Water-Energy Nexus Shared Network AMI Pilot Report - California American Water Company

Prepared for

California Public Utilities Commission

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Executive Summary

Southern California Gas Company, California American Water Company, and Valor Water Analytics partnered for a twelve-month Water-Energy Nexus pilot from February 2017-2018, per California Public Utilities Commission ruling. The objectives for Southern California Gas Company were:

- To demonstrate the feasibility of a water utility "piggybacking" meter data on the SoCalGas Advanced Metering network
- To investigate hot water leak detection analytics and potential to address residential hot water leaks
- To calculate the embedded energy savings from reduced water loss from hot water leaks
- To test the hypothesis that AMI technology results in greater water (and associated energy savings) than monthly meter read technology
- To gain insights that can inform baselines for future program performance metrics

A quasi-randomized (based on a pre-existing meter replacement schedule) experimental design was used to evaluate the potential impact of AMI on water consumption. The study set consisted of 1,190 treatment accounts in Ventura, and equivalent control accounts. The characteristic of the treatment accounts was that they had AMI water meter reads and AMI gas meter reads, while the control accounts had AMR water meter reads and AMI gas reads. Treatment accounts also had the ability to 'opt in' and access their water consumption data through customer engagement portals.

Shared network AMI was successfully implemented and performed well over the course of the pilot. Six potential hot water leaks were detected by AMI analytics over the course of the pilot. Field investigation confirmed one hot water leak and two yard-line leaks. The remaining three issues were unverifiable. A total of 1,343 gallons of water savings and 5.4 kWh embedded energy savings due to hot water leak reduction by AMI analytics was estimated.

Treatment group customers were slow to adopt water AMI customer engagement portal technology, and only 6% residential customers signed on over the course of the pilot. No behavioral effect on water consumption could be discerned or used in advanced impact analysis.

Statistical models of advanced complexity were constructed to evaluate whether AMI technology resulted in greater water (and associated energy savings) than monthly meter read technology. Despite the significant increase in number of water (hot and not hot) leaks detected through AMI technology, there was no statistically significant effects on water and gas consumption through combined AMI leak detection and customer engagement. Given the variability seen in this data, similar non-randomized experiments will need to be at least three times larger, to confidently determine plausible effects of AMI on water and gas consumption.

Water and Gas Trends Analysis revealed that gas consumption has a significant and positive correlation with water consumption, and potentially provides more information on water consumption patterns than household characteristics such as square footage and number of bathrooms. Gas consumption explained an additional 7% of the variance in water consumption between premises. Within a consistent weather period, a premise that increased its gas use also increased its water use. This finding encourages the use of joint water and gas consumption data in evaluations of policies or programs designed to affect one service demand, since it could also impact the other.

Introduction

Advanced metering infrastructure (AMI) technology allows utilities to gather data automatically and wirelessly from their meters. It has been in use for a number of years in the energy sector and is slowly gaining traction in the water sector. The focus on advanced metering for water is greater in states like California, due to drought conditions and conservation mandates.

AMI can be deployed in multiple ways; a typical scenario is to use a 'fixed network', where by a utility will install data collectors in their service areas in order to receive radio frequency data transmissions from the meter measurement devices. Given the deployment cost, length of time to deploy, and maintenance requirements of implementing a fixed network AMI solution, such solutions may not always be feasible for water utilities.

AMI technology for water utilities opens up possibilities for continual advanced meter-level data analytics, in particular around apparent loss management. Apparent water losses are the non-physical losses that occur in utility operations due to customer metering inaccuracies, systematic data handling errors in customer billing systems, and unauthorized consumption. This is water that is consumed but not properly measured, accounted for, or billed. Having knowledge of the what, why, and how much of apparent water losses, enables utilities to recover revenue where possible, optimize meter replacement programs, and undertake appropriate demand management measures. In absence of AMI data, apparent loss analysis would be restricted to detection using monthly data, and in many cases, an exercise that occurs once a year during a top-down non-revenue water audit.

Valor Water Analytics has implemented ongoing apparent loss detection at multiple clients across the USA since 2015, and identified 1.5% of top line revenue for recovery, on average. Two apparent loss indicators of high interest to many utilities are customer leaks and meter under-registration. Knowledge of customer water leaks allows utilities to engage their customers and help them better understand the issue and identify the source. This, in turn, can lead to reduced time to correct the issue and increased water and energy savings. Knowledge of water meter under-registration or dying meters allows utilities to instate effective meter asset management programs, charge customers for true consumption, and enhance water demand management. There is great value for reducing water loss and recovering revenue through proactive, ongoing apparent loss management.

In addition to apparent loss management analytics, a unique opportunity offered by shared network AMI is the ability to detect hot water leaks across customers using joint water and gas data. Without shared network AMI, this analysis would be restricted to detection via gas data only. Undetected hot water leaks can lead to property damage and wasted water and gas. Communication to customers without sufficient data confirmation and field investigation is a risky proposition. With automated and accurate detection, utilities with energy efficiency goals could work with customers to reduce instances of excess gas consumption from hot water leaks and improve on both compliance and customer satisfaction. Southern California Gas Company conducted an exploratory analysis from 2015 to 2018 and identified that approximately 30% of anomalous gas consumption investigations were the result of a hot water leak at the customer premise. There is value for accelerated and accurate detection of hot water leaks, where joint water and gas data is available, and utilities are better equipped to work with their customers to better understand and identify the source of the leak, which may lead to reduced time to correct the issue and increased water and energy savings.

Keeping the dual concepts of shared network and joint utility analytics in mind, the California Public Utilities Commission approved a twelve-month Water-Energy Nexus (WEN) Shared Network AMI Pilot in 2016. The pilot involved 3 key partners – Southern California Gas Company (SoCalGas), California American Water Company (CalAm), and Valor Water Analytics (Valor). Aclara Technologies LLC (Aclara) was the AMI vendor for this pilot, as they provide the AMI solution for SoCalGas. In order to utilize the SoCalGas AMI network infrastructure, CalAm also used Aclara technology as their pilot AMI solution.

The objectives of the pilot for SoCalGas are:

- To demonstrate the feasibility of a water utility "piggybacking" meter data on the SoCalGas Advanced Metering network
- To investigate hot water leak detection analytics and potential to address residential hot water leaks
- To calculate the embedded energy savings from reduced water loss from hot water leaks
- To test the hypothesis that AMI technology results in greater water (and associated energy savings) than monthly meter read technology
- To gain insights that can inform baselines for future program performance metrics

Pilot Background

Service Areas and Partners

The pilot was conducted within CalAm's Ventura service area, covering neighborhoods like Thousand Oaks, Newbury Park, and Camarillo. As part of CalAm's Ventura meter replacement program, approximately 1,300 meters were identified for potential replacement and conversion to AMI. CalAm desired these meters to form the experimental treatment group. Equivalent control accounts were determined, per the methodology described in sections below. The characteristic of the treatment accounts was that they had AMI water meter reads and AMI gas meter reads, whereas the control accounts had AMR water meter reads and AMI gas reads. Residential and Commercial customer classifications were included in consideration. While not specifically selected, Residential classification included a mix of low income, moderate income, multifamily buildings and rental units. Table 1 outlines the roles and responsibilities of the parties involved in the pilot.

Table 1: AMI WEN Pilot partners and their roles

Partners	SoCalGas	CalAm	Aclara	Valor
Roles	• Provide Network Infrastructure • Run Internal Gas Analytics • Leverage Valor Hot Water Leak Analytics • Investigate Potential Hot Water Leak Flags in Field (both Internal and Valor findings)	• Trial AMI Technology and Network Piggybacking • Leverage Valor Apparent Water Loss Analytics • Investigate Apparent Water Loss Flags (Valor findings) • Maintain Smart Energy Water Customer Portal for Treatment Group Customers	• Provide AMI Technology and Infrastructure Support	• Provide CalAm with Apparent Water Loss Management Solutions (Hidden Revenue Locator) • Provide CalAm with WEN Reporting (Water Energy Nexus Calculator) • Provide SoCalGas with Hot Water Leak Management Solutions (Hot Water Leak Detector) • Provide SoCalGas with WEN Reporting (Water Energy Nexus Calculator) • Perform advanced analytics on the water and gas dataset (AMI/treatment vs control, pre and post) and hypothesis testing

Data and Experimental Selection Methodology

Data Exclusions

The list of potential treatment accounts was provided to Valor in the file 'Ventura Pilot Meters for Valor.xlsx' and contained 1301 rows. A supplementary file, 'MeterDetail+(CA0560).xlsx' was used to obtain premise values for the potential treatment accounts. Accounts were reviewed for data completeness, and the following exclusions were conducted:

- 3 rows were removed since they did not connect to a premise value
- 2 rows were removed since they had duplicate SoCalGas GNN IDs
- 79 rows were removed since they did not have SoCalGas GNN IDs (no Gas AMI)
- 7 rows were removed based off information from SoCalGas (opt-out for Gas AMI, no meter transmission unit, etc.)
- 20 rows were removed that could not be appropriately segmented

Appendix 1 details the files examined and the count of accounts removed at each step of the data exclusions process. After application of data exclusion, the treatment group comprised of 1,190 accounts. Treatment/Control pairs were identified through a segmentation process, described below.

Customer Segmentation

Customer segmentation was carried out to group accounts by their customer information and use behavior. The steps are outlined below:

- Monthly Imputation: To compare equivalent customer use within equivalent time frames, the data was normalized to a monthly scale.
- Segmentation: In order to draw a sample that best represents the attributes of the underlying population, customer segmentation was done by Region (Ventura), Customer Type Classification, Meter Size, and then further based on their usage.
    - Customer Type Classification and Meter Size were pre-determined by CalAm, and included Residential, Commercial, Industrial, and Public Authority classes, and water meter sizes from 5/8 inch to 2 inch.
    - Usage was used to further segment customers into one of four possible quadrants (A-D), based on their baseline use and peaking factors.
        - Segment A: Low Users, High Peakers
        - Segment B: High Users, High Peakers
        - Segment C: Low Users, Low Peakers
        - Segment D: High Users, Low Peakers

Treatment and Control Group Determination

Once the treatment accounts were segmented suitably, controls were identified by randomly sampling from the matching segments. A pool of 20,804 premises in the Ventura service area was available for controls determination. All treatment and control accounts were re-checked for data completeness from a historical water billing perspective. Accounts were also verified by SoCalGas to be active AMI gas accounts. In instances where accounts were either opt-out for AMI gas or without a meter transmission unit, alternate accounts were selected. At the end of this process, the 1,190 treatment and 1,190 control accounts were assigned with Valor IDs using the following naming convention: Ventura Treatment accounts "T-Vent(Number)", Ventura Control accounts "C-Vent (Number)." AMI water meters were subsequently installed by CalAm for the treatment accounts over an eight-week period. The final list of 1,190 Treatment/Control pairs for Ventura used in WEN analysis is presented in Appendix 2.

Analytics reporting period

Once the AMI water meters were successfully installed and steadily transmitting hourly water data, Valor completed CalAm enterprise and water meter data integration and configuration and launched the Hidden Revenue Locator online dashboard. In parallel, Valor completed SoCalGas gas meter data integration and configuration, and launched the Hot Water Leak Detector online dashboard. The start date of the twelve-month analytical reporting period for both CalAm and SoCalGas was February 6, 2017; the date when CalAm's customer engagement portal was potentially available for treatment accounts. The analytical reporting period ended on February 6, 2018.

CalAm Sample Size Significance

The standard recommendation for experimental studies like this pilot is to include as large a sample size as practically possible. For the CalAm engagement, standard statistical estimation techniques [1] were used to determine the minimal treatment group sample size.

The minimal treatment group sample size calculation is:
$n = z^2(p*q)/ \delta^2$, with $z=2$, $p=0.5$, $\delta=0.05 \rightarrow n = 400$

It was therefore determined prior to analytics start that at least 400 treatment accounts would be needed over a twelve-month period, to make statistically plausible inferences about pilot hypotheses. It must be noted that with any statistical experiment, it is not possible to have any a priori determination [1].

SoCalGas Analytics Dashboards

A process was set up to send Valor gas data from SoCalGas two days after the gas meter read date, and for Valor to ingest and publish flags on a "next day" basis. A separate process was set up to send Valor AMI water meter data from Aclara on a daily basis, and billing and monthly water meter data from CalAm on a monthly basis. As indicated in Table 1, the analytics dashboards provided by Valor to SoCalGas were:

- Hot Water Leak Detector
- Water Energy Nexus Calculator

The Hot Water Leak Detector dashboard is a 'Call-to-Action' dashboard and ingests and analyzes water and gas data to flag potential hot water leaks in a timely manner. Two types of potential hot water leak flags are determined, depending on data source.

- Other Anomalous Gas Use (OAG): This is a potential hot water leak, predicted using hourly gas data only. The account/customer gas usage reveals the digital signature of a hot water leak; however, a corresponding pattern in the water data is not observed for the synchronized time period. The absence of the water pattern may be due to lack of availability of AMI water data, or because it does not meet the criteria for detection in the monthly water leak analysis. OAG flags are updated on a "next day" basis for both treatment and control accounts.
- Suspect Hot Water Leak (HWL): This is a potential hot water leak, predicted with high confidence, since it leverages both gas and water data. The digital signature of a leak is present in the synchronized gas and water data. HWL flags are updated on a "next day" basis for treatment accounts, and monthly for the control accounts.

The Water Energy Nexus Calculator dashboard for SoCalGas is an online 'Reporting' dashboard that quantifies water, embedded energy, greenhouse gas (GHG), and monetary savings associated with hot water leak detection. To calculate these savings, Valor measures the water saved via early detection with AMI technology as follows:

- Water Saved (Estimated): The theoretical gallons of water saved by early detection of hot water leaks in the treatment group. It is calculated by comparing the amount of excess water leakage and/or usage that would have occurred should Valor have not detected and reported the hot water leak before the end of the billing period.
- Therms Saved (Estimated): The theoretical therms of natural gas saved via early detection of hot water leaks in the treatment group. It is calculated by comparing the amount of excess leakage and/or usage that would have occurred should Valor have not detected and reported the hot water leak before the end of the billing period.
    - Excess gallons and therms detected are measuring using the formula, $Qiwg = \Delta t * BASELINEiwg$. Q is the quantity of water leaked or gas used, measured in gallons or therms, respectively, Δt is duration of the time period where a customer consumes a continuous nonzero amount of water or gas, measured in hours, and BASELINE is the minimum rate of nonzero hourly consumption of water or gas during the time period Δt. w indicates water meter data while g indicates gas meter data. i is the individual meter. Q is measured using the data provided by the AMR and AMI meters.
- kWh Saved (Estimated): The theoretical kWh of electricity saved via early detection of hot water leaks in the treatment group. It is calculated by comparing the amount of excess water leakage and/or usage that would have occurred should Valor have not detected and reported the hot water leak before the end of the billing period, and then calculating the embedded energy per water volume saved, per the 2016 CPUC Water Energy Nexus Calculator [2].
- Avoided Energy Cost (Estimated): The average annual monetary savings associated with Therms of natural gas and kWh of embedded energy avoided. The avoided energy cost was calculated per the methodology in the 2016 CPUC Water Energy Nexus Calculator [2].
- Kg CO_2 Equivalent Saved (Estimated): The total kilograms of carbon dioxide equivalent that were avoided as a result of the saved natural gas therms and embedded energy of water in hot water leaks. Carbon dioxide equivalent is a metric that describes, for a given mixture and amount of greenhouse gas, the amount of carbon dioxide that would yield the same global warming potential when measured over a timescale of 100 years. The California Air Resources Board GHG Calculator methodologies were applied for this calculation [3].

Analytics Delivery Overview

SoCalGas' receipt of approval for the Commission filing in August 2016 triggered the installation of the AMI meters for treatment accounts by CalAm and the project planning process for analytics by Valor. Figure 1 outlines the phases involved in Valor's analytics deployment process. Planning, Integration, and Configuration activities occurred October 2016 to January 2017, and the Hot

Water Leak Detector dashboard was launched in the first week of February 2017. The Water Energy Nexus Detector dashboard was launched in the first week of March 2017.

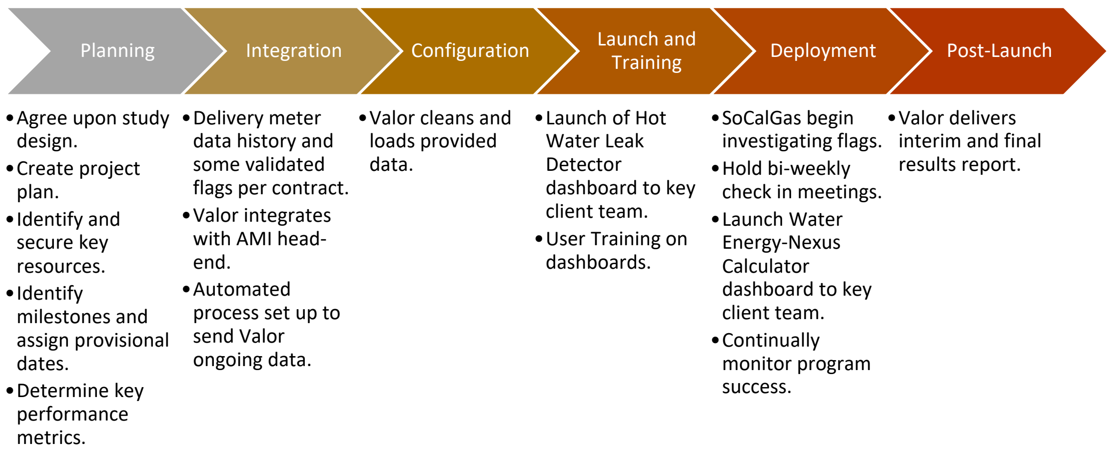

Figure 1: Analytics Deployment Phases Overview

Hot Water Leak Detector Flag Investigation and Feedback Process

An investigation process (Figure 2) was established to check the flags produced on the Hot Water Leak Detector dashboard. The field checks aligned with protocols that SoCalGas already had in place. It was determined during kickoff that SoCalGas would only validate Residential hot water leaks within pilot scope. Validation of Commercial hot water leaks would require new resources and procedures to be established, and deferred post-pilot. Information regarding hot water leak investigations were shared by SoCalGas with CalAm through email communication.

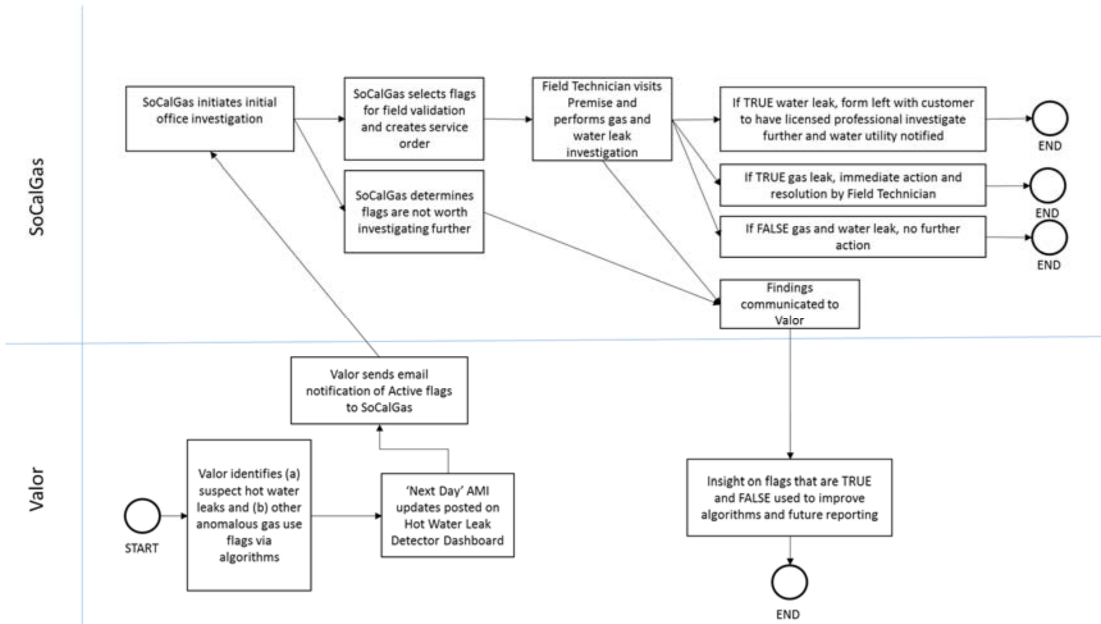

Figure 2: Schematic of Hot Water Leak Detector flag investigation and feedback process

Final Report Results Data Description

Table 2 summarizes the water and gas records included in the final report results analysis. The final billing month considered for analysis is January 2018.

Table 2: Description of water data from January 2014 to January 2018, and gas data from December 2015 to January 2018

	Treatment	Control
Unique Premises	1,190	1,190
Months of Data (Water)	49	49
Number of Meter Reads (Water)	56,992	56,434
Months of Data (Gas)	26	26
Number of Meter Reads (Gas)	26,642	27,043

Results and Discussion

Network Sharing

Network performance during the course of the pilot was monitored via Aclara-provided reports for MTU/DCU Redundancy, Installed MTU Count, MTU Transmission Frequency, MTU Read Interval Length, and MTU Read Reception Rate.

Table 3: Overall DCU Count

DCUs Installed	Ventura
Before Pilot Start	21

After Pilot Start	0
Grand Total	**21**

DCUs in Ventura

- There is a total of 21 DCUs in Ventura
- Map below highlights the service territory for California American Water (Ventura) and the DCUs within and in the surrounding area

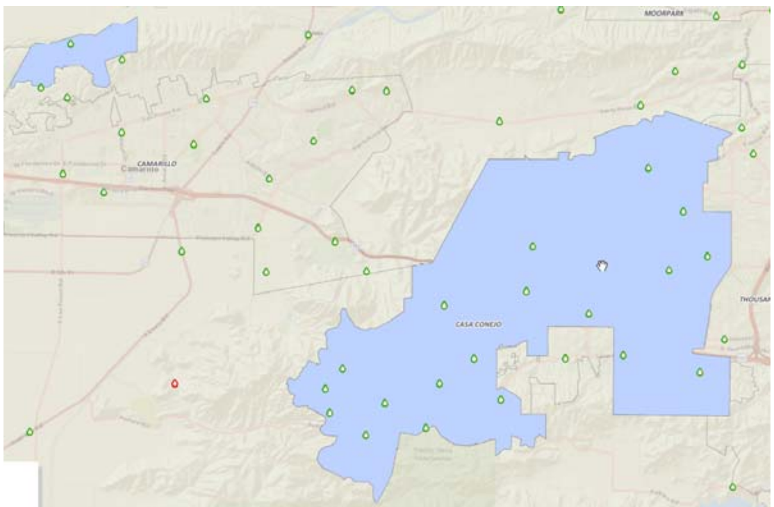

Figure 3: DCU in Ventura

The average DCU redundancy is 6. This means that each MTU is heard, on average, by 6 DCUs.

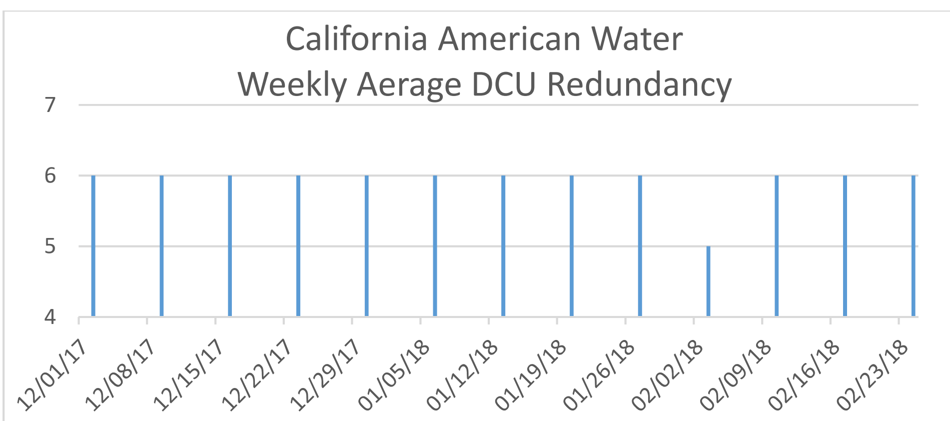

Figure 4: Average DCU redundancy

For California American Water, there are a total of 138 unique DCUs that have picked up transmissions from California American Water MTUs in that service territory. The map below plots all of the SoCalGas DCUs which have received transmissions at least once from California American Water MTU.

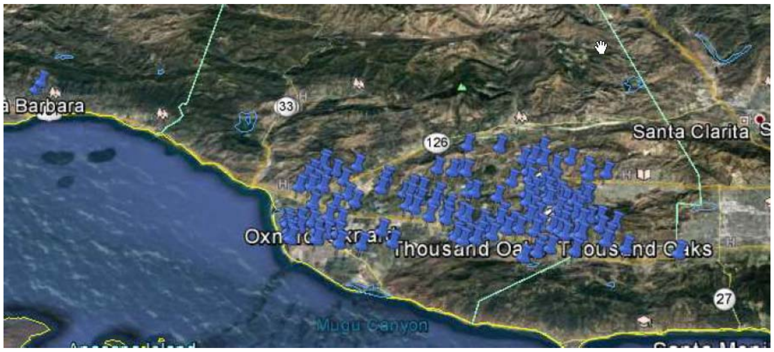

Figure 5: Ventura water MTU transmissions

The total number of installed MTUs is 1,287 (as of 2/25/18).

Table 4: MTU Installation Summary

Water Company	Installs Total	% of total Installs
California American Water	1,287	100.00

The average monthly RSR for California American Water is 98.3 for the period from August 2016 to February 2018. It is important to note that RSR is captured. Generally, RSR will increase over time as installation issues are resolved, and this is what is attributed to the peaks and valleys seen in the chart below. The average RSR for California American Water in February 2018 was 98.4.

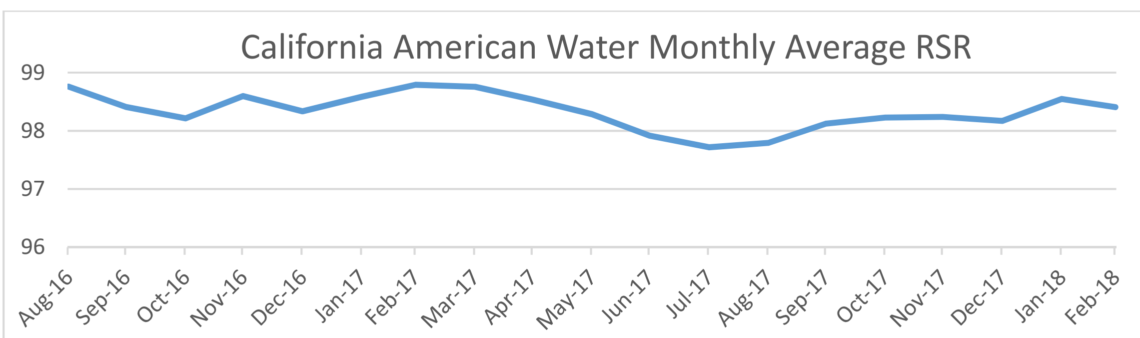

Figure 6: California American Water monthly average RSR summary

Hot Water Leak Detection and Analytics

Six potential hot water leaks were detected by Valor between February 2017 and February 2018. In general, aggregate water savings from hot water leak reduction was estimated by noting the start and end time for each leak, calculating the flow rate of that leak by comparing the flowrate during the leak period to normal consumption periods, and assuming that the leak would have continued at this flowrate until the next bill date, at which point the customer is assumed to have taken action from the high bill.

This approach is an accepted way to estimate aggregate water savings; however, it does have some limitations. The approach under-estimates water savings associated with leaks that span multiple months, since it assumes customers are prompted to action upon receipt of their bill. Another variable that is not factored in is the timeliness of outreach from the utility to the customer; it is assumed that utilities will have notified customers and/or investigated flags soon after their detection. In reality, the timeliness of leak notification may vary between flags, during which period a leak could self-resolve; this was beyond the scope of the program to analyze.

C-Vent1454 OAG

The first flag was an OAG (hot water leak signature based off gas AMI data only) on a control group account, C-Vent1454. The leak was active from July 3, 2017 to August 16, 2017 and caused an excess gas use of 21.6 therms. The premise is a single-family home with 4 bedrooms, 2 bathrooms, with 1,639 finished sq. ft. and 7,147 sq. ft. of potentially irrigated area

SoCalGas conducted a field visit and verified a gas leak on the pool heater gas line. They also confirmed that the water meter was not spinning. A form was left for the customer to contact a licensed plumber to repair the yard line leak.

C-Vent1562 OAG

The second flag was an OAG (hot water leak signature based off gas AMI data only) on a control group account, C-Vent1562. The leak was active from August 25, 2017 to September 21, 2017 and caused an excess gas use of 13.5 therms. The premise is a single-family home with 4 bedrooms, 2.5 bathrooms, with 2,589 finished sq. ft. and 10,508 sq. ft. of potentially irrigated area.

SoCalGas conducted a field check and verified a leaking gas line for a BBQ. A form was left for the customer to contact a licensed plumber to repair the yard line leak.

T-Vent1360 HWL

The third flag was a HWL (hot water leak signature based off both gas and water AMI data) on a treatment group account, T-Vent1360. The leak was active from September 29, 2017 to October 30, 2017. Excess water use of 3,456 gallons and excess gas use of 15.3 therms was observed. The premise is a single-family home with 4 bedrooms, 3 bathrooms, 1,996 finished sq. ft. and 8,404 sq. ft. of potentially irrigated area.

SoCalGas conducted a field check, and confirmed a hot water leak at this facility. The field representative logged the following notes:

- Confirmed water meter was spinning with no water in use

- There was normal registration once the water heater was not in demand
- Customer confirmed bathroom floor tile was warm
- Thermostat at water heater was left in vacation (status)
- Water heater access is outside
    - Whirlpool 40 Gal
    - 34,000 input BTU
    - Year of manufacturer – 2010

C-Vent653 OAG

The fourth flag was an OAG (hot water leak signature based off gas AMI data only) on a control group account, C-Vent653. The flag was active from November 11, 2017 to November 22, 2017 and caused an excess gas use of 11.7 therms. The premise is a single-family home with 4 bedrooms, 2.5 bathrooms, with 1,635 finished sq. ft. and 527 sq. ft. of potentially irrigated area.

SoCalGas office investigation determined that the usage appeared to be normal for heating season; a field check was not conducted.

T-Vent1600 OAG

The fifth flag was an OAG (hot water leak signature based off gas AMI data only) on a treatment group account, T-Vent1600. The flag was active from December 13, 2017 to January 2, 2018 and caused an excess gas use of 40.3 therms. The premise is a single-family home with 4 bedrooms, 3 bathrooms, with 2,855 finished sq. ft. and 4,126 sq. ft. of potentially irrigated area.

SoCalGas conducted a field check on February 2, 2018, some days after consumption returned to normal. The customer was not home; SoCalGas could therefore not evaluate appliances or discover if the customer was aware of the consumption anomaly or had made any repairs.

T-Vent1549 OAG

The sixth flag was an OAG (hot water leak signature based off gas AMI data only) on a treatment group account, T-Vent1549. The flag was active from December 19, 2017 to December 28, 2017 and caused an excess gas use of 9.1 therms. The premise is a single-family home with 4 bedrooms, 2 bathrooms, with 2,313 finished sq. ft. and 6,703 sq. ft. of potentially irrigated area.

SoCalGas conducted a field check on February 2, 2018, some days after consumption returned to normal. The customer was home and appliances were tested to ensure there was no safety concern. No repairs appeared to have been made. The customer was not aware of the consumption anomaly.

Table 5 summarizes the potential hot water leaks detected from February 2017 to February 2018, and the water savings associated with the verified hot water leak.

Table 5: Hot Water Leak Detection and Analytics, Post-treatment

	Control	Treatment
Number of OAG and HWL Flags Detected	3	3
Number of Hot Water Leaks Confirmed		1
Gallons Saved	0	1,343

An offline exercise was conducted a couple of times over the course of the pilot, where Valor's thresholds for hot water leak detection were loosened and additional 'interesting patterns' reviewed as a collaborative office exercise between SoCalGas and Valor. None of the flags determined were worthy of field investigation.

Hot water leaks were a small subset of the overall leaks established in this pilot; in total, one hundred and eighty-eight water leaks were identified using AMI water data. Established processes were used by CalAm to confirm some of the other (not hot) water leaks. Aggregate water savings for those water leaks have been estimated and shared with CalAm.

Water Customer Portal Engagement

CalAm elected to use an 'opt-in' approach to engage treatment group customers through the Smart Energy Water online portal. In addition, customers that had leaks flagged were contacted by phone and encouraged to use the portal. Despite multiple outreach attempts by CalAm, the sign on rates were low. A total of 70 residential customers in the treatment group were active on the customer portal over the course of the analytics reporting period. A total of 105 residential customers had at least one (not hot) water leak flag during the analytics period. Only four customers both elected to use the portal and had a leak flag. Although it is possible that these four customers adopted the portal after being notified of a leak, there is no average correlation between being flagged for leaks and adopting the portal. Table 6 summarizes the counts of treatment group residential customers in each combination of having leaks flagged and portal adoption.

Table 6: Portal Adoption and Leak Flags for Residential Treatment Group Premises

	Leak Flagged	No Leak Flagged	Total Residential Treatment Group
Used Portal	4	66	70
Did Not Use Portal	101	996	1,097
Total	105	1,062	1,167

The four customers with leak flags that adopted the customer engagement portal are T-Vent1187, T-Vent773, T-Vent1508, and T-Vent903. All had substantial water leaks of over 300 gallons. Figure 7 shows the water consumption pattern of these four customers superimposed with the periods where leaks were flagged. By visual inspection, for T-Vent773 and T-Vent903, the billed consumption for the billing month during which leaks were detected does appear to be larger than the same months in the previous year. For T-Vent1187 and T-Vent1508, the effect is more ambiguous. In all cases, the billed consumption for the billing month following the ones where leaks were flagged do not appear to be lower than consumption in the same month the previous year. These four customers therefore did not demonstrate any additional conservation effect due to using the portal, other than fixing a leak in response to leak flags.

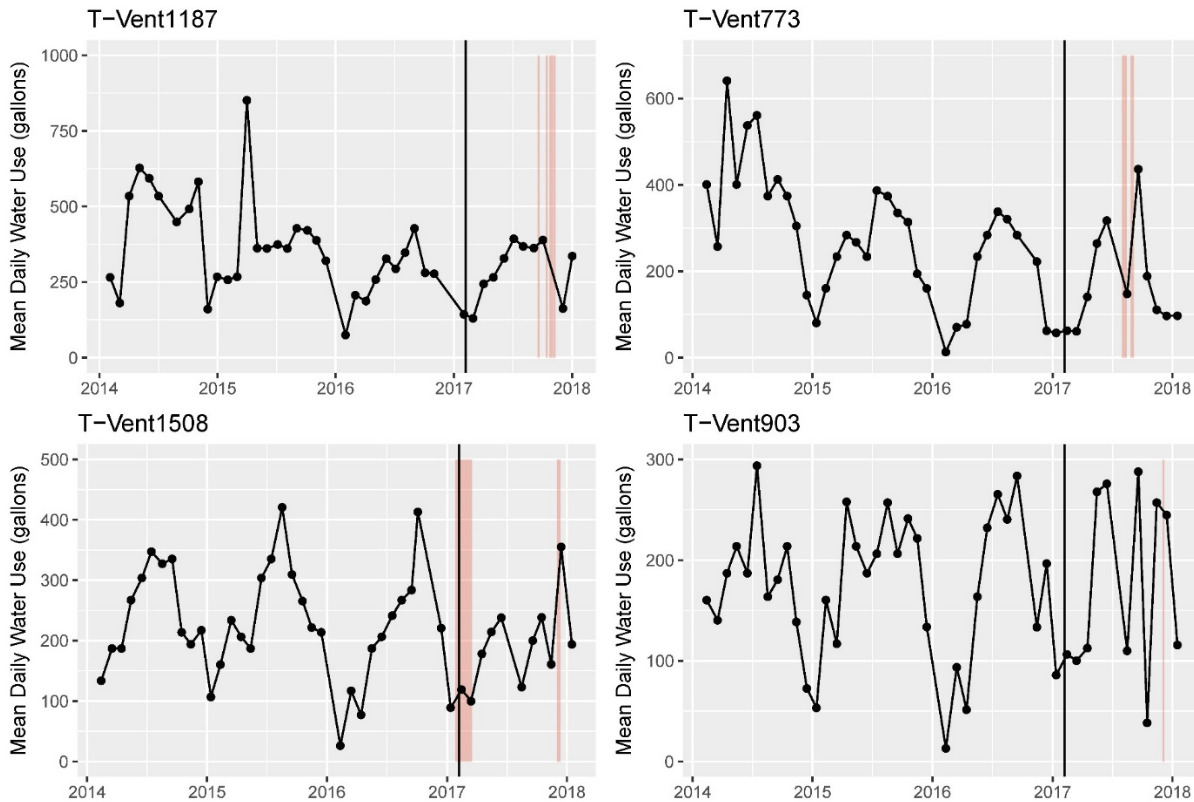

Figure 7: Water consumption patterns for residential treatment premises that experienced leaks and adopted customer engagement portal. Red shaded regions indicate flagged leak events

Water and Energy Savings

Table 7 summarizes the water and energy savings associated with hot water leak analytics and proactive intervention. Energy savings are calculated by multiplying the water savings by a constant for the average embodied energy per gallon of water produced and distributed by CalAm.

Table 7: Water and Energy Savings in Treatment Period

	Treatment	Control
Hot Water Leak/Gas Anomaly Savings (Gallons)	1,343	0
Embedded Energy Savings (kWh)	5.4	0

Advanced Statistical Modeling Results

Statistical analysis was conducted to evaluate the extent to which using AMI for water metering affected water and energy conservation—that is, caused reductions in water and gas consumption. Since only 6% of residential treatment group customers elected to use the customer engagement portal to monitor their water consumption on an hourly or daily basis, the AMI program impact on water savings was primarily from leak detection and customer notification. Improved leak detection and resolution was due to more frequent meter readings with AMI technology, enabling shorter periods between leak start and leak detection, as well due to detection of smaller leaks that may not have been picked up in leak detection algorithms based on monthly meter reads.

All of the analyses considered the effect of a binary treatment (the use of AMI analytics, without adoption of the customer engagement (CE) portal). In addition, models were specified with a secondary treatment, the use of the CE portal. Premises associated with accounts that enrolled in the CE portal at any time over the pilot are considered in this secondary treatment group; it was not possible to determine when each customer first enrolled. Among customers that did log into the portal, it was not possible to distinguish between impacts due to the enhanced resolution of water consumption information made available and conservation efforts motivated independently of and/or prior to enrollment in the portal. This is due to the voluntary, self-selected nature of the sample of customers participating in this aspect of the treatment.

Since hot water leaks represented a small portion of the 188 water leak flags, further references to 'leaks' in this section refers to 'all' water leaks.

The statistical modeling is based on a hypothesis-testing framework, where each outcome of interest has an associated null hypothesis (H_0) of there being no effect of the AMI program. The statistical models quantify the probability of observing differences between the treatment and control groups assuming that H_0 is true (i.e., that there is no difference in outcomes between the treatment and control groups). This information can be translated into a confidence interval—a range of values of the difference between the treatment and control groups with a specified probability (e.g. 95%) that the true difference is within that range. When 0 does not lie within this confidence interval, the null hypothesis is rejected in favor of an alternate hypothesis (H_1) that the difference in the outcome of interest between treatment and control groups is statistically significant. The following hypotheses were tested:

i. **Water Consumption:**
   a. H_0: There is no difference in water consumption trends between the treatment premises (those with water AMI) and the control premises
   b. H_1: Water consumption in treatment premises (those with water AMI) is different (lower) than in control premises

   The AMI treatment is hypothesized to reduce water consumption, primarily through the detection and repair of leaks faster with hourly interval data than is possible from using monthly billing data, as well as through the ability to detect smaller leaks. This is effectively a measure of the water savings resulting from the AMI treatment. While embedded energy impacts per premise could be calculated on the basis of the average change in water consumption, the dependent variable would be a constant unit conversion from water to energy units for the premises in each service area, based on the energy intensity of retail water in each service area. Thus, the effect of the AMI treatment on embedded energy in percentage terms would be the same as for water consumption.

ii. **Gas Consumption:**

a. H_0: There is no difference in gas consumption trends between the treatment premises (those with water AMI) and the control premises
b. H_1: Gas consumption in treatment premises (those with water AMI) is different (lower) than in control premises

The AMI treatment is hypothesized to reduce gas consumption, primarily through the detection and repair of hot water leaks faster than is possible from using monthly water billing data with gas AMI data. This is effectively a measure of the gas savings resulting from the AMI treatment.

iii. **Leaks Detected from monthly billing data**:
a. H_0: There is no difference in the proportion of premises being flagged for water leaks in a given billing period by the monthly leak detection algorithm between the treatment premises and the control premises
b. H_1: The proportion of treatment premises (those with water AMI) being flagged for water leaks by the monthly leak detection algorithm in a given billing period is different (lower) than the proportion of control premises being flagged

The AMI treatment is hypothesized to reduce the probability of a monthly leak detection algorithm flagging a leak, since the AMI-based leak detection algorithms would have already picked up leaks, and customers would have repaired leaks more quickly than they could otherwise. This would reduce the overall volume of outstanding leaks, and thus the probability of leaks in treatment premises being detected by monthly algorithms. This effect would be a measure of the degree to which the AMI treatment works to decrease water loss by detecting leaks more quickly.

iv. **Total Leaks Detected using all available data:**
a. H_0: There is no difference in the proportion of treatment and control premises being flagged for water leaks in a given billing period by either monthly or AMI leak detection algorithms
b. H_1: The proportion of treatment premises (those with water AMI) flagged for water leaks by either monthly or AMI algorithm in a given billing period is different (higher) than the proportion of control premises being flagged.

The AMI treatment is hypothesized to increase outright the probability of a leak being detected for given premises with a leak, due to AMI algorithms detecting smaller leaks that monthly algorithms may not be sensitive to, whether due to low flowrates or because the leak starts later in the billing cycle. The difference between this effect and effect from hypothesis (iii) above is a measure of the degree to which the AMI treatment works to decrease water loss by detecting leaks with low flowrates relative to “normal” consumption.

Model set up and initial checks

Motivation: Data availability is one limitation that informs the construction of statistical models. This section describes the data available and the initial characteristics of the study area.

Result Summary: Data available for investigation included outcome information, daily weather and precipitation, and some characteristics of residential premises available from local government tax rolls for 2016. There was substantial geographic clustering of treatment group premises, as these were pre-determined from CalAm's meter replacement program. The strong non-random component to the AMI treatment will need to be accounted for statistically. In particular, measured effects of AMI on water consumption requires cautious interpretation, since it may also be impacted by differences in water meter accuracy between the treatment and control groups.

Result Details: The following data and results were included in the advanced analysis:

- Monthly CalAm meter-level water billing records (metered consumption and bills) for treatment and control premises. Consumption data was cleaned of data entry and meter reading errors to best represent actual consumption. Meter-level data was aggregated to premise level
- SoCalGas consumption AMI data aggregated by water billing periods for treatment and control premises
- Flags of water leaks generated by Valor monthly leak algorithms
- Flags of water leaks detected by Valor AMI hourly leak algorithms

Since AMI treatment was quasi-randomized (based on a pre-existing meter replacement schedule), investigation was done on variables that might correlate with levels of water and gas consumption as well as the propensity for water leaks. A check for balance across treatment and control groups was done to ensure that the two groups were equivalent, and controls were included for these variables statistically in order to improve the precision of the treatment effect estimate and increase statistical power. A list of the variables is as follows:

- Premise-level variables – data collected:
    - Premises were address-standardized using the World Geocoding Service
    - Premise standardized addresses were geolocated using the World Geocoding Service.
    - For residential premises, other than multi-family, the following data was pulled from the Ventura County Assessors' offices:
        - 2016 Tax Assessment value of property (USD)
        - Year built
        - Lot size (sq. ft.)
        - Finished area (sq. ft.)
        - Number bathrooms
        - Number bedrooms
        - Total number of rooms
- Premise-level variables – data calculated:
    - Potentially Irrigated area (sq. ft.; Difference of Lot size and Finished area)

- Weather – data collected:
    - For all premises, weather data from PRISM, which aggregates daily climate data from all available sources into a global gridded dataset with 2km-square resolution.
    - For each premise and water billing period, the daily data for the PRISM grid cell overlapping the geocoded location of the premises was aggregated to create the following variables:
        - Average Daily Precipitation (mm)
        - Proportion of days in billing period with non-zero precipitation
        - Cooling Degree Days- base 65 (Average temperature – 65^{o}F, averaged across all days in billing period)
        - Cooling Degree Days- base 80 (Average temperature – 80^{o}F, averaged across all days in billing period)
        - Heating Degree Days (65^{o}F – Average temperature, averaged across all days in billing period)

It is important to control for weather to ensure that differences in consumption trends between the treatment and control groups are not due to differences in weather trends. In Southern California, weather affects water consumption primarily through irrigation requirements. Evapotranspiration would be a logical variable with which to control for variation in water consumption due to weather. However, evapotranspiration data in Southern California is limited to a few monitoring stations that have wide periods of missing data, and these do not provide sufficient coverage to estimate evapotranspiration variation within urbanized areas. As an alternative, weather normalization was conducted using precipitation and temperature.

Precipitation over a billing period affects water consumption through the decision of whether to irrigate, and by how much. Cooling degree days (CDD) have been calculated over each billing period. This is calculated by subtracting a base temperature from the average daily temperature and summing this value over all of the days in the billing period. This is an aggregate monthly measure of the amount of heat over the threshold base value experienced. CDD is calculated using both the standard base value of 65^{o}F as well as 80^{o}F as recommended by PG&E's Pacific Energy Center in "Guide to California Climate Zones and Bioclimatic Design" [4]. For gas consumption, instead of precipitation and CDD, we use heating degree days (HDD), which is similar to CDD except that the average daily temperature is subtracted from a base value of 65^{o}F, resulting in a monthly measure of the amount of heat likely to be demanded.

The average water price and any pricing changes faced by customers can also affect water consumption. No changes occurred in CalAm rates over the course of the analytics reporting period. Prices were therefore not considered for further investigation, as the increasing block rate would just introduce unnecessary autocorrelation into the predictor equation.

Figure 8 presents the locations of the 2,380 premises in Ventura. While the spatial distribution of control premises looks random, a high proportion of the treatment premises are tightly clustered. Treatments premises may therefore be systematically different in observed and unobserved ways from control premises. Since AMI was installed based off a pre-existing meter replacement schedule, it is possible that the older water meters in the treatment group had a higher rate of under-registration issues than water meters in the control group. The measured effects of AMI on measured water consumption could conflate real effects with measurement changes due to new meter installation within the treatment group.

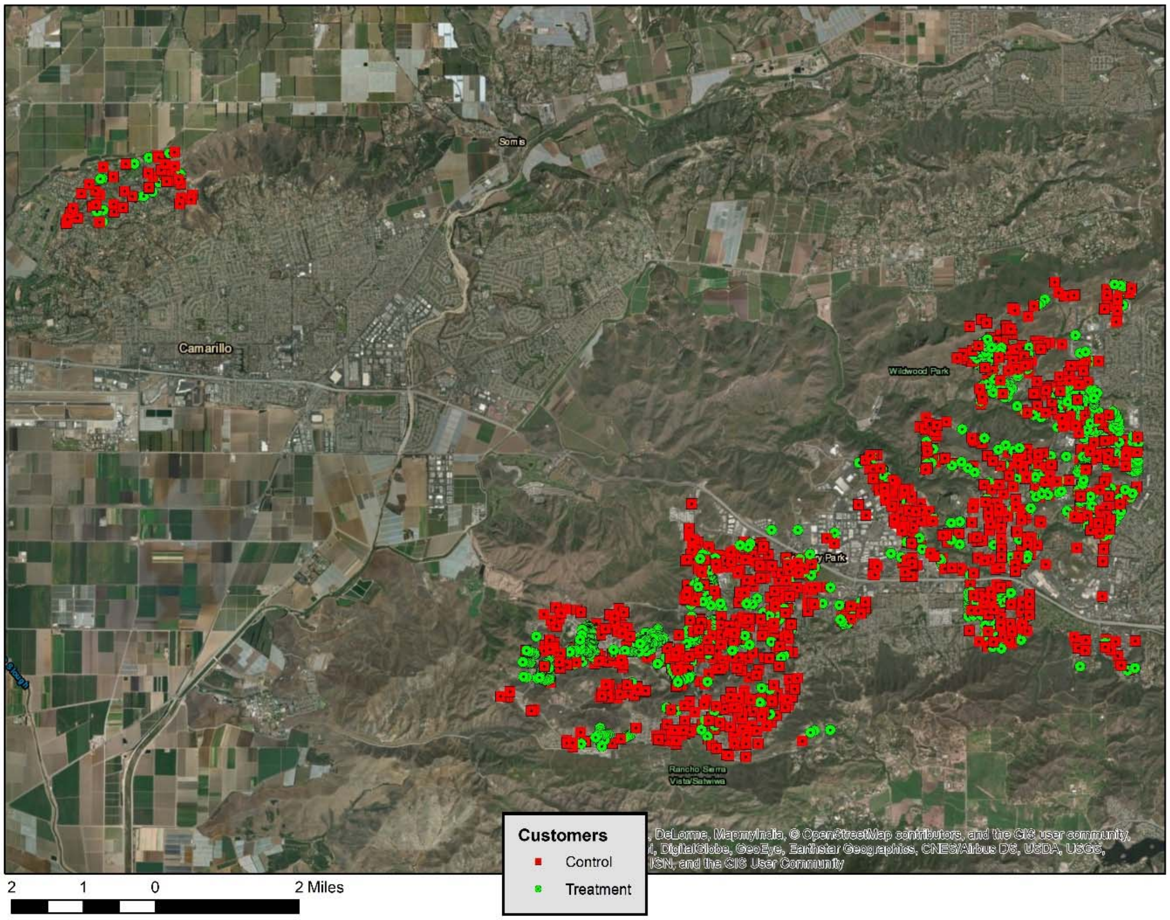

Figure 8: Spatial distribution of control and treatment premises in Ventura

Table 8 shows the average water consumption, gas consumption, number of leaks detected, climate variables and housing values for the study premises in the pre-treatment period, averaged over January 2014-January 2017.

Table 8: Ventura characteristics in the pre-treatment period, averaged over January 2014 to January 2017

Service Area	Median Water Use (Average Daily Gallons)	Median Gas Use (Average Daily Therms)	Average monthly leaks detected per premises	Average daily CDD (80F base)	Average daily HDD (65F base)	Average Daily Precipitation (mm)	Proportion days with precipitation	Average value/ sq. ft.
Ventura	516	1.57	0.007	2.79	3.49	0.77	0.1	$223

Sample Size Impact:

Motivation: Statistical hypothesis testing relies on the ability of models to construct confidence intervals that are sufficiently narrow to reject H_0, assuming that H_0 is false (i.e., that there is a true difference in outcome between groups). This requires a sufficient sample size, with generally larger sample sizes resulting in narrower confidence intervals and a higher probability of rejecting (false) H_0. This section evaluates the sufficiency of the study sample size for this purpose.

Result Summary: The sample size is likely sufficient to detect the changes in water consumption that would plausibly be caused by the AMI program at this point. The most complex statistical models may be able to detect a reduction of water and gas consumption of about 3.5%.

Result Details: A total of 2,380 premises are available for analysis, divided evenly between the treatment and control groups. Table 9 shows the full sample size in units of observations. An observation refers to a billing record (i.e. each combination of a premises with a water billing period).

Table 9: Sample Sizes for Water

	Full Sample			Residential Premises Only		
Service Area	Premises	Observations	Post-Treatment Observations	Premises	Observations	Post-Treatment Observations
Ventura	2,380	106,566	25,309	2,334	104,598	24,845

In order to determine if the sample size is of sufficient power to detect the effect of AMI with statistical significance, supposing AMI does indeed have an effect in reality, a power analysis is done to determine the effect on water consumption levels.

While the number of observations is quite large, they are not independent (since observations are repeated for the same units) and cannot be treated as such for power calculations. It is necessary to calculate the minimum detectable effect (MDE) given the data available. The MDE at 80% statistical power is the smallest true effect that would be estimated to be statistically significant with the given samples sizes at least 80% of the time in repeated experiments on the same population. The MDE of the AMI pilot in terms of percent change in water use, as measured by simple post-treatment difference in means of the logarithm of water consumption, would be calculated per the equation below:

$$MDE = (q_{1-\frac{\alpha}{2}} + q_{\lambda})\sqrt{\frac{Var(\hat{y})}{np(1-p)}}$$

In this equation $q_{1-\frac{\alpha}{2}}$ = 1.96 for two-sided 5% p-level (i.e. 95% confidence interval), q_{λ} = 0.85 for 80% power. $Var(\hat{y})$ is the variance of the outcome variable in the sample. For the purposes of power calculations, the dependent variable *y* is the natural logarithm of average daily water consumption. In this data, the variance of *y* is ~0.78. *n*=2,380 is the sample size, and *p*=0.5 is the proportion of the sample in the treatment group. With these numbers, the MDE for water consumption of the AMI program is 10.2%. For gas, in this data, the variance of *y* is ~0.6, and the associated MDE is 8.9%.

Given that similar randomized control trials of U.S. water and energy utility customer conservation and information programs typically find effect sizes between 1-5% [5,6,7], this pilot is underpowered for post-treatment only analysis. To accommodate this, panel econometric methods are used. These methods involve analyzing data collected over time following the same units, so that each unit has multiple observations. At their most simple, panel methods increase the sample size. Panel methods also allow for more complex types of analysis such as averaging the change in a response before and after a treatment across many units, while accounting for the fact that observations from the same unit are correlated. Thus, rather than comparing the average value of a response between treatment and control groups, panel methods can quantify the difference in trends between treatment and control groups.

In the econometrics literature, power calculations for panel data are still under study. However, an optimistic power calculation for the panel regression for a binary treatment with unit and time fixed effects and no other covariates is shown below [8].

$$MDE = (q_{1-\frac{\alpha}{2}} + q_{\lambda})\sqrt{\frac{Var(\hat{y})}{np(1-p)}\left(\frac{m+r}{mr}\right)}$$

Where *m* is the number of pre-treatment observation times and *r* is the number of post-treatment observation times. In this data for water, *m*=36 and *r*=12. A simple two-way fixed-effects specification thus yields a minimum detectable effect (with 80% power) of 3.4%. Additional time-varying controls such as weather, or interactions between the treatment and initial consumption can reduce the residual variation of *y* within the treatment and control groups and enable greater precision in the detection of this effect. For gas, with *m*=14 and *r* =12, the MDE is 3.5%.

The findings after detailed sample size impact analysis is that given the number of premises included in the study, the variability in water and gas consumption, and the likely range of effect sizes for the AMI program, this study is still unlikely to detect the true effect of AMI on water conservation by simply comparing average water and gas consumption or water leak detection rates between the treatment and control groups. However, by utilizing multiple observations and exploiting available information about premises structural properties and the weather, the study at the current time should be able to identify the effect on water and gas consumption levels as long as the true effect is greater than 3.5%. Unfortunately, it is quite possible that the true effect size is smaller than these values.

Assuming the sample size is sufficient to detect the true effect size, the next concern to address is whether the observed effect sizes can be interpreted as the causal effects of the AMI program.

Pre-treatment balance

Motivation: In order to interpret statistically significant differences between the treatment and control groups as causal impacts of the AMI program, the treatment and control groups need to be exchangeable, to the extent that the program would have the same average effect on the premises in the control group as on the treatment group. This is never guaranteed, even in randomized experiments. This section investigates whether there are statistically significant differences between treatment and control premises along relevant variables that are available.

Result Summary: There is some evidence for lack of balance in average initial gas consumption between the treatment and control groups in Ventura. In addition, the treatment group appears to have on average newer, more expensive, and larger houses. This motivates directly accounting for variability in premises characteristics through statistical controls or using premises fixed effects.

Result Details: Table 10 demonstrates the pre-treatment balance between treatment and control groups across the dependent variables, and the observables available for the residential premises. Mean values for the control and treatment groups are presented. The second-to-last column shows the percentage difference in means between the control group and treatment group. The last column shows the p-value for a Student's t-test comparing the two groups. Values of $p<0.05$ indicate statistically significant differences.

In general, the treatment and control groups are not balanced. Student's t-tests of the difference in means in each of these variables shows that treatment premises on average were more expensive, more recently constructed, larger in terms of square footage and number of bedrooms and bathrooms, and built on smaller lot sizes, than control premises. However, these can (and should) be controlled for either directly or with premises fixed effects.

Table 10: Pre-treatment balance with Student's t-test p-values for water and gas consumption and residential characteristics across treatment and control premises

Variable	Control	Treatment	Difference (%)	p-value
Mean Daily Water Use (Gallons)	479	472	1.30%	0.771
Mean Daily Gas Use (Therms)	1.42	1.47	-3.60%	0.195
Assessed tax Value 2016 (USD)	498,052	561,320	-12.70%	0.001
Assessed Value per Sq. Ft. (USD)	216	230	-6.50%	0.003
Year Built	1978	1979	-0.06%	0.06
Lot Size (Sq. Ft.)	14,486	13,552	8.70%	0.565
Finished Area (Sq. Ft.)	2,246	2,400	-6.90%	<0.001
Irrigable Area (Sq. Ft.)	12,583	11,154	11%	0.522
Bathrooms	2.61	2.74	-4.70%	<0.001
Bedrooms	3.77	3.9	-3.60%	<0.001
Total Rooms	7.51	7.78	-3.60%	<0.001

Dependent Variable Trends

Motivation: Given the evidence of lack of balance across the treatment and control groups highlighted above, the most robust way to estimate the impact of the water AMI program is to compare the trends in water consumption, water leaks, and gas consumption across the treatment and control groups over time. This way, the treatment and control groups are no longer required to have the same level of each of the outcomes before the AMI analytics started to make a reliable inference. Instead, the treatment and control groups are only assumed to have similar trends in the outcomes before the AMI analytics started. This section describes how the outcome variables were trimmed of outliers and examines the trends in each of the outcome variables over time.

Result Summary: Some particularly large water and gas consumers within each water meter size category had their observations trimmed from the data. Examination of trends in water and gas consumption over time show that there were generally parallel trends over time. However, the control group tended to have higher water consumption than the treatment group until 2016, when the treatment group began exhibiting higher consumption than the treatment group. There is also a general evidence for a downward trend in water consumption throughout the California drought, with consumption rising again following the end of the drought. Gas consumption trends were nearly the same between the treatment and control groups.

Result Detail: As part of Valor's standard data ingestion process, consumption data for water and gas was reviewed for meter reading and data entry errors. A secondary data review and trimming was done for the purposes of advanced analysis to remove outliers that could bias the estimate of the treatment effect among a representative sample of premises. The standard practice per published literature on water and energy information treatment experiments of removing observations with zero consumption was followed [7]. While most informational experiments of this type also remove observations of particularly high consumption, this is often used to model consumption reactions to information about overall consumption, and not leaks in particular. In addition, most evaluations use only residential data, whereas this pilot includes other customer classes. Since many leaks are characterized by abnormally high levels of consumption for a given premise, water and gas consumption data for this evaluation should be trimmed more conservatively, and any trimming should take into account the size of the premises. Finally, observations were aggregated and assigned "billing periods", such that all observations for a given premise corresponding to meter readings during a given calendar month were assigned to that month. Figure 9 presents the distribution of monthly water and gas consumption observations for each meter size in the sample in pre- and post- periods. The rules for outlier detection and removal were as follows:

- All consumption readings >8 times the interquartile range above the median for each meter size
- Consumption readings >2 times the second-highest reading within a premise that were also greater than 1.5 times the interquartile range above the median for the entire sample within a given meter size.

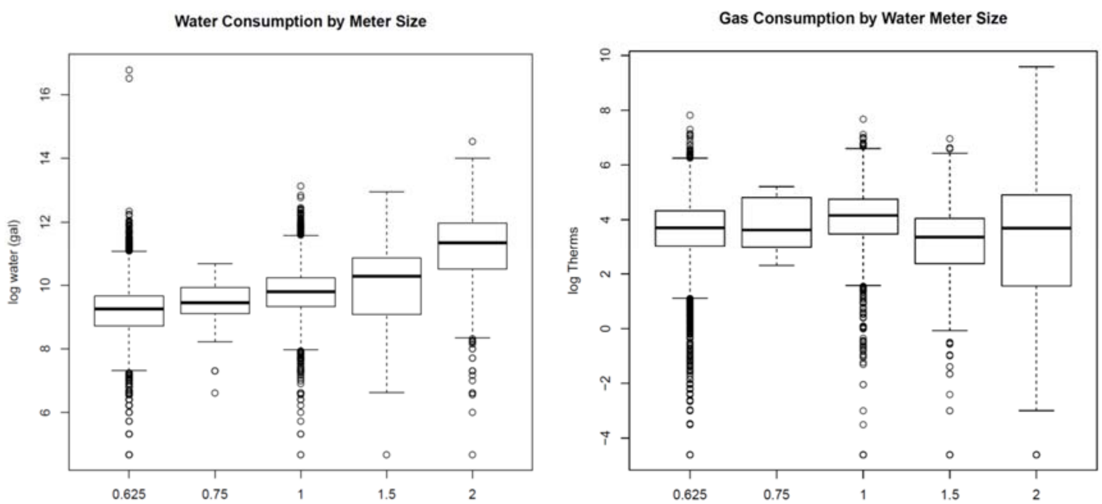

Figure 9: Monthly water and gas consumption observations for each meter size in the sample in pre-treatment and post-treatment periods

Figures 10-13 present the time trends in the nominal billing period monthly average values of mean daily water consumption (Figure 10), gas consumption (Figure 11), water leak prevalence as estimated by Valor's monthly detection algorithm (Figure 12), and water leak prevalence as estimated by both monthly and AMI detection algorithms together (Figure 13). In all figures, the panel on the top include all premises, and the panels on the bottom include only residential premises. The black vertical lines indicate the start of AMI-WEN analytics and proactive leak detection in February 2017. Each panel shows three trend lines. The orange lines denote the control group, green lines the treatment group that had access to CE online portal but did not enroll, and blue lines the treatment group premises that enrolled in the CE online portal. In Figure 10, it is seen that treatment group premises that did not use the CE portal generally had lower water consumption than the control group until about August 2016, which is about when AMR meters began to be installed. This suggests that measured water consumption in the treatment group increased relative to the control group once the new meters were installed, but not necessarily after CE was launched and analytics began. In addition, residential treatment premises that used the CE portal had higher consumption than the control group and the rest of the treatment group in the pre-AMI period. This suggests a strong self-selection effect, whereby relatively higher water users elected to use the CE portal to monitor consumption. This pattern is preserved whether or not non-residential premises are included confirming that the self-selection pattern is not being driven by a few large industrial or commercial customers.

Figure 11 presents the trends in gas consumption over time. The treatment group that did not enroll for the CE portal had higher gas consumption than the control group throughout the study period. However, the premises that enrolled in the CE portal for their water use had lower gas use than the control group.

In Figure 12, there is no divergence in prevalence (defined as the number of leak flags divided by the number of active premises in the study) of leak flags made by the monthly algorithm between treatment and control group before and after the AMI program began. There were no monthly leaks detected in the treatment group at all prior to the analytic period. Figure 13 plots similar information for the prevalence of leak flags made by combined AMI and monthly analytics. It is seen that using AMI does in fact result in more water leak flags than using monthly leak flags alone. Note that monthly and AMI leak flags do not necessarily correspond to all true positives of leaks, but merely flags of anomalous consumption that customers are notified of, and which field teams may validate. Since less than 40% of leak flags were investigated in the field, this information was not included in the analysis.

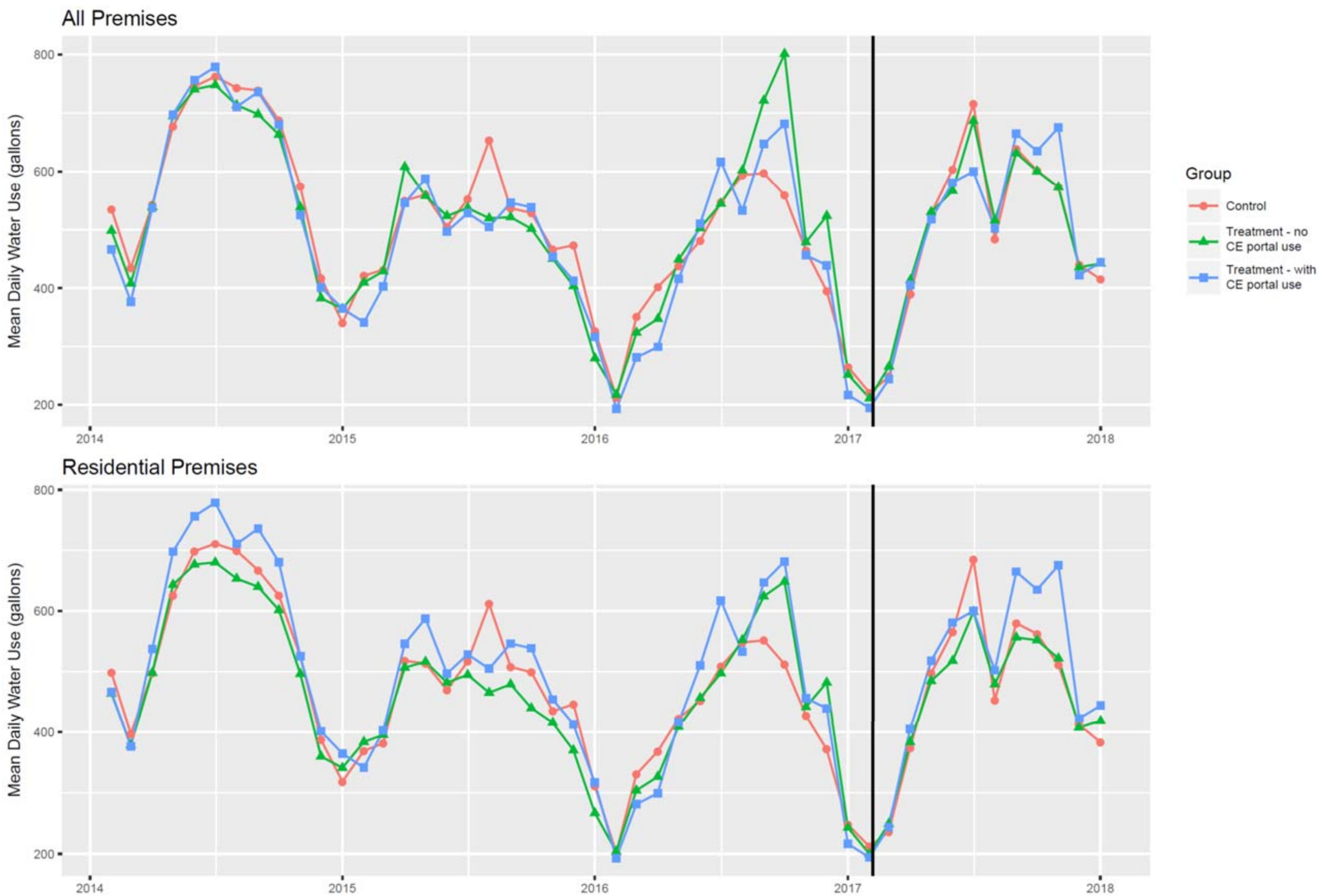

Figure 10: Average Daily Water Use (gallons) across control and treatment groups

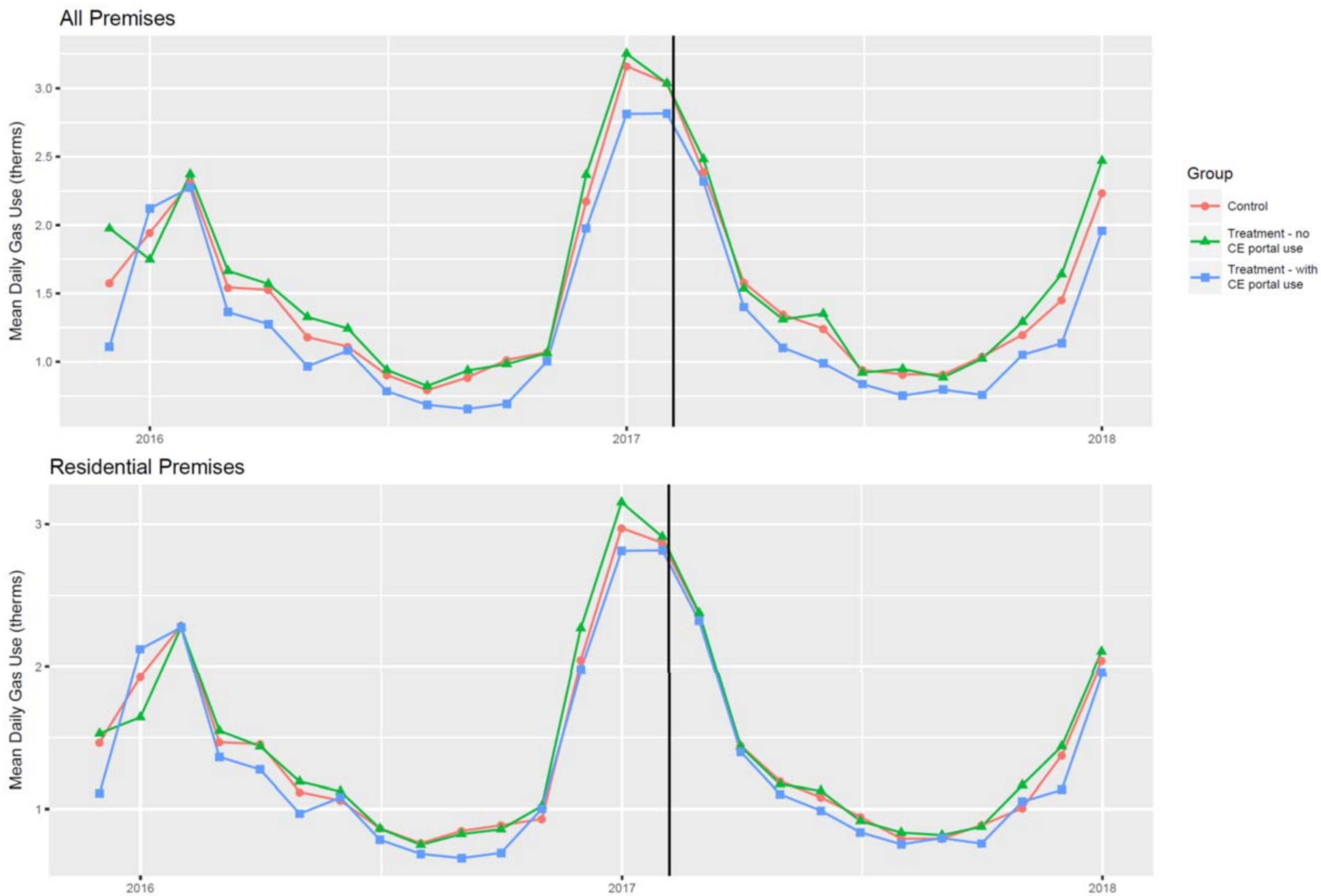

Figure 11: Average Daily Gas Use (therms) across control and treatment groups

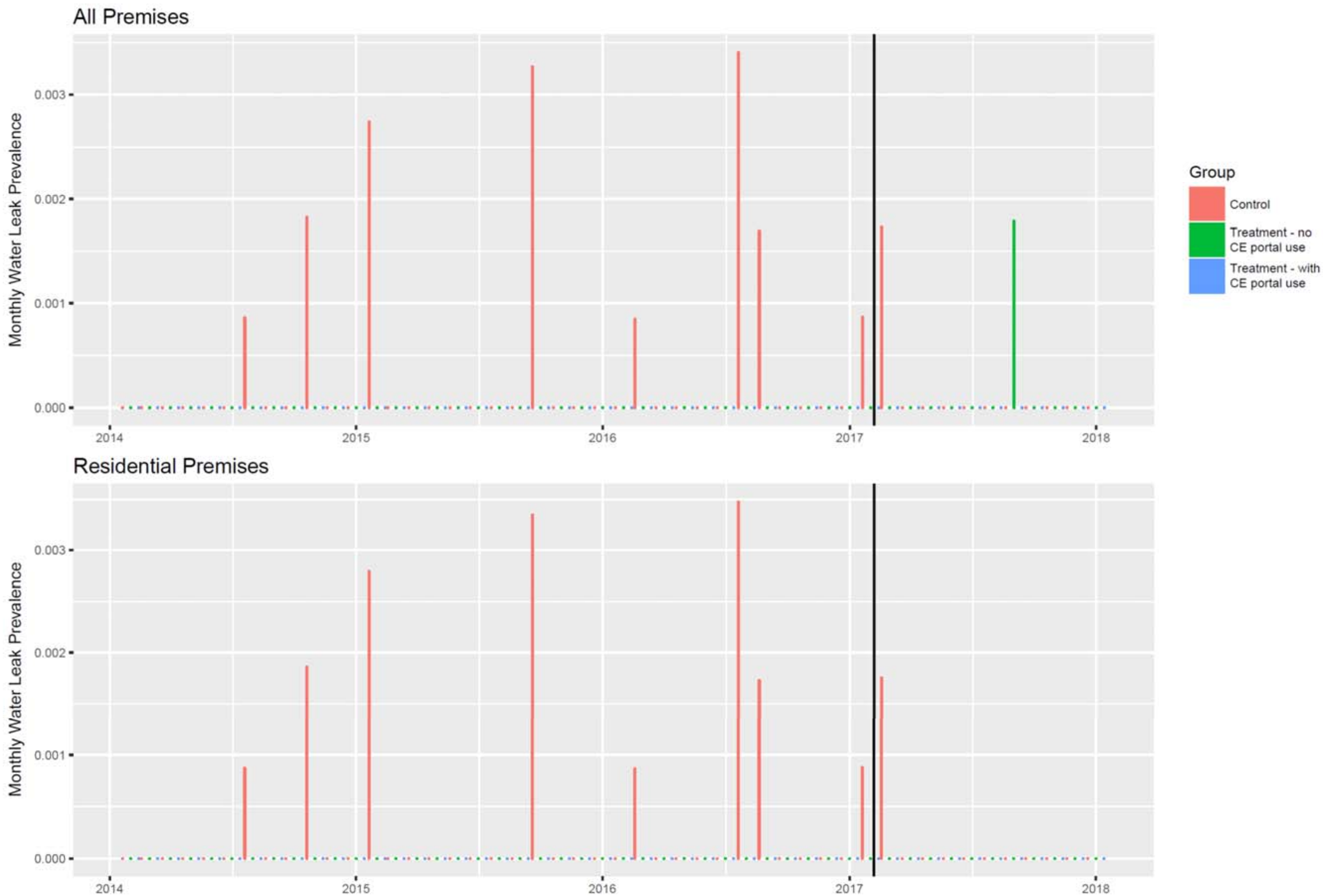

Figure 12: Monthly prevalence of Monthly water leak flags across control and treatment groups

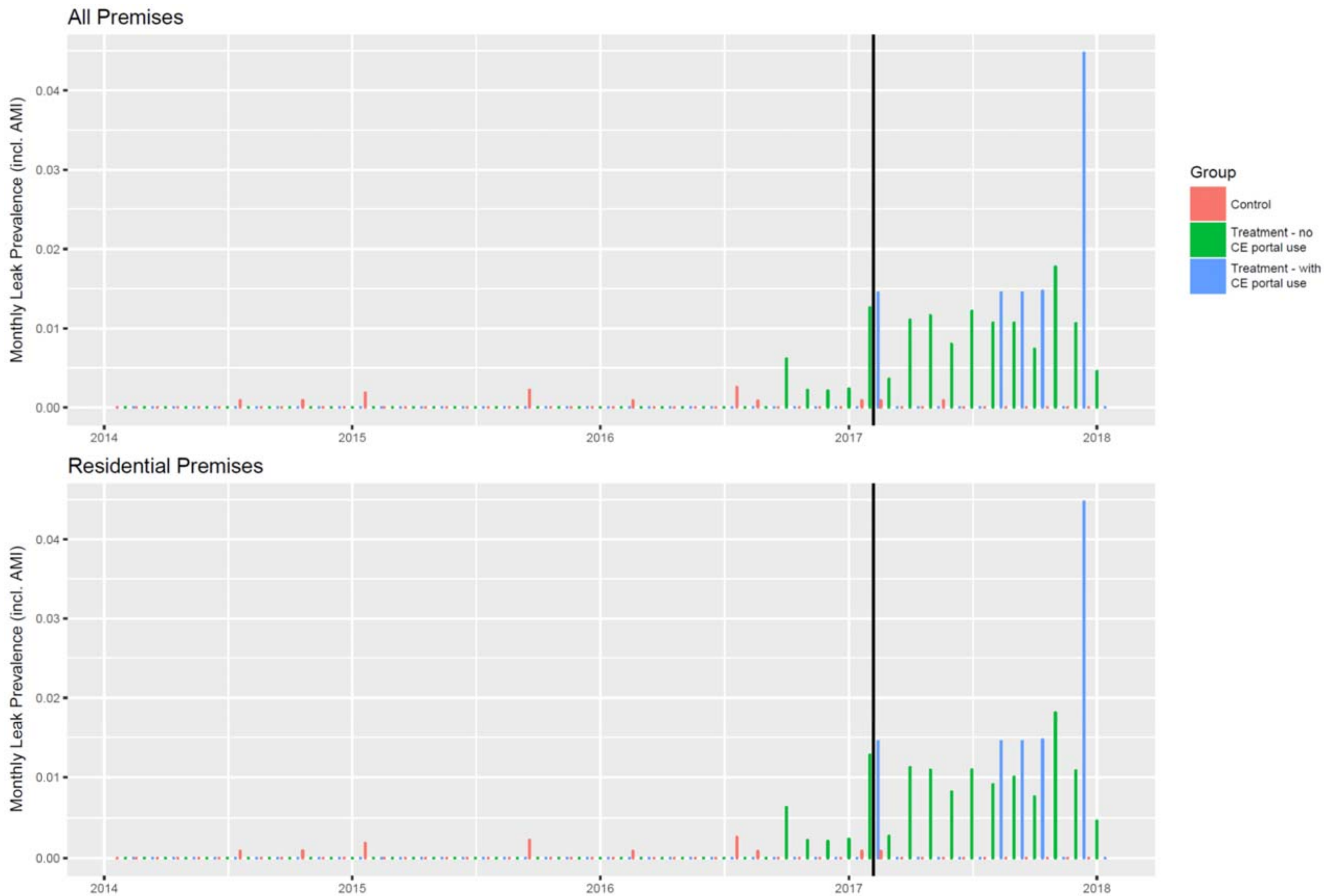

Figure 13: Monthly prevalence of consolidated AMI and Monthly water leakages across control and treatment groups

Table 11: Water Consumption, Gas Consumption, Monthly Water Leak Flags, and Monthly + AMI Water Leak Flags by Service Area and Treatment Group, Pre- and Post-Treatment Summary Statistics

		Pre-treatment	Post-treatment
Average Daily Water Use (Gallons)			
All Premises			
	Treatment that did not enroll in CE	513	489
	Treatment that enrolled in CE	502	491
	Control	515	484
Residential Premises			
	Treatment that did not enroll in CE	468	448
	Treatment that enrolled in CE	502	491
	Control	478	451
Average Daily Gas Use (Therms)			
All Premises			
	Treatment that did not enroll in CE	1.59	1.56
	Treatment that enrolled in CE	1.34	1.30
	Control	1.50	1.52
Residential Premises			
	Treatment that did not enroll in CE	1.48	1.41
	Treatment that enrolled in CE	1.34	1.30
	Control	1.43	1.39
Average Monthly Water Leak Prevalence (Monthly Algorithm)			
All Premises			
	Treatment that did not enroll in CE	0.00%	0.01%
	Treatment that enrolled in CE	0.00%	0.00%
	Control	0.04%	0.02%
Residential Premises			
	Treatment that did not enroll in CE	0.00%	0.00%
	Treatment that enrolled in CE	0.00%	0.00%
	Control	0.04%	0.02%
Average Monthly Water Leak Prevalence (Monthly and/or AMI Algorithm)			
All Premises			
	Treatment that did not enroll in CE	0.03%	0.99%
	Treatment that enrolled in CE	0.00%	0.96%
	Control	0.03%	0.02%
Residential Premises			
	Treatment that did not enroll in CE	0.03%	0.02%
	Treatment that enrolled in CE	0.00%	0.96%
	Control	0.03%	0.02%

Table 11 collapses the information contained in Figures 10-13 to the average values of the outcomes of interest by Treatment Group, and Pre/Post-Treatment. Careful inspection of the values in the table reveal the necessity for more advanced statistical analysis than post-treatment comparison of averages across the treatment and control groups. For instance, when considering residential premises post-treatment, the control group has an average water consumption of 451 gallons per day, while the treatment group that did not enroll in CE has an average of 448 gallons per day. This would seem to indicate that AMI decreased water consumption by an average of 3 gallons per day. However, in the pre-treatment period, the treatment group that did not enroll in CE consumed 468 gallons per day, and the control group 478 gallons per day. Thus, the treatment and control groups had different water use patterns to begin with. On the other hand, the pre-treatment average daily gas consumption is 1.59 therms in the treatment group that did not enroll in CE, and only 1.50 therms in the control group. This difference is likely in part due to average house size being larger in the treatment group. It is thus important, in order to make a precise and causal inference, to control for confounding sources of variation in the outcome variables than just the AMI analytics program. A variety of statistical models controlling for a number of such confounders was used. These models are explained in the next section.

Treatment Effect of AMI

Results Summary: The null hypotheses that AMI analytics had no effect water consumption, gas consumption, and water leak detection was tested with several statistical models that vary in complexity, over several subsets of data. Table 12 summarizes what each model accounts for and the estimated results.

Table 12: Advanced Statistical Analysis Summary for Ventura Premises

	Model	1.1	1.2	1.3	2.1	2.2	2.3	2.4	3
Confounding Variation Accounted For (Yes/No)	Temperature and Precipitation	No	Yes	Yes	No	Yes	Yes	Yes	Yes
	Observed Premises Characteristics	No	No	Yes	No	No	Yes	Yes	No
	Unobserved Premises Characteristics	No	No	No	No	No	No	No	Yes
	Treatment Group pre-treatment Consumption/Leaks	No	No	No	Yes	Yes	Yes	Yes	No
	Premises pre-treatment Consumption/ Leaks	No	No	No	No	No	No	No	Yes
	Common events over time (e.g. State-level drought policies, economic shocks)	No	No	No	No	No	No	Yes	Yes
Hypothesis Accepted at 95% Confidence (Increase/Decrease/Null)	Water Consumption	Null	Null	Null	Null	Null	Null	Null	Null
	Gas Consumption	Null	Null	Null	Null	Null	Null	Null	Null
	Water Leak Flags (Monthly Algorithm Only)	Null	Null	Null	Null	Null	Null	Null	Null
	Water Leak Flags (Monthly+ Hourly AMI Algorithm)	Increase	Increase	Increase	Increase	Increase	Increase	Increase	Increase

The preferred model is Model 3, which includes fixed effects for each premise and each billing period, accounting for unobserved factors for each premises and unmeasured external events occurring over time that could affect each of the outcome variables. One known event to mention is the 25% mandatory California-wide water restriction in effect from May 2015 to April 2017 due drought conditions, and associated policies and media campaigns. None of the models should be affected, since there is no particular reason the drought would have affected the treatment and control groups differently. However, Model 3 directly accounts for this by including factors for each billing month, differencing out common average demand trends between the experimental groups from the estimated effect of AMI.

Model 3, along with all the simpler models, had the same result for the preferred data subset. The null hypothesis could not be rejected for water consumption, gas consumption, or water leak detection by monthly algorithm, indicating that there was no statistically significant impact on these outcomes by AMI analytics during the study period. It should be noted that AMI treatment did reduce measured water consumption by 2.1% when comparing the control group with the treatment group that has access to but did not enroll in CE. While still statistically insignificant, the negative consumption effect can be attributed to faster leak detection and resolution. The overall effect averaged across premises was small in this case, as less than 10% of treatment premises had a leak during the study period. A statistically insignificant increase of 2% in water consumption was observed in the treatment group that enrolled in CE when compared with the control group; it was not possible to determine the reasons for this. With only four of these premises having leaks, it is not likely that the observed effect is due to increased leakage rates, but rather some other factors that drive both increased measured consumption and CE portal use. For example, it is possible that premises that adopted CE portal use tended to have higher bills due to their normal consumption patterns and were therefore interested in using CE to track consumption, even if they were unable to make any behavioral changes.

Similar signs of estimated effects were observed for gas consumption as well; while it was not possible to reject the null hypothesis, estimated effects appeared negative for treatment accounts that had access to, but did not enroll in the portal.

The null hypothesis could not be rejected for water leak detection by the monthly algorithm since there were no monthly leak flags during either the pre- and post-treatment periods in the treatment group. There were no leaks severe enough in the treatment group to be detected by the monthly algorithm at all.

The null hypothesis was rejected for combined monthly and hourly AMI-based leak detection algorithms, indicating that the total number of leak flags was increased by the program. Indeed, in the treatment group, only AMI detection provided any information of leaks. The models and detailed results are included in the sections below.

Models

We estimate variations of three basic specifications for the treatment effect:

Model 1 is a “Posttest Only” model and is of the form shown in Equation 1.

$$y_{it} = \alpha + \beta AMI_i + \varphi Portal_i + \theta X' + \epsilon_{it}, \forall Post_t = 1 \qquad (1)$$

y_{it} is the value of the dependent variable for premises *i* in billing period[1] t. α is the intercept. AMI_i is a variable indicating whether premises *i* is in the treatment group that had access to but did not enroll in CE. $Portal_i$ is a variable indicating whether premises *i* enrolled in CE (and thus were also in the treatment group). *X'* is a vector of covariates. $Post_t$ is a variable indicating whether the observation occurs after the AMI pilot program began or not, so that $\forall Post_t = 1$ refers to using only observations after the AMI pilot program began (in the treatment period). This specification is basically comparing the average value of the dependent variable between the treatment and control groups in the treatment period, controlling for X', with β being the average treatment effect on the treated (ATT). The three different specifications of this model that were run are below:

- Model 1.1 does not use any covariates *X'*. This is the simplest model. If the AMI treatment were randomized, theoretically this is all that is needed to make a valid inference about the effect of AMI. However, given the concerns about selection bias and pre-treatment balance as described in the previous sections, more complex models are needed to improve the accuracy and precision of the estimates.
- Model 1.2 includes the weather variables Cooling Degree Days (CDD), Heating Degree Days (HDD), and the proportion days with precipitation
- Model 1.3 includes the weather variables, as well as the premises characteristics including customer class (Commercial, Multi-family, or Residential), meter size. When including only residential premises, Model 1.3 also includes the characteristics of assessed tax value, number of bedrooms, number of bathrooms, irrigable area in square feet, the dwelling finished floor area in square feet, and the year the home was built.

Model 2 is a "difference-in-differences" (DID) model of the form shown in Equation 2.

$$y_{it} = \alpha + \beta AMI_{it} + \varphi Portal_{it} + \theta X'_{it} + \Gamma Post_t + \lambda T_i + \lambda Tp_i + \epsilon_{it} \quad (2)$$

This model includes all observations both before and after the AMI treatment began. AMI_{it} is now a variable indicating whether premises *i* had water AMI active (but did not enroll for the CE portal) in water billing period *t*. $Portal_{it}$ is now a variable indicating whether premises *i* ever enrolled in CE and had water AMI active in water billing period *t*. T_i indicates whether or not premises *i* was in the treatment group but did not enroll for the CE portal. Tp_i indicates whether or not premises *i* was in the treatment group and enrolled for the CE portal. This corresponds to a "difference-in-differences" model that compares the difference in the dependent variable before and after the treatment in the control group to the corresponding difference in the treatment group. This "double difference" is measured by β, which is the treatment effect. This should alleviate some of the balance issues in terms of the pre-

[1] Water customer premises have varying billing periods depending on their meter reading cycle. The billing period was taken to be the month-year corresponding to the day their meter was read for that billing cycle. For a given "billing period", consumption, leak flag, and weather data was aggregated to from the days between the meter reading of the previous billing period and the meter reading of the "current" one.

treatment differences between treatment and control groups in water and gas consumption. The four different specifications of this model that were run are below:

- Model 2.1 does not include any covariates in *X'*
- Model 2.2 includes the weather variables
- Model 2.3 includes the weather variables as well as the premises characteristics (and residential house characteristics when including only residential data)
- Model 2.4 is the same as Model 2.3 but replaces the *Post* variable with a series of indicators for each billing period, allowing the average value of the dependent variable to vary every billing period. This controls for all billing-period specific effects that affect all households in the study equally, such as state-level policies or regional economic conditions.

Model 3 is a Fixed-Effects model of the form shown in equation 3.

$$y_{it} = \alpha_i + \beta AMI_{it} + \theta X'_{it} + \tau_t + \epsilon_{it} \quad (3)$$

This model is similar to Model 2.4 but includes a fixed effect (or average level of the dependent variable) for each premise. This specification controls for all time-invariant premises characteristics, and as such, other time-invariant variables like customer class, meter size, and house characteristics are dropped from the regression. The only time-varying controls in X' are thus the weather variables. While sacrificing some additional descriptive power of the other controls, this model is the preferred specification that has the potential to give the most accurate estimates of the treatment effect.

In all models, standard errors are clustered by premises, in order to account for the non-independence of repeated observations on the same premises. Failing to do so would result in standard errors that are too small and overoptimistic characterizations of statistical significance of the treatment effect.

Dependent Variables

All the models described above were run on several dependent variables. lnw_{it} is the natural logarithm of average daily water consumption for premises *i* in billing period *t*. This is traditionally used both to dampen the effect of extremely large consumers that might skew results without a log transformation, and to interpret the treatment effect as a percentage change, since differences in natural logarithms approximate percent differences of the raw quantities. However, it is not ideal for this context, where the treatment effect should theoretically be dominated by leakage reduction, which could involve quite large percent reductions in consumption. This is because differences in logs underestimate the actual corresponding percentage change for large changes (more than ~10%). As such we also use W_{it}, the % deviation of water consumption in average daily gallons for premises *i* in billing period *t* from the average daily consumption of all premises in the control group during the treatment period. This specification has been used in studies to evaluate the impact of energy and water conservation messaging program [6,7]. This alternative specification can also be interpreted as a percentage change, but does not underestimate large changes. Similar dependent variables are used for gas: $\ln g_{it}$ and G_{it}.

In addition, dependent variables ML_{it} and AL_{it} are used. These are both binary response variables which are either 0 or take the value of 1 if premises *i* in billing period *t* has a leak flag by the monthly leak (in the case of ML) or either one of the monthly or hourly AMI leak (in the case of AL) detection algorithms. Since the treatment is binary, we keep a linear specification of the model rather than a logit or probit in order to preserve the difference-in-differences interpretation of the treatment effect. Due to only four leaks being detected in any period in the treatment group that enrolled in the CE portal, the Portal variables are omitted from models with these dependent variables.

Data Subsets

Each model was run for each dependent variable for each combination of the following study premises subsets:

- All premises
- All residential premises

This allows the investigation of whether the treatment effect varies when excluding particularly high water and gas users in the commercial and multifamily residential classes. There were few non-residential premises; however, it was still important to characterize the results for a representative sample of all customers, as well as to characterize results for residential customers unaffected by changes in demand by particularly large users.

Model Results

The main quantity of interest for all of the models is β, the coefficient on the treatment variable *AMI*. The secondary quantity of interest is φ, the coefficient on the treatment variable *Portal*. The treatment effects are summarized in the panels in Figure 14. The panels in the left column are for models using all premises, and in the right column for residential premises only. In each panel, the effects estimated by each of the eight model specifications are displayed with symbols denoted by the legend. Each point is the value of the treatment effect (β or φ), with the 95% confidence interval represented by lines. If the colored lines cross the 0 line on the y-axis, this implies that the null hypothesis cannot be rejected. Each model specification is represented by a shape/ color that is consistent across dependent variables and data subsets. Within each panel, the group of treatment effects on the left is for premises that never adopted the CE portal, and on the right for premises did adopt the CE portal. All model specification estimates are presented in order to demonstrate the sensitivity of the result to the model. However, the preferred model which controls for unobserved premises characteristics as well as common events over time is Model 3, represented by the pink stars in Figure 14 The results of this model are interpreted below.

For water consumption as measured by W_{it}, among all premises Model 3 estimated a statistically insignificant effect of -1.97% for AMI treatment customers that did not enroll for CE, and a statistically insignificant effect of about +2.32% for AMI treatment customers that enrolled for CE. For residential premises only, these estimates are -2.07% and +1.99%, respectively. Given the lack of correlation between the CE portal and leak flags and lack of information on CE portal adoption timing, it is possible that this discrepancy in effect directions is due to self-selection bias of higher water users being more likely to adopt the CE portal for tracking purposes. However, the AMI effect on water consumption was not statistically significant in either case.

For gas consumption as measured by G_{it}, among all premises, the estimated effects of Model 3 are -1.25% for AMI treatment customers that did not enroll for CE, and +0.96% for treatment customers that enrolled for CE. For residential premises only, the estimated effects are -0.99% and +1.13% respectively. The discrepancy between the effect directions of AMI with and without the CE portal aligns for gas and water consumption, suggesting that reactions to water AMI could have effects on gas consumption at about half of the magnitude. However, the effect was again not statistically significant in either case.

The bottom panel shows treatment effects of the AMI program (with or without use of the CE portal) for monthly algorithm leak flags in the left column and monthly + AMI algorithm leak flags in the right column. The y-axis is the treatment effect in percentage points (divided by 100). In terms of monthly water leak flags, the estimated effects for Model 3 were near zero with narrow confidence intervals, indicating that the AMI program had no effect on having monthly leak flags. There were no leaks severe enough in the treatment group to be detected by the monthly algorithm at all.

For the monthly and AMI flags considered together, the estimated effect for all models and data subsets was generally an increase of 1 percentage points, indicating that the AMI program flagged leaks in a greater percentage of premises than monthly algorithms could. The null hypothesis that water AMI is not associated with more overall leak flags was rejected in favor of the alternate hypothesis that water AMI is associated with more frequent combined AMI and monthly leak flags. This result is intuitive and verifies that leak detection algorithms based on water AMI data do result in more leak flags than monthly leak detection algorithms alone.

Overall, during the 12-month period of the shared network AMI pilot, there are no statistically significant effects on water and gas consumption through the AMI program's combined leak detection and customer engagement. AMI does lead to a roughly 1%-point increase in premises being flagged with water leaks in general, although not hot water leak flags in particular. There is weak, though statistically insignificant evidence that AMI analytics reduces water consumption, through prompt leak detection and resolution.

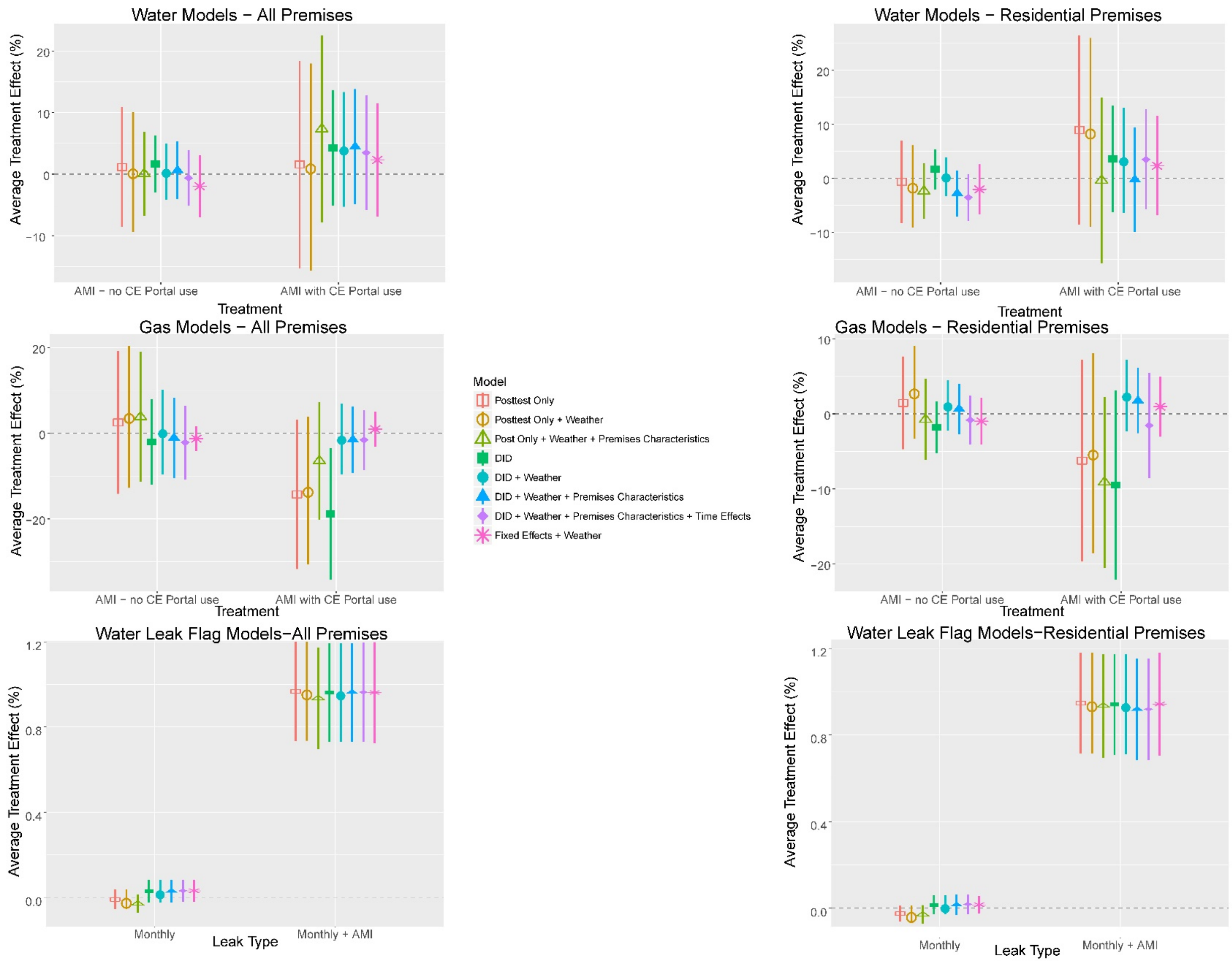

Figure 14: Estimated average treatment effects with 95% confidence intervals

Water and Gas Trends Analysis

Joint water and gas consumption information at the premises level was examined to determine if there was a correlation between these two behaviors across premises within a given service area. If such a correlation existed, then there would be potential for gas consumption data to be used jointly in analytics with water consumption data, and policies or programs designed to affect water demand could also drive changes in gas demand, or *vice versa*. In order to predict such secondary effects, a measure of relationship between water and gas demand would be a useful input for a predictive model.

The treatment group of the pilot with CalAm offers a unique sample of premises with a set of recently installed AMI water meters in conjunction with AMI gas meters. This is an opportunity for the comparison of joint water and gas consumption across premises with relatively low water meter measurement error. The most basic way to do this would be to simply pool all of the data together and compare water and gas consumption. Figure 15 shows a scatterplot, each point representing an observation of a premises at the end of one water billing month, with the y-axis showing the log of water consumption during that period, and the x-axis the log of gas consumption for that period. There is no clear relationship between the two, and the regression line has an accordingly flat slope.

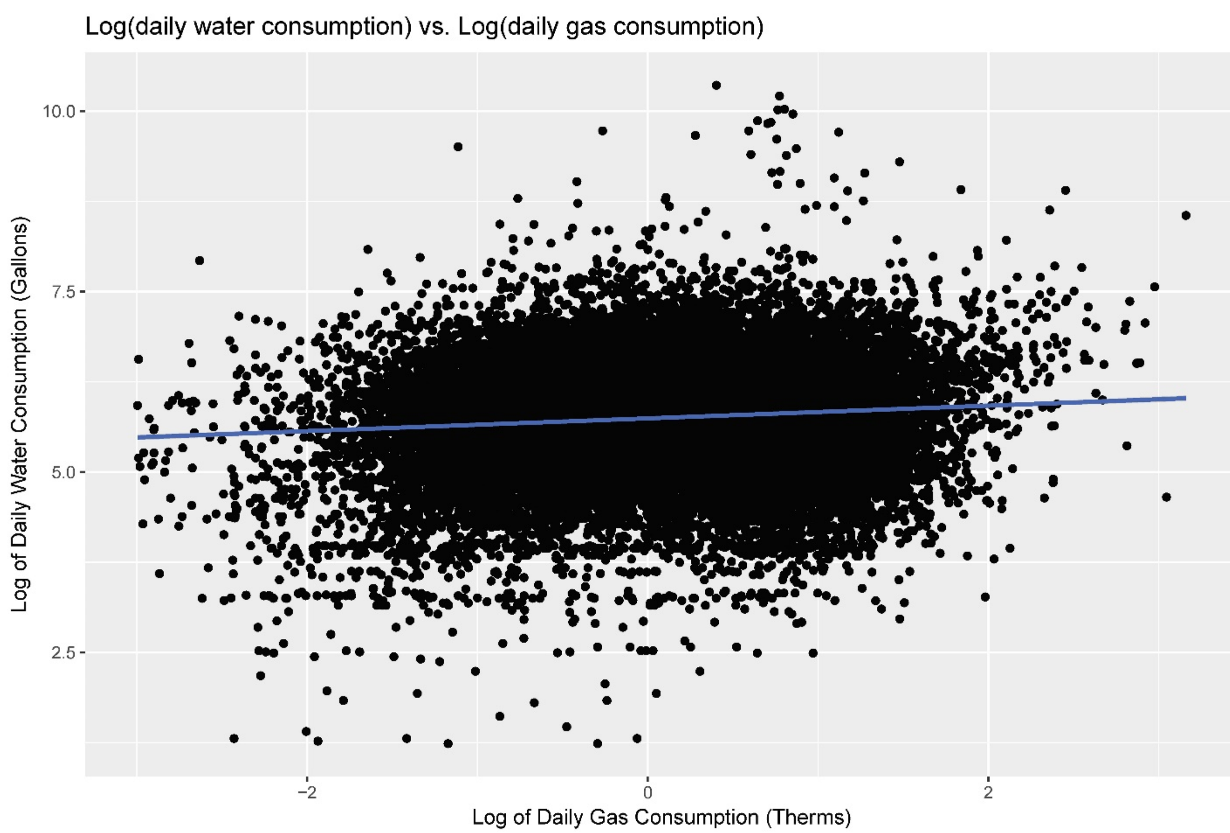

Figure 15: Average daily water consumption vs. average daily gas consumption from December 2015 to January 2018

While it may appear that there is no systematic relationship between water and gas consumption, this plot does not factor in the confounding effect of seasonality. Figure 16 plots the average daily water and gas consumption of all of the treatment premises between December 2015 (when gas consumption data are reasonably representative) and January 2018 (the end of the study period). Water consumption in gallons is measured on the left axis, and gas consumption in therms on the right axis. Water and gas consumption are countercyclical, with peak gas consumption occurring December-March, and peak water consumption July-October. Thus, a failure to control for seasonality would be expected to produce an underestimate of the average relationship between water and gas consumption.

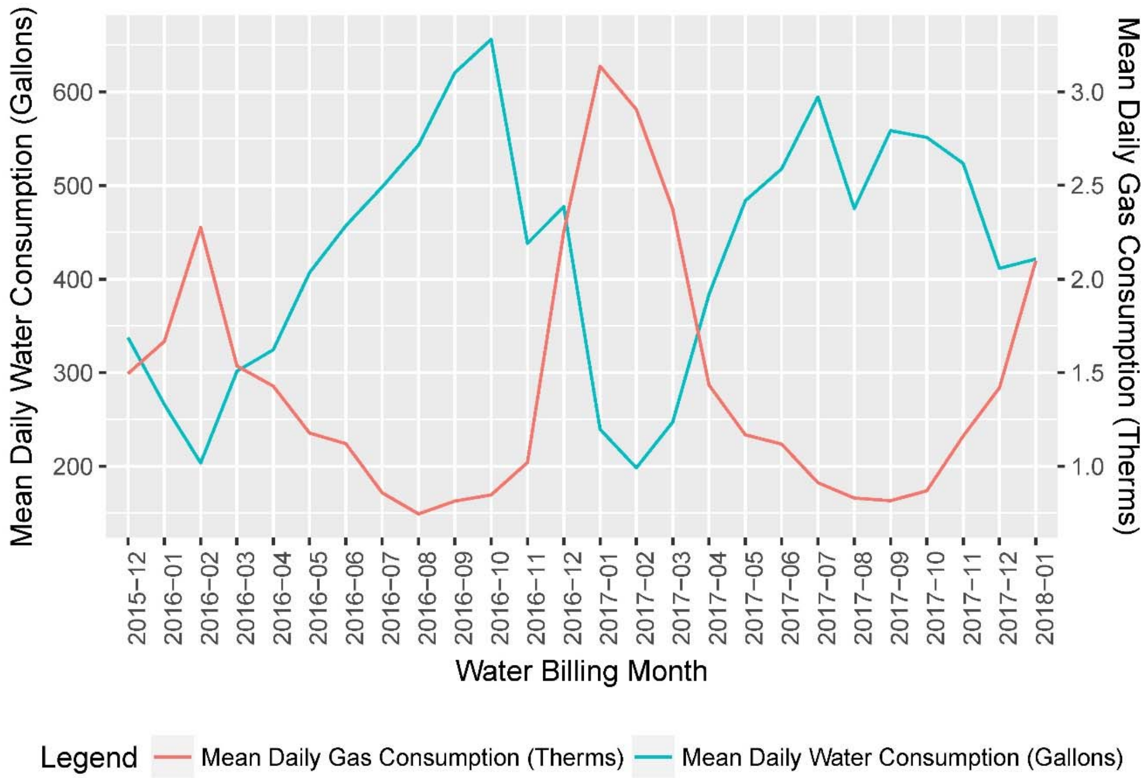

Figure 16: Mean Daily Water Consumption and Mean Daily Gas Consumption over time, from December 2015 to January 2018

Figure 17 separates out Figure 15 by season in the study period, with the hot season corresponding to July-October, the cold season to December-March, and the "normal" season all other months. It is seen that by controlling for seasonality through the simple technique of considering the data on a seasonal basis, a positive relationship between water and gas consumption emerges. To estimate the magnitude of this relationship, a statistical model was created similar to those used to evaluate the impact of AMI. The purpose of this was to estimate the extent to which similar premises under the same conditions but with different gas consumption levels exhibit systematically different water consumption levels.

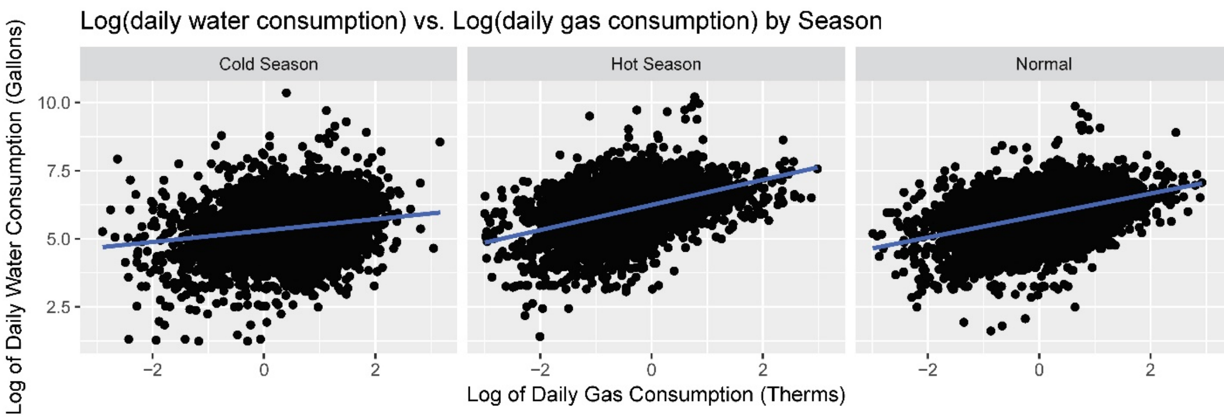

Figure 17: Average daily water consumption vs. average daily gas consumption by season. Cold Season is December-March, Hot Season is July-October, Normal Season are all the other months in the year.

Equation A represents the statistical model developed. The log of water consumption for premise *i* in water billing period *t* is $ln(w_{it})$. This is assumed to be a function of:

- $\ln(g_{it})$ – the log of gas consumption
- The Cold Season – Whether the billing period was during December-March
- The Hot Season – Whether the billing period was during July-October
- AMI – Whether the AMI program was active
- HDD – Heating degree days for that premise during that water billing period
- CDD – Cooling degree days as above
- PRCP – The proportion of days in the water billing period that had precipitation
- Bathrooms – the number of bathrooms at the premises
- Bedrooms – the number of bedrooms in the premises
- taxAssessment – The tax value (USD) of the premises assessed by the Ventura County Tax Assessor in 2016
- SqFt – The finished square footage of the premises
- IrrigableArea- The lot size – the finished square footage, an approximation of lawn area
- $\boldsymbol{\tau}$ – A vector of dummy variables, one for each year, controlling for events over time common to all of the premises that are not covered by, temperature, precipitation, and season, such as state-level economic conditions and policies.

$$(A)\ \ln(w_{it}) = \beta \ln(g_{it}) + \zeta ColdSeason_t + \mu HotSeason_t + \psi \ln(g_{it}) * ColdSeason_t + \omega \ln(g_{it}) * HotSeason_t + \gamma AMI_{it} + \delta_1 HDD_{it} + \delta_2 CDD_{it} + \delta_3 PRCP_{it} + \delta_4 bathrooms_i + \delta_5 bedrooms_i + \delta_6 taxAssessment_i + \delta_7 irrigableArea_i + \delta_8 SqFt_i + \boldsymbol{\tau}_t + \epsilon_{it}$$

Since both water and gas consumption are measured on a natural logarithm scale, β, the coefficient on $\ln(g_{it})$, can be interpreted as an elasticity. That is, β is the percent change in water consumption that is associated with a 1% increase in gas consumption during the normal (not Hot, not Cold) season. This is controlling for the status of the AMI program, the temperature and precipitation, premises characteristics, and non-weather common events accounted for by considering each year separately. ψ is the interaction between gas consumption and the Cold Season. It estimates the average difference between β and the relationship between gas and water consumption in the Cold Season relative to the normal season. ω is similar, but for the interaction between gas consumption and the Hot Season. Since we are interested in between-premises effects, this model differs from the preferred model in the AMI analysis in that fixed effects are not included for each premises. Doing so would estimate the effect of gas on water consumption on average within each premises, ignoring variation in water and gas consumption between premises. We also estimate a model with premises fixed effects, in order to estimate within-premises relationships between water and gas consumption.

We then compare these models with versions without gas consumption. This allows for an evaluation of the extent to which accounting for gas consumption improves the prediction of water consumption.

Table 13: Regression results for water and gas consumption correlation analysis shows the regression results. Columns 1 and 2 refer to the models without premises fixed effects, and so include the premises-level characteristics. Column 1 refers to the model without gas consumption, and Column 2 to the model with gas consumption. In both models, the coefficient on AMI is significant and negative. However, this is because there is no control group, AMI occurred in the latter part of the study period, and consumption in general fell over the study period. The coefficients on the weather variables are as expected. Negative effects of the Cold Season dummy, Heating Degree Days and precipitation, and positive effects of the Hot Season dummy and Cooling Degree Days is consistent with higher water use during hotter, dryer weather, and is probably associated mostly with outdoor water use. The coefficient on finished square footage is significant, and indicates that on average, a difference in of 1,000 ft^2 is associated with a difference in water consumption of about 1%. The coefficients on the other household characteristics are small.

The coefficient on gas consumption in Column 2 is significant with a p-value less than 0.01. It indicates that a difference between premises gas consumption of 10% is associated with a 3.3% difference in water consumption over the study period, during the "normal" season. Since this model does not include premises fixed effects, this effect should be interpreted as the differences in water consumption observed between premises with different levels of gas consumption. The interaction term between gas consumption and the Hot Season is positive, and the interaction term with the Cold Season is negative, but both are statistically insignificant. Thus, between-premises variation in the relationship between water and gas consumption does not appear to vary seasonally. Comparing Column 1 to Column 2, the R^2 increases from 0.294 to 0.364 with the inclusion of gas consumption, indicating that gas consumption explains an additional 7% of the variance in water consumption between premises.

Columns 3 and 4 refer to the models with premises fixed effects, and thus do not include premises-level characteristics. The estimated effects of AMI and the weather variables are similar to those in Columns 1 and 2. In Column 4, the coefficient on gas consumption is again significant with a p-value of less than 0.01. However, the effect is smaller, with a difference of gas consumption of 10% associated with a 0.9% increase in water consumption. Since premises fixed effects are included in this model, this effect should be interpreted as the increase in a given premises' water consumption between when it had relatively low gas consumption to when it had relatively high gas consumption. Here, the interaction between gas consumption and the Cold Season is statistically significant at the $p<0.1$ level, and positive, indicating a stronger relationship between gas and water consumption within a given premises on average during the Cold Season than during the "normal" season. This could be because indoor heated water use is more energy intensive during the cold season due to colder water being heated, or greater volumes of water being heated relative to total water consumption with lower outdoor water use.

Gas consumption has a significant and positive correlation with water consumption both between and within premises. This means that premises that use more water also tend to use more gas. In addition, a given premise within a consistent weather period that increases its gas use will also tend to increase its water use, with this relationship being stronger during the cold season. These correlations potentially provide more information on water consumption patterns than observable household characteristics such as square footage and number of bathrooms.

Table 13: Regression results for water and gas consumption correlation analysis

Correlation between Gas and Water Consumption, Single-Family Residential Treatment Premises

	Dependent Variable: log (Ave. Daily Water Consumption))			
	Year Effects	Year Effects - With Gas	Two-way Effects	Two-way Effects - With Gas
	(1)	(2)	(3)	(4)
ln_g		0.326^{***}		0.091^{***}
		(0.024)		(0.014)
lng.HotSeason		0.022		0.013
		(0.017)		(0.012)
lng.ColdSeason		-0.010		0.029^{*}
		(0.021)		(0.017)
AMI	-0.222^{***}	-0.180^{***}	-0.209^{***}	-0.191^{***}
	(0.017)	(0.017)	(0.015)	(0.016)
HotSeason	0.004	0.079^{***}	0.025^{***}	0.044^{***}
	(0.010)	(0.013)	(0.009)	(0.010)
ColdSeason	-0.153^{***}	-0.250^{***}	-0.163^{***}	-0.199^{***}
	(0.011)	(0.013)	(0.010)	(0.012)
HDD.mean	-0.043^{***}	-0.062^{***}	-0.039^{***}	-0.045^{***}
	(0.002)	(0.003)	(0.002)	(0.002)
CDD.80.mean	0.034^{**}	0.066^{***}	0.026^{*}	0.037^{***}
	(0.015)	(0.016)	(0.014)	(0.014)
prcp_days.mean	-0.854^{***}	-0.971^{***}	-0.896^{***}	-0.951^{***}
	(0.046)	(0.047)	(0.041)	(0.042)
taxAssessment	0.00000^{***}	0.00000^{***}		
	(0.00000)	(0.00000)		
finishedSqFt	0.0001^{***}	0.0001^{***}		
	(0.00004)	(0.00004)		
bathrooms	0.033	0.026		
	(0.035)	(0.030)		
bedrooms	0.032	0.032		
	(0.023)	(0.020)		
irrigable	-0.00000^{***}	-0.00000^{***}		
	(0.00000)	(0.00000)		
Observations	23,025	23,025	25,739	25,739
R^2	0.295	0.365	0.675	0.678
Adjusted R^2	0.294	0.364	0.660	0.663
Residual Std. Error	0.666 (df = 23010)	0.632 (df = 23007)	0.458 (df = 24583)	0.456 (df = 24580)
Note:	*p<0.1; **p<0.05; ***p<0.01			

Recommendations

Value of AMI and future AMI Benefit Quantification Studies

There are many AMI networks options in the marketplace, and shared network AMI has potential, as demonstrated by the SoCalGas/CalAm WEN engagement.

While considering AMI's impact on water and gas consumption, we recommend using the study results with caution. The study used a quasi-experimental design to evaluate a potential program, based on a previously established meter replacement schedule. However, the study was not able to reject the null hypothesis that the AMI program has no effect on water or gas consumption, despite the identification of 188 water leaks on 105 unique premises, and one hot water leak.

The learnings gained around study design can help with future AMI impact quantification programs. Here are our recommendations:

- Given the variability seen in this data, similar non-randomized experiments will likely need to be at least three times larger in sample size, to confidently determine plausible effects of AMI leak notification on water and gas consumption.
- Any replacement of potentially inaccurate older water meters with new meters introduces the possibility of increase in measured water consumption, that is not reflective of true AMI impact. This will need to be explicitly included in study design to ensure that the AMI treatment is independent of the outcome measure between treatment and control groups. Possible methods include:
    - Replace all control group premises meters with new conventional meters at the same time as treatment group premises have AMI meters installed
    - Have 2 treatment groups – one with AMI technology retrofit meters and another with new meters
    - Replace both control and treatment group meters with AMI meters, but only enable AMI analytics and/or customer engagement for the treatment group for the duration of the study period
- Consider separating the treatment impact of leak notification, and the treatment impact of general customer response to hourly consumption information. It may be possible to randomize these two levels of treatment, so to randomly select premises to have AMI analytics, and then randomly select half of these premises to receive sustained encouragement to use the customer engagement portal. Such complex treatment combinations will again require greater sample size than simpler binary treatments, and allowance will need to be made for variable customer engagement portal adoption rates.
- Collect information about the timing and frequency of customer engagement portal usage to determine the effectiveness of self-monitoring on water consumption.

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Appendix 1: CalAm Data Exclusions Updated and shared with CalAM in February 2017.

Double-click on embedded object to view full file

CalAm_DataExclusions and Sample Size Sig

Appendix 2: List of Treatment and Control Group Accounts

Double-click on embedded object to view full list

ValorID	CustomerType	MeterSize	Municipality	UseSegment
T-Vent600	Residential	0.625	Ventura	D
C-Vent600	Residential	0.625	Ventura	D
T-Vent601	Residential	0.625	Ventura	C
C-Vent601	Residential	0.625	Ventura	C
T-Vent602	Residential	0.625	Ventura	B
C-Vent602	Residential	0.625	Ventura	B
T-Vent603	Residential	0.625	Ventura	A
C-Vent603	Residential	0.625	Ventura	A
T-Vent604	Residential	0.625	Ventura	D

Appendix 3. List of AMI Water Leak Flags

Double-click on embedded object to view full list

Premises Valor ID	Leak Start	Leak End
T-Vent1011	2/2/2017 22:00	2/7/2017 18:00
T-Vent860	2/4/2017 13:00	2/9/2017 7:00
T-Vent1557	1/26/2017 0:00	2/12/2017 0:00
T-Vent820	2/9/2017 11:00	2/12/2017 11:00
T-Vent1623	2/18/2017 16:00	2/19/2017 8:00
T-Vent860	2/15/2017 20:00	2/24/2017 11:00
T-Vent870	2/8/2017 19:00	2/28/2017 17:00
T-Vent876	1/26/2017 0:00	3/2/2017 18:00
T-Vent1214	1/26/2017 0:00	3/7/2017 10:00