Free to choose: Promoting conservation by relaxing outdoor watering restrictions

A. Castledine[a], K. Moeltner[b,1,*], M.K. Price[c], S. Stoddard[d]

[a] *Department of Resource Economics, University of Nevada, Reno, MS 204, Reno, NV 89557*
[b] *Department of Agricultural and Applied Economics, Virginia Tech, 208 Hutcheson Hall, Blacksburg, VA 24061*
[c] *Department of Economics, University of Tennessee, Knoxville, 505A Stokely Management Center, Knoxville, TN 37996-0550*
[d] *Truckee Meadows Water Authority, 1355 Capital Blvd., Reno, NV 89502*

Abstract

Many water utilities in the U.S. and around the world have implemented outdoor watering restrictions based on assigned weekly watering days to induce conservation and delay costly capacity expansions. While evidence suggests such restrictions reduce system-wide use there still exists considerable uncertainty regarding the optimal design of these policies. This study takes a closer look at the relationship between weekly watering frequency, consumption, and peaks using a multi-year, household-level data set of daily residential water use. We find that the policy of assigned watering days distorts optimal watering behavior. In an effort to follow the regulation customers ignore adverse natural conditions when watering their yard. This results in excess use and peaks compared to a more flexible irrigation strategy. An exogenous policy change during our observation period adding an additional assigned day only slightly attenuates this rigidity penalty. We conclude that assigning a ceiling on the number of weekly watering days, but leaving it to the customer to distribute this total across a given week, would be a superior conservation policy.

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*Corresponding author, mobile phone: (775)560-3288
Email addresses: acastledine@cabnr.unr.edu (A. Castledine), moeltner@vt.edu (K. Moeltner), mprice21@utk.edu (M.K. Price), sstoddard@tmwa.net (S. Stoddard)

[1] Part of this research was conducted while Moeltner was a Visiting Scholar at the Luskin Center for Innovation, School of Public Affairs, University of California, Los Angeles.

Bayesian estimation, posterior simulation

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1. Introduction

The sustainable provision of water is one of the most critical natural resource challenges facing the U.S. and the world at large. Water consumption across the globe has tripled in the last 50 years, and is expected to continue to rise rapidly due to population growth, longer life expectancies, and the globalization of trade. Water scarcity is expected to be further exacerbated by global warming via rising demand, prolonged droughts, and increasing system losses (Cromwell et al., 2007). The United Nations predict that by 2030 almost half of the world's population will be living in areas of high water stress (U.N. World Water Assessment Programme, 2009). In the U.S., nearly every region has experienced water shortages due to droughts over the last five to ten years. The majority of States are expecting local, regional, or state-wide shortages by 2013, even under non-drought conditions (U.S. Environmental Protection Agency, 2008a).

Residential customers consume close to two thirds of all publicly supplied water in the United States (U.S. Environmental Protection Agency, 2002). On average, approximately 15% of residential use is allocated to landscape and lawn irrigation. In the arid west and south this proportion can be as large as 30-35%. Every day, an estimated seven billion gallons of publicly provided water are allocated for this purpose (U.S. Environmental Protection Agency, 2008b,c). It is therefore not surprising that policy makers and water utilities have directed considerable efforts to the management of residential outdoor irrigation in recent years. In most cases these conservation strategies take the form of outdoor watering restrictions at different margins, such as limits on the timing, length, and frequency of sprinkler use. There is growing evidence that these regulatory interventions are more effective in reducing irrigation amounts and thus system-wide usage than price-based policies, given the price-inelastic nature of water demand (Renwick and Archibald, 1998; Renwick and Green, 2000; Mansur and Olmstead, 2007; Olmstead et al., 2007; Worthington and Hoffman, 2008). Furthermore, there are generally fewer equity concerns and thus less political resistance to targeted usage restrictions compared to price-based policies (Renwick and Archibald, 1998; Timmins, 2003; Brennan et al., 2007).

Despite the growing importance of outdoor watering restrictions (OWRs) as a Demand-Side Management (DSM) intervention surprisingly little is known about the relative performance of different irrigation and, consequently, OWR implementation strategies. In this study we shed some light on this issue by examining daily consumption data for thousands of customers over several weeks in the summer periods of 2008 and 2010 in the Reno / Sparks area of Northern Nevada, where outdoor watering is essential for landscape survival. This temporal break affords a unique opportunity to examine an exogenous policy change in OWRs. In 2008, a twice-per-week assigned watering schedule was in place. This OWR was relaxed to three assigned days per week for the 2010 watering season. A second attractive feature of these data is that in either year many customers deviate from the assigned schedule, yielding a data set with rich variability in weekly watering patterns at the household level.

The policy change in 2010 had the expected effect of shifting the bulk of weekly watering frequencies from twice to three times per week. We also observe a slight increase in weekly consumption, and a noticeable reduction in daily peaks. However, the key finding flowing from our analysis is that the official schedule induces wasteful behavior, which undermines its intended conservation objective: Weekly water use and peaks are significantly higher during weeks that include all officially assigned watering days compared to weeks with an equal number of total watering days, but with a more flexible distribution of these days across the weekly time span. These "rigidity penalties" are substantial, amounting to 20-25% for weekly consumption, and 30-40% for weekly peaks for the typical customer. The 2010 policy change only slightly attenuates this relative inefficiency.

We hypothesize that these inefficiencies are largely driven by law-abiding customers being forced to ignore time-varying conditions when applying outdoor irrigation. For example, we show that watering events during schedule-conforming weeks are more likely to occur on windy days, compared to watering during more flexible weeks. Overall, we conclude that assigning a ceiling on the number of weekly watering days, but leaving it to the customer to distribute this total across a given week, would be a superior conservation policy.

In the next section we discuss in more detail existing OWR strategies and the related literature. Section three describes the Reno / Sparks watering restrictions and introduces the data. Section four discusses weekly watering patterns, and provides a graphical and descriptive analysis of weekly consumption outcomes. Section five describes the econometric analysis based on a correlated triple-equation system of weekly watering frequency, consumption, and peak. Section six summarizes estimation results and provides predictive policy simulations. Section seven concludes.

2. Outdoor watering restrictions

Residential irrigation restrictions have been implemented in many areas within and outside the United States. Table A1 in Appendix A gives a sample list of U.S. cities that are currently under mandatory OWR regimes. As is evident from the table most of these OWRs limit watering in a given week to between one and three days. For most municipalities the permitted watering days are assigned days-of-week (DoWs), usually based on the street address of a given residence. This strategy is designed to facilitate enforcement and avoid excessive consumption peaks on any given DoW. Most OWRs operate under a ban on any type of sprinkler on non-assigned days, but allow manual watering (e.g. via a hand-held hose) on a daily basis. In virtually all cases watering of any kind is prohibited during the hottest hours of the day.

To date, economists have primarily focused on two aspects of OWR policies: (i) the overall effectiveness of OWRs compared to an unrestricted baseline, and (ii) the welfare effects of OWRs on consumers. For example, using a daily time series of system-wide consumption during the 1984-85 drought years in Austin, Texas, Shaw and Maidment (1987) find that a one-per-five days watering restriction reduced overall demand by 3-5%. Renwick and Archibald (1998) report a reduction in water use by 16% for residential customers in two Southern Californian communities following a strictly enforced total ban on automated landscape irrigation during the 1985-92 drought in that region. Their findings are based on a survey of 119 households and their monthly water use over this six-year period. Based on a cross-sectional study of system-wide monthly consumption in eight California water utilities over the same time horizon, Renwick and Green (2000) find that OWRs of a general nature (including bans on washing cars and other non-irrigation related outdoor use) reduced consumption by close to 30%.

The second set of studies focus on welfare implications of OWRs and other drought-related water use restrictions. Typically, these studies employ non-market valuation techniques to elicit households' willingness-to-pay (WTP) to avoid such restrictions (Griffin and Mjelde, 2000; Hensher et al., 2006), or an increased risk of future restrictions (Howe and Smith, 1994; Griffin and Mjelde, 2000). In contrast, Brennan et al. (2007) model the consumer problem under OWRs as a trade-off between the production of "green lawn" via hand-held watering devices and leisure time. Using scientific input on lawn appearance under different watering regimes and calibration techniques they simulate a household's optimal watering decision under different parameter settings for lawn production and consumer preferences.

While conceptually attractive, the Brennan et al. (2007) model has yet to be validated using actual field data. Griffin and Mjelde (2000) do not specify any details on OWR in their water shortage scenarios. This leaves Hensher et al. (2006), who stipulate very detailed restriction scenarios in their choice experiment, as the most relevant welfare study for our purpose. They find that households have near-zero WTP to avoid OWRs that still allow sprinkler use on several days per week, as do most regimes currently in place in the U.S. and Australia.

While there is undoubtedly room for additional valuation studies that examine the welfare implications associated with OWR's, the available evidence suggests that the bulk of net economic gains flowing from standard OWRs may well be related to water conservation and related cost savings on the production side. It is therefore quintessential to understand how different OWR regimes affect conservation outcomes. As is obvious from Table A1, there exists considerable variability in the implementation details of OWRs across communities, even for cities in the same region or watershed. These differences remain largely unexplained. Most areas with staggered implementation stages (e.g. City of San Antonio, State of Georgia) appear to follow a paradigm of reduced weekly frequency of sprinkler operation with increasing severity of drought. As we will show, this strategy can be highly counter-productive, especially if watering is only allowed on assigned days, as is the case for most existing OWRs.

Surprisingly, the existing literature offers no guidance on the optimal implementation of OWRs. Naturally, from a welfare perspective, any regime that reaches a given conservation objective with fewer restrictions on household activities will be Pareto-superior to a more restrictive version. As we will show in this study, it is a fallacy to believe that more stringent restrictions on the household end always produce better conservation outcomes. It appears that giving customers some "freedom to choose" can actually enhance conservation.

3. Empirical Background and Data

Water provision in the Reno/Sparks urban area is managed by the Truckee Meadows Water Authority (TMWA), a non-profit, community-owned public utility. TMWA first implemented OWRs in 1992 in reaction to a prolonged drought. They became permanent in 1996 primarily to guard against future droughts through sufficient water storage, and to assure adequate flows of the Truckee River to Pyramid Lake, an important spawning habitat for trout and other fish species. The watering regulations allow automated sprinkler use in the morning and evening on assigned days per week based on the last digit of a resident's address. Manual watering is allowed on any day. These OWRs are only mildly enforced, with infrequent water patrols and nominal fines (up to $75) for repeated violations in the same calendar year.

Prior to 2010, the weekly limit was two days (Thursday and Sunday for odd addresses, Wednesday and Saturday for even addresses). This limit was increased to three days for the 2010 watering season (Wednesday, Friday, Sunday for odd addresses, Tuesday, Thursday, Saturday for even addresses). The agency anticipated that this policy change would induce a more even spread of system-wise weekly use and thus reduce daily peaks and the corresponding risk of inefficient system performance.[2]

In 2008 TMWA initiated the collection of daily water consumption data for a large sample of commercial, industrial, and residential customer in the Reno / Sparks area. Meter readings were obtained via nightly drive-by's using remote sensing devices. Two teams of readers covered the same route for 63 consecutive days between June 22 and August 23, 2008, between the hours of 9pm and 3am[3]. The daily routes were chosen under the multi-fold considerations of maximizing the number of readings, covering the entire TMWA service area, providing a representative cross-section of customer classes and building types, and working around construction projects and street closures as they arose during the course of the summer.

The same exercise was repeated between June 20 and August 21, 2010. Due to construction activities, the 2010 routes differed somewhat from the 2008 itineraries. Furthermore, the 2010 sample includes additional neighborhoods that were still under construction in 2008.

Drivers were instructed to proceed no slower than the posted speed limit to assure adequate spatial coverage. While this resulted in a large number of customers being included in the sample, it also generated some missing readings due to parked vehicles or other obstacles preventing a clean line-of-sight. Therefore, a completely uninterrupted series of 63 readings is available only for a small subset of the sample. In 2010, readings were suspended

[2] Lower peak demand can be largely satisfied via stored water, distributed by gravity. This reduces reliance on pumped water during the day, when electricity costs are highest.

[3] According to TMWA, the vast majority of households complete watering by 9pm.

for several days in week four due to equipment failure. Overall, the 2008 effort produced 909,300 readings from 17,066 households. In 2010, 966,991 observations were obtained from 19,026 residential customers.

From these original sets of households we eliminate premises with ownership changes or multiple ownerships during a given year's research period. We further drop households with a total of 14 or more readings of zero consumption to avoid the inclusion of vacation or weekend homes, and customers with four or more consecutive zero readings anywhere in the daily series to reduce the risk of including abandoned homes or properties in transition of ownership. These cleaning steps truncated the set of eligible residents by approximately 15% for each year.

Given our analysis' focus on weekly watering frequencies, only weeks (i.e. a consecutive series of days from Sunday to the following Saturday) with a full set of readings are usable for a given household. In addition, a minimum number of intact weeks (MIW) is required to identify a given household's watering days and weekly watering patterns, as discussed below. A third consideration was the desire to maximize the overlap of residents that are included in both years' samples. Naturally, this number decreases along with the total sample size as the MIW criteria becomes more stringent. In balancing these conflicting requirements we settle for an MIW threshold of five full weeks of daily readings anywhere in the series. After eliminating a few isolated cases with obvious water leaks or missing information on basic building characteristics this leaves a final sample of 8,747 residents and 52,666 weekly observations for 2008, and 7,652 households and 48,573 weeks for 2010. Importantly, 1,766 of these customers figure in both samples, although not necessarily with the exact same number of weekly observations. We will henceforth refer to this sub-sample as "overlap".

Table 1 shows the distribution of intact weeks for the full sample and the sub-sample of overlapping households for both years. As is evident from the table, a substantial number of households exceed our MIW requirement in both years, contributing six or more weeks worth of observations to the data set. This also holds for the overlap sample.

Table 2 depicts basic household characteristics for the two full samples. As is evident from the "all" blocks (last set of rows for each year), the 2010 sample comprises, on average, slightly smaller and older properties. There is also a staggering decline of 44% in average tax-assessed property value from \$270,000 in 2008 to \$151,000 in 2010. This pronounced difference is largely a manifestation of the dramatic economic downturn in Nevada that started in 2006. According to a recent real estate report (CalNeva Realty, 2010), median home prices in Reno and Sparks dropped by 31% between 2008 and

Table 1: Sample sizes for 2008 and 2010

	2008				2010			
intact weeks	HHs	%	obs	%	HHs	%	obs	%
5	3,567	40.8%	17,835	33.9%	2,084	27.2%	10,420	21.5%
6	2,284	26.1%	13,704	26.0%	826	10.8%	4,956	10.2%
7	2,041	23.3%	14,287	27.1%	4,739	61.9%	33,173	68.3%
8	855	9.8%	6,840	13.0%	3	0.0%	24	0.0%
Total	8,747	100.0%	52,666	100.0%	7,652	100.0%	48,573	100.0%
	Overlap*, 2008				Overlap, 2010			
intact weeks	HHs	%	obs	%	HHs	%	obs	%
5	679	38.4%	3,395	31.6%	1,061	60.1%	5,305	52.4%
6	435	24.6%	2,610	24.3%	121	6.9%	726	7.2%
7	463	26.2%	3,241	30.1%	584	33.1%	4,088	40.4%
8	189	10.7%	1,512	14.1%	0	0.0%	0	0.0%
Total	1,766	100.0%	10,758	100.0%	1,766	100.0%	10,119	100.0%

* "overlap" comprises households sampled in both 2008 and 2010

2010, and by over 50% since the onset of the recession. Since larger, more expensive homes were hit relatively harder by this price erosion, the decline in mean home values exceeds the change in medians.[4]

We combine our household data with the following basic climate indicators: average, minimum, and maximum daily temperature (in °F), average wind speed (over 24 hourly measurements) in knots[5], and maximum sustained wind speed in knots (measured for ten minutes every hour). As is common in this arid high-dessert climate, there were no noteworthy, system-wide rainfall events during our sampling periods. Climate statistics are shown in Table 3. As is evident from the table the summer of 2010 was slightly cooler than the summer of 2008, while the wind statistics are very similar for the two sampling periods.

[4]The change in *median* assed home values is -40% for our sample.

[5]1 knot = 1.15 mph

Table 2: Household characteristics

	age	lot size (1000 sqft)	sqft (1000s)	value ($10,000s)	fixtures	bedrms	bathrms
				2008			
mean	20.85	10.09	1.99	270.48	11.98	3.27	2.40
std.	(17.56)	(6.98)	(0.78)	(160.25)	(3.38)	(0.86)	(0.70)
min.	1.00	0.04	0.52	69.45	0.00	0.00	0.00
max.	104.00	49.66	15.22	2637.44	64.00	23.00	16.00
				2010			
mean	23.09	7.57	1.75	150.72	11.06	3.23	2.24
std.	(16.45)	(3.35)	(0.55)	(65.63)	(2.79)	(0.71)	(0.57)
min.	2.00	0.04	0.49	33.75	0.00	0.00	0.00
max.	106.00	48.79	7.69	762.84	27.00	8.00	6.00

4. Descriptive Analysis

4.1. Classification of weekly irrigation patterns

Our primary research focus lies in the effect of the policy change from two to three assigned watering days on total weekly use and weekly peak (the highest daily consumption in a given week) for a typical residential customer. However, we also want to examine if the OWR policy - in either year - truly induces superior conservation outcomes compared to weekly watering patterns that deviate form the official rule by varying degrees. This notion is largely based on the hypothesis that the temporal rigidity imposed by the official schedule may force customers with strong law-abiding preferences (and, perhaps, limited time for manual watering) to ignore time-varying natural conditions when applying their automated yard irrigation. For our research area this largely translates into high wind events, which can cause substantial irrigation losses. In addition, such "perfectly compliant" households face two-to-three day gaps between permissible watering events. This may prompt them to thoroughly soak their yard on assigned days, incurring additional losses to evaporation and drainage.

Establishing a link between irrigation outcomes and weekly watering patterns requires the identification of outdoor watering events - automated or otherwise - for a given household and day. Specifically, our objective is to group each household's series of observed consumption days into two categories: (i) days with some outdoor water use, and (ii) days with indoor-

Table 3: Climate statistics

	mean	std	min	max
2008				
avg. temp	77.93	3.27	69.40	84.20
min. temp	59.89	3.53	53.10	66.00
max. temp	95.75	3.02	89.10	102.00
avg. wind	5.23	1.44	2.80	9.30
max. wind	16.21	4.21	7.00	29.90
max. gust	23.33	4.12	15.00	30.90
2010				
avg. temp	75.82	4.66	61.70	85.40
min. temp	58.86	4.79	44.60	69.10
max. temp	92.82	5.22	78.80	102.20
avg. wind	5.72	1.27	2.50	8.30
max. wind	16.84	4.21	8.90	32.10
max. gust	24.47	5.05	14.00	37.90
Total				
avg. temp	76.92	4.13	61.70	85.40
min. temp	59.40	4.21	44.60	69.10
max. temp	94.34	4.47	78.80	102.20
avg. wind	5.46	1.38	2.50	9.30
max. wind	16.51	4.22	7.00	32.10
max. gust	23.88	4.63	14.00	37.90

only water use. This categorization is challenging since we only observe total daily use, but not specific usage for different purposes. Ideally, outdoor watering days should be clearly identifiable as pronounced spikes in a customer's series of observed consumption days. This is indeed the case for the majority of households in our sample. However, the distinction between days of outdoor and indoor use becomes blurred for households with limited outdoor needs, high fluctuations in indoor use, or daily "baseline" outdoor watering (continuous trickle irrigation, daily use of some sprinkler stations, etc) that is augmented with occasional additional irrigation. We therefore use a series of household-specific K-means clustering algorithms (MacQueen, 1967) to sort daily observations into a low use ("indoor only") and high use ("indoor plus some outdoor watering") category. We then use information of average winter consumption for each customer to further refine this sorting. The details of this identification strategy are given in Appendix B.

The cluster analysis results allow us to distinguish between different weekly watering patterns. Given our research objectives, we group them into three mutually exclusive categories of increasing deviation form the official OWRs: (i) "Schedule" (S), (ii) "Schedule-plus" (SP), and (iii) "Off-schedule" (OS). The first group comprises weeks with watering patterns that correspond *exactly* to the assigned TMWA schedule. The second category describes weeks that include *all assigned days*, plus some additional days of outdoor use. The third group exhibits the most varied weekly watering patterns, with the common feature of non-watering on (i.e "skipping") at least one of the assigned days. Thus, weeks in the the first category comprise exactly two watering days in 2008 and three days in 2010. Weeks in the second category can include frequencies of 3-7 days in 2008, and 4-7 days in 2010. Frequencies in the third category range from zero to six watering days for both years. For ease of exposition we will at times combine the first two groups under the heading "Schedule-based" (SB). Thus, $S \cup SP = SB$, and $SB \cup OS =$ entire sample.[6]

4.2. Descriptive Results

To compare outcomes of interest across these week-types, and to examine the 2010 change in OWRs on weekly use and peak, we aggregate the daily sample that formed the basis for the cluster analysis to a weekly format. This yields the sample totals previously captured in Table 1, i.e. 53,666 observations for 2008, and 48,573 observations for 2010. Table 4 provides a summary of cell counts and sample percentages for the different week-type categories, by weekly watering frequency. To conserve space the sparsely populated weekly frequencies of five and higher are captured as a single "> 4" category. The first half of the table shows results for 2008, while the second provides summaries for 2010. The table has three blocks of rows,

[6]We prefer this categorization of our sample into week-types over a grouping into household-behavioral types for several reasons. First, given our research objectives, the distinction of weekly patterns along a gradient of schedule-deviation is clearly meaningful. Second, as shown below, the vast majority of households exhibit weekly watering patterns that comprise at least two, and in many cases all three of the week-types. This makes it difficult to establish a policy-relevant grouping of households into behavioral types. Third, the week-based grouping reduces the risk of measurement error that may carry over from the cluster analysis. Specifically, had we used the cluster analysis results to identify household types (for example "perfectly compliant"' customers), a single mis-classified daily observation for a given customer would mis-categorize the entire set of observations for that individual in the main data. In contrast, the same error in the cluster analysis would only affect a single weekly observation.

corresponding, respectively, to SB weeks, OS weeks, and the combined sample. The "% of sample" column relates row counts to the entire sample size for each year. For example, the 14,497 observations for SB weeks with twice watering (i.e. the S group by our definition above) comprise 27.5% of the entire 2008 sample. In 2010, the S category, now associated with three weekly watering days, comprises 12,625 observations, for a sample share of 26%. Thus, in each year only about one forth of sample-weeks exhibit watering patterns that are perfectly consistent with the official schedule. However, in both cases this category comprises the largest sample share compared to other frequency / type combinations.

The "% all within" column reports the percentage share for a given row count that corresponds to households that have *all* their observations in that very category. For example, continuing with the S case for 2008, of the 14,497 observations in this group, 42.8% come from households that *always* water twice and on their assigned days. Analogously, 35.1% of observations in the S category for 2010 flow from households that always adhere to this watering pattern. Combined with the results on sample shares for the S group this indicates that the policy change was successful in shifting weekly watering from twice to three times per week for a considerable segment of customers and weeks.

Overall, however, the majority of weekly observations in both years correspond to watering patterns that deviate from the official schedule. In 2008, over 34% of weeks are "schedule-plus" (SP) types that augment the official assignment with additional irrigation days. Over 38% skip at least one of the assigned days and thus fall into the "off-schedule" (OS) category. The corresponding shares for 2010 are close to 30% for SP and over 54% for OS. Furthermore, as is evident from the small shares in most of the "all within" colums, the majority of customers exhibit seasonal water patterns that include a mix of different week-types and frequencies. Overall, only 18.5% of sample weeks in 2008 and 15.5% in 2010 are associated with customers that always water with the same weekly frequency.

Tables 5 and 6 depict, respectively, weekly use and peak by frequency and week-type. We stress three key results captured by these tables that hold for both years: First, consumption increases with weekly frequency, regardless of watering pattern. This is consistent with the empirical evidence from the existing literature that capping weekly watering frequency reduces total use. Second, peaks remain relatively stable across frequencies, at least in the two to four applications range, which comprises the bulk of observations. Third - and most importantly - weekly consumption and peaks are substantially higher for weeks that include all assigned days

Table 4: Cell counts and percentages by watering frequency and week-type

weekly watering days	2008 count	2008 % of sample	2008 % all w/in	2010 count	2010 % of sample	2010 % all w/in
			schedule-based			
2*	14,497	27.5%	42.8%	-	-	-
3**	6,374	12.1%	9.2%	12,625	26.0%	35.1%
4	5,595	10.6%	16.1%	3,650	7.5%	3.3%
>4	6,053	11.5%	11.6%	6,001	12.4%	15.7%
Total	32,519	61.7%	25.8%	22,276	45.9%	24.7%
			off-schedule			
0	2,924	5.6%	0.0%	2,822	5.8%	0.0%
1	4,198	8.0%	1.6%	3,979	8.2%	0.9%
2	4,795	9.1%	5.5%	8,004	16.5%	9.9%
3	4,257	8.1%	7.4%	6,256	12.9%	8.4%
4	2,610	5.0%	6.1%	3,518	7.2%	7.4%
>4	1,363	2.6%	6.5%	1,718	3.5%	2.5%
Total	20,147	38.3%	4.4%	26,297	54.1%	6.3%
			all			
0	2,924	5.6%	0.0%	2,822	5.8%	0.0%
1	4,198	8.0%	1.6%	3,979	8.2%	0.9%
2	19,292	36.6%	35.5%	8,004	16.5%	9.9%
3	10,631	20.2%	9.0%	18,881	38.9%	28.9%
4	8,205	15.6%	13.2%	7,168	14.8%	5.4%
>4	7,416	14.1%	10.8%	7,719	15.9%	12.9%
Total	52,666	100.0%	18.5%	48,573	100.0%	15.8%

*"schedule" group for 2008 / **"schedule" group for 2010

("schedule-based") compared to weeks *of identical frequency* with more flexible watering patterns ("off-schedule"). Moreover, this pattern holds for *all* frequencies. In 2008, these differences amount to 30-40% for weekly consumption, and 50-60% for weekly peak. For example, for the average S-type week we observe a weekly consumption of 5,840 gallons, and a weekly peak of 2,340 gallons. In an OS week with the same two-day watering frequency these numbers reduce to 4,200 gallons and 1,460 gallons, respectively.

In 2010 these differentials between SB- and OS-type weeks reduce to

Table 5: Weekly use by watering frequency and week-type

weekly watering days	2008 weekly use (1000 gals.) mean	std.	2010 weekly use (1000 gals.) mean	std.
		schedule-based		
2	5.84	(3.67)	-	-
3	6.72	(4.56)	5.39	(2.44)
4	7.24	(5.04)	5.95	(2.89)
>4	9.83	(7.73)	7.32	(4.41)
Total	6.99	(5.26)	6.00	(3.26)
		off-schedule		
0	2.44	(2.20)	2.03	(1.52)
1	3.38	(2.61)	2.73	(1.85)
2	4.20	(3.20)	3.82	(2.23)
3	4.80	(3.61)	4.32	(2.58)
4	5.52	(4.64)	4.75	(3.00)
>4	6.99	(5.80)	5.65	(4.53)
Total	4.26	(3.71)	3.83	(2.71)
		all		
0	2.44	(2.20)	2.03	(1.52)
1	3.38	(2.61)	2.73	(1.85)
2	5.43	(3.63)	3.82	(2.23)
3	5.95	(4.31)	5.03	(2.54)
4	6.69	(4.98)	5.36	(3.01)
>4	9.31	(7.50)	6.95	(4.49)
Total	5.95	(4.91)	4.82	(3.17)

25-30% for use and 24-26% for peak. For the S category, average weekly use is 5,390 gallons, and average peak amounts to 1,650 gallons. In contrast, for the corresponding OS category at a three-day frequency we observe average use of 4,320 gallons, and an average peak of 1,310 gallons.

The patterns captured in Tables 4 through 6 are similar for the overlap sample, which contributes 10,758 weeks in 2008 (20.4% of total) and 10,119 weeks in 2010 (20.8% of total). That is: (i) slightly over one fourth of sample weeks follow the official schedule exactly, (ii) the vast majority of observations flow from households with mixed watering patterns and frequencies,

Table 6: Weekly peak by watering frequency and week-type

weekly watering days	2008 weekly peak (1000 gals.) mean	std.	2010 weekly peak (1000 gals.) mean	std.
		schedule-based		
2	2.34	(1.68)	-	-
3	2.30	(1.85)	1.65	(0.83)
4	2.19	(1.86)	1.67	(0.96)
>4	2.43	(2.26)	1.70	(1.14)
Total	2.32	(1.86)	1.66	(0.95)
		off-schedule		
0	0.55	(0.48)	0.46	(0.34)
1	1.30	(1.29)	1.04	(0.94)
2	1.46	(1.39)	1.37	(0.98)
3	1.42	(1.28)	1.31	(0.95)
4	1.47	(1.47)	1.31	(1.04)
>4	1.67	(1.63)	1.37	(1.24)
Total	1.30	(1.32)	1.20	(0.99)
		all		
0	0.55	(0.48)	0.46	(0.34)
1	1.30	(1.29)	1.04	(0.94)
2	2.12	(1.65)	1.37	(0.98)
3	1.95	(1.70)	1.53	(0.89)
4	1.96	(1.78)	1.49	(1.01)
>4	2.29	(2.18)	1.63	(1.17)
Total	1.93	(1.75)	1.41	(1.00)

(iii) consumption is 25-35% higher for the SB category at all frequencies compared to the OS group, and SB peaks exceed OS peaks by 45-55%. In contrast to the full sample, these inter-type differentials persist for consumption, but reduce to 25-30% for peaks.[7]

Tables 5 and 6 also suggest that both use and peaks are markedly reduced in 2010 compared to 2008 for all week-types and frequencies. However, as

[7]The corresponding summary tables for the overlap sample are omitted for parsimony but are available from the authors upon request.

revealed by an analogous comparison for the overlap sample and our more complete econometric analysis below, these differences are largely driven by differences in household composition across the two years.

Figure 1 summarizes mean outcomes for the full and the overlap sample, by week-types. To allow for a more even comparison between SB and OS type weeks we only include weekly watering frequencies of two and higher in the construction of this figure. The figure illustrates that overall weekly use remains flat for the overlap sample, while peaks are slightly reduced. Importantly, both the full and the overlap sample show a sizable gap in use and peak between SB and OS type weeks, as discussed above.

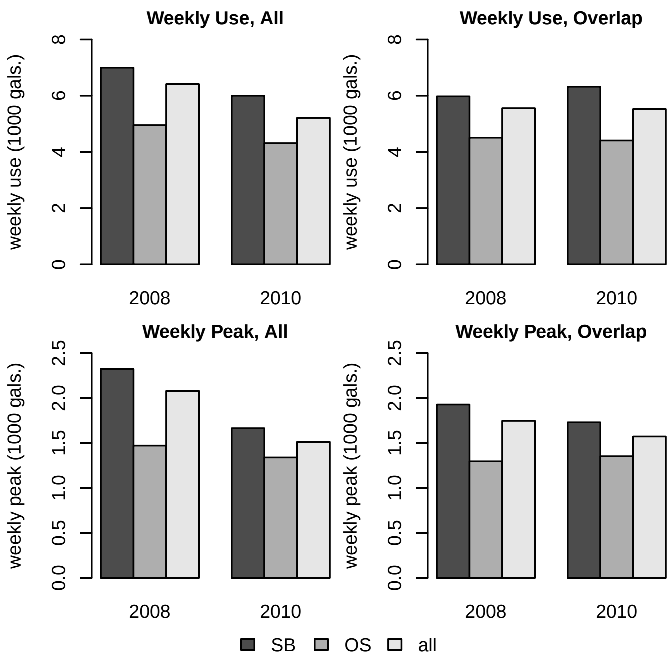

Figure 1: Average weekly use and peak, full and overlap sample

Figure 2 provides a system-wide look at the policy effect by plotting average *daily* use across all customers for the overlap segment, and by week-type. Average weekly use (in units of 10 gallons) is super-imposed as a dotted line. Overall, the policy change clearly reduced daily peaks and smoothed weekly use. This effect is especially pronounced for the schedule-based contingent. In contrast, daily peaks were already substantially lower for the off-schedule group in 2008, and changed little in 2010. Weekly consumption for this segment is almost flat before and after the policy change.

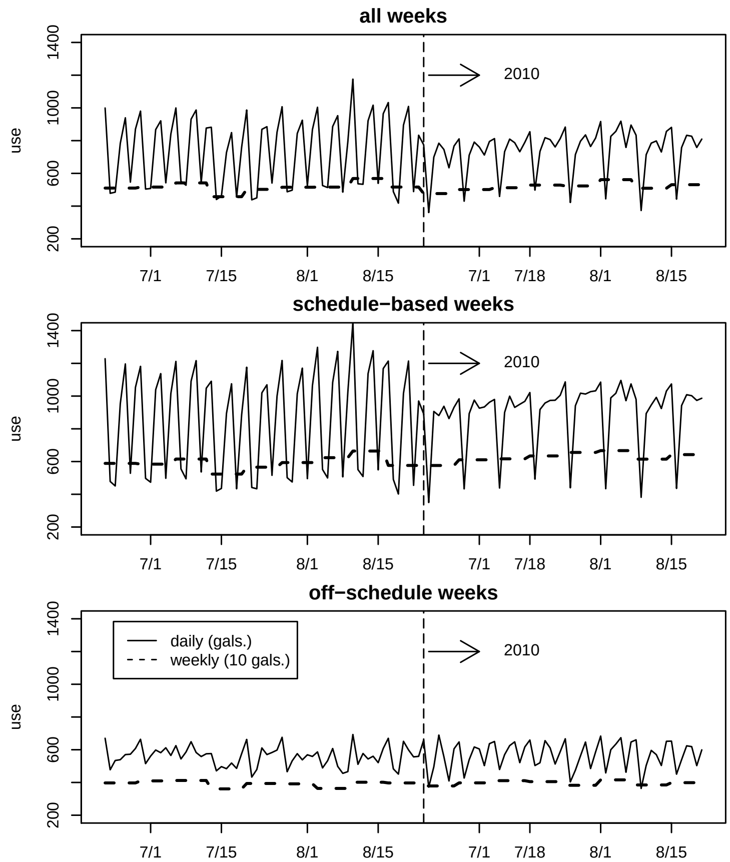

Figure 2: Aggregate daily and weekly use, overlap sample

4.3. The wind effect

Given that few customers exhibit the same weekly watering pattern throughout the entire season these pronounced differences in outcomes between weeks that more closely adhere to the official schedule and weeks with a more flexible watering pattern are unlikely to be driven by customer heterogeneity alone. Rather, the table results suggest that there is an umbrella effect at work that affects all households in similar fashion. This effect categorically reduces watering efficiency for SB-type weeks. This is consistent with the notion of a "rigidity penalty" mentioned above: weekly watering that corresponds more closely to the official schedule is more likely to produce losses due to a higher probability of coinciding with adverse natural conditions, such as high wind events. This increases both use and peak, as it takes more water per week and per daily application to provide adequate irrigation for a given landscape.

The reduced rigidity effect for 2010 is likely due to the additional flexibility afforded to law-abiding customers by the revised OWRs. Specifically, schedule-adherent households now have more options to skip or reduce daily watering on windy days (e.g. water only during the calm morning hours but omit the afternoon sprinkler run). Since the average gap between assigned days is shorter, this omission or reduction is less likely to affect yard health. As a result, customers are less likely to face the dilemma of incurring wind losses or violating official rules by making up for a skipped application on non-assigned days.

As a preliminary examination of this "wind hypothesis" we compute the the percentage of watering days, out of total watering days as identified by the cluster analysis, that fall on a windy or very windy day. As before we dis-aggregate the results by weekly watering frequency and week type. "Windy days" are flagged as days with a maximum sustained wind speed that exceed the sample mean of 16.51 knots (see Table 3). "Very windy" days are defined as days with a maximum sustained wind speed at the 75^th percentile or higher (19 knots).

The results are captured in 7. As is evident from the bottom row of the table, in 2008 the average watering day had a 51% chance of occurring on a windy day, and an 18% chance of coinciding with a very windy day. The former percentage decreases slightly for 2010, while the latter remains essentially constant. Importantly, and supporting our efficiency-loss hypothesis, these percentages are higher for the SB group compared to the OS segment at essentially all frequencies. In 2008, this difference is especially pronounced for the S category, with a share of windy days exceeding the correponding value for OS / twice a week by over 6%. In general, SB type weeks were 3-6% more likely to occur on a windy day and 2-3% more likely to fall on a very windy day than OS type weeks of comparable frequency. The difference for windy days reduces to 1-2% in 2010, while the difference for very windy days essentially vanishes.

For a more rigorous examination of the role of wind and other climate conditions on weekly outcomes, while controlling for watering patterns and weekly frequency, we now turn to our full-fledged econometric framework.

5. Econometric Framework

We maintain a weekly level of analysis for our econometric specification as this corresponds directly to the week-based design of OWR policies. We

Table 7: Wind events by watering frequency and week type

weekly watering days	2008 % windy	2008 % very windy	2010 % windy	2010 % very windy	All % windy	All % very windy
			schedule-based			
2	57.02%	21.40%	-	-	57.02%	21.40%
3	52.32%	19.50%	48.82%	18.09%	50.00%	18.57%
4	52.21%	19.37%	48.58%	17.66%	50.78%	18.69%
>4	46.75%	15.29%	47.09%	17.34%	46.92%	16.32%
Total	51.71%	18.58%	48.08%	17.72%	50.06%	18.19%
			off-schedule			
2	50.68%	19.08%	47.73%	18.38%	48.83%	18.65%
3	48.65%	16.60%	46.94%	17.67%	47.63%	17.24%
4	49.51%	17.18%	46.99%	17.25%	48.07%	17.22%
>4	47.40%	15.14%	46.58%	16.42%	46.94%	15.85%
Total	49.14%	17.09%	47.11%	17.57%	47.94%	17.37%
			all			
2	55.44%	20.82%	47.73%	18.38%	53.18%	20.11%
3	50.85%	18.34%	48.20%	17.95%	49.15%	18.09%
4	51.35%	18.67%	47.80%	17.46%	49.70%	18.11%
>4	46.86%	15.27%	46.99%	17.16%	46.93%	16.23%
Total	51.00%	18.17%	47.70%	17.66%	49.35%	17.91%

define an *observed* weekly irrigation scheme by household i in period p as a bundle of frequency y_{1ip} (zero to seven), total use y_{2ip}, weekly peak y_{3ip}, and schedule-based pattern (SB vs. OS), i.e.

$$IR_{ip} = IR\left(y_{1ip}, y_{2ip}, y_{3ip}, SB_{ip}\right), \quad i = 1, \ldots N, \quad p = 1 \ldots P \tag{1}$$

where SB_{ip} is an indicator equal to one if the weekly irrigation pattern corresponds to a schedule-based implementation, and equal to zero for an off-schedule pattern, as defined previously. The ex-post observed outcome may reflect a pre-conceived weekly implementation strategy, a mix of planned strategy and ad hoc updating throughout the week, or the result of sequential daily watering decisions.[8]

Our main policy focus lies on the effect of weekly watering frequency and degree-of-adherence to the officially assign watering days on use and peak. Thus, we aim to model $y_{jip} = y_{jip}\left(y_{1ip}, SB_{ip}\right), j = 2, 3$. However, frequency, usage, and peak are likely jointly affected by household-specific unobservables, such as: (i) vegetative cover and other physical characteristics of the yard, (ii) preferences for "greenness", (iii) disutility from breaking the official watering rule due to moral discomfort or loss in social standing (e.g Hatcher et al., 2000; Licht, 2008; Traxler, 2010), iv) knowledge of yard's water regime and needs, (v) net-utility from manual watering, and (vi) awareness of daily weather patterns. If some of these heterogeneity effects jointly contribute to observed weekly frequency and use or peak, frequency becomes an endogenous regressor in $y_{2ip}\left(y_{1ip}, SB_{ip}\right)$ and / or $y_{3ip}\left(y_{1ip}, SB_{ip}\right)$. We thus model all three outcomes as an inter-related equation system.[9]

Our econometric model thus builds on three equations with observed outcomes y_{1ip}, y_{2ip}, and y_{3ip}. The first outcome, the number of watering days in a given week, takes the form of an integer that is naturally truncated from above at $U = 7$. The remaining outcomes, weekly consumption and peak, are continuous with support over $\Re^{+}$. Each equation also includes an individual-specific unobserved effect u_{ji}, $j = 1 \ldots 3$ that is invariant over the entire watering season.[10]

To incorporate these modeling considerations in a computationally tractable fashion we combine a truncated Poisson density for the watering frequency equation with two exponential- densities for weekly consumption and peak. An application of a Poisson-Exponential system is given in Munkin and Trivedi (2003). The exponential component has similar distributional char-

[8]Our data do not allow for the identification of these underlying behavioral heuristics. Survey data would be needed to determine a household's typical sequencing of watering decisions. This would allow for the development of a structural behavioral model of outdoor watering. We leave this extension to future research.

[9]Naturally, the same problem could arise with SB_{ip} if degree of schedule-adherence is also governed by these household-specific unobservable effects. We abstract from this possibility for computational tractability and based on the notion that SB_{ip} is, at least to some extent, captured by frequency. For example, $y_{1ip} < 2$ in 2008 and $y_{1ip} < 3$ in 2010 deterministically indicate OS, and $y_{1ip} = 7$ deterministically flags SB.

[10]We also included an observation-specific error in an earlier specification. However, this dual-error model exhibited poor identification and slow mixing in our Bayesian estimation routine. Furthermore, the parameter estimates generated by that model were virtually identical to those produced by the single-error specification, and both variances and covariances associated with the observational error emerged of negligible magnitude compared to the variance component for the individual-level effect.

acteristics as the familiar log-normal regression model, but exhibits more desirable mixing properties in our Bayesian estimation framework. Adding the household effects yields our full specification, which we label the Hierarchical Truncated Poisson- Exponential (HTPE) model.

The Hierarchical Truncated Poisson (HTP) component of the HTPE is given as

$$\begin{aligned} &f\left(y_{1ip} \mid \lambda_{1ip}, 0 \leq y_{1ip} \leq U\right) = \frac{\exp\left(-\lambda_{1ip}\right) \lambda_{1ip}^{y_{1ip}}}{y_{1ip}! \left(\sum\limits_{k=0}^{U} \frac{\lambda_{1ip}{}^{k}}{k!}\right)} \quad \text{with} \\ &E\left(y_{1ip}\right) = \lambda_{1ip} = \exp\left(\mathbf{x}_{1ip}' \boldsymbol{\beta}_1 + u_{1i}\right) \end{aligned} \tag{2}$$

where the log of the untruncated expectation, λ_{1ip} , is a linear function of vector $\mathbf{x}_{ip}$ containing household and climate variables, and individual-specific effect u_{1i}.

The Hierarchical Exponential (HE) part is specified as

$$\begin{aligned} &f\left(y_{jip} \mid \lambda_{jip}\right) = \lambda_{jip} * \exp\left(-\lambda_{jip} y_{jip}\right) \\ &\lambda_{jip} = \exp\left(-\mathbf{z}_{jip}' \boldsymbol{\psi}_j - \mathbf{d}_{ip}' \boldsymbol{\delta}_j - u_{1i}\right) \\ &E\left(y_{jip}\right) = \lambda_{jip}^{-1} = \exp\left(\mathbf{z}_{jip}' \boldsymbol{\psi}_j + \mathbf{d}_{ip}' \boldsymbol{\delta}_j + u_{1i}\right), \quad j = 2, 3 \end{aligned} \tag{3}$$

where the $\mathbf{z}$-vectors capture again household and climate information, the random terms are as in (2) and E denotes the expectation operator. Importantly, vector $\mathbf{d}_{ip}$ comprises a set of U indicator variables, one for each possible value of y_{1ip} that exceeds zero. The element of $\mathbf{d}_{ip}$ corresponding to the observed value of y_{1ip} is set to one, all others to zero. More concisely:

$$d_{ip,k} = \begin{cases} 1 & \text{if } y_{1ip} = k, \\ 0 & \text{otherwise} \end{cases} \qquad k = 1 \dots U \tag{4}$$

Thus, we are allowing the intercept of the logged expectation of $y_{jip}, j = 2, 3$, to shift with the observed number of watering days compared to the implicit baseline of zero outdoor watering. This implies a proportional change of $exp\left(\mathbf{d}_{ip}' \boldsymbol{\delta}_j\right)$ for the expectation in absolute terms. The importance of allowing each possible outcome in the watering frequency stage to have a separate effect on equations two and three will become apparent in our empirical application.

The model is completed by stipulating a joint density for the household effect:

$$\mathbf{u}_i = \begin{bmatrix} u_{i1} & u_{i2} & u_{i3} \end{bmatrix}' \sim mvn\left(\mathbf{0}, \mathbf{V}_u\right) \tag{5}$$

where mvn denotes the multivariate normal density, and the variance matrix is ex ante unrestricted. If this matrix contains non-zero covariances, a naïve model ignoring the linkage across the three equations would be plagued by endogeneity bias.[11]

Letting $\boldsymbol{\beta}_2 = \begin{bmatrix} \boldsymbol{\psi}_2' & \boldsymbol{\delta}_2' \end{bmatrix}'$, $\boldsymbol{\beta}_3 = \begin{bmatrix} \boldsymbol{\psi}_3' & \boldsymbol{\delta}_3' \end{bmatrix}'$, $\boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_1' & \boldsymbol{\beta}_2' & \boldsymbol{\beta}_3' \end{bmatrix}'$, and collecting all outcomes and explanatory data in vector $\mathbf{y}$ and matrix $\mathbf{X}$, respectively, the likelihood function for our model over all individuals $i = 1 \ldots N$, unconditional on error terms, takes the following form:

$$\begin{aligned} & p(\mathbf{y}|\boldsymbol{\beta}, \boldsymbol{V}_u, \boldsymbol{X}) = \\ & \prod_{i=1}^{N} \int_{\mathbf{u}_i} \left(\prod_{p=1}^{P} \left(\frac{\lambda_{1ip}^{y_{1ip}}}{y_{1ip}! \left(\sum_{k=0}^{U} \frac{\lambda_{1ip}{}^k}{k!} \right)} \lambda_{2ip} \lambda_{3ip} \exp\left(-\left(\lambda_{2ip} y_{2ip} + \lambda_{3ip} y_{3ip} \right) \right) \right) \right) \\ & f\left(\mathbf{u}_i | \mathbf{V}_u\right) d\mathbf{u}_i \end{aligned} \tag{6}$$

Given the N multi-dimensional integrals over $\mathbf{u}_i$ this model would be challenging to estimate using conventional Maximum Likelihood procedures. We therefore embark on a Bayesian estimation path, starting with the specification of prior distributions for our primary model parameters $\boldsymbol{\beta}$ and $\mathbf{V}_u$.

We choose a standard multivariate normal prior for $\boldsymbol{\beta}$, and inverse Wishart (IW) priors for $\mathbf{V}_u$, i.e. $\boldsymbol{\beta} \sim mvn\left(\boldsymbol{\mu}_0, \mathbf{V}_0\right)$, $\mathbf{V}_u \sim IW\left(\psi_0, \boldsymbol{\Psi}_0\right)$. The IW parameters are the degrees of freedom and scale matrix, respectively. The IW density is parameterized such that $E\left(\mathbf{V}_u\right) = \left(\psi_0 - k_r - 1\right)^{-1} \boldsymbol{\Psi}_0$. We facilitate the implementation of our posterior simulator (Gibbs Sampler) by augmenting the model with draws of the error components $\{\mathbf{u}_i\}_{i=1}^{N}$. A general discussion of the merits of this technique of data augmentation is given in Tanner and Wong (1987). Applications with data augmentation involving hierarchical count data models include Chib et al. (1998) and Munkin and

[11]Our primary reason for choosing individual random effects over fixed effects is that a considerable proportion of households in our empirical sample always select the same *number* of watering days throughout the entire time period. This would cause identification problems for the marginal effects of watering frequency in the HE part of the model.

Trivedi (2003).

The augmented posterior distribution is proportional to the priors times the augmented likelihood, i.e.

$$\begin{aligned} &p\left(\boldsymbol{\beta}, \mathbf{V}_u, \{\mathbf{u}_i\}_{i=1}^N,\ |\mathbf{y}, \mathbf{X}\right) \propto \\ &p(\boldsymbol{\beta}) * p(\mathbf{V}_u) * p\left(\{\mathbf{u}_i\}_{i=1}^N |\mathbf{V}_u\right) * p\left(\mathbf{y}|\boldsymbol{\beta}, \{\mathbf{u_i}\}_{i=1}^N, \mathbf{X}\right) \end{aligned} \tag{7}$$

The last term describes the likelihood function conditioned on all error terms. Thus, the data augmentation step circumvents the need to directly evaluate the integrals in (6).

The Gibbs Sampler draws consecutively and repeatedly from the conditional posterior distributions $p\left(\boldsymbol{\beta} \mid \{\mathbf{u}_i\}_{i=1}^N, \mathbf{y}, \mathbf{X}\right)$, $p\left(\mathbf{V}_u \mid \{\mathbf{u}_i\}_{i=1}^N\right)$, and $p\left(\{\mathbf{u}_i\}_{i=1}^N\ |\boldsymbol{\beta}, \mathbf{V}_u, \mathbf{y}, \mathbf{X}\right)$. Draws of $\boldsymbol{\beta}$ and $\{\mathbf{u}_i\}_{i=1}^N$ require Metropolis - Hastings (MH) subroutines in the Gibbs Sampler. Posterior inference is based on the marginals of the joint posterior distribution. The detailed steps of the posterior simulator and the Matlab code to implement this model are available from the authors upon request.

6. Estimation Results

6.1. Posterior results

The regressors in the parameterized expectation of the frequency equation include the home characteristics log of lot size in square feet (”lnland”), and log of tax-assessed land value (”lnvalue”), plus the climate variables ”mintemp” and ”maxtemp”, capturing, respectively, the weekly average of daily minimum and maximum temperature. Additional climate indicators are ”avgwind”, the weekly average of daily average wind (in knots), ”maxwind”, the weekly average of maximum daily sustained wind, and total weekly growing degree days (”gdd”). For a given calendar day, the latter is computed as (maximum daily temperature + minimum daily temperature)/2-50. All climate indicators are measured in units of 10 for a more balanced scaling of the regressor matrix. Equation one also includes an indicator for the 2010 irrigation season (”year2010”), as well as interaction terms between ”year2010” and the climate variables.

The parameterized mean functions for weekly use and peak (equations two and three) share the same set of explanatory variables. These include the home features from equation one, plus the log of square footage (”lnsf”), number of bedrooms, number of water fixtures, and age plus age squared. We also add the same climate variables as in equation one, except for "mintemp", "maxtemp", and "gdd", which are excluded for identification purpose.

Equations two and three also feature indicators for weekly watering frequency (the elements of $\mathbf{d}_{ip}$ in (3)) with zero as the implicit baseline, and frequencies beyond four days aggregated into a single category. The resulting binary variables are labeled as "freq1" through "freq567". These frequency indicators are implicitly associated with the year 2008 and the off-schedule watering type OS, as the "2010" effect is captured by interacting frequencies with "year2010", and the "SB" effect is highlighted via interactions of the "SB" indicator with the frequency variables. In addition, we also include the two-fold interaction of "SB", "year2010", and the frequency variables to examine if any incremental changes in frequency effects for "SB" over "OS" carry over into the 2010 season. By the same token, equations two and three also include interactions of climate variables with "year2010", and two-way interactions of wind measures with "year2010" and "SB". We scale both dependent variables in equations two and three to units of 10,000 gallons for a more efficient sampler performance.

We estimate all models using the following vague but proper parameter settings for our priors: $\boldsymbol{\mu}_0 = 0, \mathbf{V}_0 = 100 * I_k, \psi_0 = 5$, and $\boldsymbol{\Psi}_0 = I_3$. We first run the model using simulated data to assure the accuracy of our computational algorithm. For the actual estimation run we discard the first 20,000 draws generated by the Gibbs Sampler as "burn-ins", and retain the following 10,000 draws for posterior inference. We assess convergence of the posterior simulator using Geweke's (1992) convergence diagnostics (CD). These scores clearly indicate convergence for all parameters. To gauge the degree of (undesirable) serial correlation in our Markov chains we also compute autocorrelation coefficients at different lags for all model parameters. These AC values drop below 0.25 by the 10th lag for most parameters, and by the 20th lag for all model elements. This indicates that our posterior simulator has reasonably efficient mixing properties.

The posterior results for the frequency equation are shown in Table 8. The table also captures the results for the elements of the error variance matrix $\boldsymbol{\Sigma}$, expressed as standard deviations and correlations. We report posterior means, posterior standard deviations, and the probability mass of a given marginal posterior that lies above the zero-threshold. The latter provides an indication if the marginal effect of a given covariate is predominantly positive, negative, or ambiguous. In acknowledgment of the popular 5% level of significance in classical analysis, we will focus in our discussion of estimation results on posteriors that have at least 95% of mass in the positive or negative realm.

With the exception of "mintemp" all the elements of $\boldsymbol{\beta_1}$ satisfy this condition. The home features have the expected positive effect, as larger, more affluent properties are likely to have higher water needs, which - in part - are covered via higher watering frequency. The same holds for "maxtemp" and "gdd". An interesting pattern emerges with respect to "avgwind" and "maxwind". The former has a pronounced negative effect on weekly frequency, while the latter increases the expected count of weekly watering days. Moreover, these wind effects, as well as the effect of "maxtemp", cancel out or are slightly reversed for the 2010 season.

We interpret this pattern as follows: In 2008, most households set their automated sprinkler systems to a default twice / week schedule, with an early morning and a late afternoon application. Many customers then added additional watering days in a given week, either via manual watering or manually controlled sprinkler runs (the average weekly frequency for 2008 is 2.8). In weeks with high average winds, i.e. breezy conditions during both morning and evening hours, the *additional* application may have been foregone, which would explain the negative effect of "avgwind", relative to the typical weekly frequency. In contrast, in weeks with predominantly calm mornings and windy afternoons (a common pattern in our research area), some households may have skipped a planned afternoon run and defer it to the following morning, thus increasing the number of weekly watering days, as captured by our data. This would explain the positive effect of "maxwind", since maximum daily wind speeds almost exclusively occur during mid-late afternoon hours.

In 2010, the default baseline frequency via automated sprinkler irrigation moved to three days / week in reaction to the policy change for many customers (mean frequency = 3.09). This general increase in frequency is also evident from the positive coefficient for the "year2010" indicator. In this case *reducing* frequency during overall windy weeks (high "avgweek") would entail re-setting the automated system for many individuals, as opposed to foregoing an extra manual application (the 2008 scenario). The relatively higher transaction costs associated with the former compared to the latter would explain the diminished negative "avgwind" effect for the 2010 season. The reduced effect of "maxwind" may be related to the "flexibility" gain mentioned earlier. A windy afternoon application may or may not be canceled, but in any case there is a less pressing need to make up for lost irrigation the next morning, as the next *scheduled* irrigation event is at most two days away. Overall, then, these results suggest that climate conditions, especially wind, have a more pronounced effect on the variability of weekly watering days when the official OWR frequency ceiling is lower.

Turning to the elements of $\mathbf{\Sigma}$ in the lower half of Table 8, we note that with exception of ρ_{13} all terms are estimated with high precision (i.e. exhibit low posterior standard deviation relative to the mean). The standard deviations are of non-negligible magnitude, which confirms the presence of unobserved household effects in all three equations. These error components are highly correlated for equations two and three, as indicated by the posterior mean of ρ_{23} of close to one, and the accompanying minute posterior standard deviation. We also find a mild, positive correlation between the frequency and the use equations, as captured by ρ_{12}.

Table 8: Estimation results for frequency equation and error terms

	mean	std.	prob (>0)
constant	-4.415	(0.519)	0.000
mintemp	-0.050	(0.050)	0.161
maxtemp	0.151	(0.048)	0.999
avgwind	-0.988	(0.281)	0.000
maxwind	0.407	(0.134)	1.000
gdd	0.022	(0.012)	0.958
lnland	0.087	(0.007)	1.000
lnvalue	0.237	(0.010)	1.000
year2010	4.129	(0.731)	1.000
mintemp * 2010	-0.198	(0.064)	0.001
maxtemp * 2010	-0.395	(0.086)	0.000
avgwind * 2010	0.760	(0.295)	0.997
maxwind * 2010	-0.281	(0.139)	0.019
gdd * 2010	0.061	(0.019)	0.999
std.'s and corr.'s for $\mathbf{u}_i$			
σ_1	0.434	0.004	1.000
ρ_{12}	0.056	0.014	1.000
σ_2	0.477	0.005	1.000
ρ_{13}	-0.005	0.014	0.364
ρ_{23}	0.985	0.001	1.000
σ_3	0.527	0.005	1.000

Posterior results for the weekly use and peak equations are summarized in Table 9. We will focus again on posteriors that lie primarily in the positive or negative realm. Regarding weekly use, the table captures four main results: First, and confirming our previous descriptive findings, consumption increases clearly with weekly frequency. This is evident from the monotonically increasing posterior means for "freq1" to "freq567". Furthermore, this result remains essentially unchanged in 2010, as can be gleaned from the near-zero means for the frequency interactions with the "year2010" indicator. Second, again supporting our descriptive results above, weeks associated with schedule-based (SB) watering exhibit increased use compared to the implicit off-schedule (OS) baseline at *any* frequency. These rigidity penalties amount to 20-23%[12], and are highest for weeks that follow the official schedule exactly ("SB * freq2"). This "SB" effect is reduced by 30-40% in 2010, a judged by the posterior means of the "SB * freq * 2010" interactions, although a considerable portion of the posterior distribution for these coefficients lies in the positive realm. Third, once we account for weekly frequency, climate effects become of secondary importance, as indicated by the relatively small posterior means and lack of posterior precision for virtually all climate indicators and their interactions. Fourth, controlling for frequency and watering pattern, the residual policy effect, as captured by the "year2010" indicator, is of negligible magnitude compared to the overall constant term, and estimated with low posterior precision.

The results for weekly peak are given in the last three columns of the table. In contrast to use, and confirming our descriptive findings above, peaks do not change much over frequency in either year, and are substantially larger for SB-type weeks compared to OS-type patterns. As can be seen from the "SB * freq" interactions, this differential increases again with decreasing weekly frequency, from approximately 26% at "freq567" to over 46% at "freq2". Focusing on the 2010 interactions, we note that while peaks tend to be slightly higher for OS-type weeks in 2010 compared to 2008[13], they decrease by 18-23% for SB-type implementations compared to the 2008 season. This supports the descriptive results in Table 6 for the SB group, and is consistent with the consumption patterns depicted in Figure 2. The remaining findings for the peak model mirror those from the weekly use equation: climate effects play only a secondary role, and there are no noteworthy residual policy effects ("year2010").

[12] We use the conversion formula of $exp(\beta) - 1$ suggested by Halvorsen and Palmquist (1980) to interpret marginal effects associated with binary variables, given the log-normal form of the parameterized mean function.

[13] This is likely due to a "transition" effect, with a considerable segment of former SB-type customers watering on the old (i.e. now wrong) assigned days-of-week. Such weeks would be captured as OS-type in the 2010 data, but would exhibit SB-type peaks.

Table 9: Estimation results for use and peak equations

	weekly use			weekly peak		
	mean	std.	prob(>0)	mean	std.	prob(>0)
constant	-10.766	(0.773)	0.000	-12.706	(0.766)	0.000
freq1	0.392	(0.025)	1.000	0.883	(0.026)	1.000
freq2	0.584	(0.025)	1.000	0.980	(0.026)	1.000
freq3	0.720	(0.026)	1.000	0.989	(0.027)	1.000
freq4	0.821	(0.029)	1.000	0.992	(0.031)	1.000
freq567	0.967	(0.036)	1.000	1.048	(0.036)	1.000
SB * freq2	0.208	(0.066)	1.000	0.379	(0.068)	1.000
SB * freq3	0.197	(0.066)	0.999	0.334	(0.068)	1.000
SB * freq4	0.179	(0.068)	0.995	0.307	(0.071)	1.000
SB * freq567	0.200	(0.071)	0.999	0.233	(0.072)	0.999
lnland	0.389	(0.010)	1.000	0.439	(0.011)	1.000
lnsf	0.170	(0.033)	1.000	0.154	(0.036)	1.000
lnvalue	0.294	(0.028)	1.000	0.344	(0.030)	1.000
fixtures	-0.002	(0.003)	0.324	-0.005	(0.004)	0.079
bedrooms	0.042	(0.009)	1.000	0.032	(0.009)	1.000
age	0.218	(0.011)	1.000	0.280	(0.012)	1.000
age2	-0.020	(0.001)	0.000	-0.025	(0.002)	0.000
avgtemp	0.051	(0.081)	0.735	-0.007	(0.079)	0.470
avgwind	-0.070	(0.453)	0.442	-0.064	(0.462)	0.453
maxwind	0.050	(0.184)	0.615	0.008	(0.188)	0.506
avgwind * SB	-0.222	(0.563)	0.349	0.002	(0.575)	0.500
maxwind * SB	0.032	(0.199)	0.567	-0.058	(0.204)	0.386
year2010	0.185	(0.740)	0.593	-0.178	(0.730)	0.403
freq1 * 2010	-0.010	(0.036)	0.393	-0.009	(0.036)	0.385
freq2 * 2010	0.034	(0.035)	0.837	0.073	(0.035)	0.978
freq3 * 2010	0.045	(0.036)	0.895	0.071	(0.036)	0.977
freq4 * 2010	0.053	(0.041)	0.901	0.092	(0.041)	0.990
freq567 * 2010	0.038	(0.049)	0.786	0.064	(0.048)	0.909
SB * freq3 * 2010	-0.052	(0.144)	0.361	-0.257	(0.147)	0.039
SB * freq4 * 2010	-0.049	(0.146)	0.357	-0.244	(0.150)	0.049
SB * freq567 * 2010	-0.041	(0.147)	0.395	-0.200	(0.151)	0.088
avgtemp * 2010	-0.025	(0.082)	0.391	0.016	(0.080)	0.583
avgwind * 2010	0.333	(0.486)	0.76	0.515	(0.500)	0.848
maxwind * 2010	-0.109	(0.187)	0.258	-0.143	(0.192)	0.240
avgwind * SB * 2010	-0.020	(0.063)	0.372	-0.033	(0.065)	0.304
maxwind * SB * 2010	0.010	(0.021)	0.688	0.021	(0.021)	0.837

6.2. Predictive analysis

For a more direct comparison of weekly consumption and peak across weeks with different watering patterns we generate posterior predictive densities (PPDs) for each irrigation type (SB vs. OS) and the predominant frequencies of two, three, and four watering days. Formally, these PPDs are given as

$$p\left(y_j \mid \mathbf{x}_{\mathrm{tf}}\right) = \int_{\boldsymbol{\theta}} \left(\int_{u_{ij}} \left(\left(y_j \mid \mathbf{x}_{\mathrm{tf}}, \boldsymbol{\beta}, u_{ji}\right) f\left(u_{ji} \mid \mathbf{V}_u\right) \right) d\, u_{ij} \right) p\left(\boldsymbol{\theta} \mid \mathbf{y}, \mathbf{X}\right) d\,\boldsymbol{\theta}, \quad j = 2, 3, \tag{8}$$

where $\mathbf{x}_{\mathrm{tf}}$ denotes a specific combination of watering pattern t$\in \{SB, OS\}$ and frequency f$\in \{2, 3, 4\}$, and vector $\boldsymbol{\theta}$ comprises the entire set of model parameters. Climate and property characteristics are set to their pooled-data sample mean.[14] In practice, we simulate these PPDs by (i) drawing 10 random coefficients from $f\left(u_{ji} \mid \mathbf{V}_u\right)$), (ii) computing λ_{ij} for each u_{ij} as given in (2), and (iii) drawing y_j from the exponential density with expectation λ_{ij}. We repeat steps (ii) and (iii) for all 10 draws of u_{ij}, and steps (i) through (iv) for all 10,000 draws of $\boldsymbol{\theta}$ from the original Gibbs Sampler.

Except for the combination t=SB, f=2, which is only meaningful for 2008, we derive separate PPDs for $y_j \mid \mathbf{x}_{\mathrm{tf}}$ for 2008 and 2010 by setting the 2010 indicator and interaction terms accordingly in the covariate matrix for the use and peak equations. However, since after controlling for climate, property features, watering pattern, and frequency there remains no inherent difference between watering behavior across the two years, we then combine these year-specific PPDs for final analysis. Overall, we thus obtain 100,000 draws of $y_j \mid \mathbf{x}_{SB,2}$ and 20,000 draws for all other combinations.

The resulting PPDs are depicted in Figure 3 for use and Figure 4 for peak. Each subplot shows PPDs for SB and OS types for a given frequency. Posterior predictive expectations are superimposed as vertical lines and labeled with their respective numerical value. As is evident from Figure 3, the SB pattern produces higher expected use than the OS pattern at all frequencies, with a slightly decreasing relative gap from 14% at f = 2 to 12% at f = 4. As shown in Figure 4 these differences in posterior predicitive expectation are even more pronounced for peak, as is the diminishing trend in gap from lower to higher frequency. Specifically, at two watering days, the SB pattern generates a peak that is approximately 28% higher than the

[14] These settings are as follows: "lnland" = 8.95, "lnsf" = 7.48, "lnvalue = 12.13, "fixtures" = 11.56, "bedrooms" = 3.25, "age" = 22.04, "avgtemp" = 75.73, "avgwind" = 5.45, and "maxwind" = 16.48.

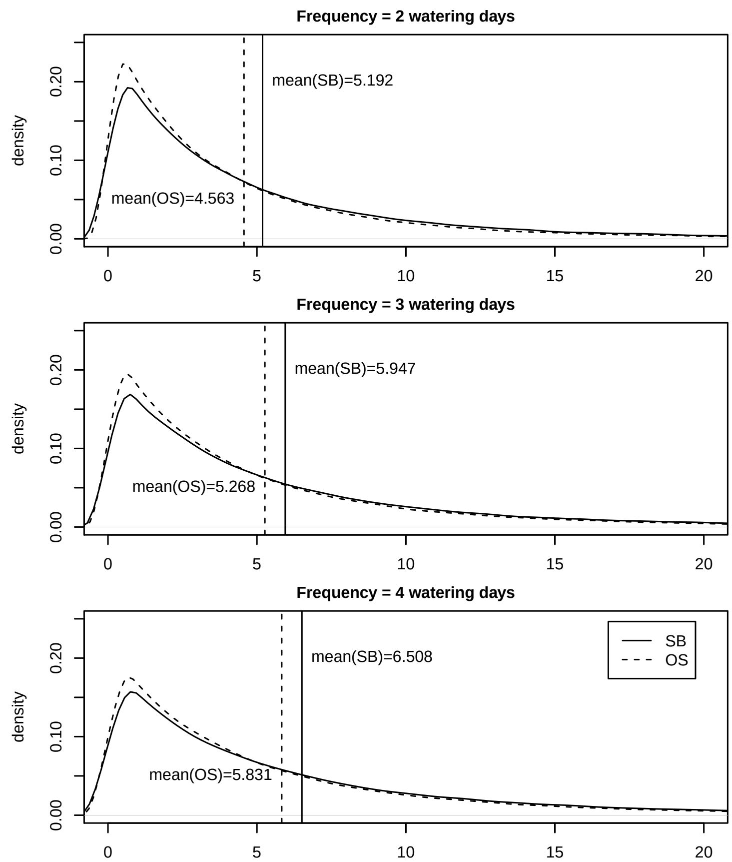

Figure 3: Predictive distributions of weekly use for a typical household (1000 gallons)

OS peak. At three watering days, this difference reduces to 22%, and at a frequency of four it amounts to close to 18%.

The figures also illustrate that the predictive densities for the two types differ little in their tail behavior. There is an approximately equal probability of high-volume outcomes for both patterns. The differences in distributional shape are more pronounced at lower consumption levels, say below 4,000 gallons for use, and 1,000 gallons for peak. At any watering frequency, there is a substantially higher probability for a typical household following an OS pattern to have a lower consumption level than the same household implementing an SB schedule.

Overall, these predictive results support our descriptive findings above. After controlling for climate and property characteristics, a watering pattern that closely follows the officially assigned days still produces noticeably higher weekly consumption and substantially higher peaks than a more flexible distribution of *the same number of watering days* across a given week.

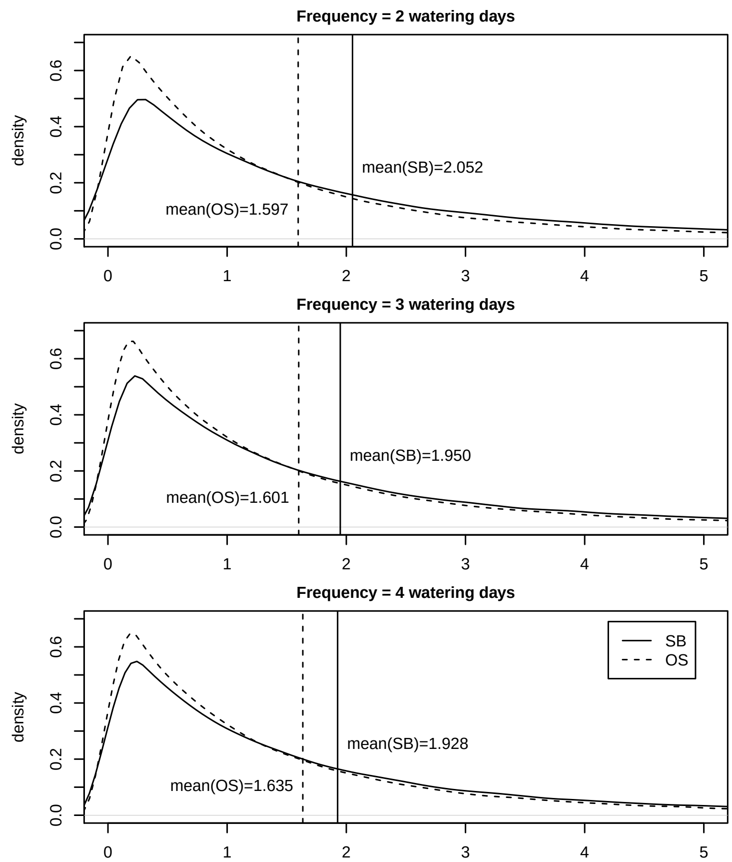

Figure 4: Predictive distributions of weekly peak for a typical household (1000 gallons)

6.3. Policy simulation

So far our results suggest that a more relaxed OWR, allowing households to choose their own watering days within the current weekly quota of three should reduce both weekly use and peak for the typical household. We can examine this conjecture more formally by generating PPDs that fit such a policy scenario. We start by assuming that the current 2010 proportion of weeks with frequencies under two and above four would remain constant under the new policy. This leaves the tf-categories $OS2$, $SB3$, $OS3$, $SB4$, and

$OS4$ for further examination. This group comprises 70% of all observations for the 2010 data set.

We consider two scenarios in terms of how the existing proportions of these t/f combinations may change under the new OWR. For each scenario we generate a mixture PPD by drawing from the type / frequency specific PPDs from the previous analysis with relative probabilities equal to stipulated population weights. We compare the resulting scenario-specific PPDs to the PPD for the status quo, which employs empirical sampling weights for 2010 in the mixture. The status quo weights for the five t/f combinations listed above are $\mathbf{w_{sq}} = [0.24, 0.37, 0.18, 0.11, 0.10]$. For both scenarios 1 and 2 we assume that 50% of existing $OS2$-type weeks will become $OS3$. This is a conservative strategy, allowing for the possibility that some 2010 customers were still habitually following the old twice / week schedule, and that they would switch to three watering days in the near future. In addition, scenario 1 stipulates for 50% of current $SB3$ and $SB4$ weeks to turn, respectively, into $OS3$ and $OS4$ patterns. This yields weight vector $\mathbf{w_{sc1}} = [0.12, 0.185, 0.485, 0.055, 0.155]$. Scenario 2 envisions a complete switch of all SB types to a respective OS pattern at unchanged frequency, resulting in $\mathbf{w_{sc1}} = [0.12, 0, 0.67, 0, 0.21]$. Thus, scenario 1 can be interpreted as a transition season, while scenario 2 could become the new long-run status quo.

The results from this simulation are captured in Table 10. The first two columns show the mean and standard deviation of predicted use and peak for the typical household and weather conditions. The third column depicts the percentage reduction in mean outcomes compared to the status quo for the specific sub-group under consideration ($OS2$, $SB3$, $OS3$, $SB4$, and $OS4$). Scaling these figures by 0.7 yields a translation of this reduction in system-wide terms. The final column expresses system-wide savings in terms of the equivalent number of customers. For weekly use this figure was derived by multiplying system-averaged per-household savings by the total number of customers served by the utility in 2010 (69,500), and dividing by the mean weekly use observed for our 2010 sample (4,820 gallons). For weekly peak we multiply system-averaged per-household savings by 1/7 of the total customer base (conservatively assuming a uniform distribution of peaks across week days), and divide by 1,410, the observed 2010 sample average for peak days.

Under transition scenario 1, system-wide savings in consumption are expected at 0.89%, which would be equivalent to taking 713 households off the utility grid. Under scenario 2, which essentially stipulates that all customers in the 2-4 frequency range will follow a more flexible weekly watering pat-

Table 10: Predicted weekly use and peak under a flexible 3-day OWR

	use (1000 gallons)				
	mean	std.	% less group	% less system	customer equivalent
s.q.	5.524	(6.819)	-	-	-
scen. 1	5.453	(6.732)	1.28%	0.89%	713
scen. 2	5.301	(6.535)	4.03%	2.82%	2,246
	peak (1000 gallons)				
	mean	std.	% less group	% less system	
s.q.	1.767	(6.819)	-	-	-
scen. 1	1.684	(6.732)	4.68%	3.28%	408
scen. 2	1.608	(6.535)	8.97%	6.28%	781

tern, system-wide savings increase to 2.82%, or an equivalent of over 2,200 households. For predicted peak, expected sytem-wide savings exceed 3% for scenario 1, and 6% for scenario 2. In the first case, this is equivalent to taking over 400 households that would have had their peak use that day off the grid. This figure almost doubles for scenario 2.

In summary, these policy simulations indicate that there could be substantial conservation gains from relaxing the assigned-day component of the existing OWR, even if the frequency cap is left unchanged. In addition, the expected lower peaks would allow for a more cost-effective water delivery, thus translating into further savings to the utility and its customers.

7. Conclusion

This study is the first to examine the impact of design features of outdoor watering restrictions on residential water use. Benefitting from a unique data set of daily consumption at the household level over multiple irrigation seasons, an inter-season policy change, and a diverse set of weekly watering patterns, we arrive at several important and novel findings. In a nutshell, both the cap on weekly frequency *and* the address-based assignment of specific watering days matter for conservation outcomes. While the former is confirmed to be necessary for curbing consumption, the latter leads to usage inefficiency and thus undermines conservation goals.

Specifically, we find that regardless of weekly watering pattern higher frequencies unambiguously translate into higher weekly use for the typical customer. This confirms the results from virtually all existing OWR studies. However, and this constitutes the key result from our analysis, weekly use and peak depend crucially on how closely a given household follows the DoW assignments. Specifically, we find a substantial "rigidity penalty" in both use and peak for schedule-adherent watering patterns, regardless of overall frequency. We interpret this finding as a regulation-imposed mandate to ignore time-varying natural conditions for the timing of yard irrigation. Supporting this notion, we find that schedule-based weekly patterns are more prone to coincide with windy conditions, which can lead to major water losses.

The policy change from two to three assigned days per week produced two main effects: First, it induced the intended switch from watering patterns based on two assigned days to patterns including three assigned days for a considerable segment of customer-weeks. Second, for this schedule-based contingent we observe a clear reduction in peaks at any frequency compared to schedule-based weeks prior to the policy. This also leads to a pronounced reduction in peaks at the system-wide level. In contrast, overall weekly use changes little in reaction to new policy, regardless of the degree of schedule-adherence. In combination, these findings suggest that the primary effect of the new policy lied in inducing many customers to spread an essentially unchanged amount of automated sprinkler irrigation over a larger number of week days.

While this policy change can thus be considered a step in the right direction, it did not fully eliminate the rigidity penalty for peak and only slightly alleviated the rigidity penalty for overall weekly use. All of our results - descriptive, analytic, and predictive, point to the potential for additional conservation gains by relaxing the assigned-day component of the regulation. We predict that such a modification, once adopted by all current schedule-adherent customers, could lead to an additional reduction in system-wide use of 2-3%, and decrease daily peaks by over 6%.

Naturally, several caveats remain. Most importantly, a "frequency-cap-only" policy would undoubtedly be more difficult to enforce than a regulation based on assigned days. One would have to literally monitor a given residence's entire week of irrigation activities to detect any violation. In addition, the current system may benefit from "police-thy-neighbor" effects, where customers more or less follow the OWRs to avoid a loss in neighborly goodwill and social standing. These self-policing effects would likely be diminished under the flexible-day implementation.

Furthermore, while intuition and our data suggest that the observed rigidity penalty is related to a reduced avoidance of adverse wind conditions, determining its exact composition would require a survey-based analysis of household watering decisions. This would also provide insights into the potential for the utility to enhance "wind awareness" before or in conjunction with the implementation of a flexible-day schedule.

If wind is indeed the main driver of this inefficiency, our results should at least generalize to other wind-prone areas in the south-west and beyond. Thus, adjusting existing OWRs according to our findings could produce substantial region-wide water savings at relatively low implementation costs. Our findings also cast doubt on the effectiveness of existing policies that reduce the number of assigned days under progressively severe drought conditions, as inefficiency penalties are highest at low frequencies. A frequency reduction combined with a "choose-your-days" policy is likely to produce superior conservation outcomes in such cases.

Appendix A. Outdoor watering restrictions in the United States

Table A.11: Examples of cities with outdoor watering restrictions (as of June 1, 2010)

city	population (1000s)	utility	restriction period	time-of-day restrictions	days per week restrictions for sprinklers	assigned watering days for sprinklers	other restrictions	special rules for manual watering
				CALIFORNIA				
Los Angeles	4,095	L.A. Dept. of Water and Power	ongoing, since June 2009, year-round	no watering 9am - 4pm	2 days / week	Mo, Thu only, all addresses	15 min. max. runtime per cycle	none
San Diego	1,376	The City of San Diego	ongoing since June 1, 2009, restrictions change across seasons	no watering 10am - 6pm	3 days / week	assigned by address	10 min. max. run-time per cycle	no restrictions on run-time
Fresno	505	City of Fresno	ongoing, restrictions change across seasons	no watering 6am - 7pm	3 days / week	assigned by address	restrictions on landscaping (no bluegrass)	none
Long Beach	495	Long Beach Water	ongoing	no watering 9am - 4pm	3 days / week	Mo, Thu, Sat only, all addresses	10 min. max. run-time per cycle	none
				NEVADA				
Las Vegas	478	Las Vegas Valley Water District	ongoing, since 2002, restrictions change across seasons	no watering 11am - 7pm (summer only)	3 days / week (spring, fall only)	assigned by address	none	allowed any time, any day
Reno /Sparks	419	Truckee Meadows Water Authority	ongoing, since 1996, summer only	no watering noon - 6pm	3 days / week[a]	assigned by address	none	allowed any time, any day

(continued on next page)

[a] 2 days 1996 - 2009, 3 days as of 2010

Table A.11, continued

city	population (1000s)	utility	restriction period	time-of-day restrictions	days per week restrictions for sprinklers	assigned watering days for sprinklers	other restrictions	special rules for manual watering
				COLORADO				
Denver	555	Denver Water	May 1 - Oct. 1	no watering 10am - 6pm	none	N/A	no watering during strong winds or rain; limitations on run-time per cycle	none
				TEXAS				
Dallas	1,189	Dallas Water Utilities	April 1 - Oct. 31	no watering 10am - 6pm	none	N/A	no watering during rain	allowed any time, any day
San Antonio	1,145	San Antonio Water System	year-round (severity of restrictions based on aquifer level)	no watering 10am - 8pm	1 day / week ("Stages 1, 2")	assigned by address	none	allowed any time, any day
Austin	657	Austin Water	ongoing, since Nov.21, 2009	no watering 10am - 7pm	2 days / week	assigned by address	none	allowed any time, any day
				GEORGIA				
Entire State placed under non-drought schedule as of June 1, 2010	9,829	Environmental Protection Division	ongoing, since June 1, 2010 (restrictions become more severe during declared drought)	none	3 days / week	assigned by address	none	none

(continued on next page)

Table A.11, continued

city	population (1000s)	utility	restriction period	time-of-day restrictions	days per week restrictions for sprinklers	assigned watering days for sprinklers	other restrictions	special rules for manual watering
				FLORIDA				
Jacksonville	835	St. John's River Water Management District	ongoing, restrictions change across seasons	no watering 10am - 4pm	2 days / week (summer schedule)	assigned by address	60 min. max. run-time per cycle	none
Miami	391	Miami - Dade Water and Sewer Department	ongoing, year-round	no watering 10am - 4pm	2 days / week (summer schedule)	assigned by address	none	allowed daily for 10 min.
Tampa	331	City of Tampa Water Department	ongoing, year-round	no watering 10am - 6pm	1 day / week	assigned by address	only one cycle allowed per day	same as sprinkler rules for lawns, else unrestricted

Appendix B. Identification of outdoor watering days

Our identification of outdoor watering days thus proceeds in the following steps:

1. We start with a simple K-means clustering algorithm (MacQueen, 1967) at the household level to classify each day as a "high use" or "low use" occurrence. Our objective is to confidently interpret high use days as days with outdoor irrigation, and low-use days as days with strictly non-irrigation consumption. We use six different clustering algorithms. The first three are based on actual daily use, the second set of three on logged use.[15] Within each set, the first algorithm uses the Euclidean distance between observation points and the current pair of cluster centroids as a sorting criterion, the second uses Euclidean distance squared, and the third absolute distance (Vinod, 1969; Massart et al., 1983). In each case we use the mean consumption on assigned and unassigned days, respectively, as starting values for the cluster centroids.

   We find that within each triplet all three algorithms agree on sorting for every single observation in both the 2008 and 2010 data sets. This indicates robustness to the choice of similarity measure, which is reassuring. As expected, the versions based on logged use, which are less sensitive to outliers and thus lower the threshold for observations to fall into the higher category, identify about 10-15% more observations as watering days than the versions based on actual use in gallons in each data set.

   However, *all six versions* are in complete agreement for all daily observations associated with 1644 (18.8%) of households in 2008, and 890 households (11.7%) in 2010. These are likely customers that exclusively water via automated sprinkler systems, producing very pronounced differences in usage between irrigation and non-irrigation days. Within these subgroups, the sorting into watering and non-watering days perfectly aligns with *assigned* watering days for 604 (6.9%) of customers in 2008, and 422 (5.5%) of customers in 2010. For these households we can be especially confident that the observations flagged as non-watering days truly and exclusively capture indoor, or non-irrigation, use. In the following, we label these households as "Full Agreement, Full Compliance" (FAFC) cases.

[15] We add an increment of one gallon to each zero-usage observation before taking logs

An inspection of sample statistics on basic building and lot characteristics assures us that these FAFC cases are not systematically different in measurable ways from the remainder of the data set.[16] Thus, we deem them suitable as a representative sub-sample that provides reliable and important information on non-irrigation use.

2. Our next goal is to utilize information on winter use and the fact that the Reno/Sparks climate precludes any water use for outdoor irrigation during the cold season to validate the cluster analysis results. Specifically, using available data on monthly consumption during the January-March period preceding our summer data collections, we compute *average daily winter use* and the ratio of daily summer use to average daily winter use for each household in both data sets. Focusing again on the FAFC observations, we then inspect the sample distribution of this ratio for unassigned days. For 2008, the mean and standard deviation for this ratio amount to 2.3 and 2.4, respectively. For 2010, the mean equals 1.85, and the standard deviation is 1.7. According to TMWA, indoor use is higher in summer for the typical household due to factors such as a larger average daily household size as school and college-age children spend more time at home, a higher level of outdoor and athletic activities, increasing water use for drinking, cleaning, laundry, and showers, increased use for the watering of indoor plants, and water use for cooling units. The lower average for 2007 is likely due to the slightly cooler summer that year, as described in the main text.

3. We interpret the above results as indicative of the typical household in the Reno/Sparks area consuming approximately twice as much water per day for non-irrigation purposes in summer than in winter. Based on the standard deviations for the FAFC segment given above, we would further expect daily non-irrigation use *for any household* not to exceed a ratio to winter use in excess of $3 * 2.4 = 7.2$ in 2008 and of $3 * 1.7 = 5.1$ in 2010.

4. For our final classification step we generally adopt the cluster analysis results based on absolute use, but we recode all observations flagged as “non-watering” days that exceed the three-standard deviation thresholds given above as “watering days”. This results in 19,479 changes

[16] These comparison tables are available from the authors upon request

(8.2% of observations originally flagged as non-watering) for the 2008 data, and 17,818 changes (8.6% of observations originally flagged as non-watering) for the 2010 set. These recoded observations are likely associated with households that employ some *daily* baseline watering system, as mentioned above. Due to the latency of the baseline irrigation the cluster analysis fails to identify these non-sprinkler days as irrigation days. Adding information on winter use to our analysis allows us to correct this shortcoming.

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Free to Choose: Promoting Conservation by Relaxing Outdoor Watering Restrictions

Anita Castledine
Klaus Moeltner
Michael K. Price
Shawn Stoddard

Presented the inaugural summer conference of the Association of Environmental and Resource Economists, Seattle, June 9-10, 2011

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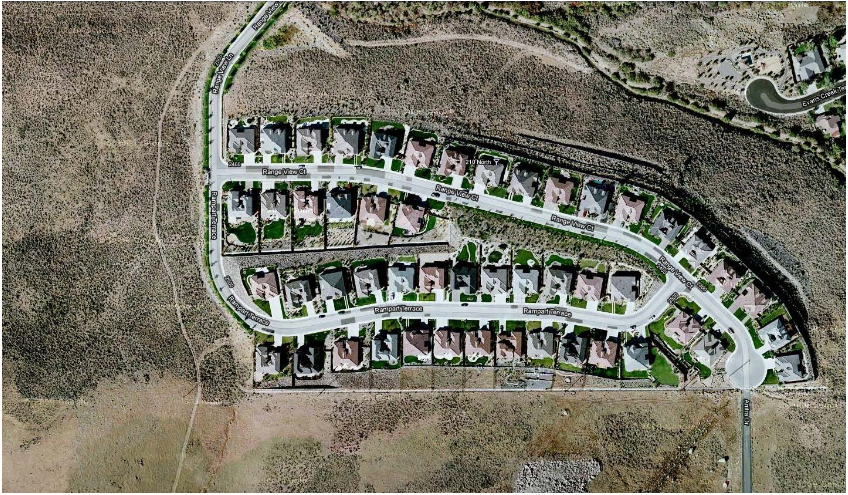

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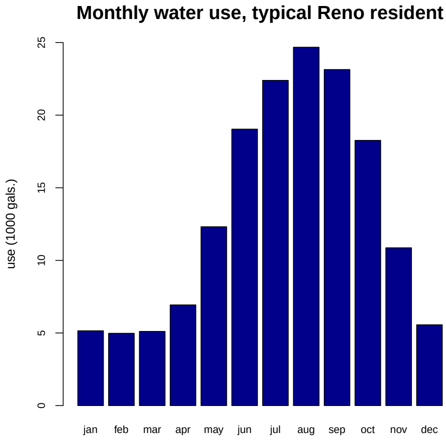

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s and 70s), watering one day a
mperatures rise (80s and 90s),
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luring the hottest part of the
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n, but evaporation is high. In
ces prohibit watering between
rough Labor Day.

local evapotranspiration (ET)
information can be found at

ubs

r, it is ideal to keep trees out of
round trees and shrubs to hold
rovide good drainage. Newly
must have the emitters located
g area. However, as the tree
ated outward, toward the tree's
that trees and shrubs require

munityforestry.org.

established. If you're planting
od, it's wise to do it in the spring
cooler and there is less stress
s to obtain a 6-week watering
w lawns. To obtain a variance,
834-8005.

Guide to Assigned-Day Watering and Lawn Care in the Truckee Meadows

Here in the high desert, lawns and other plants need strong root systems to stay healthy. This guide is designed to help you keep your yard green and healthy throughout the year, while encouraging responsible water use at all times.

During the summer, demand on the water system is extremely high. Our customers' water usage increases 400%—or about 100 million gallons per day system wide. Outdoor watering is the primary reason for this increase. Therefore, it is especially important for all customers to manage their usage during the summer. The Assigned-Day watering program is the cornerstone for efficient water management throughout the year. A direct benefit of the program is the balance and management of peak-day consumption throughout our water system. This has helped Truckee Meadows Water Authority (TMWA) avoid costly facility expansions that would increase rates for all our customers. As an added bonus, responsible water use at home and at work saves money on your water bill.

Customers often wonder if the water we save is used for growth. The answer is no. Water saved by current residents is not allowed to be used for growth. The unused water is retained for drought reserves or stays in the Truckee River. It cannot be re-allocated for new homes or buildings.

So, when preparing and irrigating your yard throughout the year, be sure to follow these helpful tips. You will keep your landscape healthy and water demands down for the entire community, all while saving money on your bill.

Questions?
For more information, visit our Web site at **www.tmh2o.com**. Expert advice on gardening can be found by calling the **University of Nevada Cooperative Extension** at **784-4848**.

Mon Tue Wed Thu Fri Sat Sun

Assigned-Day Watering

easy as 1·2·3

Even Odd

- **No watering** between **noon and 6 p.m.** from Memorial Day through Labor Day.
- **Mondays** are a **no-watering day** to replenish and maintain the water system.
- Please don't water when it's raining or windy, or when temperatures are too high.
- Check your irrigation clock routinely and adjust according to watering needs.

TRUCKEE MEADOWS WATER AUTHORITY
Quality. Delivered.

March 2010

Guide to Assigned-Day Watering and Lawn Care in the Truckee Meadows

TRUCKEE MEADOWS WATER AUTHORITY
Quality. Delivered.

Truckee Meadows Water Authority is a not-for-profit, community-owned water utility, overseen by elected officials and citizen appointees from Reno, Sparks and Washoe County.

www.tmh2o.com

Outdoor Watering Restrictions

- Standard DSM tool in many communities
- More effective than price signals
- Politically palatable
- Likely to grow in popularity
  (increasing storage costs under global warming)

Motivation

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- No existing research on optimal design of OWRs
- Exploit local policy change
  (2 assigned days $\rightarrow$ 3 assigned days)
- Exploit rich variation in weekly watering patterns

Main questions

- Did policy change affect weekly use?
- Did policy change affect weekly peaks?
- Do households that follow policy conserve more?

Main findings

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- Policy change did not affect consumption.
- Policy change lowered peaks.
- Households that follow policy more closely use more water, have higher peaks.
- This holds under old and new policy, at any weekly frequency.

Policy recommendations

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- Frequency cap is is necessary to curb consumption
- Assigned weekly watering days is counter-productive
- Let households choose their watering days

Data

- Daily consumption (drive-by remote readings)
- summer 2008: 8,747 HHs, 52,666 obs.
- summer 2010: 7,652 HHs, 48,573 obs.
- overlap: 1,766 HHs, $\sim$ 10,000 obs. / year

Data

- 2008: 2 assigned days / week
- 2010: 3 assigned days / week
- "mild" enforcement
- no restrictions on hand watering

Identification of watering days

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- K-means Cluster Analysis
- Separate for each household
- Augmented with info on winter use

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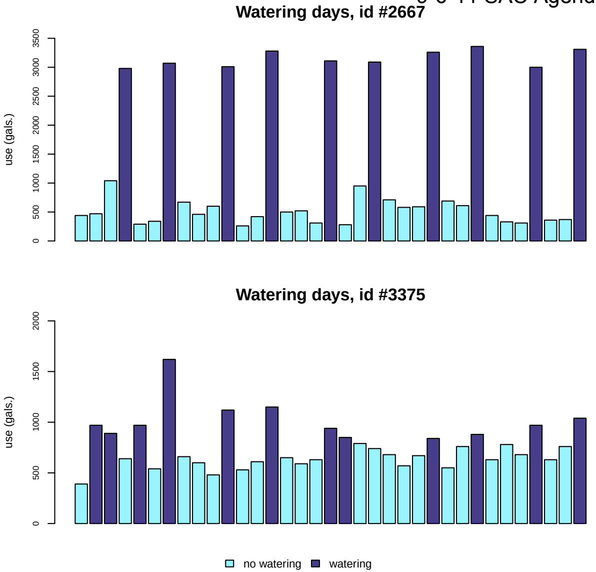

Sample composition

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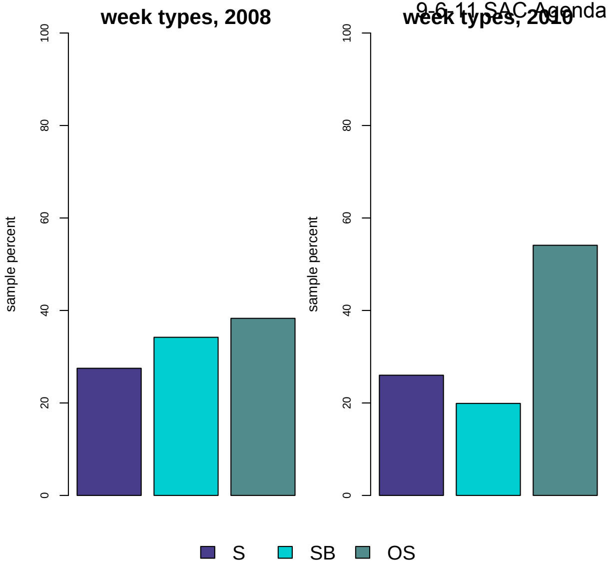
- Typical household has a variety of weekly watering patterns
- We group them into schedule-based, SB and off-schedule, OS
- SB: assigned days, plus ≥ 0 additional days
- OS: at least 1 assigned day is skipped
- SB also includes category S, a perfectly schedule-consistent week


week types, 2008
week types, 2010
sample percent
0
20
40
60
80
100
S
SB
OS

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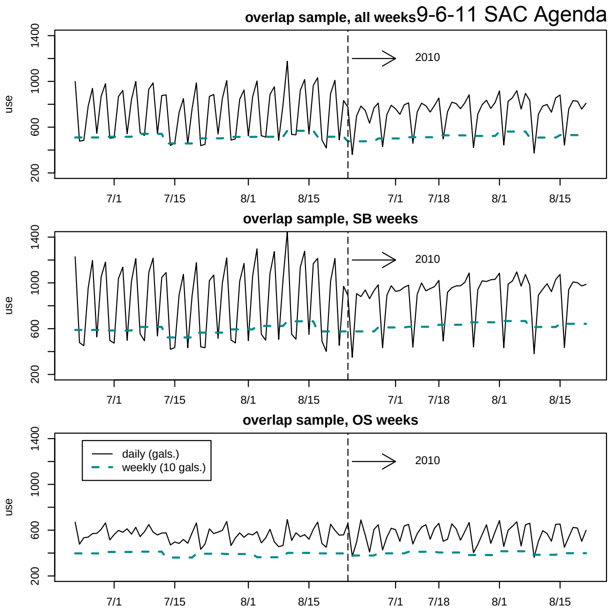

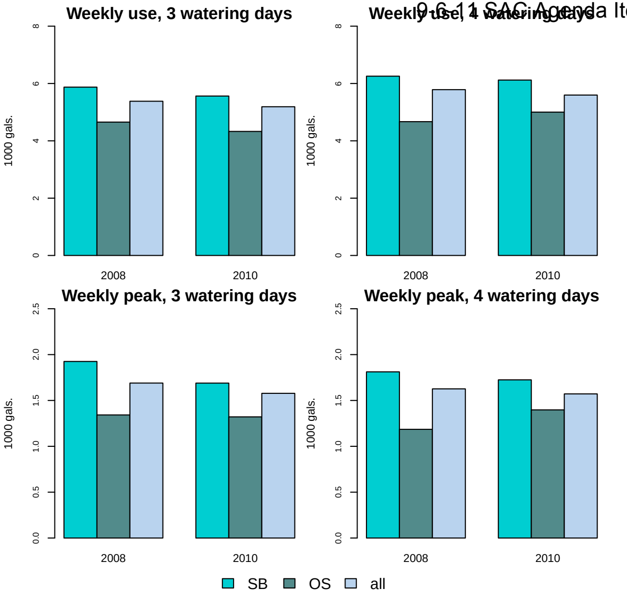
Weekly use, 3 watering days
Weekly use, 4 watering days
Weekly peak, 3 watering days
Weekly peak, 4 watering days
1000 gals.
0
2
4
6
8
0.0
0.5
1.0
1.5
2.0
2.5
2008
2010
SB
OS
all

weekly irrigation scheme by household i in period p:

$$I_{ip} = I\left(y_{1ip}, y_{2ip}, y_{3ip}, SB_{ip}\right), \quad i = 1, \ldots N, \quad p = 1 \ldots P$$

y_{1ip} = frequency (number of watering days)
y_{2ip} = weekly use
y_{3ip} = weekly peak
SB_{ip} = indicator for "schedule-based"

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Correlated triple-equation system:

$$y_{1ip} = HTP\left(\mathbf{h}, \mathbf{x}, \boldsymbol{\theta}_{\mathbf{1}}, u_{i1}\right)$$
$$y_{jip} = HE\left(\mathbf{h}, \mathbf{x}, y_{1ip}, SB_{ip}, \boldsymbol{\theta}_{\mathbf{j}}, u_{ij}\right) \quad j = 2, 3$$
$$\mathbf{u}_i = \begin{bmatrix} u_{i1} & u_{i2} & u_{i3} \end{bmatrix}' \sim mvn\left(\mathbf{0}, \mathbf{V}_u\right)$$

"HTP" = Hierarchical Truncated Poisson
"HE" = Hierarchical Exponential
u_{ij} = unobserved household effect

Estimation confirms descriptive results

- consumption increases with frequency, peaks stay flat
- SB-type has 20% higher use than OS-type at same frequency
- SB-type has 30-40% higher peak than OS-type at same frequency
- peaks are reduced for SB-types in 2010

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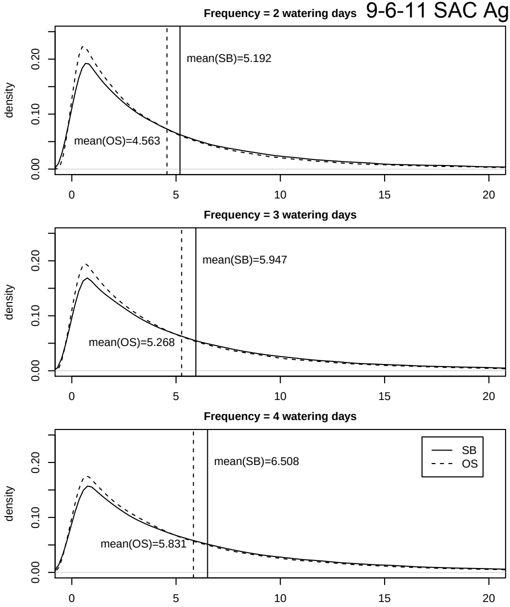

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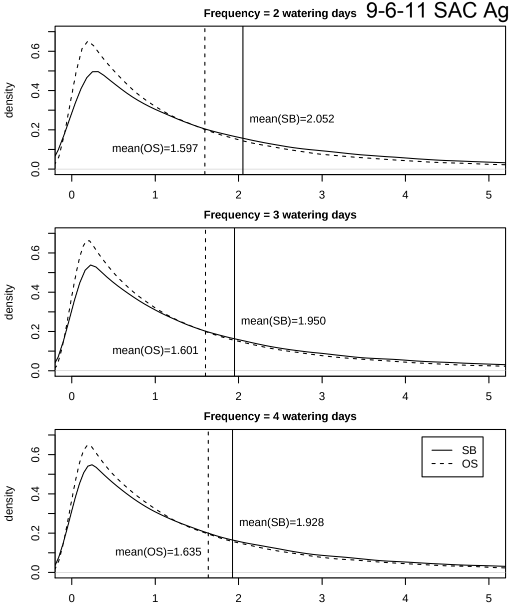

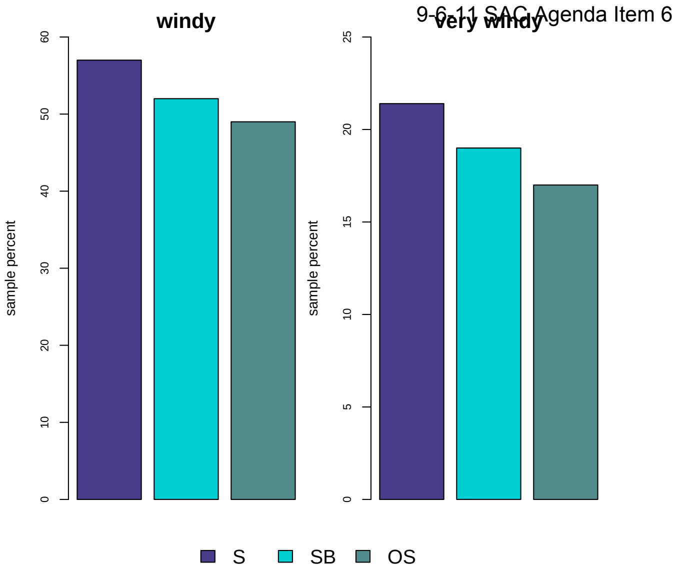
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windy
very windy
sample percent
0
10
20
30
40
50
60
0
5
10
15
20
25
S
SB
OS

Conclusion

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- Policy change was move in right direction
- HH welfare can only increase (relaxed constraint)
- Now let them choose days
- "Enforce" via outreach, nudging
- Another example of unintended consequences


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