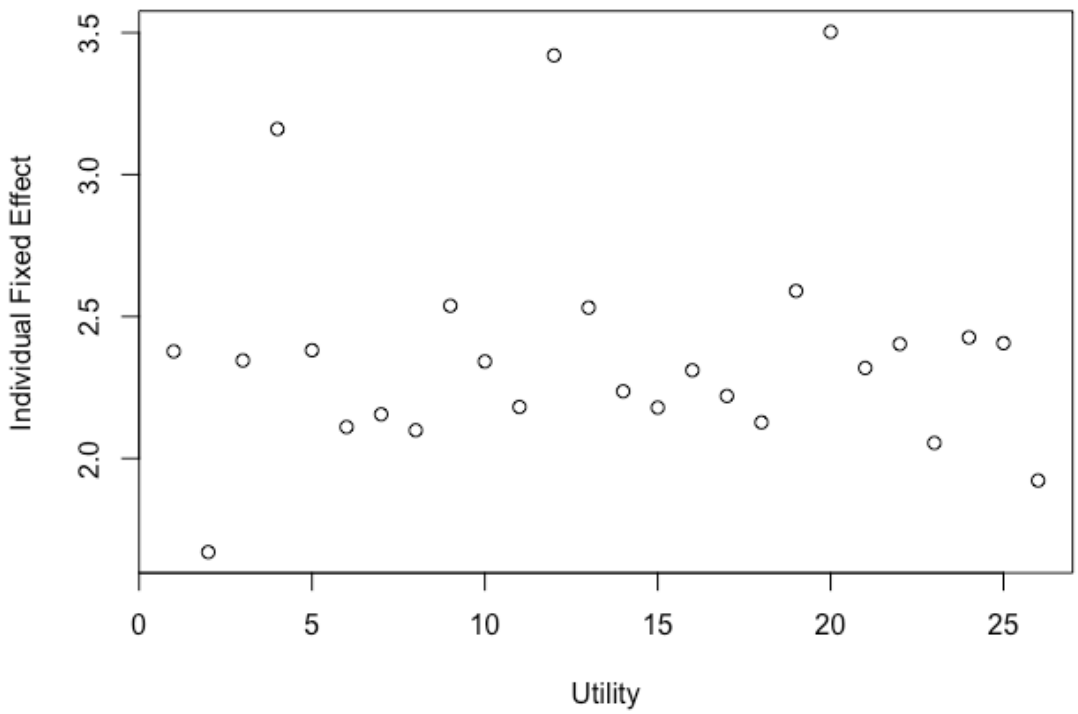
Notably, temperature is not significant in any regression and has a small coefficient in relation to water quantity. This may be because utility and year fixed effects capture some effects of temperature. Precipitation has a consistently negative coefficient, which makes intuitive sense since precipitation leads to less outdoor watering and replenishes utilities' water supply. As expected, each drought conservation tier had a negative and statistically significant coefficient, implying a decrease in consumption. It is unclear whether 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 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 less than the coefficients in Table 2, again indicating that price has more of an effect on conservation when strategically priced.

I also test whether coefficients for the conservation tier variables are statistically different from one another. A 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: CWS-Bear

Gulch, Hillsborough and Purissima Hills have fixed effects over three, while Brisbane and Westborough have fixed effects below two.

Figure 7: Individual Utility Fixed Effects



While not statistically significant, the difference-in-differences models without time and utility fixed effects show that utilities offering high-efficiency toilet rebates had a 4.8% decrease in consumption compared to those utilities that did not offer the rebates. Utilities offering high-efficiency washing machine rebates had a 0.1% reduction in consumption compared to other utilities, suggesting that washing machine rebates did not have an impact on water consumption. The utility and time fixed effects models indicate the toilet rebates resulted in a 2.8% reduction in consumption. This 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. Overall, these policies can be treated as ancillary to other California policies designed to “make conservation a California way of life,” as Governor Brown described his signing of 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 enacted to reduce consumption. This paper finds that the price elasticity of water demand decreases with the introduction of mandatory conservation tiers 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 solely through non-price measures.

Although the impact of the conservation tiers has yet to fully manifest, the findings in this paper sheds light on how California can best achieve its goal of 55 GPCPD by 2022. Rates are calculated differently for each utility, but the state public commission decides whether water conservation standards are prudent and keep the cost of water at the cost of delivery. Block prices were shown to reduce consumption more than uniform rates, though block prices may be set in ratemaking procedures in accordance with the additional strain that consumption puts on the utility system. My difference-in-difference models also show that rebates for high-efficiency toilets and washing machines may have mixed effectiveness for long-term conservation. In particular, the washing machine rebates were not effective, suggesting that other conservation efforts may be more prudent uses of the budget. My results are generally consistent with economic theory and previous work. My study can be improved with access to better data, most notably on specific non-price policies and household characteristics.

An increasing drive to fund prescriptive policies will only amplify the impact of non-price incentives on water consumption. For example, BAWSCA's conservation program budget has risen from $687,063 in 2008 to $1,369,456 in 2016. With these resources, utilities have many tools to incentivize reduced consumption, and identifying each tool is key when examining issues like water conservation. Conservation tiers will likely be useful moving forward, and each utility should have similar and coordinated reduction tactics. Questions around price increases for precious commodities like water will only continue to grow in the 21st century, as climate change reshapes our natural landscape.

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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-Differences Results

Difference-in-Differences 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