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FREE TO CHOOSE: PROMOTING CONSERVATION BY RELAXING OUTDOOR WATERING RESTRICTIONS

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ABSTRACT

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Free to choose: Promoting conservation by relaxing outdoor watering restrictions

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Abstract

Many water utilities use outdoor watering restrictions based on assigned weekly watering days to promote conservation and delay costly capacity expansions. We find that such policies can lead to unintended consequences - customers who adhere to the prescribed schedule use more water than those following a more flexible irrigation pattern. For our application to residential watering in a high-desert environment, this "rigidity penalty" is robust to an exogenous policy change that allowed an additional watering day per week. Our findings contribute to the growing literature on leakage effects of regulatory policies. In our case inefficiencies arise as policies limit the extent to which agents can temporally re-allocate actions.

Keywords: Outdoor watering, water conservation, multi-equation system, Bayesian estimation, posterior simulation
JEL classifications: C11, C30, Q25, Q58

1. Introduction

Water consumption across the globe has tripled in the last 50 years, and is expected to continue to rise rapidly. Water scarcity is expected to be further exacerbated by global warming via prolonged droughts and increasing system losses (Cromwell et al., 2007). The United Nations predicts that by 2030 almost half of the world's population will be living in areas of high water stress

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(U.N. World Water Assessment Programme, 2009) and nearly every region in the United States has experienced drought induced water shortages over the last five to ten years (U.S. Environmental Protection Agency, 2008a). The sustainable provision of water is thus one of the most critical challenges facing policy-makers in both the U.S. and world at large.

Residential households 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. However, in the arid west and south this proportion can be as large as 30-35%. In total, an estimated seven billion gallons of publicly provided water are allocated for this purpose daily (U.S. Environmental Protection Agency, 2008b,c). Policy makers and water utilities have thus directed considerable efforts to the management of residential outdoor irrigation. In most cases these efforts focus on outdoor watering restrictions (OWRs) that limit the timing, length, and frequency of sprinkler use.[2]

Such OWRs have been implemented in many areas within and outside the United States. As noted in Table A1 in Appendix A, most of these regimes limit weekly watering to between one and three assigned days determined by street address. Moreover, most of these regimes (see, e.g., San Antonio or the State of Georgia) follow a paradigm whereby the number of assigned days is reduced under progressively severe drought conditions.

To date, economists have primarily focused on two aspects of OWR policies: (i) the overall impact on water demand, and (ii) the welfare effects for residential consumers. For example, Shaw and Maidment (1987) find that a one-per-five days watering restriction reduced overall demand by 3-5% during the 1984-85 drought years in Austin, Texas. Renwick and Green (2000) examine monthly consumption for eight California water utilities during the 1985-92 drought period and find that OWRs of a general nature generated an approximate 30% reduction in use. 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).

Despite the growing importance of OWRs as a Demand-Side Management (DSM) intervention, surprisingly little is known about the relative performance of different OWR implementation strategies. Given that OWRs vary substantially across communities, such omission is particularly noteworthy. This study seeks to fill this gap in the literature. We examine daily consumption data for thousands of customers in the Reno / Sparks area of Northern Nevada during the 2008 and 2010 summer months. This temporal break affords a unique opportunity to examine an exogenous policy change in OWRs that allowed households an added assigned watering day each week during the 2010 watering season.

Our analysis uncovers an unintended consequence associated with the use of assigned watering schedules - 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 watering days but a more flexible pattern of use. These "rigidity penalties" are substantial, amounting to 20-25 percent of weekly

[2]Given the price inelastic nature of water demand, such regulatory interventions are more effective means to influence consumption than price-based policies (Renwick and Green, 2000; Mansur and Olmstead, 2007; Olmstead et al., 2007; Worthington and Hoffman, 2008). Furthermore, there are generally fewer equity concerns and less political resistance to OWRs than to price-based policies (Renwick and Archibald, 1998; Timmins, 2003; Brennan et al., 2007).

consumption and 30-40 percent of weekly peaks for the typical customer. Although the 2010 policy change had a noticeable impact on daily peaks, it had no discernible effect on weekly consumption of the associated "rigidity penalties".

Viewed in its totality, our data call into question the efficacy of OWRs that limit watering to assigned days. In this regard, our analysis extends prior work exploring the unintended consequences of policy actions that either introduce heterogeneity in standards across factories or regions (Felder and Rutherford, 1993; Fowlie, 2009) or nested state and federal regulation (McGuinness and Ellermann, 2008; Goulder and Stavins, 2011; Goulder et al., 2012).[3] Whereas the cited work focuses on leakages that arise through the spatial reallocation of actions, our paper highlights that a similar phenomena can arise if policies limit the extent to which agents can *temporally* reallocate actions. In our setting, adherence to the official water schedule requires households to ignore time-varying conditions such as high wind events that reduce the efficiency of irrigation systems.

2. 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 to guard against future droughts and assure adequate flows of the Truckee River. The watering regulations allow sprinkler use during the morning and evening of assigned days determined by the last digit of a resident's address.[4] Prior to 2010, the policy allowed households two assigned watering days per week. During the 2010 watering season, the OWR was relaxed and allowed a third weekly watering 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.

In 2008 TMWA initiated the collection of daily water consumption data for a large, representative sample of customers. 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.[5] The same exercise was repeated between June 20 and August 21, 2010 although the routes differed somewhat from the 2008 itineraries due to construction activities.[6]

Overall, we observe approximately 1.9 million daily meter readings from approximately 20,000 unique residential customers. In preparing the final data set, 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 and customers with four or more consecutive

[3] Unintended consequences have also been documented in a number of other settings. For example, Davis and Kahn (2010) show that while trade in used vehicles between Mexico and the United States following the passage of NAFTA lowers average vehicle emissions per mile in both countries, aggregate greenhouse gas emissions rise due to lower retirement rates of used cars in Mexico. Bento et al. (2011) show how policy changes in California that allowed single-occupancy, ultra-low emission vehicles access to HOV lanes significantly increased travel times for carpoolers and had no impact on travel times for those in non-HOV lanes.

[4] There are no restrictions on watering via *hand-held* hoses.

[5] The readings were obtained between the hours of 9pm and 3am. According to TMWA, the vast majority of households complete watering by 9pm.

[6] 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 readings is available only for a small subset of the sample.

zero readings anywhere in the daily series to lower the risk of including non-permanent residences and vacation homes. These cleaning steps truncated the set of eligible residents by approximately 15% for each year.

Given our focus on weekly watering frequencies, only weeks for which we obtain a full set of readings for a given household are usable. Further, to identify a household's watering days and weekly watering patterns, a minimum number of intact weeks (MIW) was required. Yet, to maximize the number of residents present in both sample periods, we had to consider the relationship between the stringency of our MIW criterion and the size of our overlap sample. In balancing these requirements we settle for an MIW threshold of five full weeks of daily readings. After eliminating a few isolated cases with obvious water leaks or missing information on basic building characteristics we generate a final sample that includes 52,666 weekly observations from 8,747 residents for 2008 and 48,573 observations from 7,652 unique residents for 2010. Of these households, 1,766 appear in both the 2008 and 2010 samples and comprise our "overlap" sample. Table 1 shows the distribution of intact weeks for both the full and overlap samples by year.

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

The top half of Table 2 depicts basic household characteristics for the two full samples. The 2010 sample comprises, on average, slightly smaller and older properties. There is also a 44% decline in average tax-assessed property value from 2008 to 2010 reflecting the severe economic downturn in Nevada over the sample period.

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), and maximum sustained wind speed (in knots, measured for ten minutes every hour). As is common in arid high-dessert climates, there were no noteworthy rainfall events during our sampling periods. Climate statistics are shown in the bottom half of Table 2. Although the summer of 2010 was slightly cooler than the summer of 2008, the wind statistics are very similar for the two sampling periods.

Table 2: Household and climate characteristics

	2008				2010			
	mean	std.	min.	max.	mean	std.	min.	max.
age	20.9	17.6	1.0	104.0	23.1	16.4	2.0	106.0
lot size (1000 sqft)	10.1	7.0	0.0	49.7	7.6	3.3	0.0	48.8
sqft (1000s)	2.0	0.8	0.5	15.2	1.8	0.6	0.5	7.7
value ($10,000s)	270.5	160.2	69.4	2637.4	150.7	65.6	33.8	762.8
fixtures	12.0	3.4	0.0	64.0	11.1	2.8	0.0	27.0
bedrms	3.3	0.9	0.0	23.0	3.2	0.7	0.0	8.0
bathrms.	2.4	0.7	0.0	16.0	2.2	0.6	0.0	6.0
avg. temp (F)	77.9	3.3	69.4	84.2	75.8	4.7	61.7	85.4
min. temp	59.9	3.5	53.1	66.0	58.9	4.8	44.6	69.1
max. temp	95.7	3.0	89.1	102.0	92.8	5.2	78.8	102.2
avg. wind (knots)	5.2	1.4	2.8	9.3	5.7	1.3	2.5	8.3
max. wind	16.2	4.2	7.0	29.9	16.8	4.2	8.9	32.1
max. gust	23.3	4.1	15.0	30.9	24.5	5.0	14.0	37.9

3. Identification of Policy Effects

3.1. Definition of Treatments

We aim at identifying the impact of two design features of the Truckee Meadows OWRs on weekly water use and peak (maximum daily consumption in a given week)[7]: (i) the total number of permissible watering days per week, and (ii) the "pinning" of the allowable number of days to specific days of the week (say, Wednesday, Saturday), versus letting households choose their watering days in a more flexible fashion.

For the former objective, we hypothesize that granting more watering days will induce a more even distribution of weekly irrigation, and thus reduce weekly peaks for the typical household. In addition, this smoother distribution, by reducing the gap between permitted days, may curb losses due to runoff and evaporation, as households are less likely to over-soak their lawn on assigned days.

For the latter objective, we separate weekly watering patterns into three categories: (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 ("illegal") days of outdoor use. The third group exhibits the most varied weekly watering patterns, with the common feature of *non*-watering on at least one of the assigned days. For ease of exposition we will at times

[7]System-wide consumption peaks are important to utilities as they are closely related to the cost of water provision. Specifically, lower peak demand can be satisfied via stored water, distributed by gravity. Storage units can then be replenished at night at lower pumping costs. In contrast, high peak use forces daytime pumping, when electricity costs are highest. If this occurs frequently, the utility may have to undergo costly capacity expansions for water storage. Therefore, a utility generally tries to implement water use policies that reduce daily peaks at the household level.

combine the first two groups under the heading "Schedule-based" (SB). Thus, $S \cup SP = SB$, and $SB \cup OS =$ entire sample. This centers the analytical focus squarely on the degree to which the official schedule influences or "guides" irrigation patterns.

We hypothesize that S types are nudged inadvertently towards wasteful behavior for two main reasons: First, they face the "large gaps" problem mentioned above, which can lead to over-watering and corresponding losses to runoff and evaporation. Second, adherence to the official schedule requires that such households ignore time-varying natural conditions such as (common) high wind events that can further exacerbate irrigation inefficiency. Both effects are likely to increase weekly consumption and, especially, weekly peaks.

In comparison, SP types may be less prone to over-watering, as they distribute weekly irrigation over more-than-permitted days, but may still experience wind losses in their persistence to incorporate the assigned days. In contrast, we surmise that OS types pay the least attention to the official schedule, and more attention to their yard's actual water needs and / or random fluctuations in weather conditions. This makes them the most disobedient, but perhaps also the most efficient TMWA customers.

In summary, we set forth to explore whether compliance with Reno's OWR policy introduces unintended consequences that compromise conversation aims. We will henceforth refer to water losses induced by the day-of-week assignment as "*rigidity effect*".

3.2. Identification strategy

We have exogenous variation in the number of permitted watering days - the policy change from two to three assigned days between 2008 and 2010. Ideally, we would have also been able to exogenously randomize the flexibility with which a household can allocate these days over the course of a week, i.e. assignment to S, SP, and OS categories. Unfortunately, such exogenous policy variation did not occur during our research period.

Instead, we rely upon an alternate strategy for identification - other exogenous shocks that sort a given household into one type or other in an given week. Conditional on the existence of such shocks we can then exploit both cross-sectional and within household variation in weekly watering patterns to estimate the rigidity effect. This is because there are relatively few customers that follow the same weekly irrigation strategy (S, SP, or OS) for the entire observation period. Most households display a mixed pattern of weekly irrigation, both in terms of frequency and timing. Therefore, identification can draw on both within and between household variation.

The challenge at hand is thus to (i) identify plausible exogenous drivers that induce customers to change watering patterns, and (ii) convincingly rule out confounding effects that could drive both weekly watering patterns and outcomes of interest, i.e. weekly use and peak.

With respect to exogenous factors we provide some evidence in the empirical section that SB versus OS choices are likely driven by randomly fluctuating daily wind patterns. Specifically, a given household may want to avoid wind-induced water losses - a common problem in this rain shadow / foothill location - by transferring watering events from a windy day to the next calm day. For the Reno/Sparks case this usually means foregoing the evening application and instead watering on the next (potentially unassigned) day. *Inter*-household differences in "wind awareness" or ability to flexibly manipulate irrigation systems then drives much of the observed cross-household variation in adherence to the official schedule. Naturally, some customers may also be intrinsically more reluctant to break the official rules, and may require "stronger wind shocks" to transfer watering to an off-day. This would add additional cross-sectional variation in observed behavior.

In addition, there may be *intra*-household, time-varying differences in the daily ability to react to the threat of irrigation losses due to wind. For example, the entire household or the person in charge of the irrigation system may not be at home or unavailable on a given day to adjust the system. Similarly, on a given day the household may anticipate being unable to irrigate the next morning, and thus be reluctant to skip that day's evening application despite windy conditions. This would explain intra-household variations in the observed weekly irrigation patterns.

Regarding potentially confounding effects, our econometric specification controls for unobserved, invariant household effects, as well as weekly climate conditions. Therefore, the main concern in this respect would be confounding effects that vary both over time and across households. Most notably, one might surmise that whenever a household anticipates a week with high water need, it may switch to a more conservative watering pattern consistent with official regulations to lower the risk of fines. This would confound any causal link between the degree of adherence to the official schedule and water use. This conjecture builds on two underlying assumptions: (i) Households' weekly irrigation needs change from week to week in a heterogeneous fashion, and (ii) households care about enforcement and fines. We argue that neither one is very likely.

To start, the most plausible reason that could drive a sudden need to use more water in a given week for *irrigation* purposes would be an extreme climate event, such as the anticipation of a very hot or dry week. Perhaps some households are more vulnerable to such extreme events than others, given vegetation cover, soil quality, and other landscape-related features. However, as is evident from Table 2 the local climate during our summer research period is uniformly hot and dry. There is not a single day of precipitation, and the daily temperature range is quiet narrow. The only variation comes through *daily* and rather random wind patterns, and those cannot be anticipated on a weekly basis. Thus, it is rather unlikely that any given customer experiences pronounced changes in weekly irrigation *demand* over our research period.

In addition, it is equally unlikely that the threat of a penalty would induce customers to switch from a flexible to a compliant weekly pattern, even if such heterogeneous, time-varying changes in water need existed. As stated above, the enforcement of the official watering schedule is very lenient, and fines are nominal. A household receives two warnings for blatant violations before a fine of \$75 is issued. Thus, it is rather unlikely that the threat of low fine, collected with low probability, is sufficient to induce a change in behavior, irrespective of weekly water need.

Appendix B provides further evidence against this "comply if anticipated use is high" hypothesis. In summary, we feel confident to proceed with our analysis even in absence of an ideal setting with exogenous policy variation for all treatments of interest.

4. Descriptive Analysis

4.1. Classification of weekly irrigation patterns

Establishing a link between consumption and weekly watering patterns requires the identification of outdoor watering events for a given household and day. Specifically, our objective is to sort the daily observations for each household into two categories: (i) days with some outdoor water use, and (ii) days with indoor-only water use.

This categorization is challenging since we only observe total daily use rather than usage for different purposes. Ideally, outdoor watering days should be clearly identifiable as pronounced spikes in a customer's series of observed consumption days. However, the distinction between categories becomes blurred for households with limited need for outdoor watering or high fluctuations in indoor use. 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. The details of this identification strategy are given in Appendix B.

4.2. Descriptive Results

Our analysis of OWR design effects requires aggregating the daily sample to a weekly format. Table 3 provides a summary of cell counts and sample percentages for the different week-type categories and watering frequencies. For ease of exposition we combine S and SP weeks into the broader SB category, as defined above.[8] 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, corresponding to SB weeks, OS weeks, and the combined sample. The "percent of sample" column relates row counts to the entire sample size for each year. For example, SB weeks with twice watering (i.e. the S group by our definition above) comprise 27.5% of the entire 2008 sample. Overall, watering patterns that are perfectly compliant with the official schedule comprise the largest sample share and account for just over a quarter of all sample weeks.

The "percent 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, approximately 42.8% of the observations in the S category for 2008 come from households that *always* water twice and on their assigned days. Yet, the majority of customers exhibit seasonal water patterns that include a mix of different week-types and frequencies - 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. This is important for our analysis below as it suggests that the observed differences in use and peaks between SB and OS *week*-types are *not* driven by unobserved household characteristics.

Table 4 depicts weekly use and peak by frequency and week-type. We stress three key results captured by this table. First, regardless of watering pattern, consumption increases with weekly frequency. This is consistent with prior work showing that capping weekly watering frequency reduces total use. Second, peaks remain relatively stable across frequencies in the two to four applications range. Third - and most importantly - weekly consumption and peaks are substantially higher for weeks that include all assigned days ("schedule-based") compared to weeks *of identical frequency* with more flexible watering patterns ("off-schedule"). In 2008, these differences amount to 30-40% for weekly consumption and 50-60% for weekly peak. In 2010 these differentials are slightly attenuated amounting to 25-30% for use and 24-26% for peak.[9]

[8] We stress that our classification into different watering patterns applies to a given *household-week*, not a specific *household* across the entire research period. As discussed in the next section, the majority of households switches frequently between weekly watering patterns. Therefore, there does not exist a clear and systematic classification at the household level that distinguishes along this key dimension of decreasing schedule-adherence. However, we do control for observable and unobservable household characteristics in our econometric specification.

[9] The patterns captured in Tables 3 and 4 are qualitatively similar for the overlap sample. Consumption is approximately 25-35% higher for the SB group than the OS group at all frequencies. Similarly, SB peaks exceed OS peaks by 45-55%. Summary statistics for the overlap sample are available from the authors upon request.

Table 3: Cell counts and percentages by watering frequency and week-type

	2008			2010		
weekly watering days	count	% of sample	% all w/in	count	% of sample	% 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

5. Econometric Framework

To examine if these descriptive results hold up when controlling for climate variations, household characteristics, and unobserved household effects we now turn to our econometric analysis. We assume that over the course of a week a given household makes daily choices on watering occurrence and total use, given watering. From the analyst's perspective these choices will be observed as joint weekly outcomes on frequency, use, and peak. We thus define such an *observed* weekly irrigation scheme (IR) 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.

Table 4: Weekly use and peak by watering frequency and week-type

weekly watering days	weekly use (1000 gals.) 2008 mean	std.	2010 mean	std.	weekly peak (1000 gals.) 2008 mean	std.	2010 mean	std.
	schedule-based				schedule-based			
2	5.84	(3.67)	-	-	2.34	(1.68)	-	-
3	6.72	(4.56)	5.39	(2.44)	2.30	(1.85)	1.65	(0.83)
4	7.24	(5.04)	5.95	(2.89)	2.19	(1.86)	1.67	(0.96)
>4	9.83	(7.73)	7.32	(4.41)	2.43	(2.26)	1.70	(1.14)
Total	6.99	(5.26)	6.00	(3.26)	2.32	(1.86)	1.66	(0.95)
	off-schedule				off-schedule			
0	2.44	(2.20)	2.03	(1.52)	0.55	(0.48)	0.46	(0.34)
1	3.38	(2.61)	2.73	(1.85)	1.30	(1.29)	1.04	(0.94)
2	4.20	(3.20)	3.82	(2.23)	1.46	(1.39)	1.37	(0.98)
3	4.80	(3.61)	4.32	(2.58)	1.42	(1.28)	1.31	(0.95)
4	5.52	(4.64)	4.75	(3.00)	1.47	(1.47)	1.31	(1.04)
>4	6.99	(5.80)	5.65	(4.53)	1.67	(1.63)	1.37	(1.24)
Total	4.26	(3.71)	3.83	(2.71)	1.30	(1.32)	1.20	(0.99)
	all				all			
0	2.44	(2.20)	2.03	(1.52)	0.55	(0.48)	0.46	(0.34)
1	3.38	(2.61)	2.73	(1.85)	1.30	(1.29)	1.04	(0.94)
2	5.43	(3.63)	3.82	(2.23)	2.12	(1.65)	1.37	(0.98)
3	5.95	(4.31)	5.03	(2.54)	1.95	(1.70)	1.53	(0.89)
4	6.69	(4.98)	5.36	(3.01)	1.96	(1.78)	1.49	(1.01)
>4	9.31	(7.50)	6.95	(4.49)	2.29	(2.18)	1.63	(1.17)
Total	5.95	(4.91)	4.82	(3.17)	1.93	(1.75)	1.41	(1.00)

Thus, we have three outcomes of interest - 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 $\Re^{+}$. We wish to identify the effect of weekly watering frequency and degree-of-adherence to the OWR on use and peak. If household decisions on use and peak were completely independent from decisions related to weekly frequency, the three outcomes of interest could, in theory, be analyzed via independent estimation. For example, the use and peak equations could be estimated via simple random effects (RE) regression that includes difference-in-difference type interaction terms to capture the incremental effects of weekly frequency, irrigation pattern (SB vs. OS) and policy change (2008 vs. 2010).

However, if the frequency equation shares common unobservables with either or both of the use or peak equation, such naïve independent analysis would produce misleading results, as the right-hand-side variable "frequency" would introduce endogeneity problems. We find this to indeed be the case in comparative estimation runs.[10] Thus, a plausible econometric model for this application must accommodate the following key features: (i) Limitations on the natural range of the dependent variable, (ii) household-specific effects to control for unobserved heterogeneity, and (iii) an ex-ante unrestricted covariance matrix for these unobserved effects, i.e. full correlation of all three equations. To incorporate these modeling challenges in a computationally tractable fashion we deviate from a standard linear regression framework and classical estimation, and turn instead to a hierarchical system approach, estimated via Bayesian tools.

As point of departure, we combine a truncated Poisson density for the watering frequency equation with two exponential densities for weekly consumption and peak (see e.g. Munkin and Trivedi, 2003).[11] 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

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

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}.[12]

The Hierarchical Exponential (HE) part is specified as

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

where the **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:

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

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.

[10]The results for these RE regressions and a discussion thereof are provided in Appendix E.

[11]The exponential component has similar distributional characteristics as the familiar log-normal regression model, but exhibits more desirable mixing properties in our Bayesian estimation framework.

[12]It should be noted that the restrictive mean-variance equality that is a prominent feature of the standard Poisson density no longer holds under truncation (e.g. Rider, 1953). A second reason for the mean-variance equality to break down is the inclusion of the random household effect. See for example Hausman et al. (1984).

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. As mentioned above, if this matrix contains non-zero covariances, a naïve model ignoring the linkage across the three equations would be plagued by endogeneity bias, since the frequency indicator $\mathbf{d}_{ip}$ appears on the right hand side of both the use and peak equation.[13]

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 $i = 1 \dots N$, 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 employ a Bayesian estimation framework.

We begin by specifying the prior distribution for the 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 $\{\mathbf{u}_i\}_{i=1}^N$.[14] The augmented posterior distribution is proportional to the priors times the augmented likelihood, i.e.

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

where the last term describes the likelihood function conditioned on all error terms.

The Gibbs Sampler draws consecutively and repeatedly from the conditional posterior distributions $p\left(\boldsymbol{\beta} \mid \{\mathbf{u}_i\}_{i=1}^N, \mathbf{y}, \mathbf{X}\right)$, $p\left(\mathbf{V}_u \mid \{\mathbf{u}_i\}_{i=1}^N\right)$,

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[13] We also included an observation-specific error in an earlier specification. 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.

[14] The data augmentation step circumvents the need to directly evaluate the integrals in (6). 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 Trivedi (2003).

and $p\left(\{\mathbf{u}_i\}_{i=1}^N \mid \boldsymbol{\beta}, \mathbf{V}_u, \mathbf{y}, \mathbf{X}\right)$. 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.[15]

6. Estimation Results

6.1. Posterior results

The regressors in the parameterized expectation of the frequency equation include a combination of home characteristics and climatic variables to control for temperature and wind speed, in addition to an indicator for the 2010 irrigation season and the interaction of this indicator with the various climate variables. The parameterized mean functions for use and peak include additional home characteristics that control for indoor water use and exclude some of the climate variables for identification purpose. These equations also feature indicators for weekly watering frequency, the interaction of these terms with indicators for the 2010 watering season and schedule based weekly watering patterns, and the two-fold interaction of the schedule based and 2010 indicators with both our frequency variables and different wind measures.[16]

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 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 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 10^{th} lag for most parameters, and by the 20^{th} 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 5. The table also captures the results for the elements of the error variance matrix $\boldsymbol{\Sigma}$, expressed as standard deviations and correlations. For each parameter we report posterior means, posterior standard deviations, and the probability mass of a given marginal posterior that lies above the zero-threshold. The effects of our various climatic controls are as expected. For example, the frequency of weekly watering events is higher on weeks with higher maximum daily temperatures and lower on weeks with higher average daily wind speeds. Interesting, however, the effect of such controls are attenuated for the 2010 season. Taken jointly, our data thus suggest that climate conditions have a more pronounced effect on the variability of watering frequency when the official OWR ceiling is lower.

Turning to the elements of $\boldsymbol{\Sigma}$ in the lower half of Table 5, 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 (labeled $\sigma_j, j = 1 \ldots 3,$) are of non-negligible magnitude, which confirms the presence of unobserved household effects in all three equations. Household unobservables are highly correlated for equations two and three, and we find a mild, positive correlation between the frequency and the use equations.[17]

Posterior results for the weekly use and peak equations are summarized in Table 6. Regarding weekly use, the table captures three main results. First, consumption increases clearly with weekly

[15]The detailed steps of the posterior simulator and the Matlab code to implement this model are available from

Table 5: 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

mean = posterior mean,
std. = posterior standard deviation,
prob(>0) = share of posterior density to the right of zero

frequency. Furthermore, this result remains essentially unchanged in 2010. Second, 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 percent, and are highest for weeks that follow the official schedule exactly.[18] Third, controlling for frequency and watering pattern, the residual policy effect is of negligible magnitude.

The results for weekly peak are given in the last three columns of the table. In contrast to use, peaks do not change much over frequency in either year. However, as for use, peaks are substantially larger for SB-type weeks compared to OS-type patterns in 2008, and this difference is greater at lower frequency levels. This gap diminishes in 2010, as peaks for SB-type implementations decrease by 18-23 percent compared to the 2008 season, and peaks for OS-types increase slightly (by 6-9 percent). The reduction in the "rigidity penalty" for peaks in 2010 compared to 2008 likely reflects

the authors upon request.

[16]Details on household and climate regressors are provided in Appendix D.

[17]As illustrated in the Appendix E, this linkage via unobservables between equations one and two is sufficient to produce inconsistent parameter estimates for both use and peak models if the system is estimated via independent random effects regressions.

[18]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.

the additional flexibility afforded to compliant customers by the revised OWRs. Schedule-adherent households now have more options to reduce daily watering on windy days and 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.

However, we also acknowledge that to some extent this reduction in rigidity gap, especially via increased peaks for OS-types, might be an artifact of our classification scheme: Some 2010 customers may have been sluggish to adjust to the new schedule. As a result, the "rigid" weeks produced by these residents, classified as SB in 2008, are counted as OS-types in 2010.[19] As such, our estimates can be interpreted an upper bound on the effect of the policy change on the rigidity penalty for peak use.

The remaining findings for the peak model mirror those from the weekly use equation: namely, there are no noteworthy residual policy effects. Overall, we conclude that the results produced by our complete econometric specification support the descriptive findings from the preceding section.

Table 6: 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
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

(results for household and climate variables are omitted for brevity, but are given in Appendix D)

mean = posterior mean,
std. = posterior standard deviation,
prob(>0) = share of posterior density to the right of zero

[19] Recall that every SB designated week must include outdoor use on *all* assigned days. Hence, any 2008 schedule-adherent household who fails to adjust to the new OWRs by watering on the third allowable day and switching to the new assigned week-days during 2010 would produce OS-type weeks for that year - even if there was no change in the actual watering pattern relative to the 2008 season.

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). Formally, these PPDs are given as

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

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. 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. We combine these year-specific PPDs for final analysis as there is discernible difference in watering behavior across these years once we control for climatic and household specific variables. The latter are set to their grand sample means for this predictive analysis.

The resulting PPDs are depicted in Figure 1 for use and Figure 2 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 (in 1000 gallons). As is evident from Figure 1, the SB pattern produces higher expected use than the OS pattern at all frequencies, with a slightly decreasing relative gap from 14 percent at f = 2 to 12 percent at f = 4. As shown in Figure 2 these differences in posterior predictive expectation are even more pronounced for peak. At two watering days, the SB pattern generates a peak that is approximately 28 percent higher than the OS peak. At three watering days, this difference reduces to 22 percent, and at a frequency of four it amounts to close to 18 percent. Overall, these predictive results support our descriptive and analytical findings - a watering pattern that closely follows the officially assigned days 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.

7. The Wind Effect

As mentioned at the onset, we believe that the assignment of household-weeks into different watering patterns is largely driven by exogenous shocks in the form of high wind events. Specifically, some customers switch to more flexible irrigation patterns to avoid wind-induced water losses. Conversely, households that follow the assigned schedule are more likely to water under 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.

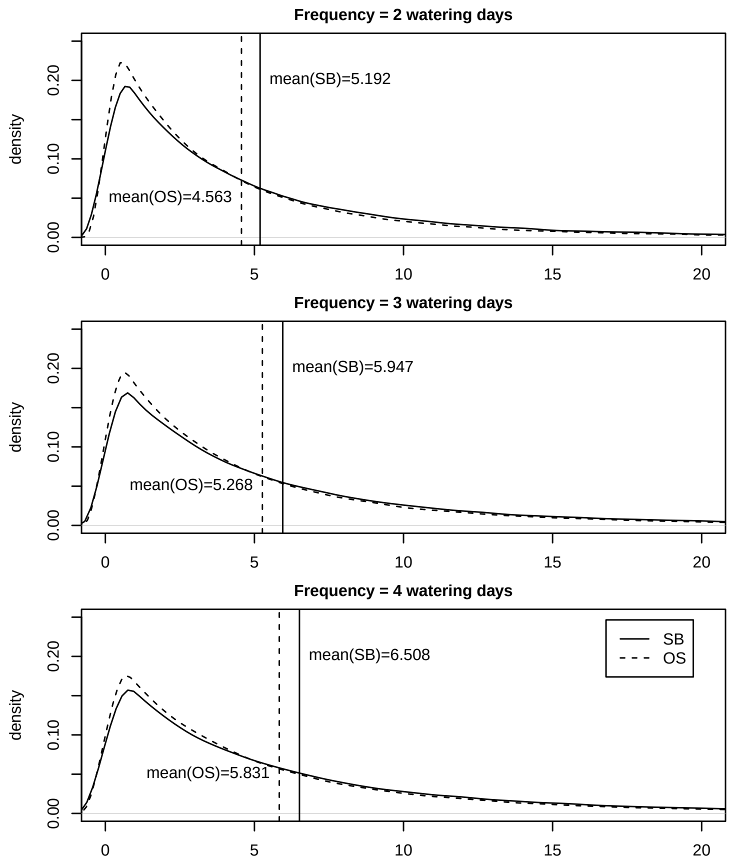

Figure 1: Predictive distributions of weekly use for a typical household (1000 gallons)

To explore this conjecture in greater detail, we compute the percentage of watering days that fall on either a windy or very windy day.[20] The results are captured in Table 7. 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. Importantly, 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 - the share of windy days exceeds 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. In 2010, which had slightly fewer windy days overall compared to 2008, the difference in the relative frequency of wind events across week-types reduces to 1-2% for windy days and falls below the 1% mark for very windy days. However, as for 2008, the S category experiences the highest risk of wind exposure.

To provide more rigorous support for this "wind hypothesis" we estimate a Probit models of *daily* watering decision on average daily temperature (F), an indicator for "windy day" (with max. sustained speed exceeding the sample mean of 16 knots), an interaction term for "windy" and "SB",

[20] "Windy days" are those with a maximum sustained wind speed that exceeds the sample mean (16.51 knots). "Very windy" days are defined as those with a maximum sustained wind speed at the 75th percentile (19 knots) or higher.

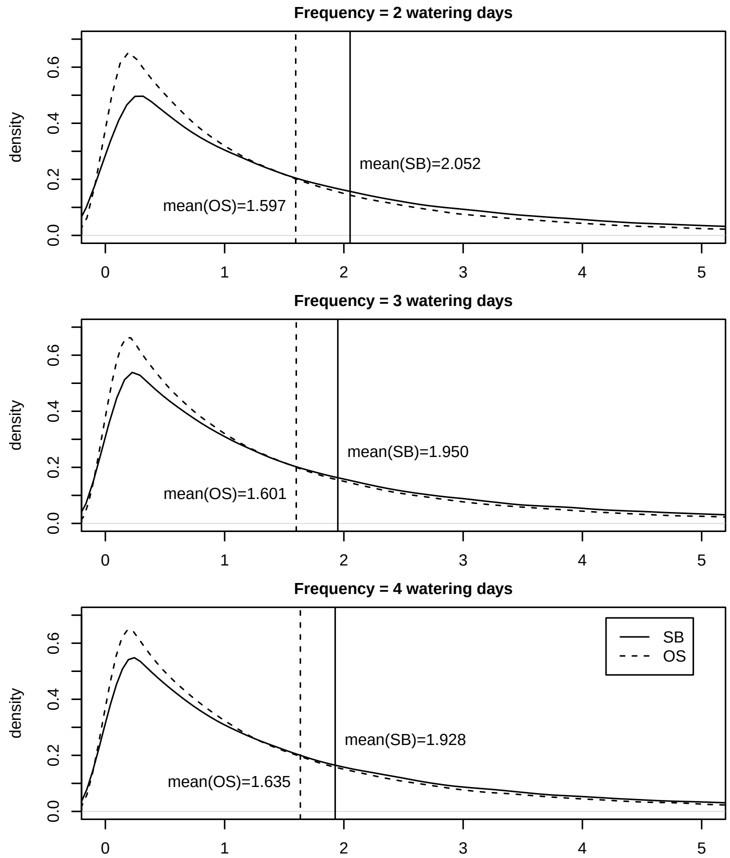

Figure 2: Predictive distributions of weekly peak for a typical household (1000 gallons)

and a random household effect. We estimate separate models for the two sample years, and weekly frequencies of 2, 3, and 4 watering days.

The results are captured in Table 8. For ease of interpretation, the estimated coefficients are presented as marginal effects, conditional on a random effect of zero. As can be seen from the table, in 2008 the probability of a observed watering day to coincide with above-average wind conditions is approximately 5% higher for an "SB" type HW compared to an "OS" type. This difference shrinks to 1-3% in 2010, but is still significant. Thus, the Probit estimates pair up well with our descriptive insights in supporting the conjecture that wind events may well be the main driver of the observed variability in weekly watering patterns, and associated differences in use and peaks across irrigation types.[21]

[21] Irrigation losses due to wind can easily amount to 40-50% in arid climates, even under moderate wind speeds of 10 mph (8-9 knots) or less (Bauder, 2000; Duble, 2013). Naturally, these losses are further exacerbated if even the water that hits the ground completely misses its target, which is a common occurrence for the relatively small yards in our research area.

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%

8. Conclusion

This study is the first to examine how the *design* of outdoor watering restrictions impacts residential water use at the household level. Using a unique, customer specific data set of daily consumption over multiple irrigation seasons that include an inter-season policy change, we arrive at several important and novel findings. Most centrally, 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 undermines conservation goals.

We find that higher frequencies unambiguously translate into higher weekly use. However, we uncover an unintended consequence of OWRs with days-of-week assignments: weekly use and peak are higher the more closely a given households follows the assigned schedule. These "rigidity penalties" are substantial and amount to approximately 20-25 percent of weekly consumption and 30-40 percent of weekly peaks.

The policy change from two to three assigned days per week produced two main effects. First, it induced the intended switch in watering patterns for a considerable segment of customer-weeks. Second, we observe a pronounced reduction in peaks at the system-wide level - an effect driven predominantly by lower peaks for schedule-based weeks. In contrast, overall weekly use changes little in reaction to the new policy.

Table 8: Random Effects Probit Estimation of Daily Watering Decision (translated into Marginal Effects)

	2008				2010		
	weekly frequ. = 2 (n = 135,044)						
	coeff.	s.e.	z				
windy	0.074	0.004	17.870				
windy*SB	0.049	0.004	12.070				
avg. temp.	0.011	0.000	25.190				
	weekly frequ. = 3 (n = 74,417)				weekly frequ. = 3 (n = 132,167)		
	coeff.	s.e.	z		coeff.	s.e.	z
windy	0.033	0.005	6.290	windy	0.003	0.004	0.670
windy*SB	0.053	0.005	9.900	windy*SB	0.013	0.004	3.030
avg. temp.	0.005	0.001	8.380	avg. temp.	0.001	0.000	2.730
	weekly frequ. = 4 (n = 57,435)				weekly frequ. = 4 (n = 50,176)		
	coeff.	s.e.	z		coeff.	s.e.	z
windy	0.055	0.006	8.510	windy	0.000	0.006	0.070
windy*SB	0.053	0.006	8.430	windy*SB	0.016	0.006	2.470
avg. temp.	0.009	0.001	12.310	avg. temp.	0.001	0.000	1.450

For policy-makers, our results suggest that adjusting existing OWRs to allow for flexible watering patterns could produce substantial water savings at relatively low implementation costs. Moreover, as inefficiency penalties are highest at low frequencies, our findings also cast doubt on the effectiveness of policies that reduce the number of assigned days under progressively severe drought conditions. In such situations, a frequency reduction combined with a "free-to-choose" policy is likely to promote greater conservation. Naturally, violations of allowed weekly frequencies would be more difficult to detect under such a policy, since permissible applications would no longer be pegged to a given day-of-week for a given address. However, the fact that many current customers adhere - at least loosely - to the official regulations despite weak enforcement by the utility suggests that social norms and "neighborly supervision" may be stronger drivers of compliance than officially posted fines. These norms would still be in force under more flexible policies, as nearby neighbors can easily keep track of other households' weekly watering frequency.

Our analysis extends prior work exploring the unintended consequences of nested policies, and those that introduce heterogeneous standards across firms and/or regions. Whereas the extant literature focuses on leakages generated by the spatial reallocation of effort, our paper highlights another channel through which leakages may arise - by hampering the temporal reallocation of effort. In our setting, adherence to the official watering schedule requires households to ignore time-varying weather patterns that reduce the efficacy of outdoor watering.

It is easy to envision other domains where similar patterns could arise. For example, many utilities have explored time-of-day pricing as a means to manage residential energy consumption and associated greenhouse gas emissions. To the extent that such pricing schemes cause a shift in demand from peak to non-peak hours, the overall impact on carbon could fall short of expectations as the marginal fuel source during peak hours is often less carbon intensive than base load generators (the marginal fuel source during non-peak periods). The identification of such temporal leakages and the design of policies that are robust to such unintended consequences should provide ample opportunities for future research.

Appendix A. Outdoor watering restrictions in the United States

Table A.9: 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.9, 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

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Table A.9, 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. Evidence against confounding effects

If there were any other time-varying factors that drive water need in a heterogeneous fashion we should see pronounced variation over time in the fraction of different watering types. Table B.10 shows, for each week of our research period, the number of households included in the sample, and the percentage of watering types. The last two columns of the table capture the two types we use in our empirical model, SB and OS. For additional insight, we also show the percentage, of the total sample, of perfectly compliant types, or S types (which are nested within SB). We further split these S types into the percentage of household-weeks (HWs) that come from households that *always* follow the schedule (labeled as "always" in the table), and the remaining share of HWs contributed by "occasional" perfect compliers (labeled as "occ") in the table.

Table B.10: Percentages of watering types over time

			S			
week	sample	always	occ.	total	SB	OS
			2008			
1	8468	12%	15%	28%	60%	40%
2	8270	13%	16%	29%	61%	39%
3	8572	12%	16%	28%	64%	36%
4	2488	9%	15%	24%	58%	42%
5	3163	9%	15%	25%	60%	40%
6	5825	10%	16%	26%	59%	41%
7	7774	12%	17%	29%	62%	38%
8	7235	12%	14%	26%	66%	34%
9	871	14%	16%	30%	63%	37%
			2010			
1	5765	9%	14%	24%	38%	62%
2	7338	9%	15%	24%	43%	57%
3	1853	9%	15%	24%	47%	53%
4	7317	9%	17%	26%	48%	52%
5	7420	9%	18%	27%	48%	52%
6	6074	9%	19%	28%	50%	50%
7	5512	9%	18%	27%	44%	56%
8	7294	9%	18%	27%	47%	53%

SB = schedule-based (all assigned days are used)
OS = off-schedule (not all assigned days are used)
S = schedule-exact, perfect compliance
S / always = from households that always show perfect compliance
S / occ. = from households that occasionally show perfect compliance

As can be seen from the table, there are no pronounced shifts in the proportion of type assignments over time. This puts in question the proposition that a substantial share of OS types become SB types due to a systematic weekly shock that affects water need. Table 2 in the main text and table B.10 combined also show that the hottest weeks in 2008 (week 3) and 2010 (week 4) do *not* produce the highest proportion of S or SB types in the overall watering pattern.

It is also obvious from B.10 that perfectly compliant HWs, or S types constitute the minority of SB types in any given week. Most HWs that are SB have a watering pattern that adds one or more days to the official schedule. In other words, they are already cheating to some extent. Throughout our analysis we compare SB types and OS types *conditional on the same weekly frequency.* This means that an OS type cheats just slightly more than an SB type of the same frequency. Therefore, the probability of detection and fines should not be all that different between the two types.

Furthermore, if the "behave to avoid fines when water needs are high" conjecture were to hold, we would expect to see higher use for S types compared to one-off SB types. For example, in 2008, an S type would water exactly twice. We can then compare the resulting weekly use to that of an $SB-3$ type that uses one additional day. In the same vein, we can compare an S type for 2010 (3 allowable watering days) to an $SB-4$ type. In both cases we would expect use to increase under the S regime under the conjecture.

However, as is evident from Figure B.3, the one-off SB types use *more* water than perfect compliers and have comparable peaks to S types in both years. This picture is more consistent with the notion that when a households needs more water, it simply adds an additional day. This directly contradicts the "revert to S when need is high" hypothesis.

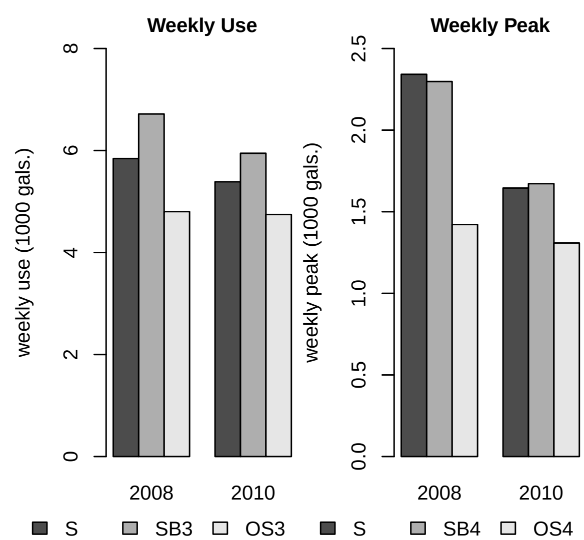

Figure B.3: Weekly Use and Peak for S and "one-off" Types

Appendix C. 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.[22] 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 percent 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 percent) of households in 2008, and 890 households (11.7 percent) 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 percent) of customers in 2008, and 422 (5.5 percent) 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.

   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.[23] 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

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

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

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 (8.2 percent of observations originally flagged as non-watering) for the 2008 data, and 17,818 changes (8.6 percent 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.

Appendix D. Details on Econometric Specification and Results

The household and climate regressors in the frequency equation are: log of lot size in square feet ("lnland"), log of tax-assessed land value ("lnvalue"), the weekly average of, respectively, daily minimum and maximum temperature ("mintemp", "maxtemp"), the weekly average of daily average wind in knots ("avgwind"), the weekly average of maximum daily sustained wind ("maxwind"), 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.

Equations two (weekly use) and three (weekly peak) include the additional home features log of square footage ("lnsf"), number of bedrooms, number of water fixtures, and age plus age squared. The dropped climate variables (for identification purpose) are "mintemp", "maxtemp", and "gdd".

The full results for equations two and three are given in TableD.11.

Table D.11: Estimation results for use and peak equations, Bayesian model

	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

Appendix E. Independent Random Effects Regressions

If the random household effects were not correlated across the three equations, the parameters in the use and peak models could in theory be consistently estimated via simple, independent random effects regressions. For the coefficients in the mean function consistency in such a naïve independent framework would hold even if equations two and three were correlated, as long as their respective correlations with equation one is truly zero. This is because the dependent variable of equation one, weekly watering frequency, enters the other two equations on the right hand side (in form of binary indicators), and would thus cause endogeneity problems if there existed a link between equation one and the other two models via the unobservable household effects.

From Table 5 in the main text we see that ρ_{13} is negligible with large posterior uncertainty, but ρ_{12}, while small, is positive and estimated with relatively high precision. To examine to what extent ignoring this correlation would affect parameter estimates, we run two independent random effects (RE) regressions for weekly use and peak with the exact same regressors as in our Bayesian Hierarchical Exponential (HE) models. The dependent variables are in log-form.

If endogeneity is not an issue, the two frameworks, Bayesian HE, and classical RE, should produce asymptotically identical results for the following reasons: (i) both are based on the same log-linear parameterized mean function, which assures the same interpretation for marginal effects, (ii) the normal density, which forms the basis for the RE regressions, and the exponential density which underlies the HE model, are both in the family of linear exponential distributions. Therefore, a mis-specification of the (combined) variance of error terms in the likelihood function should not affect consistency of coefficient estimates in the parameterized mean function (see e.g. Cameron and Trivedi, 2005, ch.5), and (iii) while the RE regression has an additional normally distributed idiosyncratic error, both preliminary runs of an expanded Bayesian model and the RE results indicate that the variance of that error term is small compared to the variance of the household effect.[24] Finally, with over 100,000 observations, we would expect good asymptotic properties from both frameworks.

Table E.12 depicts the full results for the RE regressions. Comparing these results to the posterior means in Table 1, we see that the RE models systematically under-estimate the incremental increase in use and peak at any frequency for SB-type weeks (variables "SB*freq2" through "SB*freq567"). Expressed in percentage terms, this bias is of considerable magnitude, ranging from 7-11% for use and 15-21% for peak. Furthermore, the RE models estimates pure policy effects for use peak ("year2010") that are 30-40% larger, respectively, than the small effects produced by the correlated Bayesian system.

Finally, the RE model under-estimates the reduction in peak for SB-types compared to 2008 ("SB*freq3*2010" through "SB*freq567*2010") by approximately 5%. We thus conclude that the additional complexitities in estimation from switching to a fully correlated triple-equation system are justified for our application.

[24] The RE output indicates that 82-86% of total error variability is assigned to the household effect.

Table E.12: Estimation results for the independent RE regressions

	weekly use			weekly peak		
	mean	std.		mean	std.	
constant	-8.039	(0.255)	***	-10.186	(0.301)	***
freq1	0.457	(0.006)	***	0.870	(0.008)	***
freq2	0.669	(0.006)	***	0.980	(0.008)	***
freq3	0.818	(0.007)	***	1.026	(0.008)	***
freq4	0.935	(0.008)	***	1.056	(0.009)	***
freq567	1.076	(0.009)	***	1.118	(0.011)	***
SB * freq2	0.101	(0.015)	***	0.186	(0.019)	***
SB * freq3	0.099	(0.015)	***	0.151	(0.019)	***
SB * freq4	0.089	(0.016)	***	0.116	(0.019)	***
SB * freq567	0.136	(0.016)	***	0.093	(0.020)	***
lnland	0.426	(0.009)	***	0.482	(0.009)	***
lnsf	0.258	(0.027)	***	0.266	(0.030)	***
lnvalue	0.134	(0.019)	***	0.176	(0.022)	***
fixtures	0.005	(0.003)	***	0.001	(0.003)	
bedrooms	0.021	(0.007)	***	0.012	(0.008)	
age	0.019	(0.001)	***	0.025	(0.001)	***
age2	0.000	(0.000)	***	0.000	(0.000)	***
avgtemp	0.011	(0.002)	***	0.007	(0.002)	***
avgwind	-0.026	(0.011)	***	-0.020	(0.013)	
maxwind	0.015	(0.004)	***	0.010	(0.005)	*
avgwind * SB	-0.014	(0.013)		-0.003	(0.016)	
maxwind * SB	0.002	(0.004)		-0.003	(0.006)	
year2010	0.530	(0.174)	***	0.288	(0.215)	
freq1 * 2010	-0.004	(0.009)		0.007	(0.011)	
freq2 * 2010	0.013	(0.009)		0.040	(0.011)	***
freq3 * 2010	0.015	(0.009)		0.045	(0.011)	***
freq4 * 2010	0.026	(0.010)	**	0.063	(0.013)	***
freq567 * 2010	0.006	(0.012)		0.031	(0.015)	**
SB * freq3 * 2010	-0.002	(0.033)		-0.164	(0.041)	***
SB * freq4 * 2010	-0.005	(0.034)		-0.147	(0.042)	***
SB * freq567 * 2010	-0.009	(0.034)		-0.128	(0.042)	***
avgtemp * 2010	-0.007	(0.002)	***	-0.004	(0.002)	*
avgwind * 2010	0.043	(0.012)	***	0.051	(0.014)	***
maxwind * 2010	-0.019	(0.005)	***	-0.021	(0.006)	***
avgwind * SB * 2010	-0.021	(0.015)		-0.027	(0.018)	
maxwind * SB * 2010	0.009	(0.005)	**	0.016	(0.006)	***

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