Prescriptive Drought Policy and Water Supplier Compliance

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Abstract

Governments often cannot use prices to induce water conservation, and the need to understand the impacts of alternate methods is growing due to increased variability in water resources. During the 2012-2016 drought in California, a period that may presage the future of water management in a warmer climate, the state attempted to manage water use through a set of mandatory restrictions that assigned each of California's 412 largest urban water suppliers to one of nine conservation tiers; those with greater historic usage needed to conserve more. I find that even though significant statewide savings occurred, only half of all suppliers complied with their conservation target. Moreover, the increased savings were not caused by the tiered design of the mandate: evidence from a regression discontinuity design shows that suppliers that just missed a stricter conservation tier actually conserved more. Additionally, water use rebounded after the regulation was removed, implying that variable adjustments in demand contributed more to water use savings than fixed cost household investments. Given the significant costs of water regulation and the high probability of future droughts, the policy implication is that both governments and water suppliers may benefit from investments in water supply reliability and less complex prescriptive policies.

Keywords: government mandates, water scarcity, conservation, urban utilities, supplier behavior

JEL Codes: D22, L95, Q25, Q28, Q58

1 Introduction

Effective water management has always been important for public health, economic growth, and political stability, yet is becoming more difficult in many communities: there is an increase in the frequency of extreme weather events, a reduction in the reliability of current water supplies, and a growing concern about the environmental effects of new supply projects. During periods of drought, expanding public water capacity is typically not feasible and therefore water suppliers must often find ways to reduce demand. Pricing mechanisms are one way to encourage conservation, yet water prices generally do not reflect scarcity.[1] Water restrictions are seen as a policy tool that can immediately reduce demand and have become one of the most common conservation strategies (Buck et al., 2016a); these target end users. Another option is to target water suppliers, but there remains little empirical evidence of the impacts of such policies.

Prescriptive water programs are often used when raising water prices is politically challenging. For example, during California's 2012-2016 drought, ACWA/CMUA (2016) found that only 8% of surveyed water suppliers adjusted their rates in direct response to the drought. Such policies generally target single-family residential households because they are considered to have the lowest value use; restricting commercial or industrial use is expected to result in large job losses and output effects (Mansur and Olmstead, 2012). In California, the residential sector accounts for roughly one-half to two-thirds of urban water use in most communities. Therefore, the largest costs of use restrictions are consumer welfare losses that result from the reduction of water consumption (Buck et al., 2016a). In the long run, such prescriptive policies may also provide little incentive for the innovation or diffusion of water conserving technologies.[2]

In April 2015, for the first time in California's history, mandatory restrictions were imposed on large water suppliers in order to achieve a 25% statewide reduction in potable urban water use.[3] I exploit this statewide mandate in order to improve our understanding of water supplier behavior, and the empirical estimation has two goals. The first is to examine the effectiveness of the mandate, where I study cutoff-specific savings for suppliers at each conservation tier. The second goal is to see whether the mandate led to more persistent changes in water consumption, where I test for evidence of hysteresis after the emergency regulation was lifted.

California's water system is facing an uncertain future with hotter temperatures and shorter and more intense wet seasons (Lund and Medellín-Azuara, 2018). However, their situation is not unique. States such as Arizona, Colorado, Nevada, New Mexico, and Texas, as well as Australia and South Africa, are facing similar issues (Buck et al., 2016b). Moreover, while California's drought was exceptionally hot and dry, it ended in 2017 with one of the wettest years on record. Known as "precipitation whiplash," climate projections show that this phenomenon is likely to

[1] Water prices are aimed at pursuing not only greater allocative efficiency but also objectives of equity, public health, financial stability, and public acceptability (Arbues et al., 2013). The result is artificially low water prices that create inefficient land-use patterns or more generally overuse (Mansur and Olmstead, 2012).

[2] One reason for this is that if a supplier invests heavily in conservation, and thus their customers use very little water, they would still need to conserve more under such a policy, and achieving further reductions in use under such a scenario can be quite costly.

[3] Table 1 shows how the regulation grouped these 412 urban water suppliers into nine conservation tiers based on their 2014 summer usage. Those with greater historic per capita use were required to save more, with mandated savings ranging from 4% to 36%. Note that a primary concern with a measure of cumulative savings is that it may incentivize waste or other perverse actions when there are no regulations in place because increasing investment in non-rationed years increases the marginal cost of compliance in rationed years.

become more common (Mount et al., 2018; Swain et al. 2018). Supplier conservation targets may be used more frequently in the future because of this, and thus this paper provides a thorough analysis of their impacts in order to assist policymakers and water practitioners.

The paper proceeds as follows: Section 2 briefly summarizes the related literature, Section 3 discusses the research setting, Section 4 describes the data, Section 5 contains methodology, Section 6 presents the results, Section 7 provides a discussion, and Section 8 concludes.

2 Related Literature

The literature has generally focused on user-targeted conservation strategies, with little evidence on supplier-targeted ones. Within this consumer-focused work, minimal research exists on non-price conservation programs, despite the fact that many water suppliers have tended to rely on these demand management strategies during times of drought.[4] Of the limited non-price research, we have a good understanding of the household-level effects of restrictions that an individual supplier implements, often in the Southwestern United States and Australia (e.g., Cooper et al., 2012; Dolnicar et al., 2012; Wichman et al., 2016).

Additionally, Halich and Stephenson (2009) find that mandatory restrictions with low information efforts did not reduce water use when implemented at the state-level. Grafton and Ward (2008) further argue that such approaches can impose significant welfare losses. For example, Buck et al. (2016b) and Nemati et al. (2018) find welfare losses of $203 million in Northern California and $794 million in Southern California from the 2015 drought mandate; they determine that an efficient mandate would have saved households $180 million. Nevertheless, to the best of my knowledge, a systematic examination of supplier behavior under state- or country-level conservation targets is missing from the literature. Given that non-price conservation programs will continue to be utilized in the future, this paper attempts to improve our understanding of the effectiveness of supplier-level conservation targets.

3 Research Setting: California

California has maintained considerable water security despite the significant seasonal, annual, and geographic variability in hydrology and water demands; Figure 1 shows this regional and seasonal heterogeneity over time. However, because the state is heavily dependent on precipitation and snowpack to replenish its surface water and groundwater supplies, it is increasingly vulnerable to the risks associated with climate change (Gonzales and Ajami, 2017). Currently, over 400 urban water suppliers serve more than 90% of the state's residents, as seen in Figure 2.[5] These large utilities often rely on imported water from the Sacramento-San Joaquin Delta, the Colorado River, and other distant locations. Most utilities are public agencies with locally

[4] The literature has mainly focused on pricing mechanisms, where a large body of research examines the price elasticity of residential water demand.

[5] Approximately 2,500 smaller utilities serve rural and some suburban communities; they are often geographically isolated and rely on local groundwater. New investments incur high costs per customer, while large utilities can spread fixed infrastructure costs over a wide customer base. They also often have several water sources and considerable technical expertise (Hanak et al., 2018).

elected boards, but privately owned utilities also exist and serve about 16% of Californians (Hanak et al., 2018).

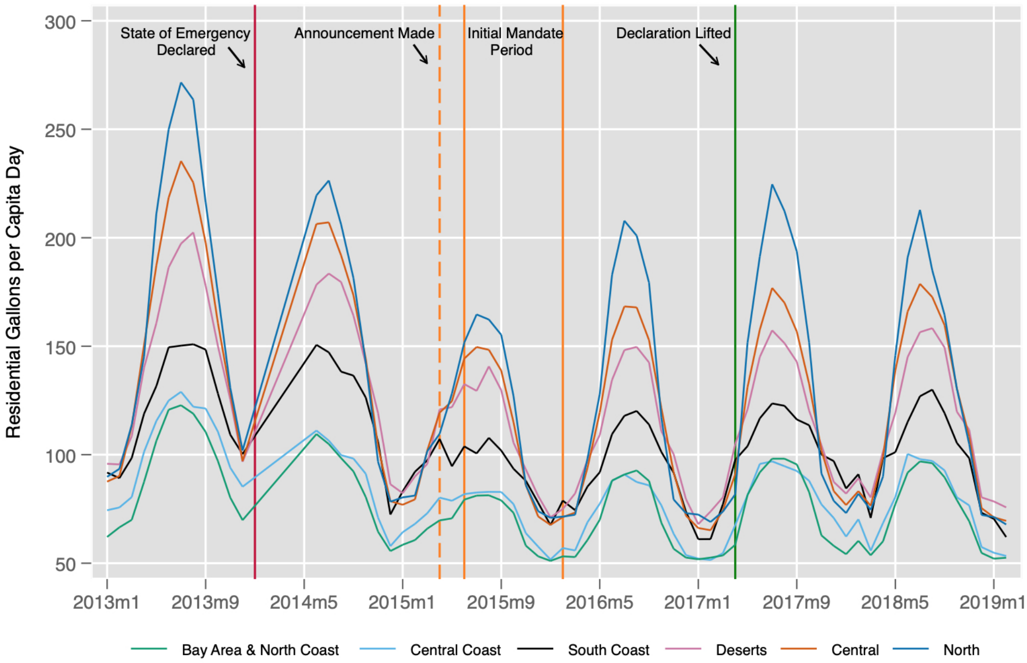

Figure 1: Residential Water Consumption in California by Region

Note: Mandatory supplier reporting began in June 2014 and thus data before this represent SWRCB estimates.
Source: California State Water Resources Control Board (Water Conservation and Production Reports)

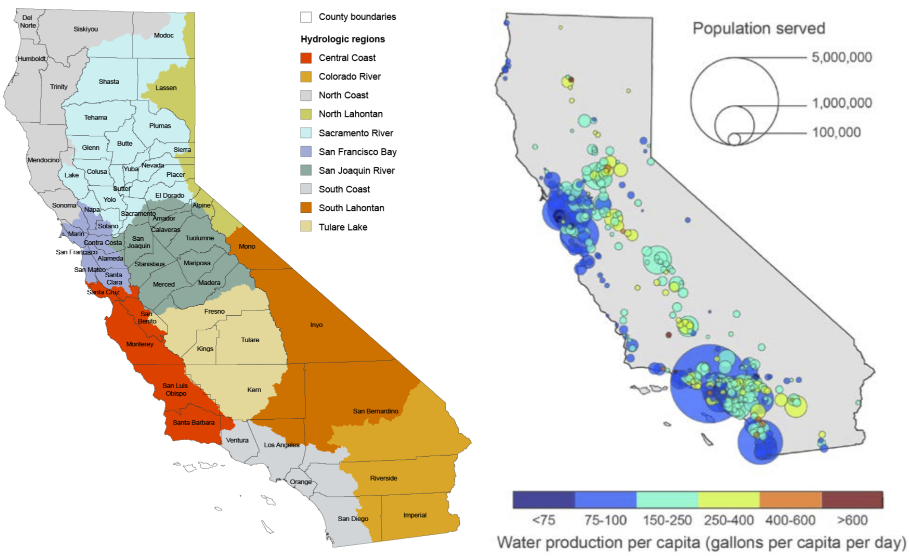

Figure 2: Map of the Hydrologic Regions in California (Left) and Urban Water Suppliers by Size and Use in 2013 (Right)

Source: CA Department of Water Resources and Mitchell et al. (2017)

Drought Legislation

The 2012-2016 drought in California saw a significant amount of legislation passed.[6] The most relevant for this examination, Executive Order B-29-15, was issued on April 1, 2015. For the first time in state history, the Governor directed the State Water Resources Control Board (SWRCB) to implement mandatory restrictions on potable urban water use at the supplier-level. Effective June 1, 2015, the 25% statewide reduction was to occur by February 2016, and Table 1 shows how the emergency regulation assigned each water supplier a conservation standard. The targets ranged from 4% to 36% and were based on per capita residential use from July to September 2014.[7] An individual supplier could determine how best to incentivize local conservation, such as restricting outdoor watering days or providing rebates for water-efficient appliances and lawn replacement, but if they failed to meet their target, the SWRCB issued informational orders, conservation orders, and cease and desist orders. Suppliers that violated cease and desist orders were subject to a civil liability of up to $10,000 a day.[8]

Table 1: Urban Water Supplier Conservation Tiers from Executive Order B-29-15

Tier	R-GPCD Range		# of Suppliers in Range	Conservation Standard
	From	To		
1	Reserve		4	4%
2	0	64.99	27	8%
3	65	79.99	23	12%
4	80	94.99	42	16%
5	95	109.99	61	20%
6	110	129.99	45	24%
7	130	169.99	81	28%
8	170	214.99	61	32%
9	215	612.00	68	36%
Statewide			412	25%

Notes: The mandate assigned each urban water supplier a conservation standard based on their residential gallons per capita per day (R-GPCD) for the months of July-September 2014. This was announced in April 2015 and each supplier had from June 2015 to February 2016 to achieve their standard. *Source*: California State Water Resources Control Board

While conservation standards were determined using the residential use measure of gallons per capita day (R-GPCD), the SWRCB determined compliance based on cumulative tracking of total potable water production, which includes residential, commercial, industrial, and institutional water. Starting in June 2015, conservation savings were added together from one month to the next and compared to the amount of water used during the same months in 2013. The formula used to determine savings for each utility in a given month was

$$1 - \frac{\sum_{\text{month}} (\text{Total Monthly Potable Water Production})_{\textit{month starting in June 2015}}}{\sum_{\text{month}} (\text{Total Monthly Potable Water Production})_{\textit{same months but starting in June 2013}}}, \quad (1)$$

but to make it more concrete, the cumulative percent savings for a given utility in September

[6]Figure C.2 contains a comprehensive list of these regulations.

[7]Water suppliers whose source of supply did not include groundwater or water imported from outside the hydrologic region in which the supplier is located, and that had a minimum of four years' supply in reserve, were placed into Tier 1.

[8]Note that information on the actual instruments used to achieve conservation at the supplier-level was not available. I contacted each agency and attempted to run a survey through two agencies representing many of the suppliers, but did not receive any meaningful responses.

2015 would be calculated as $1 - \frac{\text{Total Production for June, July, August, and September 2015}}{\text{Total Production for June, July, August, and September 2013}}$.

Another executive order, B-36-15, was issued on November 13, 2015 and extended the 25% mandate to October 31, 2016, conditional on the drought persisting through January 2016. It also directed the SWRCB to consider modifying the restrictions. When the drought persisted, they made credits to water suppliers' assigned targets in March 2016 based on climate, investments, and water-efficient growth. Conservation targets were updated again in June 2016, where in response to "stress tests" of supply reliability, 341 utilities received a target of 0%.[9] These final conservation standards remained in place until January 2017 and the emergency declaration was lifted in April 2017; Figure 3 shows how these targets became weaker over time.

The extension of the compliance period and weakening of the targets should be understood within the context of California's water system dynamics. Reservoirs are first measured and a decision is made as to whether or how much water needs to be saved. Ideally, prices should be raised when the reservoir starts to be drawn down, but this is politically challenging and the state often waits until the situation is quite dire. Suppliers make investments accordingly, then there is realization of rainfall (as its stochastic), and policies can be updated accordingly.

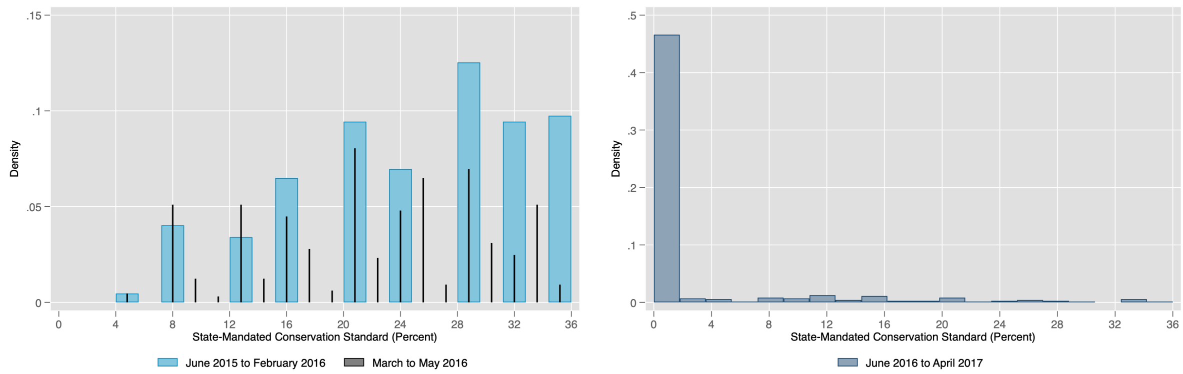

Figure 3: Distribution of Conservation Targets over Time

4 Data and Compliance

The empirical analysis utilizes 57 consecutive months of urban water supplier-level data from California. These water suppliers span the entire state and thus the data represents rich spatial and temporal variation in weather conditions, water consumption, and demand management programs. All urban water suppliers that have 3,000 or more service connections must report their potable water production and conservation activities to the SWRCB each month. This data is available from June 2014 to February 2019 for 404 of the 415 residential water suppliers meeting this criteria; similar information exists for 2013, but they are SWRCB estimates. Note that the most current data supersedes all previously released material, as data can be updated by either the supplier or the SWRCB.

[9]The requirement for suppliers was to have at least a three-year water supply under extended drought conditions. Those that failed this test (36 suppliers) were required to meet a state-imposed conservation standard equal to the shortage level. Note that self-certification of supply levels was optional. Water suppliers that did not submit self-certifications retained their conservation standard from March 2016, which 32 decided to accept.

I also incorporate census data from the 2012-2016 American Community Survey (ACS) 5-year estimates. This allows me to control for income, education, employment, race, and housing tenure at the census block group level, which I aggregate up to the water supplier level. I then overlay this with spatial data on water agencies from the Department of Water Resources. I then combine this with water enterprise data from the California State Controller's Financial Transactions Reports (2003-2016) for both cities and special districts, which matches to 78% of the SWRCB data because it does not include information on investor-owned utilities. Lastly, I incorporate data from the Department of Water Resources' Water Loss Audit from 2016. Summary statistics by hydrologic region are in Table 2, or by year in Table B.1, where the substantial regional variation is evident.

Table 2: Summary Statistics by Region Through December 2018

	South Coast	Central Coast	Bay Area & North Coast	Deserts	Central	North
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
Per Capita Income (year)	32714.0	33587.4	43486.4	22605.4	22551.5	29294.0
	14508.9	12622.5	16932.7	5737.6	6683.7	7842.4
Percent White	62.4	78.8	61.0	71.3	73.2	76.2
	16.2	8.7	18.8	13.1	13.1	13.4
Some College or More (%)	62.0	63.2	71.0	53.1	49.1	65.0
	16.1	17.8	9.8	9.8	12.3	10.6
Employed (%)	91.7	93.2	92.8	87.0	88.4	90.2
	2.4	1.6	2.5	4.3	2.7	2.6
Owner Occupied (%)	59.4	57.9	60.8	61.2	59.2	62.3
	12.4	10.6	9.8	9.6	9.2	11.9
Severe Poverty (%)	5.5	5.9	4.8	9.3	7.9	6.8
	2.1	4.0	2.6	3.1	3.0	3.5
Median House Value	514304.6	543387.1	680563.4	194054.2	214344.4	296445.2
	255520.4	269542.0	376079.3	76536.0	70787.2	119289.6
R-GPCD	118.8	76.5	72.5	115.5	119.8	129.4
	297.2	36.3	34.3	59.6	61.5	75.0
Total Population Served	116421.2	40046.9	112056.5	51811.5	61116.3	56270.8
	328125.8	32556.6	234439.7	62755.1	84056.6	77626.2
Observations	9747	1772	3488	1793	3142	2605

4.1 A Descriptive Examination of Compliance

Before discussing the empirical strategies and results in Sections 5 and 6, respectively, it is worthwhile to examine compliance more thoroughly. Table 3 shows the trends in supplier compliance at key dates. The rapid and large changes in compliance are quite striking, but also that 252 utilities (62%) were already "compliant" in June 2015, the start of the compliance period. Such an occurrence is due to the policy's design, as cumulative tracking was used to determine compliance (Equation 1) and June 2013 was the first reference month for comparison. Table 3 also shows how the compliance status of individual suppliers changed over time. Note that only 16 suppliers (4%) became compliant by the proposed end of the mandate in February 2016, while 70 (17%) lost compliance.

The large increase in suppliers achieving compliance in March 2016 and again in June 2016 can be attributed to the fact that targets were lowered and became effective in those months. The significant changes in conservation targets are seen most clearly in Figure 3, where the distribution of assigned targets up until February 2016 first-order stochastically dominates the distribution from March to May 2016, which then first-order stochastically dominates the distribution from June 2016 onwards; 341 utilities were given a target of 0% in June 2016.

Table 3: Compliance Status at Important Legislative Dates

	June 2015	Nov. 2015	Feb. 2016	March 2016*	June 2016*	Nov. 2016	April 2017
Compliant	252	245	198	271	397	393	401
Non-Compliant	154	161	208	135	9	13	5
Total	406	406	406	406	406	406	406

*Conservation standards were updated for the 3-month period of March to May 2016 and again in June 2016 (until April 2017), as seen in Figure 3. In April and May 2016, there were 278 and 279 compliant utilities, respectively.

Compliance Status Change over Relevant Time Periods

	June 2015 to Feb. 2016	June 2015 to Nov. 2015	Nov. 2015 to Feb 2016	Feb. 2016 to Nov. 2016	Nov. 2016 to April 2017
Became Compliant	16	25	5	195	8
Remained Compliant	182	220	193	198	393
Lost Compliance	70	32	52	0	0
Remained Non-Compliant	138	129	156	13	5
Total	406	406	406	406	406

Notes: June 2015 was the beginning of the compliance period and February 2016 was its proposed end. Because the drought continued, it was extended to November 2016 (announced in November 2015). April 2017 was end of the drought.

Therefore, I chose February 2016 as the main date for analysis, as it was the last month to achieve compliance under the first executive order.

Figure 4 shows the pattern of compliance for each water supplier in February 2016. The 45 degree line defines perfect compliance and 48.8% of suppliers were compliant by the proposed end of the mandate. What is striking is that suppliers placed into lower tiers saved considerably more than required. While still less in absolute terms, savings were intended to be more difficult to achieve at lower tiers, as those utilities had less water being used per person going into the drought; in principle, households should have found it difficult to save more and/or suppliers should have exhausted many of their possible conservation strategies. Moreover, while there was significant variation in percent saved within a tier, the distributions were quite similar across tiers, as seen by the interquartile ranges of savings for each tier. Note that for tiers two through four, a supplier at Q1 is over-compliant, while in tiers seven through nine, a supplier near Q3 is barely compliant.

That said, the trend in savings is upward sloping but relatively flat, meaning that suppliers in higher tiers saved slightly more than those in lower tiers. Taken together, Figure 4 suggests that the policy may have grouped suppliers on the wrong margin and thus was likely quite inefficient.[10] Note that a significant amount of savings may be attributed to what is defined as "behavioral" (or voluntary) conservation by Gonzales et al. (2017). Since there was a period of voluntary conservation before the mandatory savings period, any additional savings beyond what was saved before the mandate can be defined as "non-behavioral" conservation.[11]

[10] There is, however, considerable geographic heterogeneity in terms of assignment of targets and compliance, as seen Figures C.3 and C.4. The Central Coast, Bay Area, and North Coast had generally lower targets and significantly over-complied; Figure C.5 shows that this variation in savings does not seem to be driven by differences in population served.

[11] This is expressed graphically by region and supplier in Figures C.6 and C.7, respectively.

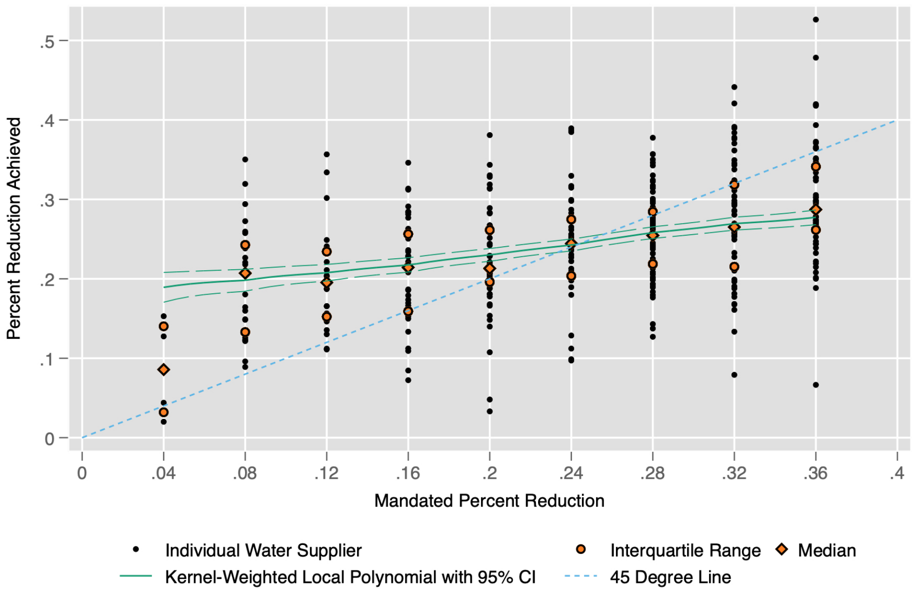

Figure 4: The Distribution of Mandated and Observed Percentage Reductions in February 2016

Notes: "Percent Reduction Achieved" is the cumulative percent saved from June 2015 to February 2016 relative to 2013 usage for the same months. Points above the 45 degree line indicate suppliers that exceeded their conservation target.

4.1.1 Adjustments to Conservation Standards based on Compliance

Table B.2 shows the adjustments given to suppliers in March 2016 by compliance status in February 2016. 88% of those found non-compliant received a positive credit (i.e., a lower target), with approximately 11% of those that remained non-compliant receiving a credit of greater than or equal to 8%. Since only non-negative adjustments were given, I estimate a tobit model to examine how compliance status affected the credit received. The results in Table B.3 show that relative to suppliers that became compliant by February 2016, all other groups received higher credits. The suppliers that remained non-compliant were credited the most.

A key limitation of the tobit model, however, is that the probability of a positive value and the actual value, given that it is positive, are determined by the same underlying process. Therefore, I also estimate a Cragg model, as it allows these outcomes to be determined by separate processes. More specifically, the first stage incorporates a probit model while the second utilizes a truncated normal model. The first stage results in Table B.4 show that relative to the suppliers that became compliant, those that lost compliance and remained non-compliant both had a greater probability of receiving a credit. While the second stage estimates are not significant at the 5% level, they show that conditional on receiving a credit, credits were higher among those that became compliant.[12]

4.1.2 Predictors of Compliance

Given the patterns of compliance found in the previous subsection, I use linear probability, probit, and logit models to examine the predictors of compliance. For ease of exposition, the

[12]Note that of the 16 suppliers that became compliant, 9 of them received a credit of 0%.

general specification for supplier i in time t is

$$P(compliance_{it} = 1|\mathbf{X}) = F(\beta_0 + \beta_1 log(population_{it}) + \beta_2 resiuse_{it} + \beta_3 log(june2013prod_i) \\ + \beta_4 investorowned_i + \beta_5 target_i + \mathbf{ACS}\boldsymbol{\gamma}), \tag{2}$$

where F is a function that depends on the model being estimated, $compliance_{it}$ is a dummy variable for either monthly compliance or compliance in February 2016, $log(population_{it})$ is the log of population served, $resiuse_{it}$ is the percentage of urban water used for residential purposes, $log(june2013prod_i)$ is the log of total potable water production in June 2013 (the reference month for determining compliance), $investorowned_i$ is a dummy variable for whether the water utility is investor-owned, $target_i$ is the state mandated percentage reduction (updated twice), and **ACS** is a vector of census variables at the water supplier level.[13]

Estimating equation (2) gives us the predictors of compliance, which are presented in Tables B.5 (marginal effects) and B.6 (standard coefficients) for February 2016.[14] They are robust to model choice and show that the probability of compliance increased with residential use, investor-ownership, the base month production level, percentage of renters, and penalties issued by a supplier in a given month (divided by the population served) for violations of local ordinances and/or the statewide mandates. The probability of compliance decreased with population served, assigned target, and percentage of households below the poverty level.

Given data availability, I cannot determine the exact mechanisms driving these results, but potential mechanisms are that it may be more challenging for the industrial or commercial sectors to reduce water use relative to the residential sector (Worthington, 2010; Mansur and Olmstead, 2012), investor-owned utilities can adopt more aggressive conservation strategies (Teodoro et al., 2018), a higher or potentially inefficient base production level makes it easier to reduce water use during the compliance period using "low-hanging fruit" strategies (if you are already a very efficient supplier, reducing more is often quite costly), those with more renters were assigned to be in lower tiers, and households respond to penalties.

The negative correlation between population and probability of compliance may be due to logistical constraints, such as it being more costly to incentivize reductions when serving more people in both a financial and operational sense. This could also be due to the fact that such suppliers can spread a fixed fine over a larger customer base and generally have more political capital, so being non-compliant may not be much of a concern. Higher targets are more difficult to achieve, while households below the poverty level may be unable to invest more in water savings or do not have large lawns or easy mechanisms to significantly reduce water use.

[13]Putting aside data constraints, population was selected because water consumption is likely impacted by the number of individuals in a community, residential use because levels of commercial or industrial use are important to consider, June 2013 production and supplier conservation target because the law was designed based on historical use, investor-owned because different ownership structures may impact financial incentives and ability to comply, and census information to control for observable characteristics of the community. Unfortunately, there is no reliable information on what methods were used to achieve a target (such as rebates, fines, or lawn replacement programs), historical investments or water rates, or alternative water supplies. Lastly, the logarithm of both population and historical production are used given right skewness of these variables in the data.

[14]The results for compliance in every month up through May 2016 are in Tables B.7 and B.8.

4.1.3 Dose Response Model

Lastly, to examine compliance in a regression framework, I also estimate a dose response model that incorporates treatment intensity using

$$saved_{it} = \sum_{j=2}^{9} \beta_j tier_j + \mathbf{X\Phi} + \mathbf{ACS}\boldsymbol{\gamma} + \delta_t + \sigma_s + \epsilon_{it}, \tag{3}$$

where $saved_{it}$ is cumulative percent saved of supplier i up to month t relative to the same months in 2013, $tier_j$ is a dummy variable for each tier $j \in \{2, 9\}$, $\mathbf{X}$ is a vector of supplier covariates, **ACS** is a vector of census variables, δ_t are month fixed effects, and σ_s are water source fixed effects.

The results of estimating equation (3) are in Table 4 and they reaffirm the fact that there were significant savings. However, they also show there was considerable over-compliance at lower tiers and some under-compliance at higher tiers. If suppliers responded to the mandate as it was intended, the difference in coefficients should have been exactly 0.4, as each successive tier should have induced 4% more savings. However, looking at any of the models and starting with the coefficient on tier two, there is a steady increase of approximately 1% to 2% for every tier. This shows that suppliers given higher conservation target saved more, but not as the policy intended. Note that the results from the t-tests from Model (1) show that we can reject the null that the majority of the coefficients are equal to each other. Put differently, the coefficients on higher tiers are statistically different than each other, and we can only not reject the null of $\beta_{tier2} = \beta_{tier3}$ and $\beta_{tier3} = \beta_{tier4}$.

Similar to the results in Table B.5 on predictors of compliance, we see that the coefficients on covariates in models two through four are similar in sign. Specifically, investor-owned utilities and suppliers with more residential users and more penalties assessed saved more. Additionally, water districts with higher median home values and more renters saved less, while ones with more educated households saved more.

5 Methods

The empirical estimation has two goals. The first is to examine the effectiveness of the mandate, where I study the cutoff-specific savings for suppliers at each tier and determine whether the tiered design of the mandate policy had any impact on savings. The second goal is see whether the mandate led to more persistent changes in water consumption, where I test for evidence of hysteresis after the emergency regulation was lifted.

5.1 Determining the Effectiveness of the Mandate

In order to examine the cutoff-specific savings for suppliers at each tier, I use a multi-cutoff regression discontinuity (RD) design.[15] The main estimation strategy finds cutoff-specific treatment effects, where the outcome is water savings, the running variable and cutoffs are summer

[15] Cattaneo et al. (2016) warn that estimating a pooled RD treatment effect by normalizing the score variable may not fully exploit all the available information, but that it provides a useful benchmark.

Table 4: The Impact of Treatment Intensity on Percentage Saved: OLS and T-Test Results

	(1)	(2)	(3)	(4)
2.tier	0.157***	0.157***	0.156***	0.153***
	(0.0186)	(0.0178)	(0.0180)	(0.0203)
3.tier	0.168***	0.166***	0.165***	0.172***
	(0.0186)	(0.0176)	(0.0178)	(0.0201)
4.tier	0.177***	0.166***	0.165***	0.169***
	(0.0183)	(0.0176)	(0.0177)	(0.0200)
5.tier	0.191***	0.176***	0.175***	0.189***
	(0.0181)	(0.0174)	(0.0176)	(0.0199)
6.tier	0.210***	0.195***	0.194***	0.203***
	(0.0182)	(0.0175)	(0.0177)	(0.0200)
7.tier	0.220***	0.204***	0.203***	0.217***
	(0.0180)	(0.0173)	(0.0174)	(0.0196)
8.tier	0.239***	0.220***	0.220***	0.232***
	(0.0182)	(0.0175)	(0.0177)	(0.0200)
9.tier	0.261***	0.235***	0.234***	0.247***
	(0.0181)	(0.0175)	(0.0177)	(0.0198)
investor		0.0269***	0.0261***	0.0280***
		(0.00316)	(0.00308)	(0.00301)
logpop		0.00116	0.00107	0.00202
		(0.00109)	(0.00107)	(0.00107)
resuse		0.000558***	0.000641***	0.000419***
		(0.0000976)	(0.0000967)	(0.0000959)
warnings_percap		0.901**	0.337	-0.177
		(0.282)	(0.308)	(0.348)
penalties_percap		0.975*	0.873*	0.795*
		(0.382)	(0.371)	(0.361)
logpercapincome		0.0123	0.0140	-0.0381**
		(0.0114)	(0.0112)	(0.0116)
perc_somecoll		0.000956***	0.000936***	0.00122***
		(0.000214)	(0.000212)	(0.000208)
perc_rent		-0.000622***	-0.000601***	-0.00103***
		(0.000160)	(0.000158)	(0.000148)
perc_belowpoverty		-0.00101**	-0.00102**	-0.000689
		(0.000377)	(0.000370)	(0.000370)
logmedianhousevalue		-0.0130**	-0.0136**	0.0184***
		(0.00499)	(0.00488)	(0.00486)
_cons	0.0593***	0.0389	0.00842	0.145
	(0.0179)	(0.0932)	(0.0920)	(0.0956)
Month FE	No	No	Yes	Yes
Source FE	No	No	No	Yes
N	3654	3645	3645	3645

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

T-Test (H_0)	p-value
$\beta_{tier1} = \beta_{tier2}$	0.0000
$\beta_{tier2} = \beta_{tier3}$	0.1295
$\beta_{tier3} = \beta_{tier4}$	0.1651
$\beta_{tier4} = \beta_{tier5}$	0.0026
$\beta_{tier5} = \beta_{tier6}$	0.0001
$\beta_{tier6} = \beta_{tier7}$	0.0149
$\beta_{tier7} = \beta_{tier8}$	0.0000
$\beta_{tier8} = \beta_{tier9}$	0.0000

Notes: The dependent variable in the regression models is cumulative percent savings during the mandate period relative to the same months in 2013, and the base category is Tier 1 in all models. Standard errors are clustered at the supplier.

2014 residential consumption, and the treatments are different conservation targets. I utilize a standard RD specification to test the magnitude of reductions around each cutoff or conservation tier j with

$$saved_{it} = \alpha + \beta RGPCD_{i,2014} + \gamma_j D_i + \epsilon_{it}, \tag{4}$$

where $saved_{it}$ is the cumulative percent savings of supplier i up to month t relative to the same months in 2013, $RGPCD_{i,2014}$ is the forcing variable of summer 2014 consumption, and $D_i = 1(c_{j+1} > RGPCD_{i,2014} > c_j)$ is the treatment variable. c_j is the threshold based on each conservation tier j from Table 1, with $j \in \{1, 2, 3, 4, 5, 6, 7, 8\}$, and note that D_i varies for each supplier i depending on the cutoffs. γ_j is the parameter of interest, which captures the aforementioned cuttoff-specific treatment effect. While RDDs are a cross sectional design, there are several important legislative dates, and so equation (4) is estimated for June 2015, February 2016, and November 2016. It is also common in multiple cutoff RD designs to normalize the running variable and pool the data to obtain more observations, and so I determine the pooled RD treatment effect and vary the bandwidth around this normalization.

5.2 Testing for Hysteresis

Hysteresis is an effect that persists after the cause that brought it about has been removed. For this part of the analysis, I check to see if and to what extent water use changed after the drought ended and the emergency declaration was removed. Using two measures of water use, average total monthly potable water production and average R-GPCD, I examine the nine-month compliance period from June 2015 to February 2016 and the period immediately after it. For each of these use measures and time periods, I use t-tests to compare changes by compliance status one and two years later.

6 Results

6.1 Determining the Effectiveness of the Mandate

The results of estimating equation (4) in February 2016 are in Table 5, where each column represents a tier-specific treatment effect; the relevant linear and polynomial RD plots are in Figures C.8.[16] While the estimates are not a precise zero, they are insignificant and thus imply that the mandate did not induce the intended differential savings at each tier, a finding that is also supported in Figure 4. If it had, these estimates should have been positive and four percent; they also rule out any large significant changes in water savings. Moreover, a peculiar yet interesting conclusion from the linear plots is that suppliers in lower targets that were

[16] The bandwidth selection procedure is from Calonico, Cattaneo, and Titiunik (2014), who utilize both direct plug-in rules based on mean squared error expansions and cross validation; these bandwidths range from approximately 2 to 7 gallons on each side of the cutoff, except for the largest two tier groupings (7 to 8 and 8 to 9), which are 9.5 and 19.6, respectively. The estimation is conducted using a local-linear estimator with a local-quadratic bias-correction estimate, with a triangular kernel. The standard error estimators are the ones proposed by Calonico, Cattaneo, and Titiunik (2014) computed using three nearest-neighbors. Note that the multi-cutoff RD provides a local estimate at each tier and is non-parametric, while the dose response model from Section 4.1.3 imposes more structure, i.e., linearity.

slightly above their cutoff saved less, while those slightly above their cutoff in higher tiers saved slightly more.

Table 5: Sharp RD estimates for February 2016 using local linear regression

From Tier	(2 to 3) Savings	(3 to 4) Savings	(4 to 5) Savings	(5 to 6) Savings	(6 to 7) Savings	(7 to 8) Savings	(8 to 9) Savings
RD_Estimate	-0.0243	-0.0631	0.184	-0.0500	-0.0954	0.0222	0.0290
	(0.0654)	(0.0845)	(0.0972)	(0.0750)	(0.0538)	(0.0386)	(0.0693)
Observations	49	64	103	106	126	142	124

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The dependent variables are cumulative percentage savings from June 2015 to February 2016 relative to 2013.

I re-estimate equation (4) for the onset of the mandate and at completion of its extension. These results can be found in Tables B.9 and B.10, with respective RD plots in Figures C.10 and C.11, and they are similarly statistically insignificant. This consistent lack of statistical significance may be driven by rational supplier behavior or foresight, especially given the lack of regulatory "teeth" or financial penalty for non-compliance.

It may also be due to the fact that the measure of cumulative savings prevents a "sharp" response from being detected, or due to power, as there are generally few suppliers (observations) close to a given tier cutoff. To address the latter, it is common in multiple cutoff RD designs to normalize the running variable and pool the data to obtain more observations. I determine the pooled RD treatment effect and vary the bandwidths around this normalization. The results of this exercise are in Table 6 and Figure C.9, and regardless of bandwidth, they indicate that those slightly above their cutoffs saved marginally less than if the were slightly below it.

Table 6: Pooled RD estimates for February 2016 using local linear regression

Sample Restriction	(3 R-GPCD) Savings	(5 R-GPCD) Savings	(7 R-GPCD) Savings	(9 R-GPCD) Savings
RD_Estimate	-0.0596	-0.0402	-0.0350	-0.0293
	(0.0743)	(0.0533)	(0.0442)	(0.0387)
Observations	94	160	211	238

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The dependent variables are cumulative percentage savings from June 2015 to February 2016 relative to 2013. Data was restricted to a given bandwidth, then the Calonico, Cattaneo, and Titiunik (2014) procedure was used.

6.2 Testing for Hysteresis

Table B.11 presents the results from two-tailed t-tests by compliance status in February 2016 for both average monthly production and average monthly R-GPCD. They show that regardless of the time period considered (the actual compliance period or the period immediately after it), the mean difference in water use during and one or two years after the drought ended was statistically different from zero. The differences were in fact always statistically greater than zero, meaning that water use increased for all compliance groups and that there is no evidence of hysteresis. These results suggest that the savings achieved during the drought were done more with variable adjustments in individual demand and less with fixed cost investments at the household level.

7 Discussion

I find that while the state achieved significant savings, only half of all suppliers became compliant by the proposed end of the mandate. I also find that the mandate did not induce the intended differential savings at each tier. There was significant variation in savings within a given tier, but the distributions of savings across tiers were similar. Put another way, there was significant over-compliance at lower tiers and under-compliance at higher tiers. Lastly, urban water use significantly increased when the regulation was removed, implying that variable adjustments in individual demand contributed more to water use savings than fixed cost household investments.

The tiered design of the mandate did not cause increased conservation, and it is likely that either suppliers used similar non-marginal conservation strategies that provided a certain baseline amount of savings or there was considerable uncertainty in the impact of local conservation policies. Note that compliance may have become costly at higher tiers due to possible technological or financial constraints with marginal conservation strategies. This leads to concerns over both efficiency and equity, as the intended margin for grouping did not induce the desired savings. Moreover, suppliers were subject to a civil liability of up to $10,000 a day for non-compliance, but no supplier was outwardly punished; without a transparent and easily enforceable mechanism for ensuring compliance, it may not be surprising that the policy was ineffective at inducing the intended differential savings.

While there was no explicit punishment for non-compliance, this drought was managed by California's State Water Resources Control Board. They have the ability to revoke water rights and have a fining infrastructure in place for maintaining water quality standards; the fear of losing one's water rights should alone induce meaningful conservation efforts. This is in contrast to the Department of Water Resources, which does not have the ability to fine or revoke water rights, but has managed previous droughts. Thus, the significant savings can fit into the framework of voluntary contributions or compliance, with additional drivers being fear of future legislation and public outrage from perceived inaction.

7.1 Municipal- versus Investor-Owned Utilities

A dimension that should be considered is utility ownership. Almost 85% of California's water utilities are municipal-owned (MOUs). MOUs are thus considered to be self-regulated entities, but they must adhere to the political will of their constituents and cannot be profit centers. The remaining utilities are investor-owned (IOUs) and are regulated by the California Public Utilities Commission (CPUC). The CPUC has many roles, one of which is that they ensure IOU rate setting abides by the cost of service principle. This principle limits utilities to only recover their actual cost of providing service, plus a legally sanctioned rate of return on capital investment. The CPUC must then guard against the subsequent incentive to over-invest.

Two major distinctions between these forms of ownership are their financial structure and their incentives to conserve. These differences are driven by decoupling, which refers to the separation of a firm's revenues from the amount of its product consumed. IOUs are decoupled, while MOUs are not, and this has allowed IOUs to adopt potentially unpopular conservation strategies because they are shielded from political backlash and the financial risk from lower household consumption (Teodoro et al., 2018). In California, there are automatic rate increases that guarantee sufficient revenue for IOUs if conservation causes profit shortfalls; this is known as the Water Revenue Adjustment Mechanism (WRAM). For example, implementing outdoor water restrictions would decrease household consumption and thus would hurt MOU revenues. However, for IOUs, the WRAM would be triggered under such a scenario, which potentially could counteract (some of) the losses in revenue.

Teodoro et al. (2018) suggests that the political and financial shielding of IOUs allows them to adopt more aggressive conservation strategies, be able to induce more savings, and thus be more likely to comply with a conservation mandate. I test these three hypotheses in Tables B.12 and B.13. Table B.12 shows that during the mandate, IOUs had a greater percentage of days when outdoor irrigation was prohibited, or that they equivalently allowed less watering days per week. Table B.13 shows that IOUs saved on average about 3% more water than MOUs and subsequently were approximately 18% more compliant.

8 Conclusion

Water restrictions have become one of the most common user-targeted conservation strategies in regions facing drought, but there has been little systematic study of effectiveness of supplier-targeted conservation targets up until this point. These programs may be used more frequently in the near future due to growing concerns over water security. Therefore, I use the 2015 statewide mandate in California to examine how and to what extent did suppliers comply over time, what were the tier-specific impacts on production and conservation activities, and whether there was evidence of hysteresis.

I find that while the state obtained significant water savings, only half of individual water suppliers became compliant by the proposed end of the mandate. Moreover, the mandate did not induce the intended differential savings around each tier. Urban water use also increased when the regulation was removed, implying that variable adjustments in individual demand contributed more to water use savings than fixed cost household investments. Put another way, the mandate did not lead to more persistent changes in water consumption

This paper provides insight into how suppliers comply with prescriptive policies over time. They were able to induce short term reductions in use (conservation) rather than longer term changes (efficiency gains). Additionally, because of how the policy was structured, if a supplier increased investment in non-rationed years, they would have increased their marginal cost of compliance in rationed years. This incentivizes waste and other perverse actions when there are no regulations in place. Even if this type of policy design is not a concern, the significant distribution of savings within a given tier suggest that suppliers were grouped on the incorrect margin (historic per capita use).

Climate change is expected to fundamentally change water supplies in semi-arid regions, but there are ways to adapt. Some strategies include increasing the storage of water in aquifers, increasing investment in new water supplies, and generating improvements in water efficiency. While alternative water supplies may provide relief during droughts, improvements in the allocation mechanism of water supplies could offset some of the losses from reduced water supplies, or even raise total economic surplus (Bruno and Jessoe, 2018); this can include a market-based alternative, such as water conservation credits or trading, or the improvement of the targeting of prescriptive policies.

Put another way, urban water supply sector is capital intensive and therefore many of the costs are fixed. Therefore, there is a need for regulatory instruments targeted at securing water efficiencies and encouraging behavioral change. Temporary and permanent water restrictions are common tools, but the former is used as a temporary emergency response to critically low water supplies, while the latter can be used to reduce the need to augment water supply. Determining the optimal policy, or regulatory instrument, mix is an important area for future research.

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Conflict of Interest

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A Additional Savings Analysis

The focus thus far has been the impact of the mandate on water savings, and this section performs three additional saving analyses, specifically on energy savings, supply-side cost savings, and voluntary savings.

Energy and Emissions Savings

California saved 385,360 MG during the mandate period relative to 2013, as seen in Table A.1. Using UC Davis's Center for Watershed Sciences H2Open Portal, this translates into 1,349,698 MWh in total electricity savings and a greenhouse gas (GHG) emissions reduction of 384,664 metric tonnes of carbon dioxide equivalent. For comparison, the total electricity savings linked to water conservation are approximately 10% greater than those achieved by investor-owned electricity utilities' efficiency programs for roughly the same time period. These GHG savings from water conservation represent the equivalent of taking approximately 81,843 cars off the road for a year.

Table A.1: Total Monthly Production and Cumulative Savings over Mandate Period

Date	Monthly Production (MG)	2013 Monthly Production (MG)	Cumulative Savings
2015m6	159300	219800	27.51
2015m7	164100	238700	31.25
2015m8	171500	234800	26.97
2015m9	157100	212800	26.18
2015m10	146400	188200	22.19
2015m11	121800	152600	20.19
2015m12	110400	135000	18.24
2016m1	99240	119800	17.17
2016m2	100400	113900	11.91
Total	1230240	1615600	23.85

The Supply-Side Cost of Savings

Due to the increased probability of extreme weather events in the near future, it is expected that traditional sources of water will remain constrained in the future. Therefore, additional water supplies may need to come from non-traditional sources such as recycling and desalination. A recent California Public Utilities Commision (2016) report analyzed the costs of approximately twenty different sources of water and their results are in Table A.2.

Table A.2: Costs of Water Sources Per Acre-Foot (AF)

	Traditional	Recycling	Desalination
Lowest Cost	$25/AF	$396/AF	$2367/AF
Average Cost	$793/AF	$1335/AF	$3389/AF
Highest Cost	$1456/AF	$5800/AF	$5100/AF

Notes: An acre-foot of water is equivalent to 325,851 gallons.
Source: California Public Utilities Commision (2016)

While I do not perform welfare analysis in this paper, I use the "Average Cost" row to determine the supply-side cost savings made using total monthly potable water production data. The aforementioned 385,360 MG saved by February 2016 is equivalent to 1,182,626 AF. If all this water savings came from an average traditional source, this is equivalent to $938 million dollars. For recycling and desalination, this translates to $1.6 billion and $4 billion, respectively.

The "Jerry Brown" Effect

There are other reasons why the mandate may not have been effective at inducing differential savings at each assigned tier, which may include the fact that suppliers were afraid of future regulation or losing their water rights, there was uncertainty about how their policy decisions would affect household savings, they threw their available "kitchen sink" of policies to try to comply with the mandate, or statewide initiatives played a role. One particular statewide initiative or announcement stands out: Governor Jerry Brown declared a statewide drought emergency in January 2014 and called on all Californians to (voluntarily) save 20%. While they fell short of this target, there was a significant positive yet regionally varied response, as seen in Figure A.1, or in the regression results of Table A.3.

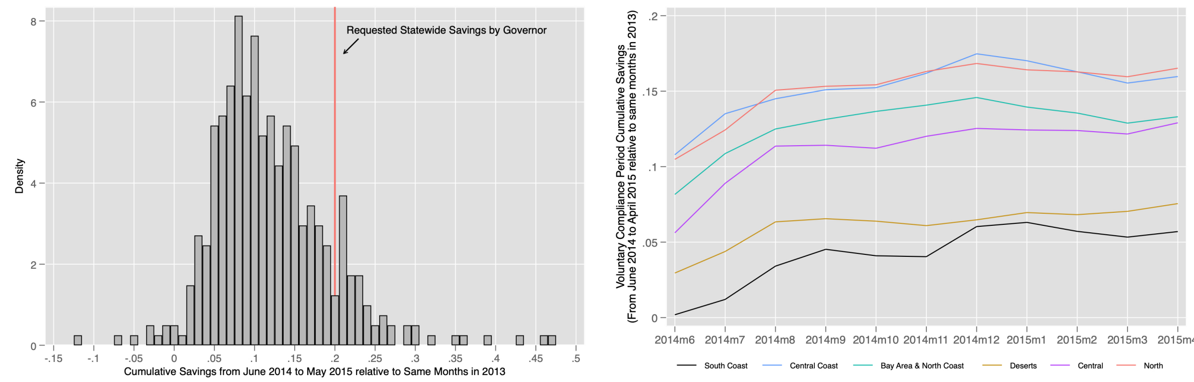

Figure A.1: Cumulative Savings during the Voluntary Compliance Period

Note: Cumulative savings was calculated beginning in June 2014 and relative to the same months in 2013. Note that data from January 2014 to May 2014 was not systematically collected.

To further investigate this, Figures A.2 and A.3 show trends in cumulative and monthly production savings, respectively. Interestingly, Figure A.2 shows that suppliers assigned to lower tiers saved a significant amount before the mandate but were the lowest savers thereafter. Moreover, once the mandate was enacted, cumulative savings decreased for all tiers, when its intentions were to induce more savings.

Table A.3: Regional Differences in Cumulative Savings during Voluntary Compliance Period

	(1)	(2)	(3)	(4)
	csavings	csavings	csavings	csavings
Central Coast	0.110***	0.111***	0.111***	0.112***
	(0.00571)	(0.00528)	(0.00519)	(0.00663)
Bay Area & North Coast	0.0859***	0.0837***	0.0832***	0.0932***
	(0.00361)	(0.00385)	(0.00377)	(0.00613)
Deserts	0.0194***	0.0290***	0.0287***	0.0305***
	(0.00423)	(0.00544)	(0.00537)	(0.00564)
Central	0.0698***	0.0811***	0.0809***	0.0856***
	(0.00296)	(0.00428)	(0.00415)	(0.00509)
North	0.110***	0.113***	0.113***	0.128***
	(0.00377)	(0.00438)	(0.00427)	(0.00593)
investor-owned		-0.00272	-0.00248	-0.00167
		(0.00239)	(0.00228)	(0.00241)
logpopulation		0.000632	0.000683	-0.000229
		(0.000957)	(0.000935)	(0.000940)
residentialuse		0.000468***	0.000435***	0.000368***
		(0.0000736)	(0.0000727)	(0.0000720)
logppincome		-0.00886	-0.00848	-0.0175
		(0.0126)	(0.0122)	(0.0123)
perc_somecoll		0.000135	0.000136	0.000273
		(0.000229)	(0.000223)	(0.000221)
perc_rent		-0.000758***	-0.000771***	-0.000783***
		(0.000125)	(0.000122)	(0.000121)
perc_belowpoverty		0.000134	0.000145	0.0000873
		(0.000352)	(0.000342)	(0.000347)
logmedianhousevalue		0.0165**	0.0164**	0.0185***
		(0.00522)	(0.00508)	(0.00506)
_cons	0.0424***	-0.1000	-0.0853	-0.0223
	(0.00115)	(0.0983)	(0.0959)	(0.100)
Month FE	No	No	Yes	Yes
Source FE	No	No	No	Yes
N	4427	4416	4416	4416

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The ommitted group is South Coast.

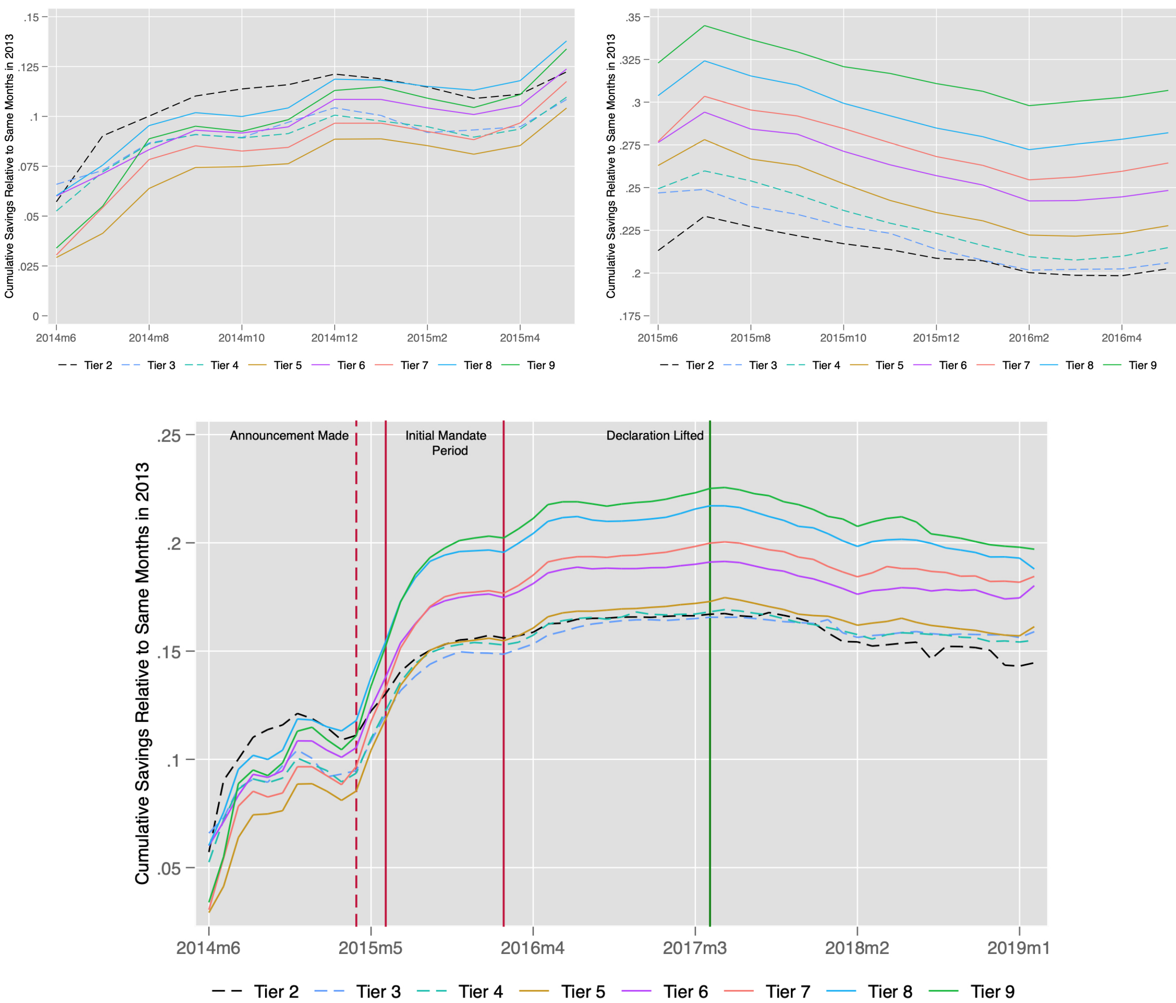

Figure A.2: Trends in Cumulative Production Savings

Notes: The left figure captures cumulative savings starting in June 2014 relative to the same months in 2013. The right figure captures cumulative savings starting in June 2015 relative to the same months in 2013. The bottom figure captures cumulative savings from June 2014 to Feburary 2019, where the vertical orange lines are for the original mandate and the dotted brown line is when the conservation standards were severely weakened.

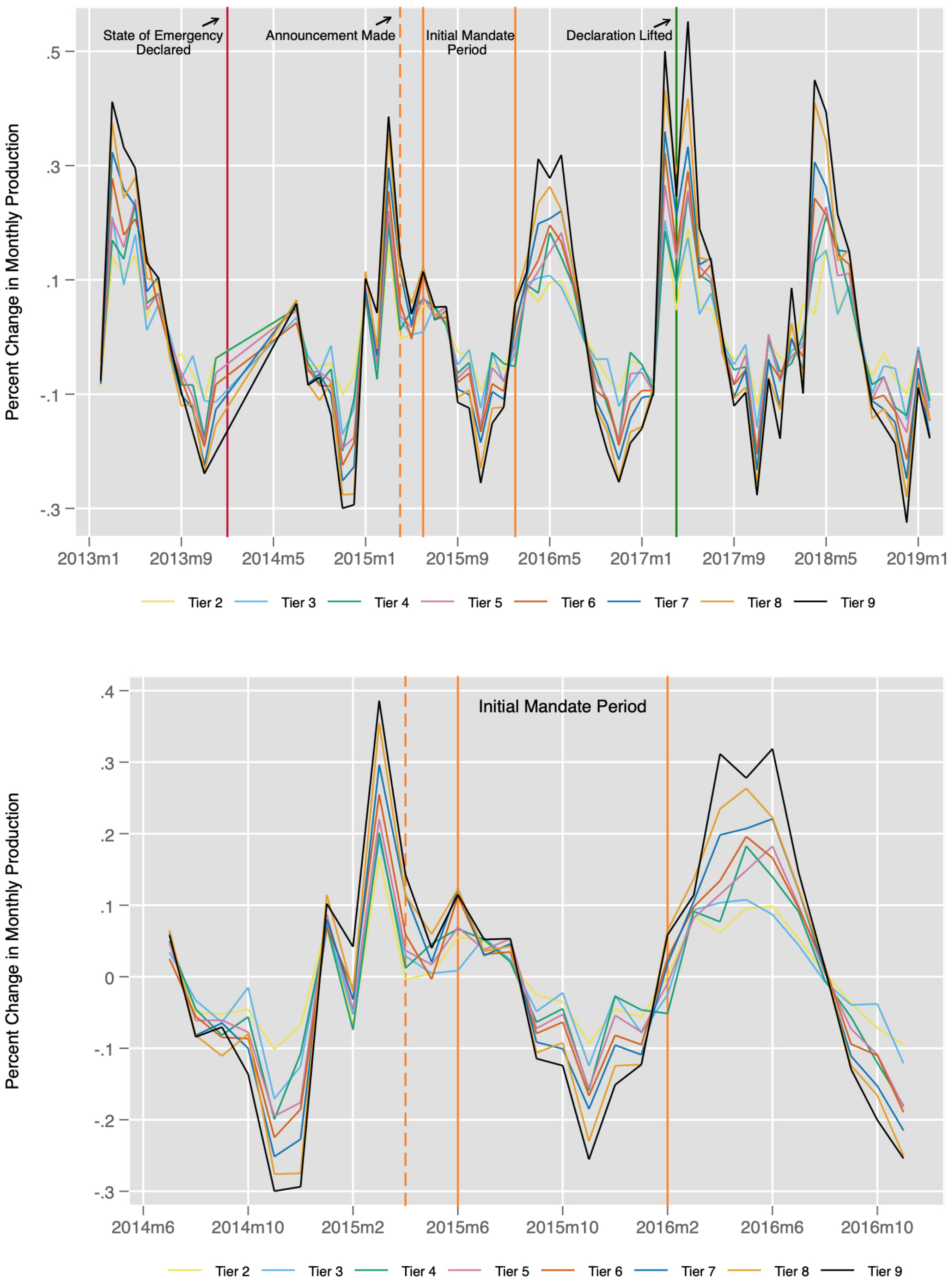

Figure A.3: Percentage Changes in Monthly Production over Time

Notes: The top figure shows monthly percentage changes over the available data, but note that data before June 2014 are SWRCB estimates. The bottom figure captures monthly changes in production from the voluntary conservation period through the self-certifcation period.

B Additional Tables

Table B.1: Summary Statistics by year until December 2018

	2014	2015	2016	2017	2018
Total Monthly Potable Water Production	444.96	347.98	346.85	368.96	387.49
in Million Gallons	(960.96)	(802.58)	(802.25)	(849.32)	(882.41)
Total Monthly Residential Use	292.66	230.01	230.16	245.06	255.23
in Million Gallons	(630.75)	(529.88)	(531.48)	(563.10)	(559.95)
Residential Gallons per Capita Day	127.52	96.19	95.47	101.06	101.93
	(75.19)	(45.18)	(52.08)	(57.57)	(55.21)
Total Population Served	88200.48	88378.22	88725.48	89450.75	93222.05
	(233806.51)	(235045.36)	(237875.63)	(240570.45)	(249025.36)
Observations	2816	4879	4901	4860	4540

Notes: Standard deviations are in parentheses, and 2014 does not represent a full year (only from June).

Table B.2: Credit Given in March 2016 Based on Compliance Status through February 2016

Credit Given (Percent)	Became Compliant	Remained Compliant	Lost Compliance	Remained Non-Compliant	Total
0	9	86	6	19	120
0.01	0	7	3	5	15
0.02	0	26	15	30	71
0.03	4	27	20	27	78
0.04	1	12	13	28	54
0.05	0	1	1	5	7
0.06	0	1	2	3	6
0.07	0	10	4	6	20
0.08	2	12	6	12	32
0.12	0	0	0	1	1
0.18	0	0	0	1	1
0.22	0	0	0	1	1
Total	16	182	70	138	406

Table B.3: Adjustments to Conservation Standards: Tobit Results

	Credit Given in March 2016
Remained Compliant	0.00285
	(0.0101)
Lost Compliance	0.0271*
	(0.0107)
Remained Non-Compliant	0.0277**
	(0.0102)
_cons	0.00525
	(0.00978)
sigma	0.0352***
	(0.00157)
N	406

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: "Became Compliant" is the reference category for February 2016 compliance status.

Table B.4: Adjustments for Compliance: Cragg Results

First Stage (Probit)	Credit dummy
Remained Compliant	0.226
	(0.328)
Lost Compliance	1.525***
	(0.380)
Remained Non-Compliant	1.248***
	(0.342)
_cons	-0.157
	(0.315)
Second Stage (Truncated Normal)	**Credit in March**
Remained Compliant	-0.0123
	(0.0155)
Lost Compliance	-0.0137
	(0.0159)
Remained Non-Compliant	-0.00684
	(0.0154)
_cons	0.0384*
	(0.0150)
sigma _cons	0.0325***
	(0.00252)
N	406

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable in the first stage is a dummy for whether a positive adjustment to a conservation standard was made in March 2016 based on compliance status in February 2016. The dependent variable in the second is the amount of adjustment, conditional on receiving a positive adjustment. "Became Compliant" is the reference category in both.

Table B.5: Probability of Compliance in February 2016 (Marginal Effects)

	(LPM) febcompliant	(Probit) febcompliant	(Logit) febcompliant
logpopulation	-0.124***	-0.299***	-0.452***
	(0.0185)	(0.0412)	(0.0496)
perc_residentialuse	0.00288***	0.00558***	0.00675***
	(0.000538)	(0.000842)	(0.000956)
logjune2013production	0.103***	0.265***	0.405***
	(0.0194)	(0.0419)	(0.0494)
investor-owned	0.122***	0.159***	0.177***
	(0.0198)	(0.0278)	(0.0304)
logpercapincome	0.143***	0.0539	0.116
	(0.0433)	(0.0979)	(0.106)
perc_somecoll	0.0000976	0.00185	0.00132
	(0.000888)	(0.00180)	(0.00196)
perc_rent	0.00227**	0.00455***	0.00275*
	(0.000868)	(0.00126)	(0.00136)
perc_belowpoverty	-0.0119***	-0.0184***	-0.0172***
	(0.00178)	(0.00297)	(0.00322)
logmedianhousevalue	-0.0707*	-0.0665	-0.0806
	(0.0283)	(0.0417)	(0.0449)
target	-0.0366***	-0.0531***	-0.0658***
	(0.00129)	(0.00240)	(0.00315)
warnings_percap	3.183	4.251	4.974
	(1.897)	(2.688)	(2.812)
penalties_percap	5.003**	5.785*	6.254*
	(1.901)	(2.417)	(2.603)
N	3645	3645	3645

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The data used in these regressions is from June 2014 until February 2016. *febcompliant* is a dummy variable for compliance in February 2016. The linear probability model does not include a constant, and the Probit and Logit models present marginal effects evaluated at the means of covariates.

Table B.6: Probability of Compliance in February 2016

	(LPM) febcompliant	(Probit) febcompliant	(Logit) febcompliant
logpopulation	-0.123***	-0.750***	-1.807***
	(0.0188)	(0.103)	(0.198)
perc_residentialuse	0.00283***	0.0140***	0.0270***
	(0.000554)	(0.00211)	(0.00383)
logjune2013production	0.101***	0.665***	1.622***
	(0.0201)	(0.105)	(0.198)
investor-owned	0.123***	0.398***	0.707***
	(0.0199)	(0.0697)	(0.122)
logpercapincome	0.122	0.135	0.463
	(0.0664)	(0.245)	(0.425)
perc_somecoll	0.000456	0.00464	0.00529
	(0.00124)	(0.00451)	(0.00785)
perc_rent	0.00231**	0.0114***	0.0110*
	(0.000874)	(0.00316)	(0.00543)
perc_belowpoverty	-0.0124***	-0.0461***	-0.0686***
	(0.00206)	(0.00745)	(0.0129)
logmedianhousevalue	-0.0700*	-0.167	-0.323
	(0.0284)	(0.105)	(0.180)
target (%)	-0.0365***	-0.133***	-0.263***
	(0.00131)	(0.00600)	(0.0126)
warnings_pc	3.184	10.66	19.90
	(1.897)	(6.737)	(11.25)
penalties_pc	5.056**	14.50*	25.02*
	(1.906)	(6.058)	(10.41)
_cons	0.217	-2.042	-8.176*
	(0.522)	(1.920)	(3.390)
N	3645	3645	3645

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The data used in these regressions is from June 2014 until February 2016. *febcompliant* is a dummy variable for compliance in February 2016. Probit and Logit models present full effects.

Table B.7: Probability of Compliance in Every Month through May 2016 (Marginal Effects)

	(LPM) compliant	(Probit) compliant	(Logit) compliant
logpopulation	-0.0683***	-0.0730***	-0.134***
	(0.0160)	(0.0190)	(0.0315)
perc_residentialuse	0.00402***	0.00518***	0.00581***
	(0.000466)	(0.000588)	(0.000655)
logjune2013production	0.0912***	0.105***	0.161***
	(0.0167)	(0.0204)	(0.0316)
investor-owned	0.155***	0.199***	0.210***
	(0.0174)	(0.0233)	(0.0243)
logpercapincome	0.0480	0.131	0.142
	(0.0379)	(0.0744)	(0.0778)
perc_somecoll	0.00176*	0.00134	0.00149
	(0.000775)	(0.00138)	(0.00142)
perc_rent	0.000956	0.00108	0.00106
	(0.000760)	(0.000950)	(0.000995)
perc_belowpoverty	-0.00984***	-0.0104***	-0.00990***
	(0.00156)	(0.00221)	(0.00230)
logmedianhousevalue	-0.0370	-0.0693*	-0.0770*
	(0.0246)	(0.0306)	(0.0323)
target (%)	-0.0311***	-0.0389***	-0.0431***
	(0.00110)	(0.00149)	(0.00192)
warnings_pc	1.905	2.869	3.068
	(1.808)	(2.229)	(2.218)
penalties_pc	-1.766	-1.781	-1.843
	(1.499)	(1.677)	(1.697)
N	4860	4860	4860

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The data used in these regressions is from June 2014 until November 2016. *compliant* is a dummy variable for compliance in every month. The LPM does not include a constant, and the Probit and Logit models present marginal effects evaluated at the means of the independent variables.

Table B.8: Results for Probability of Compliance in Every Month through May 2016

	(LPM) compliant	(Probit) compliant	(Logit) compliant
logpopulation	-0.0693***	-0.203***	-0.622***
	(0.0163)	(0.0527)	(0.147)
perc_residentialuse	0.00406***	0.0144***	0.0270***
	(0.000479)	(0.00163)	(0.00306)
logjune2013production	0.0927***	0.290***	0.748***
	(0.0173)	(0.0566)	(0.148)
investor-owned	0.155***	0.553***	0.975***
	(0.0174)	(0.0649)	(0.113)
logpercapincome	0.0621	0.364	0.660
	(0.0582)	(0.207)	(0.362)
perc_somecoll	0.00152	0.00373	0.00691
	(0.00108)	(0.00383)	(0.00658)
perc_rent	0.000927	0.00301	0.00491
	(0.000765)	(0.00264)	(0.00462)
perc_belowpoverty	-0.00954***	-0.0288***	-0.0460***
	(0.00181)	(0.00614)	(0.0106)
logmedianhousevalue	-0.0375	-0.192*	-0.358*
	(0.0247)	(0.0852)	(0.150)
target (%)	-0.0312***	-0.108***	-0.200***
	(0.00112)	(0.00423)	(0.00946)
warnings_percap	1.905	7.968	14.26
	(1.808)	(6.191)	(10.31)
penalties_percap	-1.795	-4.947	-8.565
	(1.502)	(4.659)	(7.886)
_cons	-0.146	-2.746	-6.535*
	(0.458)	(1.597)	(2.839)
N	4860	4860	4860

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The data used in these regressions is from June 2014 until November 2016. *compliant* is a dummy variable for compliance in every month. Probit and Logit models present full effects.

Table B.9: Sharp RD estimates using local polynomial regression for June 2015

From Tier	(2 to 3) Savings	(3 to 4) Savings	(4 to 5) Savings	(5 to 6) Savings	(6 to 7) Savings	(7 to 8) Savings	(8 to 9) Savings
RD_Estimate	-0.0283	-0.0321	0.108	-0.120	-0.111*	0.0614	-0.0450
	(0.0712)	(0.130)	(0.116)	(0.0752)	(0.0462)	(0.0426)	(0.0669)
Observations	49	64	103	106	126	142	124

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.10: Sharp RD estimates using local polynomial regression for November 2016

From Tier	(2 to 3) Savings	(3 to 4) Savings	(4 to 5) Savings	(5 to 6) Savings	(6 to 7) Savings	(7 to 8) Savings	(8 to 9) Savings
RD_Estimate	-0.0162	-0.0821	0.255	-0.0141	-0.0797	-0.00654	-0.000125
	(0.0708)	(0.117)	(0.147)	(0.0487)	(0.0529)	(0.0412)	(0.0639)
Observations	49	63	102	106	126	142	124

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.11: Results for Two-Tailed T-Tests, H_a: mean(diff) $\neq 0$ (Hysteresis)

Monthly Production in Gallons (Average Over Given Time Period)

	obs	(03/18-01/19)	(03/16-01/17)	diff	st. error	t-value	p-value
became compliant	15	1.38E+08	1.25E+08	1.35E+07	3012581	4.45	0.0005
lost compliance	67	3.97E+08	3.71E+08	2.61E+07	4120461	6.35	0
remained compliant	175	3.52E+08	3.28E+08	2.42E+07	3389961	7.15	0
remained non-compliant	130	4.70E+08	4.38E+08	3.24E+07	5298436	6.1	0
	obs	(06/17-02/18)	(05/15-02/16)	diff	st. error	t-value	p-value
became compliant	15	1.41E+08	1.17E+08	2.37E+07	5595428	4.25	0.001
lost compliance	70	4.16E+08	3.47E+08	6.89E+07	1.07E+07	6.45	0
remained compliant	182	3.57E+08	3.04E+08	5.31E+07	6682600	7.95	0
remained non-compliant	138	4.66E+08	4.01E+08	6.44E+07	1.13E+07	5.7	0

Monthly R-GPCD (Average Over Given Time Period)

	obs	(03/18-01/19)	(03/16-01/17)	diff	st. error	t-value	p-value
became compliant	15	86.506	78.711	7.795226	2.2845	3.4	0.004
lost compliance	67	117.1205	108.956	8.164579	1.7285	4.7	0
remained compliant	175	85.5325	80.2915	5.240766	0.6485	8.1	0
remained non-compliant	130	124.3495	117.2015	7.148371	1.261	5.65	0
	obs	(06/17-02/18)	(05/15-02/16)	diff	st. error	t-value	p-value
became compliant	15	85.3715	73.6695	11.70222	3.8455	3.05	0.009
lost compliance	70	122.9515	102.572	20.3795	2.818	7.25	0
remained compliant	182	90.2565	76.09	14.16682	0.933	15.2	0
remained non-compliant	138	130.6555	112.6915	17.96363	1.5635	11.5	0

Table B.12: The Impact of Investor Ownership on Stringency of Irrigation Restrictions

	(1) irrigationrestrictions	(2) irrigationrestrictions	(3) weeklywaterdays	(4) weeklywaterdays
investor	2.410^{**}	2.160^{*}	-0.169^{**}	-0.151^{*}
	(0.822)	(0.849)	(0.0575)	(0.0594)
state_mandate		0.421		-0.0295
		(3.600)		(0.252)
resuse		0.00658		-0.000461
		(0.0204)		(0.00143)
groundwatervolp		0.573		-0.0401
		(1.261)		(0.0883)
purchasedvolp		-1.140		0.0798
		(1.329)		(0.0930)
logpop		-0.317		0.0222
		(0.300)		(0.0210)
perc_somecoll		-0.162^{***}		0.0114^{***}
		(0.0359)		(0.00251)
perc_poor		-0.134		0.00937
		(0.121)		(0.00844)
perc_black		0.0541		-0.00379
		(0.0615)		(0.00430)
meanmedincome		0.000145^{***}		-0.0000102^{***}
		(0.0000205)		(0.00000144)
_cons	64.48^{***}	69.80^{***}	2.487^{***}	2.114^{***}
	(0.313)	(5.055)	(0.0219)	(0.354)
N	3600	3483	3600	3483

Standard errors in parentheses; Month FEs included in models 2 and 4.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.13: The Impact of Investor Ownership on Savings and Compliance during Mandate

	(1) savings	(2) savings	(3) compliant	(4) compliant
investor	0.0149^{***}	0.0320^{***}	0.191^{***}	0.180^{***}
	(0.00370)	(0.00320)	(0.0228)	(0.0203)
state_mandate		0.385^{***}		-2.714^{***}
		(0.0134)		(0.0854)
resuse		0.000601^{***}		0.00283^{***}
		(0.0000767)		(0.000488)
groundwatervolp		-0.0149^{**}		-0.0756^{*}
		(0.00470)		(0.0299)
purchasedvolp		-0.0122^{*}		-0.0345
		(0.00492)		(0.0313)
logpop		-0.00264^{*}		-0.000406
		(0.00112)		(0.00710)
perc_somecoll		0.0000986		-0.000688
		(0.000135)		(0.000856)
perc_poor		-0.00420^{***}		-0.0248^{***}
		(0.000453)		(0.00288)
perc_black		-0.00108^{***}		-0.00275
		(0.000231)		(0.00147)
meanmedincome		0.000000104		-0.000000435
		(7.70e-08)		(0.000000489)
_cons	0.269^{***}	0.176^{***}	0.585^{***}	1.318^{***}
	(0.00140)	(0.0189)	(0.00865)	(0.120)
N	3636	3519	3636	3519

Standard errors in parentheses; Month FEs are included in Models 2 and 4.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.1 Balance Tables

Table B.14: Balance Table for June 2015

	(Compliant)		(Non-Compliant)		(Difference)	
	mean	sd	mean	sd	diff	t-stat
Conservation Standard	0.22	0.08	0.29	0.07	0.07***	(8.74)
Cumulative Savings	0.31	0.08	0.22	0.09	-0.09***	(-10.54)
Missed Conservation Standard By %	-0.09	0.07	0.07	0.06	0.16***	(25.10)
Tier	5.48	2.06	7.19	1.80	1.70***	(8.74)
Residential Gallons per Capita Day	98.83	46.53	159.18	321.14	60.35*	(2.32)
% Residential Use	69.49	13.43	66.88	17.70	-2.60	(-1.57)
Total Population Served	90388.58	157180.88	85442.93	326127.82	-4945.65	(-0.18)
Monthly fine (pp) if non-compliant	10.60	13.33	31.79	218.44	21.19	(1.20)
Water Days Allowed/Week	2.48	1.05	2.83	1.35	0.35**	(2.76)
Observations	252		154		406	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.15: Balance Table for February 2016

	(Compliant)		(Non-Compliant)		(Difference)	
	mean	sd	mean	sd	diff	t-stat
Conservation Standard	0.20	0.08	0.29	0.06	0.09***	(12.45)
Cumulative Savings	0.26	0.08	0.23	0.06	-0.04***	(-5.38)
Missed Conservation Standard By %	-0.07	0.06	0.06	0.05	0.13***	(24.45)
Tier	4.97	2.05	7.23	1.56	2.26***	(12.45)
Residential Gallons per Capita Day	86.77	378.36	81.34	27.07	-5.43	(-0.20)
% Residential Use	70.46	13.85	70.92	16.06	0.46	(0.31)
Total Population Served	89241.67	169849.90	88575.71	287087.73	-665.96	(-0.03)
Monthly fine (pp) if non-compliant	23.31	177.43	12.73	46.17	-10.57	(-0.81)
Water Days Allowed/Week	2.40	1.31	2.28	1.32	-0.13	(-0.97)
Observations	198		208		406	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.16: Balance Table for November 2016

	(Compliant)		(Non-Compliant)		(Difference)	
	mean	sd	mean	sd	diff	t-stat
State-mandated Conservation Standard	0.02	0.05	0.25	0.06	0.23***	(13.29)
Cumulative Savings	0.23	0.07	0.18	0.09	-0.06	(-2.18)
Missed Conservation Standard By %	-0.22	0.07	0.07	0.06	0.29***	(15.07)
Tier	6.10	2.14	7.25	1.60	1.15*	(2.42)
Residential Gallons per Capita Day	94.08	220.90	90.82	26.07	-3.27	(-0.24)
% Residential Use	70.84	14.76	68.36	22.76	-2.47	(-0.37)
Total Population Served	91272.02	244028.77	25648.00	13701.34	-65624.02***	(-5.08)
Monthly fine (pp) if non-compliant	18.87	137.32	15.48	8.43	-3.39	(-0.46)
Water Days Allowed/Week	3.86	2.26	3.08	1.88	-0.78	(-1.40)
Observations	393		12		405	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Additional Figures

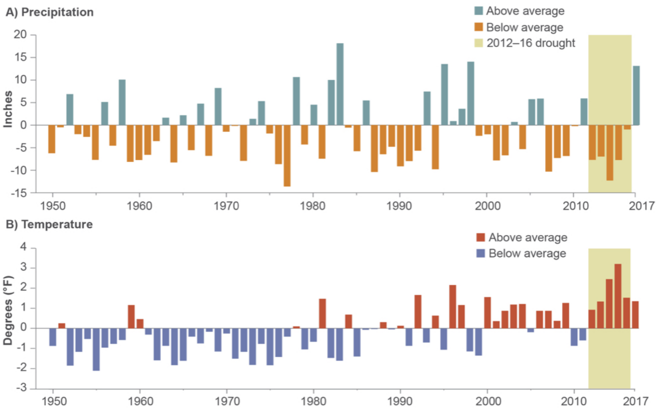

Figure C.1: Precipitation and Temperature Trends in California

Notes: Bars in panel A show the number of inches above and below the 1981-2000 annual average of 25.8 inches for the entire state. Bars in panel B show degrees above or below the average statewide temperature for 1981-2000 (57.8° F). Both series are measured in water years (October-September). *Source*: Mount et al. (2018) & Western Regional Climate Center

2014

January

- Governor declares State of Emergency due to drought.
- State Water Resources Control Board (SWRCB) temporarily modifies flow and water quality requirements for state and federal water project operations in the Delta.

April

- Governor issues Executive Order to extend State of Emergency, expedite drought response activities and implement water conservation requirements.
- SWRCB and the Governor's Office of Emergency Services begins allocation of more than $32 million for drought-related emergency projects including drinking water.

May

- Through 2016, SWRCB adopts and renews emergency regulations to help protect threatened and endangered fish species in high priority watersheds.

June

- SWRCB adopts general order expanding authorized uses of recycled water.

July

- SWRCB institutes new temporary restrictions on outdoor water use and new water use reporting requirements for urban water suppliers.

September

- Legislature passes package of bills implementing the Sustainable Groundwater Management Act.
- Governor issues Executive Order to address drinking water shortages.

November

- California voters pass $7.5 billion water bond, the Water Quality, Supply, and Infrastructure Improvement Act of 2014 (Proposition 1).

PROP 1
GOVERNOR EDMUND G. BROWN, JR.
WATER BOND 2014
RELIABILITY | RESTORATION | RESILIENCE

Governor Brown has signed...

7 Gubernatorial Actions

— and —

24 drought bills

These actions address immediate health, safety and ecosystem needs while also accelerating improvements to water infrastructure and habitat that will have a permanent effect on our ability to withstand drought.

2015

April

- DWR conducts annual snow survey, confirms statewide snowpack contains less water content than any comparable survey measurement since 1950.
- Governor issues Executive Order imposing 25 percent statewide urban water reduction and initiating state-funded turf removal and water-efficient appliance programs.

May

- DWR installs temporary rock barrier at West False River to keep tidal salt water from flowing too far into the Delta.

July

- New Water Efficient Landscape Ordinance permanently increases water efficiency standards for new and retrofitted landscapes.

October

- Governor declares State of Emergency for epidemic of drought-related tree die-off.

2016

January

- SWRCB adopts emergency regulations for measuring and reporting water diversions.

Februray

- SWRCB expands low financing program for recycled water projects.

April

- Since 2013, Californians save 1.19 million acre-feet of water, enough to supply nearly 6 million people for a year.

May

- Statewide average water conservation rate grows to 28 percent.

June

- DWR and SWRCB connect East Porterville to the City of Porterville's water system, bringing a reliable water supply to nearly 1,800 homes that lacked safe water.

August

- Shasta, the state's largest reservoir, reaches 110% of historical average.

2017

January

- Statewide water savings surpass 20 percent.

February

- Statewide snow water equivalent is 30.5 inches, 174% of average for that date.
- SWRCB extends existing water conservation regulations.

April

- Governor Brown lifts drought emergency declaration, retains prohibition on wasteful practices, and advances measures to make conservation a way of life.

Figure C.2: Milestones of the Drought

Source: California Department of Water Resources

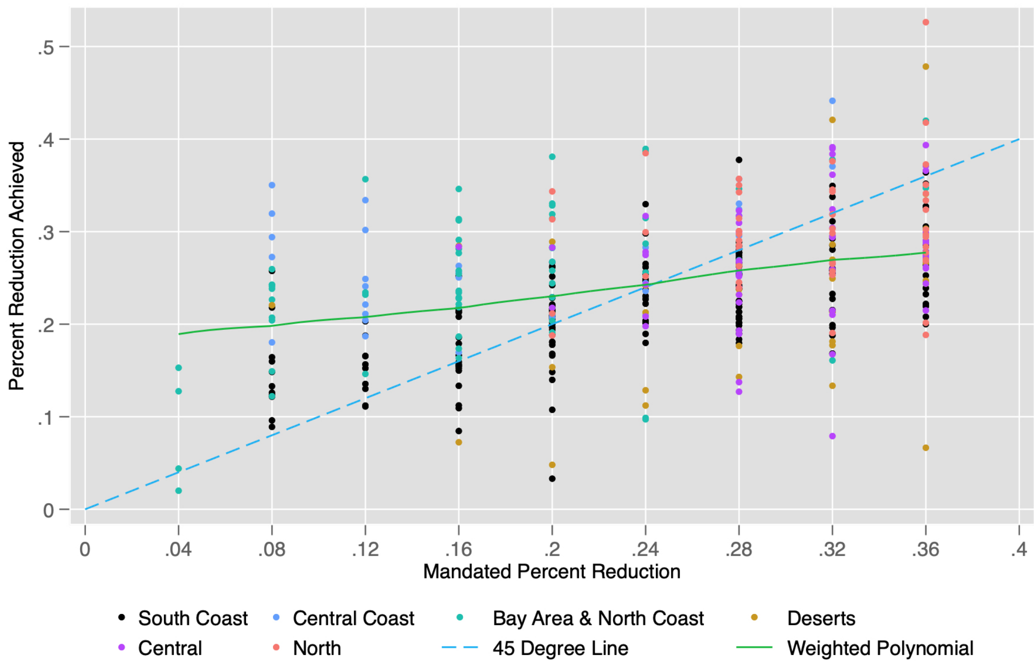

Figure C.3: The Distribution of Mandated and Observed Percentage Reductions at Supplier-Level in February 2016 by Region

Notes: "Percent Reduction Achieved" is the cumulative percent saved from June 2015 to February 2016 as compared to 2013 usage for the same months. The 45 degree line defines perfect compliance.

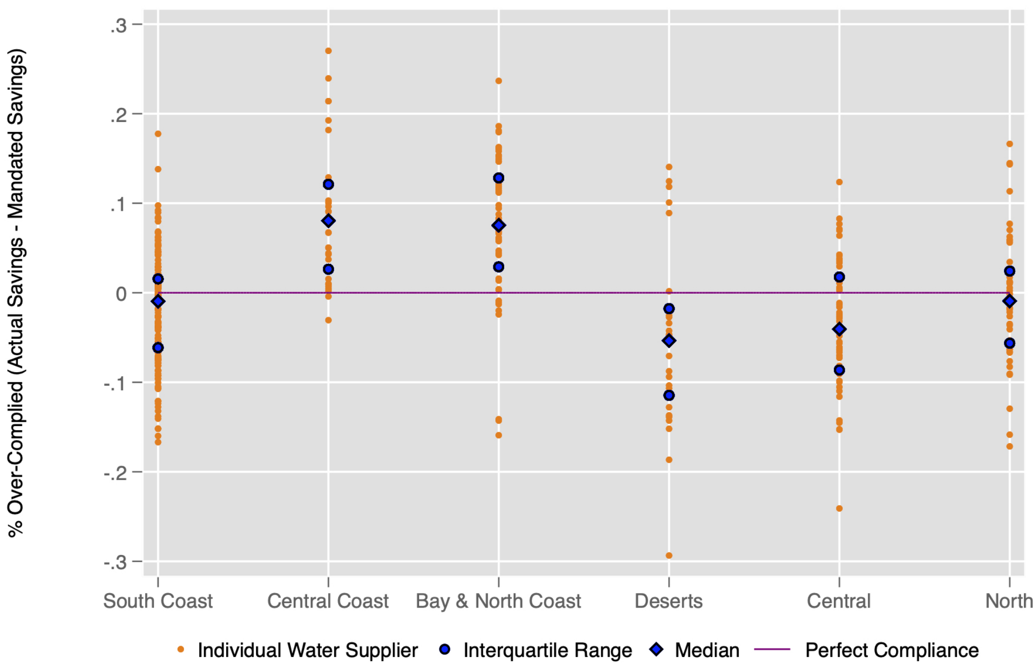

Figure C.4: Regional Distribution of Over-Compliance in February 2016

Notes: The vertical axis defines over-compliance as the difference between actual savings and mandated savings.

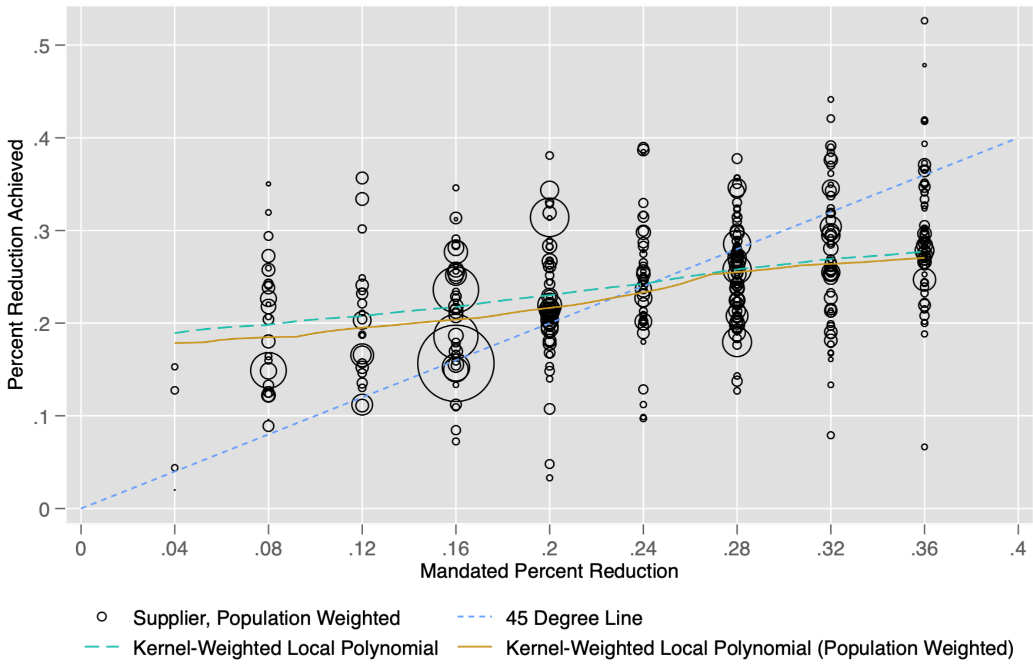

Figure C.5: The Distribution of Mandated and Observed Percentage Reductions at Supplier-Level in February 2016 (Weighted by Population Served)

Notes: "Percent Reduction Achieved" is the cumulative percent saved from June 2015 to February 2016 as compared to 2013 usage for the same months. The 45 degree line defines perfect compliance.

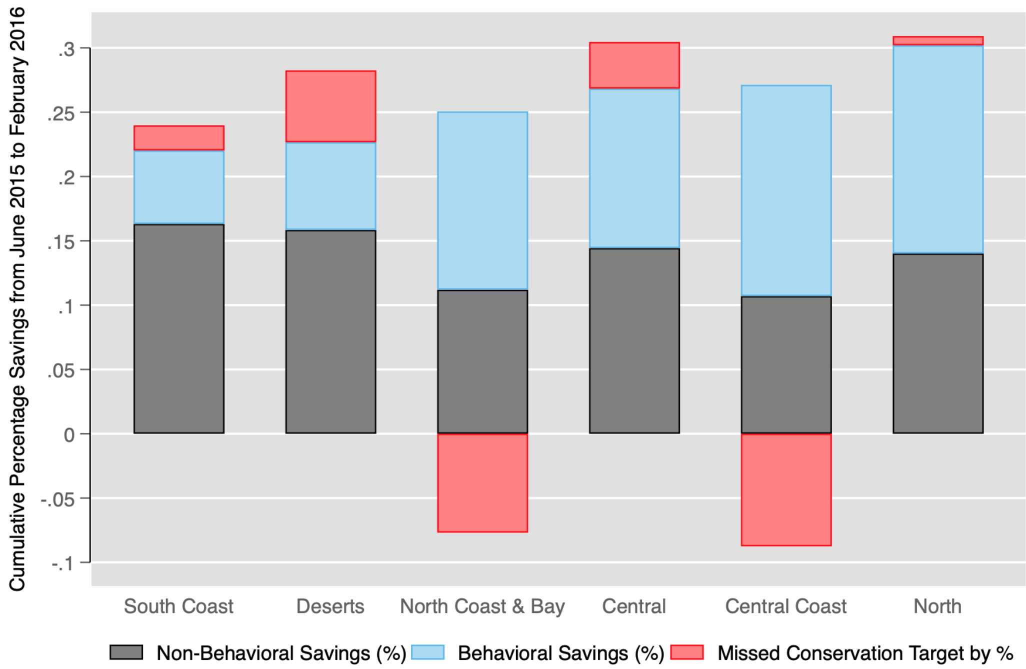

Figure C.6: Composition of Cumulative Savings by Region in February 2016

Note: When a "missed conservation standard" is negative or below zero, it represents the extent of over-compliance or savings beyond the mandated standard. The bars are ordered by total cumulative savings until February 2016.

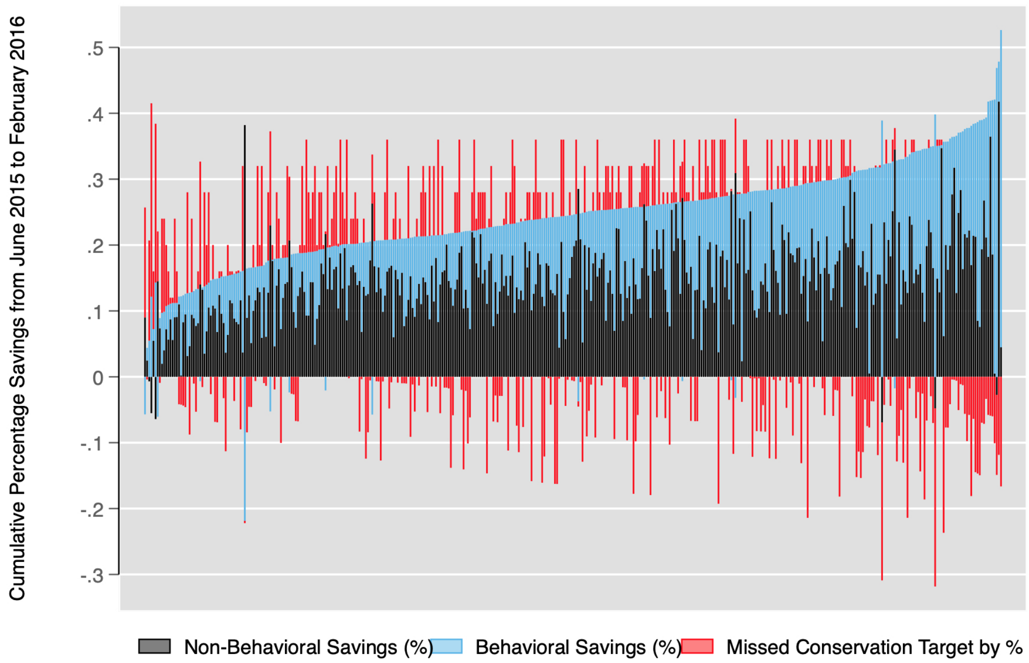

Figure C.7: Composition of Cumulative Savings by Suppliers in February 2016

Notes: When a "missed conservation standard" is negative or below zero, it represents savings beyond the mandated standard or the extent of over-compliance. The bars are ordered by total cumulative savings until February 2016.

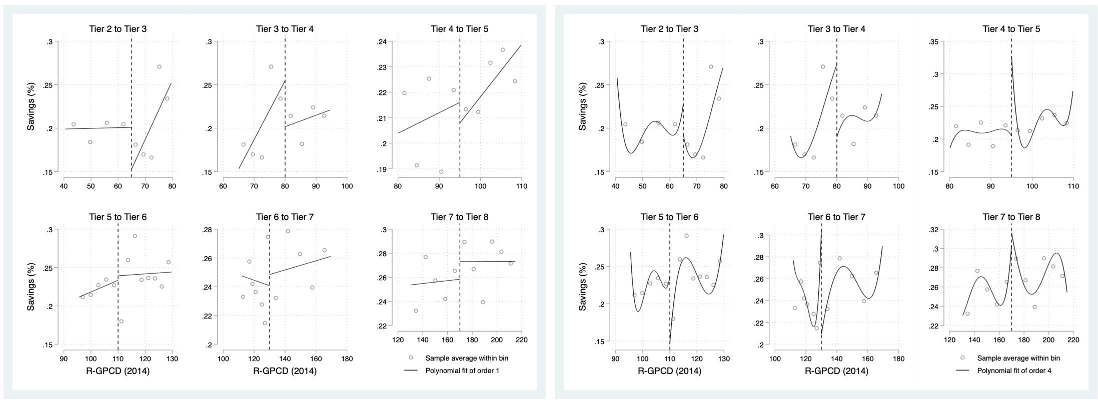

Figure C.8: Sharp RD Plots at Each Relevant Threshold for February 2016

Notes: Tier 1 is excluded as it only had 4 suppliers, and the plot for Tier 8 to Tier 9 is excluded for ease of visualization.

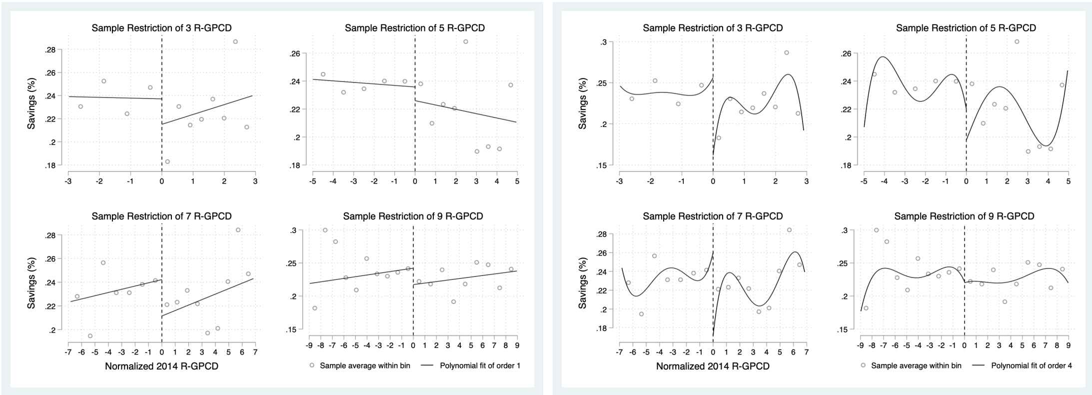

Figure C.9: Pooled RD Plots in February 2016

Notes: The running variable (horizontal axis) is normalized and the outcome variable (vertical axis) is cumulative savings from June 2015 to February 2016 relative to the same months in 2013. The bandwidth selection procedure from Calonico, Cattaneo, and Titiunik (2014) was used separately for each of the four restricted samples.

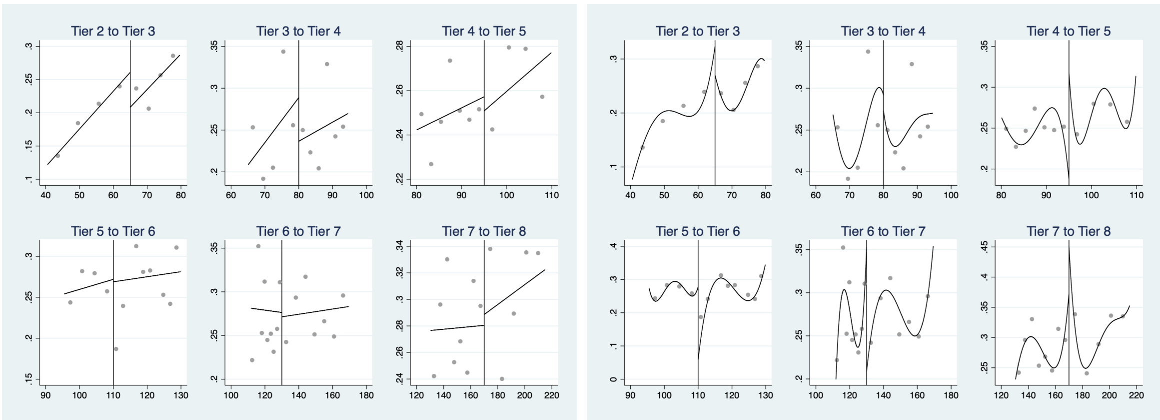

Figure C.10: RD Plots at Each Relevant Threshold for June 2015

Notes: Grey dots are the sample average within bin. The black lines are either a linear (Left) or a polynomial (Right) fit of order 4. The running variable (horizontal axis) is supplier level R-GPCD in the Summer of 2014 and the outcome variable (vertical axis) is cumulative savings until June 2015.

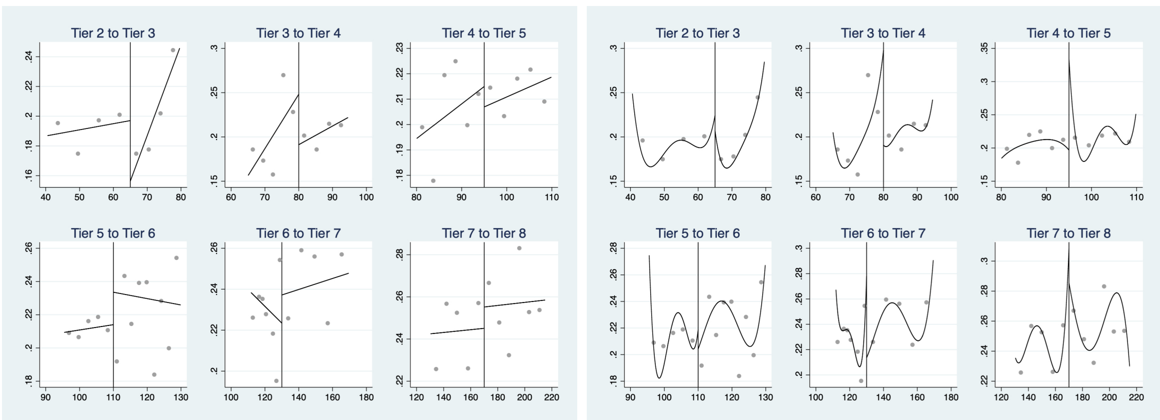

Figure C.11: RD Plots at Each Relevant Threshold for November 2016

Notes: Grey dots are the sample average within bin. The black lines are either a linear (Left) or a polynomial (Right) fit of order 4. The running variable (horizontal axis) is supplier level R-GPCD in the Summer of 2014 and the outcome variable (vertical axis) is cumulative savings until November 2016.