Residential Unaccounted For Water Leak Detection Pilot Program

Funded by the Water Foundation and Sonoma County Water Agency

Pilot conducted in collaboration with North Marin Water District

Report prepared by Sonoma County Water Agency

Statistical analysis performed by Western Policy Research

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1. Executive Summary

- The purpose of the Residential Unaccounted For Water Leak Detection Pilot Program (Pilot) is to assess whether water 'lost' due to the inability of water meters to measure low flows can be reduced with the installation retrofit of an add-on device, called an Unmeasured-Flow Reducer (UFR).

- The Pilot was made possible by a grant awarded by the Water Foundation, with additional funding provided by the Sonoma County Water Agency.

- The Pilot involved the installation of 101 UFR devices on residential water meters in collaboration with North Marin Water District. The devices were installed between October, 2014 and April, 2015. Water usage data for these meters, together with a control group, was then analyzed before and after the device installation date.

- A control group was used as a benchmark to account for water-using behavior unrelated to the installation of the UFR devices. Statistical analysis indicates that the properties of the treatment and control groups were well matched prior to the installation of the devices.

- A statistical demand model was used to compare the treatment and control groups over time. The model indicates an increase in billed water usage of approximately 6.4% resulting from the installation of the UFR devices.

- Drought restrictions imposed during the study period may have resulted in an increase in low flows through residential water meters, compared to a normal year. This phenomenon would not be corrected by a well matched control group and may result in the amount of the increase in billed water use being overestimated.

- The Pilot provides positive evidence that the retrofit of UFR devices on residential water meters does reduce the amount of water 'lost' due to low flows.

2. Introduction & Objectives

The Pilot seeks to address the problem of water loss due to leaks on the customer side of the meter that are not registered by the water meter. Non-revenue water (NRW), is water produced by a water utility that is 'lost' due to the meter's inability to measure low flows and in turn is not billed to the customer.

The Sonoma County Water Agency (Water Agency) sought to assess whether NRW resulting from non-detected, unmeasured low flows, less than 1/8 gallon per minute, on customer water meters could be reduced through the use of an add-on device, called an Unmeasured-Flow Reducer (UFR).

The Water Agency is the wholesale water provider in Sonoma County and provides potable water to nearly 600,000 people in Sonoma and Marin counties, as well as sanitation, flood protection, and stream maintenance services. The mission of the Water Agency is to effectively manage the water resources in our care for the benefit of people and the environment through resource and environmental stewardship, technical innovation, and responsible fiscal management.

The Pilot involved the retrofit of UFR devices on residential water meters and subsequent analysis of metered water usage data. Meter readings from those meters with a UFR device installed were compared to those for a control group to determine if the device resulted in an increase in billed water usage.

3. Background & Program Funding

In 2011, the California Single-Family Residential End Use Study[1] documented that 18% of residential water use is attributed to leaks, an estimated average of 30.7 gallons per household per day. Today, typical water meters have a low flow range down to 1/8 gallon per minute. Flows below the range captured by the water meter result in unmetered flows that contribute to a water utilities NRW, and which are not billed. Water utilities can quantify this NRW and the lost revenue, but cannot identify its source.

The findings of this report may not apply to new water meters that may be more accurate at measuring low flows than those used in the Pilot.

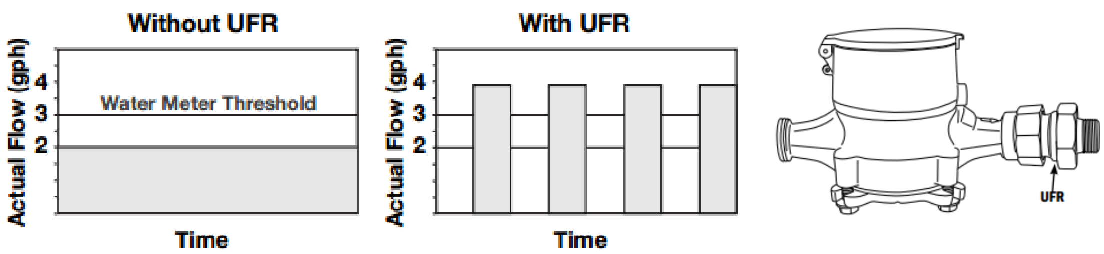
The total budget for the Pilot was $50,000. The Water Foundation awarded the Water Agency a grant of $30,000 in support of the Pilot. The balance was provided by the Water Agency.

4. UFR Device Information

The UFR devices installed were manufactured by A.Y. McDonald Co. The AY McDonald 7201 Series UFR single check and non-check meter couplings[2] are a design that allows low volumes of water usage to be measured by batching the usage.

[1] DeOreo, W.B. and Mayer, P.W. et al, *California Single-Family Water Use Efficiency Study*, Aquacraft, Inc., Boulder, CO, 2011.
[2] http://ay.2rmqa.com/en-US/No-lead-Ufr-straight-coupling-check-and-non-check-valves.html

The UFR works by changing the way water flows through the meter at low-flow rates when there is not enough energy in the flow to activate the water meter. With the UFR installed, the low linear flows are divided into batches that are forced through the meter at a higher flow rate that can be registered by the water meter, as shown in the charts below.



5. Pilot Program Design

The Pilot was designed to be coordinated by the Water Agency with additional work conducted by a partner retail water agency. The retail water agency randomly selected a group of single-family residences that met a set of criteria. From this group approximately 100 were selected and retrofitted with a UFR device, and an additional 100 were selected for a control group. Those meters retrofitted with a UFR device were pressure tested before and after installation to determine if the device had a significant impact on water pressure. Water usage data was collected for both groups for approximately 2-years pre-retrofit and 1-year post-retrofit. The data collected was used to conduct a statistical impact analysis.

The Water Agency collaborated with North Marin Water District (NMWD) on the Pilot. NMWD serves a suburban population of 61,000 people situated in and about the City of Novato which is located in a warm inland coastal valley of Marin County, California and several small improvement districts in the West Marin area near the coast.

The role of NMWD was to select suitable sites for the Pilot, install the UFR devices, conduct pressure tests, and compile and report water usage data. The work conducted by NMWD was funded at a rate of $230 per installation, up to a maximum of $23,000. Further information regarding site selection and data collection is provided in Appendix B.

6. Pilot Program Implementation

101 UFRs were retrofitted on residential meters between October 21, 2014 and April 10, 2015. All meters in the Pilot were 5/8". The majority of the meters used by NMWD are the Badger Meter Recordall Model 25. NMWD also has some Badger Meter Easy-Read meters. The Recordall is a nutating disc positive displacement meter. This type of meter technology is one of the most accurate at low flow rates. The 2011 Water Research Foundation and U.S. EPA report[3] indicates that new 5/8" nutating disc positive displacement meters are consistently accurate above 95% at the minimum AWWA flow rate of 0.25 gpm. The report also showed that the most accurate meters of this type are consistently more than 99% at 0.25 gpm and 97% at 0.125 gpm, but that accuracy drops off significantly at flows below this level. Nutating disc meters were also found to remain accuracy over their full life cycle.

As noted above the findings of this report may not apply to new water meters that may be more accurate at measuring low flows than those used in the Pilot. Initial studies indicate that the newest ultrasonic and electromagnetic meters may be significantly more accurate than mechanical meters at flow rates down to 1/16 gpm. Manufacturers of meters of this type commonly specify that they are capable of accurately measuring flow rates down to 0.11 gpm or lower.

The age of the meters with the UFR device installed was known for 66 meters and ranged from 1984 to 2013. The age of the meters in the control group was known for 65 meters and ranged from 1984 to 2013. The meters with an unknown installation date are likely to have been installed prior to 1984, which is when NMWD began keeping electronic records.

NMWD bills its customers bimonthly, approximately every 60 days. Bimonthly water usage data was collected and recorded for each residential meter. All meter reads in the Pilot were taken manually. Water usage for a control group of 100 residential meters was also collected and recorded. NMWD provided usage data in gallons for each meter with the current and previous read date, as well as the number of days in the billing cycle. Water usage data was collected until June 2016 to ensure that there was at least 1 year of post installation data available.

It is noted that the possibility of misreads exists when using manual meter reads. The potential for misreads applies equally to the treatment group and the control group and is considered unlikely to have a significant impact. The potential impact of misreads is also mitigated by frequent changes in the meter reader for each meter over time.

Statistical modelling of the water usage data was conducted by Anil Bamezai PhD, Principal, Western Policy Research. Western Policy Research used regression models to estimate if the installation of the UFR devices resulted in an increase in measured water usage. Appendix A describes the modelling approach in greater detail.

[3] Barfuss, S. L., Johnson, M. C., and Neilsen, M. A., Accuracy of In-Service Water Meters at Low and High Flow Rates, Water Research Foundation, 2011

7. Impact Analysis

a. Conceptual Framework

Evaluations aim to quantify the impact of an intervention on a group of subjects by comparing outcomes after the intervention to what the outcomes would have been in the absence of the intervention. Participant outcomes in the absence of the intervention are fundamentally unobservable—they have to be inferred either through pre-intervention longitudinal data, or through the behavior of a control group.

There are many aspects of water-using behavior of the treatment group properties that remain unobservable, such as, family size increasing or decreasing, plumbing fixtures or water-using appliances being replaced due to normal wear and tear, etc. Furthermore, onset of a severe drought in 2014 also altered water using behavior of the treatment group unrelated to the UFR retrofits. The approach adopted in this study for dealing with these confounding factors is to monitor the water-using behavior of a control group that is also selected at random from the same pool of single-family properties as the treatment group. As long as the two groups are well matched, the impact of the confounding factors should be considerably attenuated.

Appendix A discusses in greater detail the specification, testing, and sensitivity analyses of the estimated models. The methodology takes the billing data structure with staggered read dates across customers as is, without any tampering such as interpolation into calendar months. Instead, to account for weather, our methodology matches weather exactly to the time period that is covered by a read, by working with daily weather data. Weather is captured using daily rainfall adjusted reference ETo from CIMIS's Novato station (#187).

b. Study Sample Development

A sample of 300 single-family properties was randomly selected for this study from NMWD's service area. Approximately 100 of these were allocated to the treatment group for retrofit with the UFRs. Another 100 properties were earmarked for the control group. The remaining 100 properties were retained to substitute for cases in the treatment and control groups that made them ineligible for the study. The factors that caused a property to be rejected for detailed analysis include:

1. Pre-treatment billing history for current residents was less than 1 year long
2. The water meter was less than 1 year old
3. Meter size was other than 5/8" or 3/4"
4. Inadequate water pressure

The sample screening process led to a final size of 101 treatment group and 100 control group properties. Only treatment group properties were screened for abnormal pressure—the vast majority of these (83 out of 101) had a pre-retrofit water line pressure of between 50-70 PSI. The age distribution of the water meters was also comparable between the treatment and control groups.

Unmeasured Flow Reducers were installed at different times between October, 2014 and April, 2015.

1. 31 retrofits were completed during October, 2014
2. 41 retrofits were completed during February, 2015
3. 23 retrofits were completed during March, 2015
4. 6 retrofits were completed during April, 2015

Billing data for both the treatment and control group properties were compiled from January, 2012 onward (to provide at least two years of pre-retrofit data) until August, 2016 (to provide at least one year of post-retrofit data).

Prior to commencing the statistical analysis, billing, account and meter data were screened to identify problematic patterns, such as, stuck meters, resident turnover during the post-retrofit period, insufficient length of post-retrofit history, etc. This caused the final analysis sample to drop to 83 treatment group properties and 83 control group properties with clean and complete data. It is merely a coincidence that after data editing we end up with the same number of properties in each group.

c. Impact of UFR Retrofits on Water Pressure

Pre and post retrofit pressure readings were taken in order to understand what impact installing the UFR device has on household water pressure. Water pressure readings were taken for 100 of the 101 residential meters. Water pressure was measured at the hose bib at the front of the home prior to installation of the UFR and again immediately after the installation of the UFR. A Wika Instruments brand pressure gauge was used.

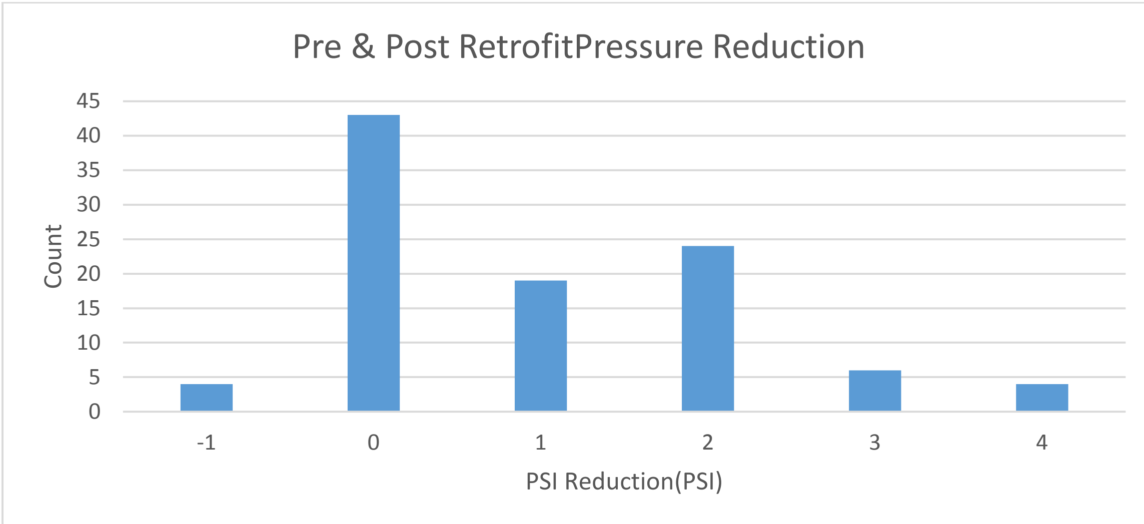
The range of pressure readings recorded was from 41 PSI to 90 PSI. The mean pressure reading was 61 PSI and the median was 60 PSI. 83 of the 100 meters had a pre-retrofit pressure reading in the range 50 to 70 PSI.

Figure 1 summarizes the observed change in pressure following installation of the UFR device.

- 43 meters registered no change in pressure.
- 19 meters registered a 1 PSI reduction in pressure.
- 24 meters registered a 2 PSI reduction in pressure.
- The mean reduction in pressure was 1 PSI and the median was 1 PSI.

No relationship was found between the pre-retrofit pressure reading and the magnitude of the change in pressure.

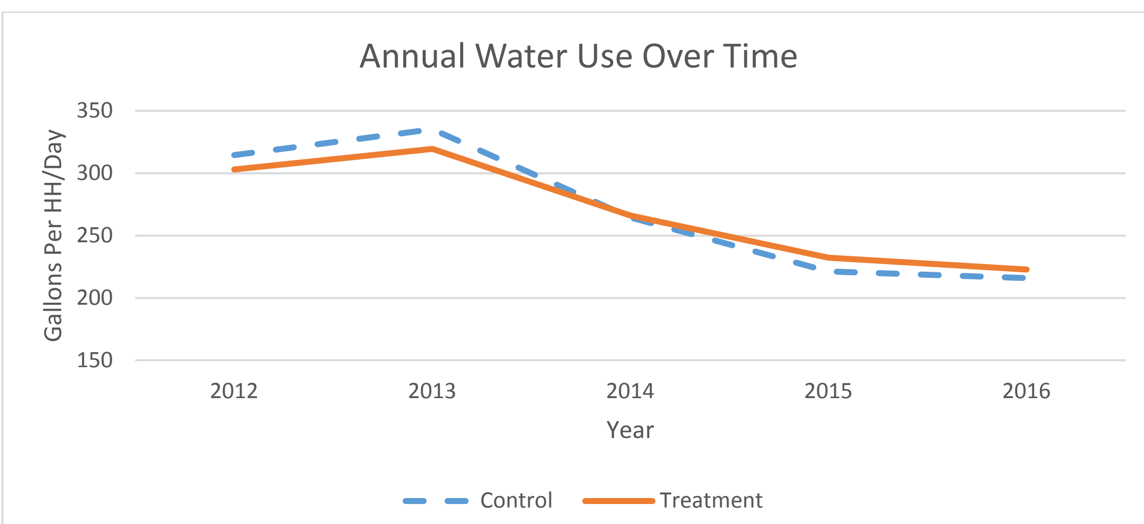
Figure 1 Pre and Post Retrofit Pressure Reduction



d. Impact of UFR Retrofits on Billed Water Usage

Figure 2 shows raw trends in annual water use for the control and treatment groups over time (2016 estimates reflect a partial year, being based on reads taken until August, 2016). These trends should be treated as notional because they are derived from staggered billing data without any adjustment for weather or retrofit date. For example, to estimate 2012 average use, all bill reads taken in 2012 were first added together for each account and divided by the number of days represented by these 2012 reads. These were then converted into account-specific estimates of daily per household gallon usage for each year. Finally, these account-specific estimates were averaged across accounts in the treatment and control groups to derive group-level estimates of water use. The trends clearly show a crossover right around the year (2014) when UFR retrofits first began to be undertaken. Since then, the treatment group's billed use has remained consistently higher than that of the control group.

Figure 2 Annual Water Use Over Time



While notional trends indicate that UFR retrofits had the expected effect, it is necessary to develop statistical models to estimate their actual impact. Appendix A discusses in greater detail both model development and findings. Here we only highlight the key findings.

The first step in the model-based impact evaluation was to verify whether water use among the treatment and control properties was well matched before the UFR retrofits occurred, and that both groups responded to drought restrictions and messaging in roughly equal ways. This was assessed in two ways. We first tested for this by estimating a water demand model using billing data prior to October 21st, 2014 for both groups, which is the date when the first batch of retrofits were undertaken. In a variation on this approach we re-ran the models using pre-treatment histories that included data up to the time an account was retrofitted making the pre-treatment billing histories unequal for the treatment group properties. For the control group properties in this latter approach, billing data were included until April, 2015, which is when the last batch of UFR retrofits occurred. With this latter approach one is able to observe for a few more months the impact of drought restrictions on the later-retrofitted properties.

Both approaches demonstrate that the water demand of treatment and control group properties was well matched prior to the retrofits (i.e., the estimated average difference was statistically insignificant), meeting the first key requirement of a valid impact evaluation.

Next, a full demand model was estimated using data from January, 2012 until August, 2016 including a retrofit indicator that takes on the value of 1 for the post-treatment billing history, 0 otherwise. This indicator takes on the value of 0 for all control group billing data. The coefficient on this indicator variable estimates how much billed usage changed after the UFR retrofits. The models indicate that UFR retrofits caused billed usage to increase by roughly 6.4% (statistically significant).

A caveat to keep in mind about the estimated impact of UFR retrofits is that the percentage of time that water meters experienced low flows would have been greater during the 2014-2016 period due to drought restrictions, compared to a normal year (Figure 2). It's possible that this may be biasing upward the percentage estimated impact of UFR devices compared to what it would be in a normal year. A well-matched control group cannot correct for this problem since both groups would be subject to this phenomenon. A longer-term follow-up of these properties should be considered to shed further light on this question. If the above surmise is correct, however, it also follows that UFRs may offer a higher benefit in drought-affected years when revenue shortfalls are most pronounced.

Appendix A—Model Specification and Estimation

a. Conceptual Model

A logical way of modeling staggered billing data is to conceive the model at a daily level and then scale it up to the meter-read level. Equation (1) expresses logarithmically transformed daily consumption (U_{it}) for customer (i) at time (t) as a function of the daily weather index (W_t), say, the evapotranspiration rate, customer characteristics (X_i), daily intercept terms (α_t) and random error (ε_{it}). This model is very flexible insofar the intercept terms and weather coefficients are conceptually allowed to vary on a daily basis. Intercept terms are necessary because intervening human factors make consumption's relationship with weather somewhat sticky. Irrigation decisions, to some extent, are based upon experience and "gut feel." A weather index alone is therefore unlikely to fully capture variation in consumption by time of year.

$$Ln(U_{it}) = \alpha_t + \beta_t W_t + \eta X_i + \varepsilon_{it} \qquad (1)$$

where $\varepsilon_{it} \sim N(0, \sigma^2)$

Daily consumption is logarithmically transformed because water consumption is generally distributed with a long right-hand tail. And usually, even after accounting for customer heterogeneity and seasonality, model error does not exhibit a normal distribution. A couple of explanations can be offered for skewed model error. First, the most seasonal component of consumption—irrigation—is a discrete event, even when scheduled according to scientific principles. A landscape is supposed to be irrigated when daily evapotranspiration has depleted the soil water content below a certain threshold (Snyder and Sheradin, 1992). When daily evapotranspiration is low and uncertain, or rainfall is received periodically, average daily consumption may exhibit a rightward skew. Second, landscape professionals often set irrigation schedules by varying a preset baseline schedule in proportion to changes in the evapotranspiration rate. Errors are therefore proportionally magnified or diminished.

Averaging consumption across the (N) days included in a read taken at time (T) yields the meter read-level model (Equation 2). Throughout, summation operators are subscripted backward in time because meter read-dates signal the end of a consumption period. If consumption days (N) vary markedly across reads, averaging insures error homoscedasticity at the meter-read level when daily error is homoscedastic. Of course, in spite of averaging, meter read-level error will be heteroscedastic if daily error itself is heteroscedastic, in which case (2) should be estimated using generalized least squares. Autocorrelation is a different matter, however. Because of error averaging, autocorrelation at the meter-read level should be low to nonexistent even if daily error is highly autocorrelated. It can be mathematically shown that if daily autocorrelation is as high as 0.9, even then observed autocorrelation will only be 0.092 for 30-day cycle reads, and 0.025 for 61-day cycle reads (Bamezai, 1997).

$$\frac{1}{N}\sum_{t=T}^{T-N} Ln(U_{it}) = \sum_{t=T}^{T-N}\alpha_t \frac{1}{N} + \sum_{t=T}^{T-N}\beta_t \frac{W_t}{N} + \eta X_i + \frac{1}{N}\sum_{t=T}^{T-N}\varepsilon_{it} \tag{2}$$

where $\frac{1}{N}\sum_{t=T}^{T-N}\varepsilon_{it} \sim N(0,\sigma^2)$

Estimation of (2) as it stands requires the creation of at least 365 daily indicator variables (equal to *1/N* for days included in the read) for capturing the daily intercepts and another 365 interactions of these indicators with the daily weather index to capture the daily weather response. For days not included in a specific meter read, the corresponding daily indicators and their interactions take on the value of zero. Such an enormous estimation exercise is unlikely to succeed not only because of the immense computing resources required, but also because of multicollinearity among many of the daily indicator variables. Meter reads must be available for every day in the year to provide the variation necessary for estimating these daily parameters, but read-dates are often clustered by design. Thus, for estimation purposes, it is necessary to impose some simplifying restrictions on these daily parameters.

One option is to assume that the daily intercepts (α_t) and the weather response coefficients (β_t) are equal for all days in a given month. Doing so reduces the estimation problem down to 12 monthly intercepts, 12 weather coefficients, and other customer characteristics included in the model. It is not necessary to place the same restrictions on (α_t) and (β_t). For example, the daily intercept terms (α_t) may be fit with piece-wise linear or cubic splines (Suits et al., 1978; Robb, 1980), while the weather coefficients (β_t) may be assumed constant for either all days in a month or all days in a season. The daily intercepts may also be captured using Fourier harmonics (Bamezai, 1996).

Because monthly restrictions are perhaps the most obvious choice with billing data that follow a 30-day cycle, the implication of these restrictions is developed in greater detail. Equation (3) shows what these restrictions imply for meter reads that span a total of (*N*) days, with (*m*) days falling in one month and (*n*) days in the next.

$$\frac{1}{N}\sum_{t=T}^{T-N} Ln(U_{it}) = \alpha_m \frac{m}{N} + \alpha_n \frac{n}{N} + \beta_m \sum_{t=T}^{T-m}\frac{W_t}{N} + \beta_n \sum_{T-m-1}^{T-m-n}\frac{W_t}{N} + \eta X_i + \frac{1}{N}\sum_{t=T}^{T-N}\varepsilon_{it} \tag{3}$$

To estimate (3) it is necessary to allocate the total number of days covered by a meter read to each calendar month. In other words, 12 monthly variables must be created of which 2 take on the values (*m/N*) and (*n/N*) for any given read, the rest being zero. Similarly, the daily weather index during a read interval must also be split into month-specific aggregates. Once again, 12 weather variables are required of which only at most 2 take on a nonzero value for any given read. Meter reads taken bimonthly can be handled just as easily in the above framework, the only difference being that such reads are likely to span 3 instead of 2 months.

Construction of the dependent variable in (3), however, still poses a minor problem. The dependent variable is equal to the sum of logarithmically transformed daily consumption. But billing histories yield only the sum of daily untransformed consumption which, after a logarithmic transformation, does not equal the desired dependent variable (Equation 4).

$$\frac{1}{N}\sum_{t=T}^{T-N} Ln(U_{it}) \neq Ln(\frac{1}{N}\sum_{t=T}^{T-N} U_{it}) \tag{4}$$

The above inequality, however, can easily be resolved by leaning on well-known properties of a lognormal distribution.

If $$Ln(U_{it}) \sim N(\mu_t, \sigma^2)$$

then $$E(\frac{1}{N}\sum_{t=T}^{T-N} Ln(U_{it})) = \frac{1}{N}\sum_{t=T}^{T-N} \mu_t \tag{5}$$

Similarly

$$Ln(E(\frac{1}{N}\sum_{t=T}^{T-N} U_{it})) = Ln(\frac{1}{N}\sum_{t=T}^{T-N} e^{\mu_t + \frac{\sigma^2}{2}}) = \frac{1}{N}\sum_{t=T}^{T-N} \mu_t + \frac{\sigma^2}{2} + Ln(\frac{1}{N}\sum_{t=T}^{T-N} e^{\varepsilon_t}) \tag{6}$$

where $$\varepsilon_t = \mu_t - \frac{1}{N}\sum_{t=T}^{T-N} \mu_t$$

Under most plausible scenarios of the rate of change in average daily consumption (μ_t) over the course of 30 or 61 days, the last term in (6) converges to zero. In other words, the two quantities cited in (4) differ approximately by a constant (that is, half of the daily variance), hence are readily substitutable.

b. Approximating Nonlinearity and Reducing Measurement Error

If data and model diagnostics indicate that the weather index (say, the evapotranspiration rate) should either be logarithmically transformed or that higher powers should be included as well, the framework developed in (1) through (6) can easily include such possibilities. One such case is discussed below for illustration.

Assume daily consumption is a quadratic function of weather instead of a linear function (Equation 7).

$$Ln(U_{it}) = \theta_t + \omega_t W_t + \psi_t W_t^2 + \eta X_i + \varepsilon_{it} \tag{7}$$

where $\varepsilon_{it} \sim N(0, \sigma^2)$

Under the assumption of monthly restrictions, estimation of (7) now requires 12 additional variables to capture the weather index's second power. But, by applying a linear approximation to (7), both the computational burden and the impact of measurement error can be minimized. The daily weather index is first re-expressed in terms of deviations from the daily mean, but then higher powers of the deviations are dropped (Equation 8).

$$Ln(U_{it}) = \theta_t + \omega_t(\overline{W_t} + \Delta W_t) + \psi_t(\overline{W_t} + \Delta W_t)^2 + \eta X_i + \varepsilon_{it} \tag{8}$$

$$\Rightarrow Ln(U_{it}) \approx \alpha_t + \beta_t \Delta W_t + \eta X_i + \varepsilon_{it}$$

where $\alpha_t = \theta_t + \omega_t \overline{W_t} + \psi_t \overline{W_t}^2$

$$\beta_t = \omega_t + 2\psi_t \overline{W_t}$$

After the linear approximation, the essential structure of (8) is identical to (1). By working with daily deviations in the weather index, however, an approximate nonlinear weather specification is implicitly assumed without any increase in the computational burden. Bamezai (1997) demonstrates the validity of this approximation. Two additional benefits also accrue from the above approximation. First, the daily intercepts (or monthly if so constrained) provide a direct measure of average consumption on a particular day (or month) in a normal weather year—the differenced weather index is centered at the mean by construction. Second, a systematic time bias in the weather index's mean caused by lack of information about plant material by customer is likely to influence the deviations significantly less. A differenced weather specification (8) therefore simultaneously minimizes the impact of systematic measurement error while capturing an approximate nonlinear weather response. Even if weather response is linear, a differenced weather index is preferable to an undifferenced index: either index will yield identical results in the absence of measurement error, but the former is likely to be more accurate in the presence of measurement error.

c. Weather Index Construction

For the analyses that follow, weather variation is captured through a rainfall adjusted evapotranspiration-rate index (Equation 9). The evapotranspiration rate measures a plant's total water demand. It is necessary to subtract effective rainfall from the evapotranspiration rate to accurately predict net irrigation demand. The daily evapotranspiration and rainfall data are obtained from CIMIS.

$$W_t = \max[0, (ET_t^R K_t^C - P_t u)] \tag{9}$$

where

W	daily weather index (inches)
ET^R	daily reference evapotranspiration rate (inches)
K^C	crop coefficient
P	daily precipitation (inches)
u	effective proportion of precipitation

CIMIS's ET^R represents the water demand of 4- to 6-inch-tall, cool-season grass transpiring at its maximum rate. In reality, plant height, plant roughness, plant age, ground shading, and other factors, all influence actual evapotranspiration needs of a plant (Snyder, 1993). If plant material is known, (fixed or time-varying) crop coefficients can be incorporated into Equation 9 to correct the reference evapotranspiration rate. For example, Meyer and Gibeault (1987) provide estimates of monthly crop coefficients for cool season turf. Half of daily rainfall is assumed to be effective as per CIMIS's recommendation, but when effective rainfall exceeds total evapotranspiration demand, net evapotranspiration demand is floored at zero. As mentioned earlier, the science underlying irrigation is essentially a stock and flow problem (Snyder and Sheradin, 1992). Soil moisture content (stock) must be maintained within a certain threshold. Evapotranspiration (flow) reduces the stock on a daily basis, effective rainfall intermittently adds to it, with irrigation acting as the balancing lever. A weather index constructed using a stock and flow framework is likely to be a better predictor of irrigation demand—the most weather-sensitive portion of total demand.

The CIMIS station in Novato (station #187) was used for depicting weather in the study area of North Marin County.

d. Model Results

Water reductions achieved through the UFR retrofit program were estimated by analyzing pre- and post-retrofit billing histories, controlling for weather and other unobserved time-invariant differences (fixed effects) across the single-family properties included in the study. A matched control group was also included. The bill read that includes the retrofit date is excluded from the models since it represents a mix of pre- and post-retrofit use. The model relates the logarithm of average daily consumption to a vector of covariates including monthly indicators, yearly indicators, weather deviation variables, and an indicator variable for each single-family property that captures differences in average use across them. Weather effects were pooled across contiguous months where estimated coefficients appeared insignificantly different, leading to three distinct seasons in a year.

Table 1 and Table 2 display the two key estimated model results. The models include monthly indicators to capture the normal seasonality in water use from month to month. February is treated as the reference month, although any month could be assigned to play this role. The other monthly indicators capture how much greater or lower water use was relative to February. Given that all the other monthly indicators are positive implies that water use reaches a minimum during February in North Marin County (a fairly typical pattern observed in other parts of California as well on account of precipitation being the greatest in February).

The models also include indicator variables for the first and second half of years 2014, 2015, and 2016. These capture the impact of drought messaging and restrictions in these time periods relative to the base period of 2012 and 2013. Once again, the coefficients reveal a credible pattern showing that drought restrictions reached their maximum effect during the second half of 2015, and were continuing to impact water use throughout 2016 relative to the base period. Finally, a post-retrofit indicator captures the impact of the UFR retrofits on billed use relative to the control group, which the model estimates to have been roughly an increase of 6.4% in billed use.

Table 2 has a similar specification as Table 1, except that it also includes measures for deviations in weather from what might be considered normal in any given season. Normally, this specification works well to capture the impact of mildly abnormal weather. However, it is not clear that these measures are able to capture the impact of severe weather perturbations, such as, a severe drought that leads to calls for restrictions and supply curtailment. An indication of this can be seen in some of the patterns exhibited by Table 2's coefficients. For example, the coefficient on abnormal weather during summer is estimated to be negative and significant. This should not be the case. Normally a hotter-than-average summer would lead to increased demand, unless of course restrictions were causing it to be lower.

Although the estimated impact of UFR retrofits is greater in Table 2 (roughly 8%) we think it is safer to pin greater confidence in the simpler model's results (Table 1). In the simpler model, the effect of abnormal weather, messaging, and supply restrictions are removed implicitly by including a well-matched control group in the analysis and time indicators to capture declining use during the restriction-affected years. Inclusion of explicit weather controls in the model are probably interfering with the estimated impact of the restrictions, possibly leading to less reliable results regarding the impact of UFR retrofits.

Table 1 Fixed Effects Model for Overall UFR Effect

Dependent Variable – Ln(Use Per Day)

Covariate	Coefficient	Std. Error	t-statistic
January Month Indicator	0.330	0.173	1.9
February Month Indicator (Reference, Omitted)			
March Month Indicator	0.407	0.163	2.5
April Month Indicator	0.364	0.068	5.3
May Month Indicator	0.990	0.156	6.4
June Month Indicator	0.920	0.090	10.2
July Month Indicator	1.142	0.149	7.7
August Month Indicator	1.069	0.092	11.6
September Month Indicator	0.933	0.154	6.1
October Month Indicator	0.933	0.087	10.7
November Month Indicator	0.365	0.165	2.2
December Month Indicator	0.169	0.068	2.5
Year 2014, First Half Indicator	-0.087	0.020	-4.3
Year 2014, Second Half Indicator	-0.246	0.020	-12.0
Year 2015, First Half Indicator	-0.268	0.023	-11.8
Year 2015, Second Half Indicator	-0.463	0.024	-19.3
Year 2016, First Half Indicator	-0.360	0.023	-15.4
Year 2016, Second Half Indicator	-0.391	0.032	-12.1
Post Retrofit Indicator	0.064	0.023	2.8
Constant	-1.682	0.090	-18.6
R-Square	0.491		

NOTE: t-statistic > 1.96 means the coefficient is significant at 5 percent level or better. Estimated fixed effects are not shown for brevity, but are included in the model.

Table 2 Fixed Effects Model for Overall UFR Effect with Weather Variables

Dependent Variable – Ln(Use Per Day)

Covariate	Coefficient	Std. Error	t-statistic
January Month Indicator	0.317	0.171	1.9
February Month Indicator (Reference, Omitted)			
March Month Indicator	0.431	0.161	2.7
April Month Indicator	0.274	0.069	4.0
May Month Indicator	0.886	0.154	5.8
June Month Indicator	0.856	0.090	9.5
July Month Indicator	1.197	0.148	8.1
August Month Indicator	1.121	0.091	12.3
September Month Indicator	0.967	0.153	6.3
October Month Indicator	0.876	0.088	10.0
November Month Indicator	0.371	0.164	2.3
December Month Indicator	0.200	0.067	3.0
Year 2014, First Half Indicator	-0.111	0.020	-5.5
Year 2014, Second Half Indicator	-0.230	0.023	-10.1
Year 2015, First Half Indicator	-0.214	0.024	-9.1
Year 2015, Second Half Indicator	-0.441	0.026	-17.0
Year 2016, First Half Indicator	-0.282	0.026	-11.0
Year 2016, Second Half Indicator	-0.340	0.036	-9.5
Weather Index Deviation, Spring	10.232	1.104	9.3
Weather Index Deviation, Summer	-6.636	2.049	-3.2
Weather Index Deviation, Fall	9.416	1.647	5.7
Weather Index Deviation, Winter	4.049	1.132	3.6
Post Retrofit Indicator	0.080	0.023	3.6
Constant	-1.731	0.089	-19.4
R-Square	0.510		

NOTE: t-statistic > 1.96 means the coefficient is significant at 5 percent level or better. Estimated fixed effects are not shown for brevity, but are included in the model.

Appendix B – North Marin Water District (NMWD) Site Selection and Data Collection

a. NMWD Scope of Work

Task 1: Site Selection and Installation and Maintenance of UFRs

a. Select 100 Program sites as installation sites for UFRs, 100 Program sites for the control group, and 100 backup sites for the control and installation sites.
b. Install 100 UFRs provided to NMWD by Water Agency at selected installation sites.
c. Conduct pre-and post-UFR installation pressure tests.

Task 2: Data Collection and Reporting

a. Compile data from Task 1 and provide to Water Agency within 3 months of the end of the 1 year monitoring period.
b. Compile water usage data for 1 year before UFR installation and 1 year after UFR installation for Program installation and control group sites and provide to Water Agency within 3 months of the end of the 1 year monitoring period.
c. Prepare monthly progress reports. Submit one copy to Water Agency on the first of each month during the term of this Agreement.
d. Monthly progress reports shall include the following:
   i. A detailed list of work performed including but not limited to UFRs installed and Program observations.
   ii. Program data collected during the previous month if available.

b. Selection of Study Sites

Sites for the Pilot were selected by NMWD as follows:

- 300 total random selections based on criteria for site selection
  - 100 sites for installation of device and monitoring
  - 100 sites for a control group for monitoring
  - 100 sites as backup for additional installation sites/control group if budget allows or if other issues arise with the other sites

The criteria used by NMWD to select sites for the Pilot were:

- Meter installed at least 1 year prior to study
- Account history of at least 1 year
- 5/8” or 3/4” meters
- No automatic fire sprinkler system
- Sufficient water pressure

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