Water-Energy Nexus Shared Network AMI Pilot Report - San Gabriel Valley Water Company

Prepared for

Southern California Gas Company

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Executive Summary

Southern California Gas Company, San Gabriel Valley Water Company, and Valor Water Analytics partnered for a twelve-month Water-Energy Nexus pilot from October 2016-2017, per California Public Utilities Commission ruling D.16-06-010. 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 randomized experimental design was used to evaluate the potential impact of AMI on water consumption. The study set consisted of 244 treatment accounts in Los Angeles County and 248 treatment accounts in Fontana, 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 manual 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. Water utilities in Southern California have an alternate AMI Option for consideration, assuming it is available commercially.

Three potential hot water leaks were detected by AMI analytics over the course of the pilot. Two of these leaks were confirmed through field investigation. A total of 15,824 gallons of water savings and 121 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 <10 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 randomized experiments will likely need to be at least four times larger in sample size, and non-randomized experiments will need to be at least six 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. A difference between premises gas consumption of 1% was associated with a 0.47% difference in water consumption over the study period. 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 faulty/dying/broken 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), San Gabriel Valley Water Company (SGVWC), 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, SGVWC 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 is conducted within SGVWC's Los Angeles County (LAC) and Fontana Water Company (Fontana) service areas. LAC's service areas include El Monte, Hacienda Heights, and Whittier in the central Los Angeles basin. Fontana's service areas include Fontana and Rialto communities to the east. Budgeting considerations at SGVWC allowed for approximately 1000 accounts to be investigated. An experimental selection methodology, described in sections below, was used to generate approximately 250 treatment accounts in LAC and 250 treatment accounts in Fontana, and equivalent control accounts. The characteristic of the treatment accounts is that they have

AMI water meter reads and AMI gas meter reads, whereas the control accounts have manual water meter reads and AMI gas reads. Residential and Commercial customer classifications are included in consideration. While not specifically separated out in experimental selection, Residential classification includes 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	SGVWC	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 Loss Analytics • Investigate Apparent Loss Flags (Valor findings) • Maintain AquaHawk Customer Portal for Treatment Group Customers	• Provide AMI Technology and Infrastructure Support	• Provide SGVWC with Apparent Water Loss Management Solutions (Hidden Revenue Locator) • Provide SGVWC 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

In order to select treatment and control group accounts, Valor received and reviewed meter and billing data for 152,912 SGVWC accounts from 2011 to 2015. The number of accounts in this instance is the number of accounts that have ever had a usage record for these service areas and is defined per tuples of the form (Division, Office, Book, Sequence, Seq Extn, Customer Count). Usage files for these accounts were reviewed for Account

Status, Billing Information, and Meter/Customer Information, and the following decisions were made during the data cleaning process to identify eligible study accounts from which to subsequently sample:

- Accounts had to be active for all months since 2013
- Accounts had to have billing histories with no discrepancies
- Accounts had to include meter and customer information that was complete, clean, and unambiguous

Meters and Meter Detail files for the accounts that met these criteria were examined, and any accounts that did not meet the complete, clean, and unambiguous condition were excluded. Lastly, a Geocoding check was conducted, and accounts that could not be geocoded were excluded. Appendix 1 details the count of accounts removed at each step of the data exclusions process.

Customer Segmentation

On completion of data exclusion, a process of 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. Attention was restricted to accounts that existed in both 2013 and 2015. 48,886 accounts did not have sufficient water use information to establish a water use pattern, and were removed from the eligible study accounts pool.
- Segmentation: In order to draw a sample that best represents the attributes of the underlying population, customer segmentation was done by Region (LAC or Fontana), Customer Type Classification, Meter Size (Bill Size), and then further based on their usage.
    - Customer Type Classification included were Residential, Multi-Family Residential and Commercial.
    - Other Customer Types ['PUBLIC AUTHORITY', 'DUPLEX INDIVIDUALLY METERED', 'INDUSTRIAL', 'FIRE', 'CONSTRUCTION', 'COMMERCIAL RECYCLED', 'PUBLIC AUTHORITY RECYCLED', 'PUBLIC AUTHORITY MULTI-FAMILY'] had fairly low percentages among the total population and were excluded.
    - The Meter Size (Bill Size) considered were all the possible meter sizes that belonged to the particular combination of (Region, Customer Type Classification)
    - 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

At the end of Data Exclusions and Customer Segmentation processes, there were 76,348 accounts that were representative of the population and eligible candidates for sampling treatment and control groups. A draw of approximately 250 treatment accounts for LAC and 250 treatment accounts for Fontana that were also representative of the underlying population was randomly obtained using the distribution of segmentation characteristics described above for year 2013. The year 2013 is considered to be the "last normal year" of water use, prior to the recent California drought [1]. Due to the small draw size, there were instances where the percentages in the various segments (Region, Customer Type Classification, Meter Size, Use/Peak quadrant) rounded to zero. Such segments were excluded. Once the treatment accounts were obtained, controls were identified by randomly sampling from the matching segments.

All treatment and control accounts were screened by SoCalGas and confirmed to be active AMI gas accounts. In instances where accounts were either opt-out for AMI gas or without a meter transmission unit, alternative accounts were selected. At the end of this process, 247 treatment and 247 control accounts were generated for LAC, and 250 treatment and control accounts were generated for Fontana. Valor IDs were assigned using the following naming convention: LAC Treatment accounts "T-LA(Number)", LAC Control accounts "C-LA(Number)", Fontana Treatment accounts "T-Font(Number)", Fontana Control accounts "C-Font(Number)."

AMI water meters were subsequently installed by SGVWC for the treatment accounts over an eight-week period.

Analytics reporting period

Once the AMI water meters were successfully installed and steadily transmitting hourly water data, Valor completed SGVWC enterprise and water meter data integration and configuration and launched the Hidden Revenue Locator online dashboard. In parallel, Valor completed SGVWC 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 SGVWC and SoCalGas is October 17, 2016; the date when SGVWC's customer engagement portal was potentially available for treatment accounts. The analytical reporting period ended on October 17, 2017.

Accounts removed post-launch

Valor encountered data challenges with a small number of accounts after the start of the analytics reporting period. The following Valor IDs were removed from analysis: 'T-LA7', 'C-LA7', 'T-LA25', 'C-LA25', 'T-LA189', 'C-LA189', 'T-Font1', 'C-Font1', 'T-Font5', 'C-Font5'. The final list of 244 Treatment/Control pairs for LAC, and 248 Treatment/Control pairs for Fontana used in WEN analysis is presented in Appendix 2.

SGVWC Sample Size Significance

The standard recommendation for experimental studies like this pilot is to include as large a sample size as practically possible. A sample of 500 treatment accounts was suggested by SGVWC on their resource budget, and standard statistical estimation techniques [2] were used to determine if this met the minimal treatment group sample size condition.

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 [2].

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 SGVWC on a monthly basis. As indicated in Table 1, the analytics dashboards provided by Valor to SoCalGas are:

- 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 = Δt * 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 manual 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 [3].
- 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 [3].
- 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 [4].

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 SGVWC, 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 Aug-October 2016, and launch of the

Hot Water Leak Detector dashboard occurred in the last week of October 2016. The Water Energy Nexus Detector dashboard launch occurred in the third week of December 2016.

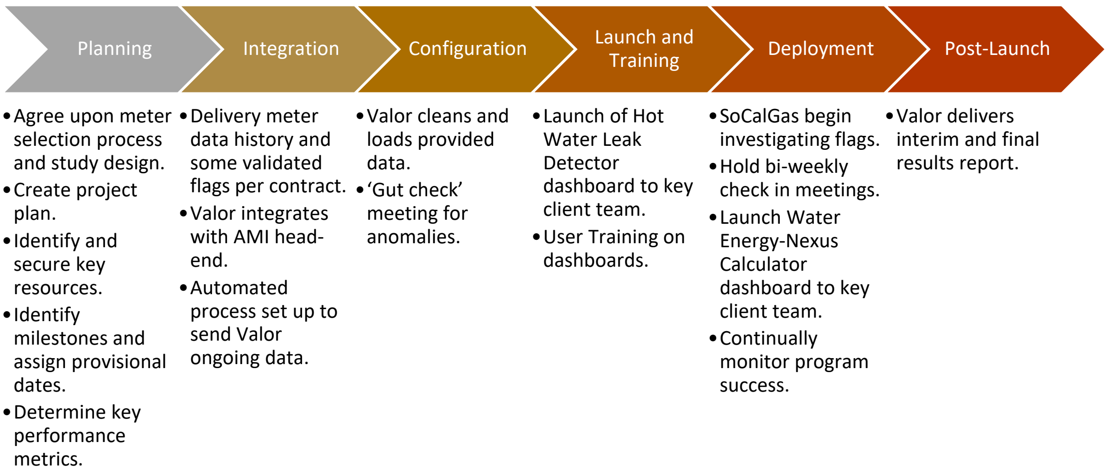

Figure 1: Analytics Deployment Phases Overview

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 SGVWC, through email communication.

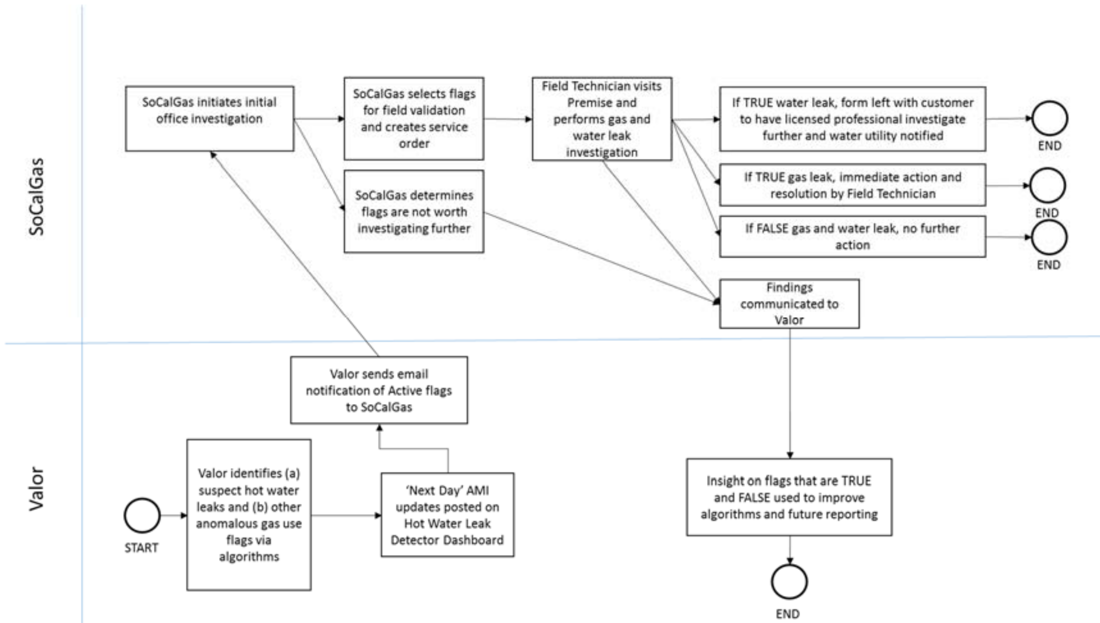

Figure 2: Schematic of Hot Water Leak Detector flag investigation and feedback process

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 October 2017.

Table 2: Description of water data from January 2011 to October 2017, and gas data from June 2015 to October 2017

	Fontana Treatment	Fontana Control	LAC Treatment	LAC Control
Unique Premises	248	248	244	244
Months of Data (Water)	81	81	81	81
Number of Meter Reads (Water)	18,530	18,482	18,578	18,432
Months of Data (Gas)	28	28	28	28
Number of Meter Reads (Gas)	5,868	5,834	6,690	7,263

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	Fontana	LAC	Total
Before Pilot Start	50	43	93
After Pilot Start	1	0	1
Grand Total	**51**	**43**	**94**

DCUs in LAC

- There is a total of 43 DCUs in LAC
- Map below highlights the service territory for the LAC and the DCUs within and in the surrounding area

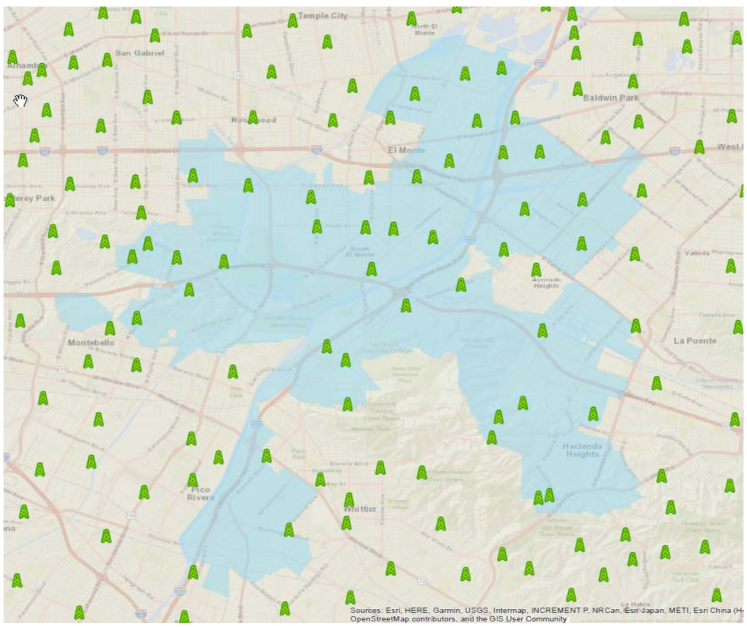

Figure 3: DCU in LAC

DCUs in Fontana

- There is a total of 51 DCUs in the Fontana
- Map below highlights the service territory for the Fontana Division and the DCUs within and in the surrounding area

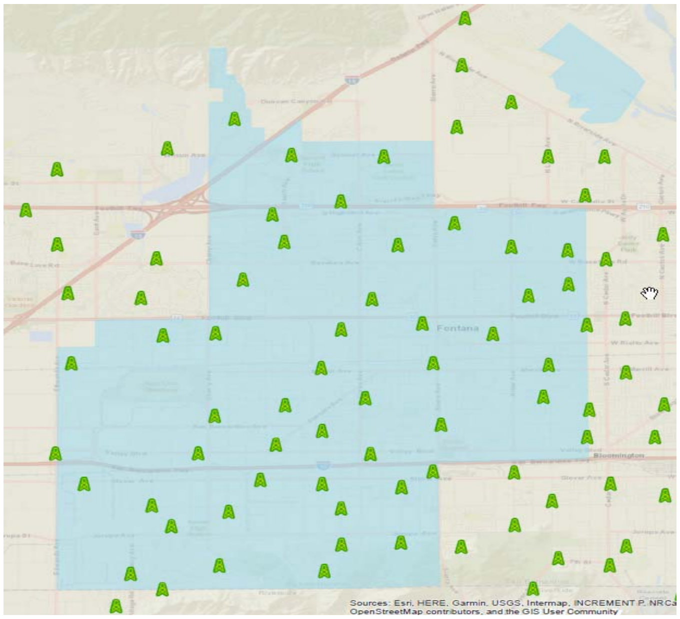

Figure 4: DCU in Fontana

The average DCU redundancy is 35 in LAC. This means that each MTU is heard, on average, by 35 DCUs. The average DCU redundancy in Fontana is 19.

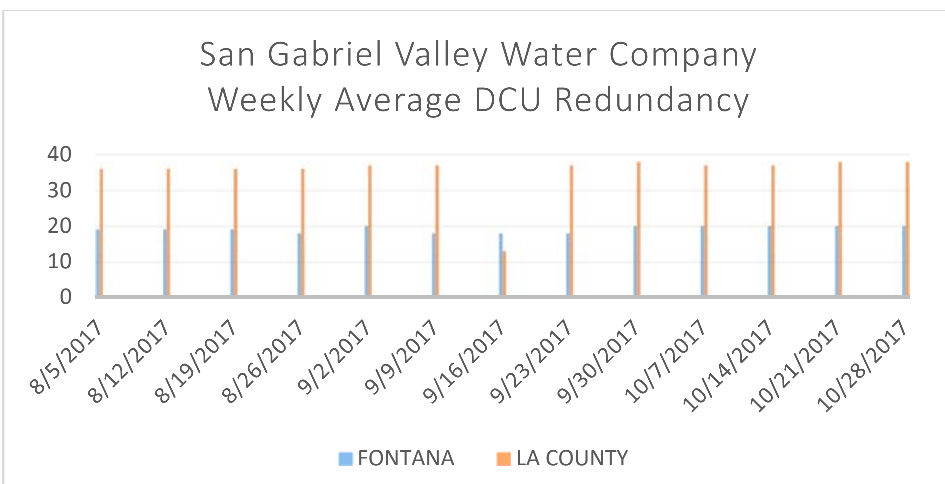

Figure 5: Average DCU redundancy

For LAC (SGVWC), there are a total of 919 unique DCUs that have picked up transmissions from LAC water MTUs in that district. The map below plots all of the SoCalGas DCUs which have received transmissions at least once from a LAC water MTU.

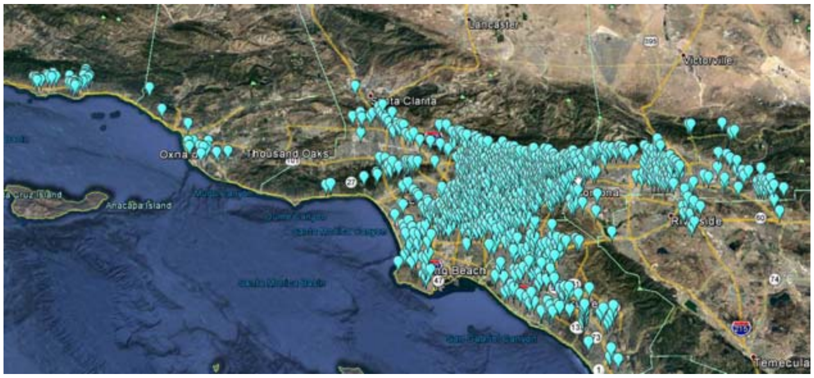

Figure 6: LAC water MTU transmissions

For Fontana (SGVWC), there are a total of 337 unique DCUs that have picked up transmissions from Fontana water MTUs in that district. The map below plots all of the SoCalGas DCUs which have received transmissions at least once from Fontana water MTU.

Figure 7: Fontana water MTU transmissions

The total number of installed MTUs is 535 (as of 10/08/17).

Table 4: MTU Installation Summary

Water Company	Installs Total	% of total Installs
San Gabriel Valley Water Company	535	100.00

The average monthly RSR in LAC is 98.7 for the period from August 2016 to October 2017. For Fontana, it was 96.7. 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 LAC and Fontana in October 2017 was 96.4.

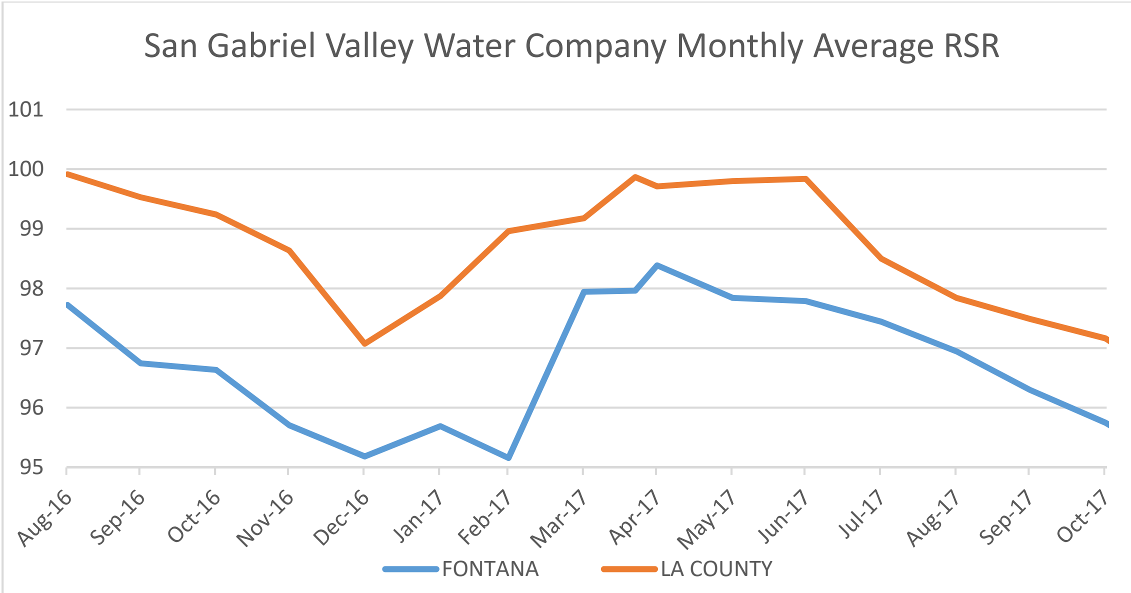

Figure 8: SGVWC monthly average RSR summary

Hot Water Leak Detection and Analytics

Three potential hot water leaks were detected by Valor between October 2016 and October 2017. 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 and across service areas, during which period a leak could self-resolve; this was beyond the scope of the program to analyze.

C-Font218 OAG

The first flag was an OAG (hot water leak signature based off gas AMI data only) on a control group account, C-Font218. The leak was active from 11/8/16 to 2/8/17. The premise is a single-family home with 5 bedrooms, 2 bathrooms, with 1,396 finished sq. ft. and 6,704 sq. ft. of potentially irrigated area.

SoCalGas conducted a field visit and verified that the customer had a hot water leak. Notes from the field visit are as follows:

- Hot water leak validated (constant water consumption)
  - Clock-test confirmed no gas leak, but continuous water flow at water heater confirmed
  - Hot water heater was turned OFF by Field Technician due to damaged burner seal & separated vent
- Customer appears to have turned heater back ON and not completed necessary repairs – leak became active again until Feb.

In order to estimate the total volume of water for this leak, in the absence of granular water data, the difference between metered water consumption over this period (about 84,500 gallons) to the average water consumption at this premise in the same three months for the previous 5 years (about 54,500 gallons) was determined (Figure 9).

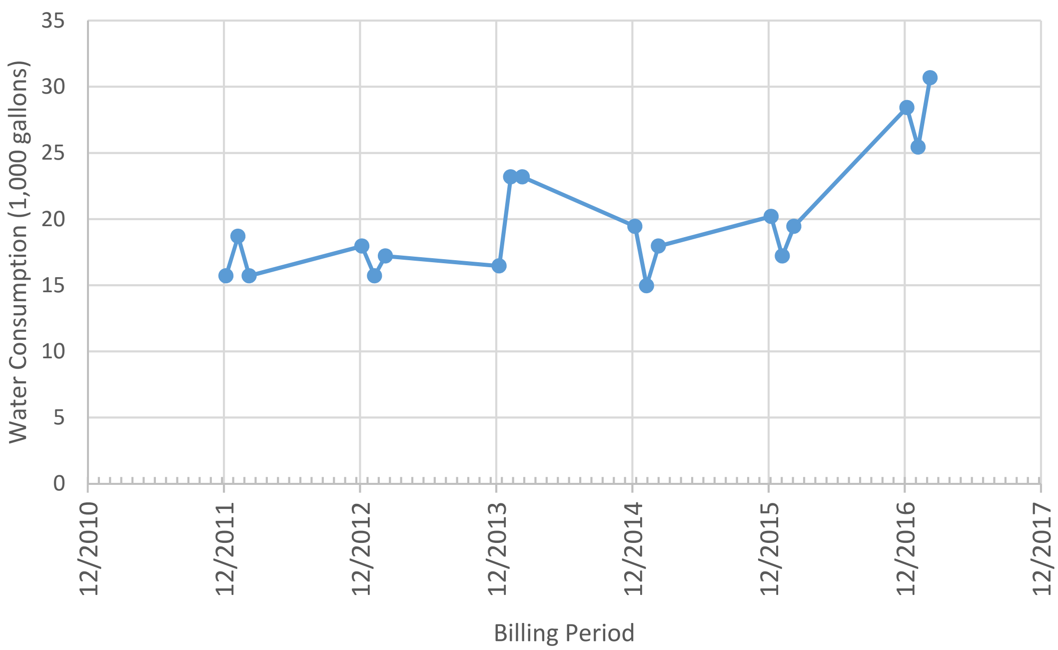

Figure 9: C-Font218 Average Water Consumption for December, January, February billing periods from 2012 to 2017

No move in/out occurred during this period to our knowledge, and there are no gaps in meter reads or changes in billing cycle. It is therefore plausible that this one hot water leak in the study period represented a loss of about 30,000 gallons of water over 92 days, or about 326 gallons per day. Without heater specifications, it is not possible to make further inferences on how often the hot water heater was emptied on a daily basis, other than to say that the field observation of water heater running continuously makes sense. The hot water leak appears to be of a reasonable size; however, it was not flagged as part of Valor's monthly water leak analysis run for SGVWC. Water savings of 9,780 gallons were estimated for detecting this hot water leak, by assuming that the leak would not have been determined until the delivery of the next water bill on March 10, 2017, or 30 days of additional consumption at the same leaked flowrate.

T-Font245 HWL

The second flag was a HWL (hot water leak signature based off both gas and water AMI data) on a treatment group account, T-Font245. The leak was active from 7/14/17 to 8/2/17. The premise is a single-family home with 6 bedrooms, 3.5 bathrooms, with 2,081 finished sq. ft. and 6,919 sq. ft. of potentially irrigated area.

SoCalGas conducted a field visit and verified that the customer had a hot water leak. Notes from the field visit are as follows:

- Customer was left off for Houseline leak, the customer had a tank less WH it looked like it might have been replaced recently.
- Isolated 2 line valves near MSA and line valves at Water Heater, Dryer and Heater (FAU)
- Form left to have customer contact a licensed plumber to repair the Houseline leak

Water savings of 6,044 gallons was estimated for detecting this hot water leak, by assuming that the leak would not have been determined until the delivery of the next water bill on August 21, 2017, or 19 days of additional consumption at the same leaked flowrate.

C-LA174 OAG

The third flag was an OAG (hot water leak signature based off gas AMI data only) on a control group account, C-LA174. The leak was active from 8/4/17 to 8/22/17. The premise is a single-family home with 2 bedrooms, 1 bathroom, with 1,104 finished sq. ft. and 4,197 sq. ft. of potentially irrigated area.

SoCalGas had a field visit scheduled for 8/22/17 that they cancelled due to consumption returning to normal. Since there was no confirmation of the hot water leak, water savings were not estimated.

Table 5 summarizes the total number of hot water leaks detected and the associated water savings from October 2016 to October 2017.

Table 5: Hot Water Leak Detection and Analytics in Treatment Period

	Control	Treatment
Fontana		
Number of Hot Water Leaks Detected	0	1
Gallons Saved	0	9,780
LAC		
Number of Hot Water Leaks Detected	1	1
Gallons Saved	6,044	0

Combined		
Number of Hot Water Leaks Detected	1	1
Gallons Saved	6,044	9,780

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 these flags were considered worth of field investigation.

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

Customer Portal Engagement

SGVWC elected to use an 'opt-in' approach to engage treatment group customers through the AquaHawk online portal. Despite multiple outreach attempts by SGVWC, the sign on rates were very low. A total of <10 customers were active on the portal over the course of the analytics reporting period.

Water and Energy Savings

Table 6 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 SGWVC.

Table 6: Water and Energy Savings in Treatment Period

	Treatment	Control
Fontana		
Hot Water Leak/Gas Anomaly Savings (Gallons)	0	9,780
Embedded Energy Savings (kWh)	0	73
LAC		
Hot Water Leak/Gas Anomaly Savings (Gallons)	6,044	0
Embedded Energy Savings (kWh)	48	0
Combined		
Hot Water Leak/Gas Anomaly Savings (Gallons)	6,044	9,780
Embedded Energy Savings (kWh)	48	73

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, lead to reductions in water and gas consumption. Since a very small subset of 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. Since hot water leaks represent a small portion of the 171 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 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 a 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 two study areas. The characteristics of the study areas inform the decision of whether to analyze AMI program impact in Fontana and LAC separately or together.

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 2015. Minor weather differences and somewhat substantial differences in housing quality and water consumption patterns were observed between the two service areas, which could motivate analyzing Fontana and LAC premises separately. However, given the lack of power ($n<400$) and that the treatment was randomized within the two areas, it is reasonable to pool the samples to avoid sacrificing sample size, and analyze AMI program impact on Fontana and LAC together, rather than separately.

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

- Monthly SGVWC 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 premises 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

Even though AMI treatment was randomized, 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 are 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 Los Angeles and San Bernardino County Assessors' offices:
    - 2015 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°F, averaged across all days in billing period)
- Cooling Degree Days- base 80 (Average temperature – 80°F, averaged across all days in billing period)
- Heating Degree Days (65°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°F as well as 80°F as recommended by PG&E's Pacific Energy Center in "Guide to California Climate Zones and Bioclimatic Design" [5]. 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°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. SGVWC have an increasing block tier rate structure, and no changes occurred over the course of the analytics reporting period. Prices were therefore not considered for further investigation, as it would just introduce unnecessary autocorrelation into the predictor equation.

Figure 10 presents the locations of the 984 premises in Fontana and LAC. While there is evidence of slight clustering of treatment and control groups, in general the spatial distribution appears random. Table 8 shows the variation in average water consumption, gas consumption, number of leaks detected, climate variables and housing values for the selected premises in Fontana and LAC in the pre-treatment period, averaged over January 2011 to September 2016. On average, premises served by Fontana exhibited higher water use, lower gas use, and slightly higher monthly leak prevalence than the LAC premises. In terms of weather, Fontana has a higher CDD average, a higher HDD average, and a higher average amount of precipitation than LAC. In terms of housing characteristics, the average tax assessed home value per square foot is higher in LAC. These differences indicate the possibility of differences in the average AMI effect between the two service areas, and motivate analyzing the trials separately in each service area. However, given the lack of power (n<400) and that the treatment was randomized within the two areas, it is reasonable to pool the samples to avoid sacrificing sample size. Statistical analyzes have therefore been conducted on the entire sample, with each area also analyzed separately as a robustness check.

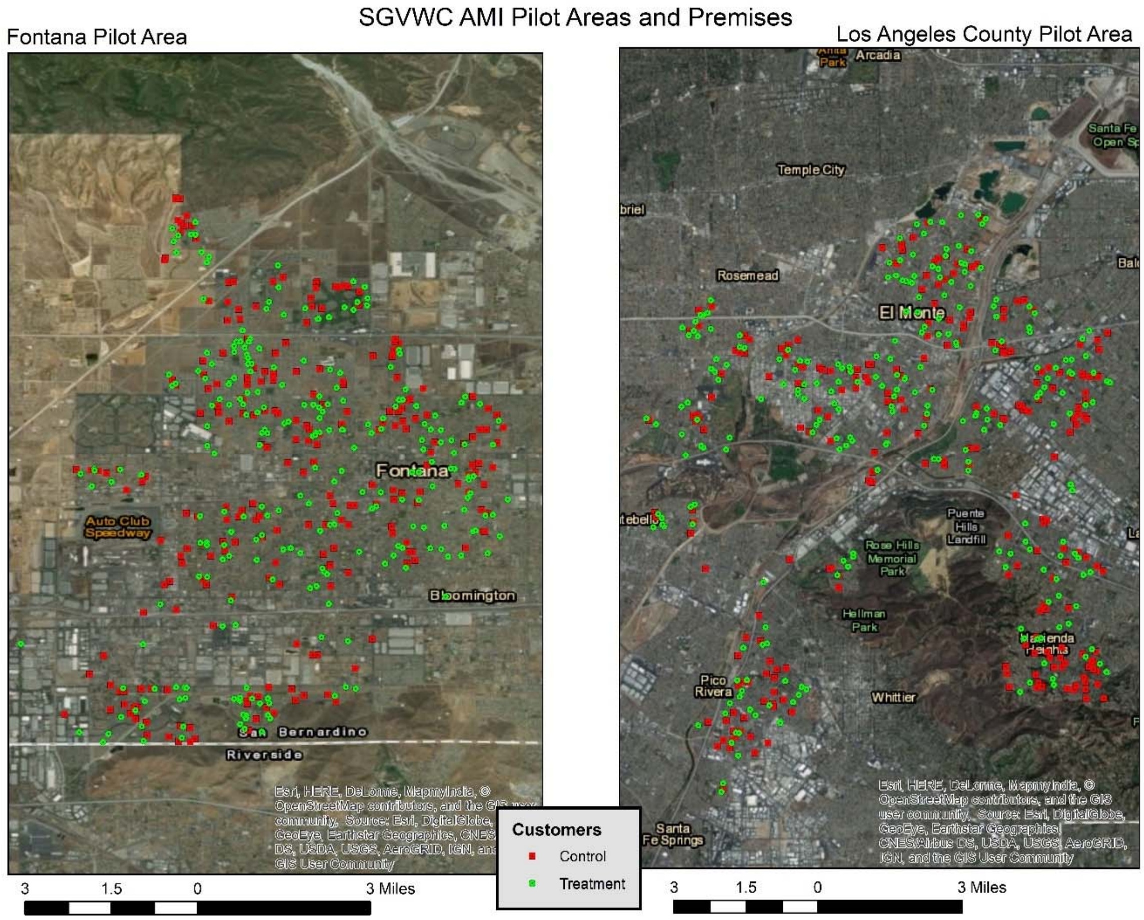

Figure 10: Spatial distribution of control and treatment premises in Fontana and LAC

Table 7: Fontana and LAC characteristics in the pre-treatment period, averaged over January 2011 to September 2016

Service Areas	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.
Fontana	462	0.83	0.180	0.43	5.52	0.67	0.12	$130
LAC	319	0.89	0.170	0.25	5.45	0.58	0.11	$166

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 to be insufficient to detect the changes in water consumption that would plausibly be caused by the AMI program at this point. The most complex statistical models conducted for this pilot may be able to detect a reduction of water consumption of about 5%. The effects on gas consumption are unlikely to be judged statistically significant with this sample size.

Result Details: When the Fontana and LAC service areas are combined, a total of 984 premises are available for analysis, divided evenly between the treatment and control groups. Table 8 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 8: Sample Sizes for Water

	Full Sample			Residential Premises Only		
Service Area	Premises	Observations	Post-Treatment Observations	Premises	Observations	Post-Treatment Observations
Fontana	496	34,432	2,355	462	32,020	2,198
LAC	488	34,317	2,489	420	29,602	2,152
Combined	984	68,749	4,844	882	61,622	4,450

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 sample 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 ~0.75. *n*=984 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 14%. For gas, in this data, the variance of *y* is ~0.79, and the associated MDE is 16%.

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% [6,7,8], 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 [9].

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

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*=69 and *r*=12. A simple two-way fixed-effects specification thus yields a minimum detectable effect (with 80% power) of 4.9%. For gas, with *m*=1 and *r* =12, the MDE is 6.1%. The study is likely to be underpowered still, so additional time-varying controls such as weather, or interactions between the treatment and initial consumption will likely be necessary to reduce the residual variation of *y* within the treatment and control groups and enable the detection of plausible program effects.

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 consumption levels as long as the true effect is greater than about 5%, and for gas if the true effect is greater than 6%. Unfortunately, it is quite possible that the true effect size is smaller than these values. In addition, due to the more limited time period for which gas consumption data is available, effects on gas consumption are not likely to be detectable with this sample size.

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 water consumption between the treatment and control groups in Fontana, and in the initial average gas consumption between the treatment and control groups in LAC, and in the number of bathrooms among residential premises in LAC. These three findings motivate analyzing the service areas separately, and directly accounting for variability in premises characteristics through statistical controls of premises characteristics, which requires restricting the analysis to residential premises

Result Details: Table 9 demonstrates the pre-treatment balance between treatment and control groups across the dependent variables, and the observables available for the residential premises. This combines observations from Fontana and LAC. Overall, the treatment and control groups appear balanced, with no statistically significant differences on the observed variables except for bathrooms, where control premises had slightly more bathrooms on average, with a marginally significant p-value of 0.1.

Table 10 shows the pre-treatment balance in Fontana, and Table 11 in LAC. While no observed variables show statistically significant differences in either service area, there is a concerning divergence between the two areas. In Fontana, the control group had greater average water use than treatment group, while in LAC the opposite was the case. This implies that despite randomization, the treatment group had different levels of the dependent variable pre-treatment than the control group. Thus, analysis that controls for these differences is required to make valid inferences about the effect of the AMI treatment.

Moreover, across treatment and control groups, average levels of water consumption tend to be about 150 gallons per day higher in Fontana than in LAC. This suggests differences in overall water consumption patterns between the two service areas that motivates examining them separately. However, given the low overall sample size, analysis will also be required using all of the data pooled together.

Table 9: Pre-treatment balance with Student's t-test p-values for water and gas consumption and residential characteristics across treatment and control, both service areas

Variable	Control	Treatment	Difference (%)	p-value
Mean Daily Water Use (Gallons)	423	421	-0.3%	0.936
Mean Daily Gas Use (Therms)	0.95	0.91	-4.3%	0.170
Assessed Tax Value 2015 (USD)	245,705	236,907	-3.6%	0.344
Assessed Value per Sq. Ft. (USD)	145	148	2.3%	0.507
Year Built	1973	1972	0.0%	0.605
Lot Size (Sq. Ft.)	8,739	8,462	-3.2%	0.558
Finished Area (Sq. Ft.)	1,712	1,636	-4.4%	0.084
Irrigable Area (Sq. Ft.)	7,031	6,824	-2.9%	0.659
Bathrooms	2.23	2.10	-5.9%	0.010
Bedrooms	5.50	5.46	-0.8%	0.595
Total Rooms	10.32	10.24	-0.8%	0.696

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

Variable	Control	Treatment	Difference (%)	p-value
Mean Daily Water Use (Gallons)	495	482	-2.5%	0.580
Mean Daily Gas Use (Therms)	0.92	0.89	-3.9%	0.382
Assessed Tax Value 2015 (USD)	226,098	217,807	-3.7%	0.358
Assessed Value per Sq. Ft. (USD)	130	130	-0.3%	0.906
Year Built	1984	1983	0.0%	0.621
Lot Size (Sq. Ft.)	8,852	8,758	-1.1%	0.904
Finished Area (Sq. Ft.)	1,751	1,702	-2.8%	0.417
Irrigable Area (Sq. Ft.)	7,108	7,057	-0.7%	0.947
Bathrooms	2.29	2.17	-5.2%	0.058
Bedrooms	5.46	5.39	-1.3%	0.394
Total Rooms	10.11	10.01	-1.0%	0.648

Table 11: Pre-treatment balance with Student's t-test p-values for water and gas consumption and residential characteristics across treatment and control, LAC

Variable	Control	Treatment	Difference (%)	p-value
Mean Daily Water Use (Gallons)	343	354	3.2%	0.519
Mean Daily Gas Use (Therms)	0.97	0.93	-4.6%	0.289
Assessed Tax Value 2015 (USD)	267,921	259,686	-3.1%	0.626
Assessed Value per Sq. Ft. (USD)	162	170	5.4%	0.365
Year Built	1960	1958	-0.1%	0.441
Lot Size (Sq. Ft.)	8,612	8,108	-5.8%	0.302
Finished Area (Sq. Ft.)	1,668	1,559	-6.5%	0.085
Irrigable Area (Sq. Ft.)	6,944	6,546	-5.7%	0.396
Bathrooms	2.2	2.0	-6.9%	0.071
Bedrooms	5.5	5.5	-0.3%	0.913

Total Rooms	10.6	10.5	-0.6%	0.870

Dependent Variable Trends

Motivation: Given the sample size insufficiencies and 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: Examination of trends in water and gas consumption over time show that while there were differences between treatment and control customers for water consumption in Fontana and for gas consumption in LAC, prior to the implementation of water AMI, the trends were parallel between the treatment and control groups. Moreover, the initial levels and trends in water consumption prior to AMI analytics across treatment and control groups across both service areas looked identical when excluding non-residential premises. This is evidence for the validity of using the panel data models, while lending the most credibility to the models that examine residential premises only. The models also allow the ability to make causal inferences by controlling for confounding sources of variation in the outcome variables than just the AMI analytics program.

Result Detail: As part of Valor's standard data ingestion process, consumption data for water and gas is 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 [8]. 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. Figure 11 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.
- For water, the following observations were set to missing:
    - T-Font7.2016-12 (2 inch meter) [>9000ccf]
    - T-LA2.2016-08 (1 inch) [>700ccf]
    - T-Font178.2012-08 (5/8 inch) [>210 ccf]

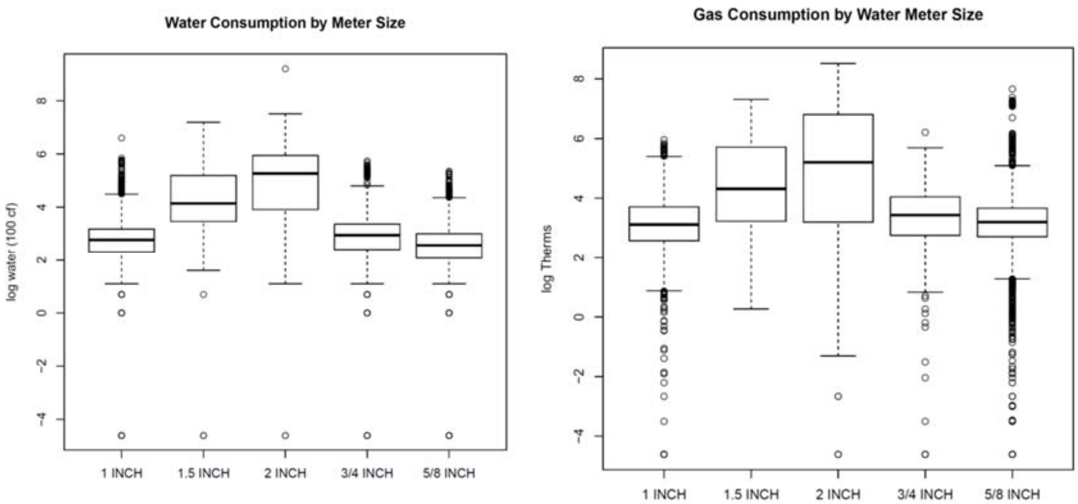

Figure 11: Monthly water and gas consumption observations for each meter size in the sample in pre-treatment and post-treatment periods

Figures 12-15 present the time trends in the nominal billing period monthly average values of mean daily water consumption (Figure 12), gas consumption (Figure 13), water leak prevalence as estimated by Valor's monthly detection algorithm (Figure 14), and water leak prevalence as estimated by both monthly and AMI detection algorithms together (Figure 15). In all figures, the panels on the left include all premises, and the panels on the right include only residential premises. In all figures, the top row presents Fontana premises, the middle row presents LAC premises, and the bottom row pools all observations across both service areas. The black vertical lines indicate the start of AMI-WEN analytics and proactive leak detection in October 2016. As seen from Figure 12, the control group had lower average water use in LAC and higher average water use in Fontana in the pre-treatment period. In Figure 13, gas consumption is seen to be higher in the LAC control group. These balance issues are eliminated when only considering Residential premises. A few but large Commercial or Multi-Family accounts may be driving the average values of the dependent variables across the treatment and control groups apart in the pre-treatment period. It is probably necessary to either control for premises class and meter size, or to analyze only residential premises. Since the trends in water and gas consumption between treatment and control groups do not seem to diverge after October 2016, even without statistical tests it is apparent that any average effects of AMI analytics on these outcomes may not be significant or detectable.

Figure 14 reveals no divergence in prevalence (defined as the number of leak flags divided by the number of active premises in the pilot) of leak flags made by the monthly algorithm between treatment and control group before and after the AMI program began. Figure 15 plots similar information for the prevalence of leak flags made by combined AMI and monthly analytics, and it is seen that using hourly 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 abnormally high consumption that customers are notified of, and which field teams may validate. Since only 13% of leak flags were investigated in the field, this information was not included in the analysis.

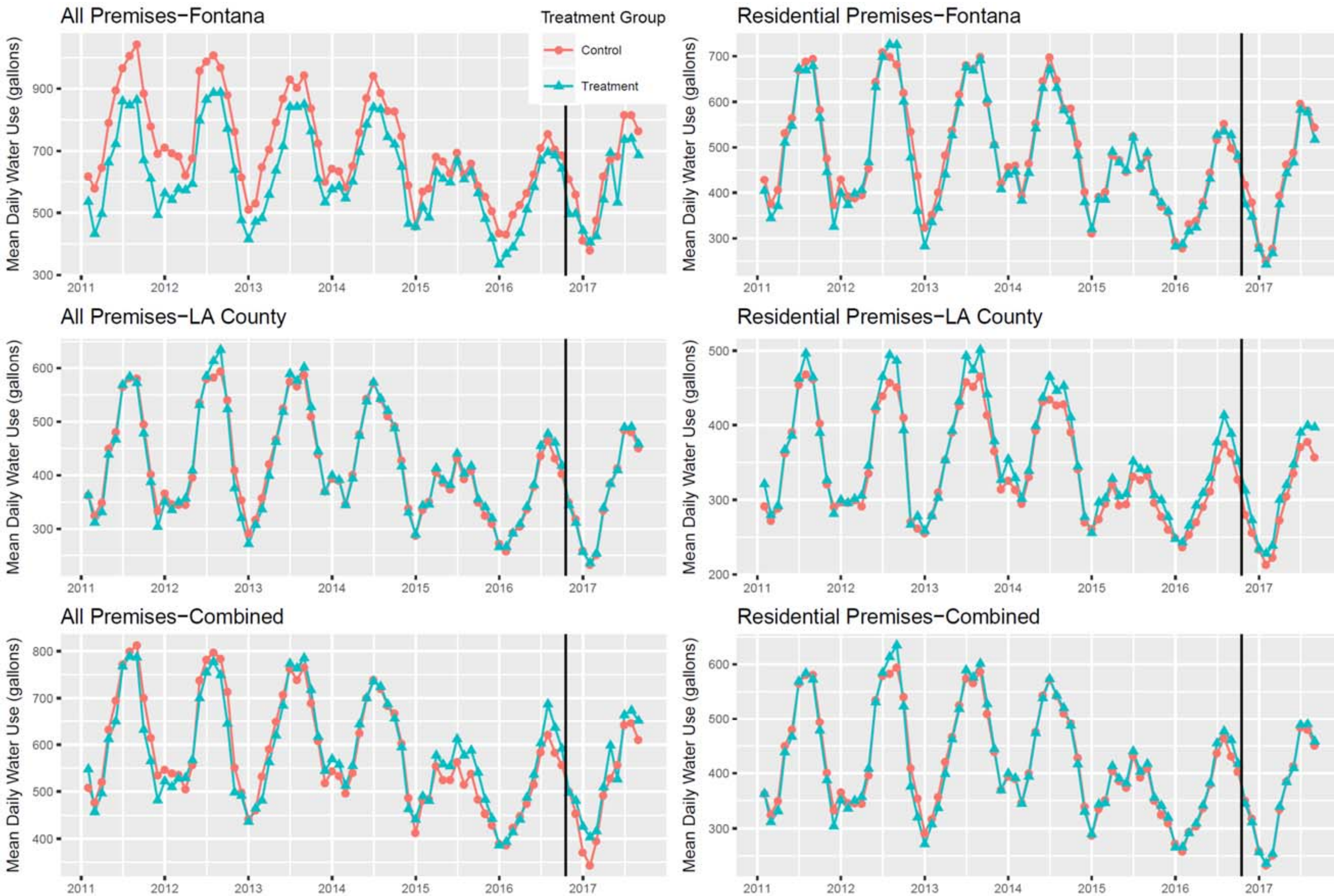

Figure 12: Average Daily Water Use (gallons) across control and treatment groups and by service area

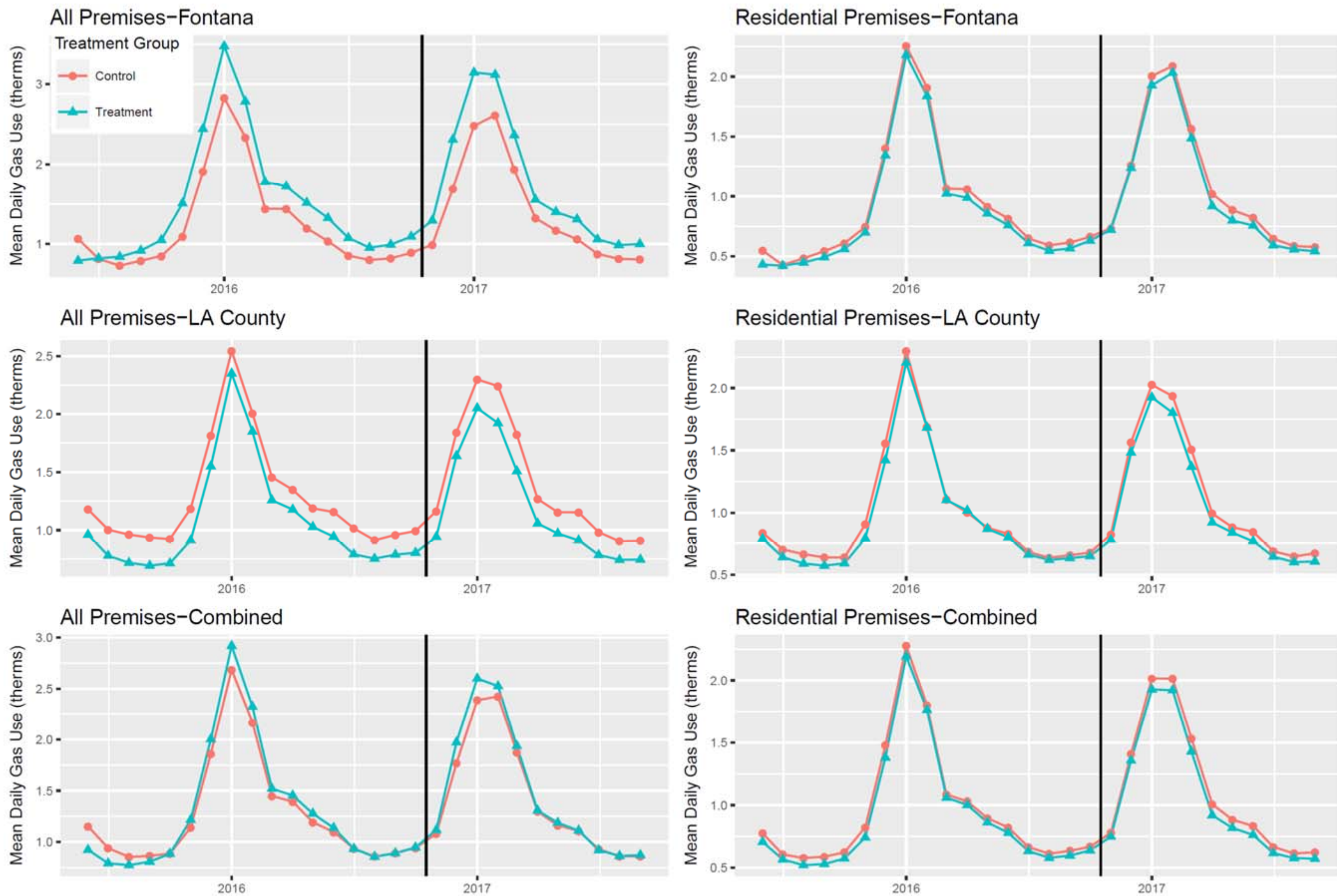

Figure 13: Average Daily Gas Use (therms) across control and treatment groups and by service area

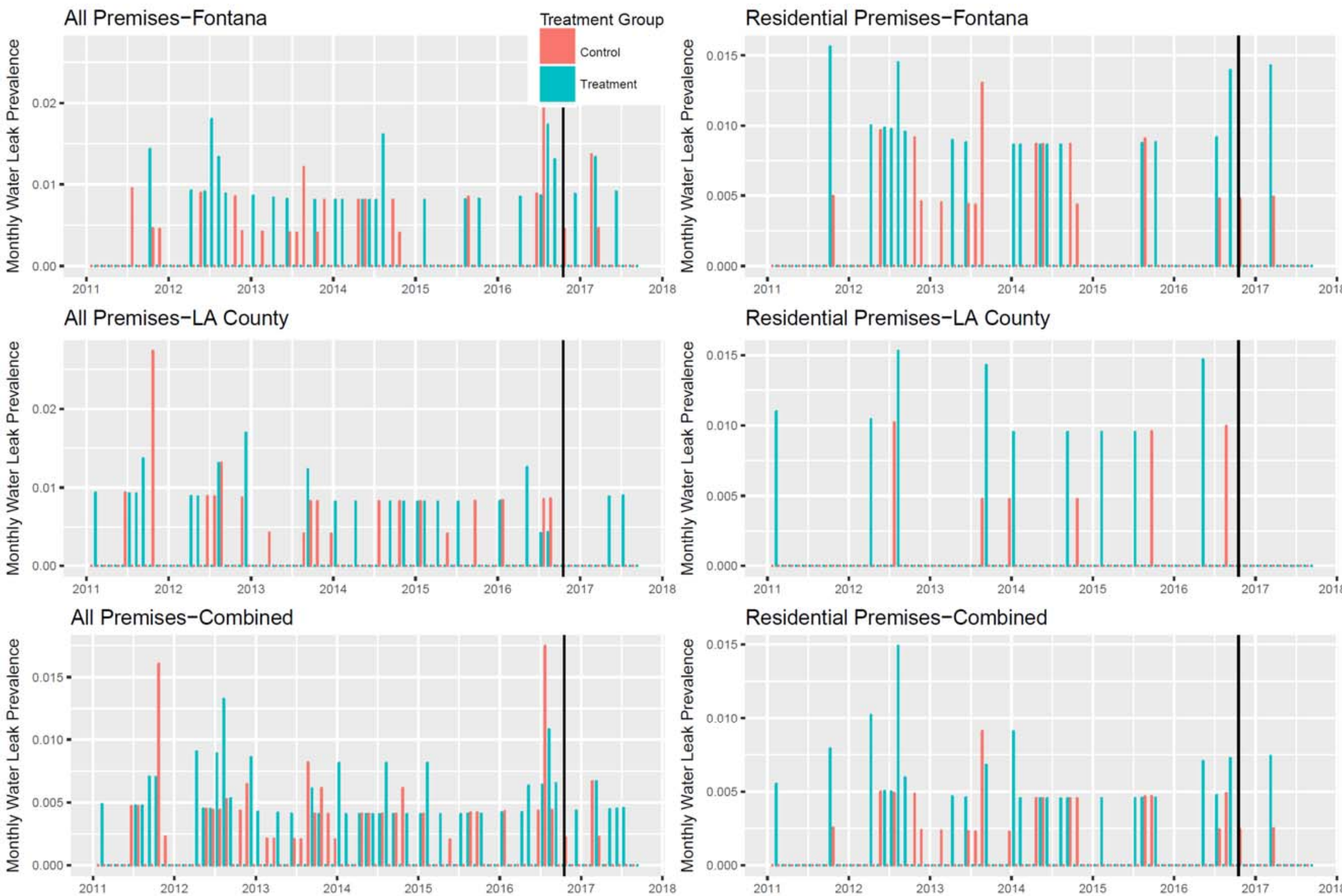

Figure 14: Monthly prevalence of Monthly water leak flags across control and treatment groups and by service area

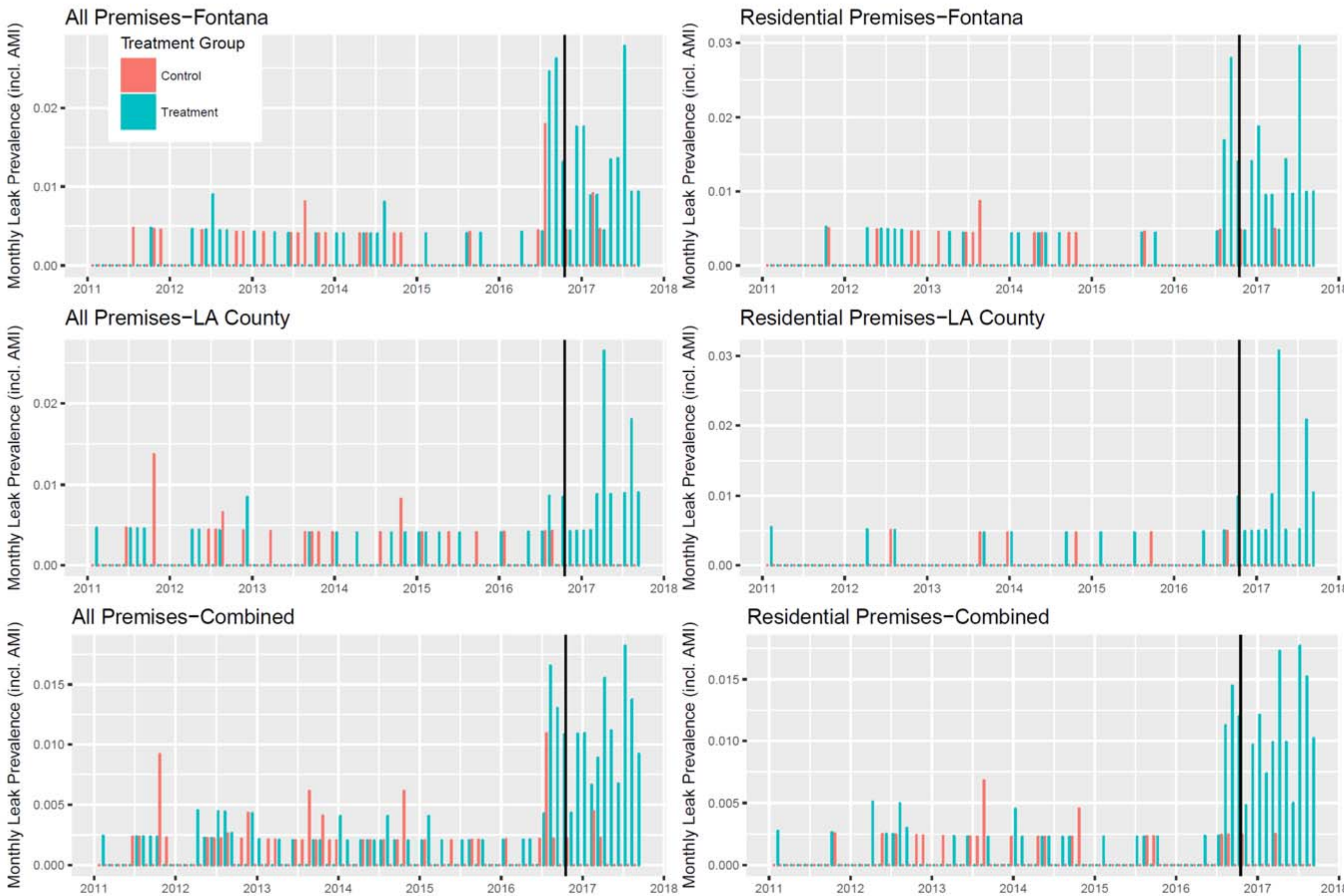

Figure 15: Monthly prevalence of consolidated AMI and Monthly water leakages across control and treatment groups and by service area

Table 12: 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

	Fontana		LAC		Combined	
	Pre	**Post**	**Pre**	**Post**	**Pre**	**Post**
Average Daily Water Use (Gallons)						
All Premises						
Treatment	623	569	546	494	585	531
Control	717	623	447	393	583	504
Residential Premises						
Treatment	482	405	354	342	421	360
Control	494	422	313	293	422	358
Average Daily Gas Use (Therms)						
All Premises						
Treatment	1.59	1.75	1.08	1.19	1.30	1.47
Control	1.25	1.43	1.30	1.40	1.28	1.42
Residential Premises						
Treatment	0.89	1.05	0.94	1.05	0.92	1.05
Control	0.94	1.10	0.99	1.12	0.97	1.11
Average Monthly Water Leak Prevalence (Monthly Algorithm)						
All Premises						
Treatment	0.34%	0.28%	0.29%	0.15%	0.32%	0.21%
Control	0.22%	0.20%	0.24%	0.00%	0.23%	0.10%
Residential Premises						
Treatment	0.25%	0.13%	0.15%	0.00%	0.20%	0.07%
Control	0.15%	0.09%	0.06%	0.00%	0.11%	0.04%
Average Monthly Water Leak Prevalence (Monthly and/or AMI Algorithm)						
All Premises						
Treatment	0.23%	1.23%	0.16%	0.85%	0.19%	1.03%
Control	0.14%	0.16%	0.13%	0.00%	0.14%	0.08%
Residential Premises						
Treatment	0.19%	1.22%	0.04%	0.00%	0.14%	1.06%
Control	0.10%	0.09%	0.09%	0.89%	0.07%	0.04%

Table 12 collapses the information contained in Figures 12-15 to the average values of the outcomes of interest by Service Area, 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, in Fontana, when considering all premises post-treatment, the treatment group has an average of 569 gallons per day whereas the control group has an average water consumption of 623 gallons per day. This would seem to indicate that AMI reduced water consumption. However, in the pre-treatment period, the treatment group in Fontana also consumed less than the control group. This indicates that the treatment and control groups had different water use patterns despite stratified randomization on customer class. In LAC, the treatment group in the post-treatment period appears to consume more water than the control group. It is thus important, in order to make a 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. The preferred subset of data includes only residential premises due to aforementioned issues of imbalance between the treatment and control groups, and pools Fontana and LAC observations together due to inadequate sample size in either service area alone. Table 13 summarizes what each model accounts for and the estimated results.

Table 13: Advanced Statistical Analysis Summary for Residential Premises, Combined Service Areas

	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-AMI Consumption/Leaks	No	No	No	Yes	Yes	Yes	Yes	No
	Premises pre-AMI 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 is no statistically significant impact on these outcomes by AMI analytics during the study period. 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. 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.

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

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. *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. Since the AMI treatment was randomized, theoretically this is all that is needed to make a valid inference about the effect of AMI. However, given the relatively low sample size and minor concerns about 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), 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

[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.

value, number of bedrooms, number of bathrooms, irrigable area in square feet, and the dwelling finished floor area in square feet.

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

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

This model includes all observations both before and after the AMI treatment begins. AMI_{it} is now a variable indicating whether premises i had water AMI active in water billing period t. T_i indicates whether or not premises i was in the treatment group. This model 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-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 regional economic conditions, the California drought conditions and associated policies and media campaigns occurring over time that could affect each of the outcome variables.

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 and water price. 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 [8,9]. This alternative specification can also be interpreted as a percentage change, but does not underestimate large changes. Similar dependent variables are used for gas: $\lg_{it}$ 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.

Data Subsets

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

- All premises
- All residential premises
- All premises in Fontana
- All residential premises in Fontana
- All premises in LAC
- All residential premises in LAC

This allows the investigation of whether the treatment effect varies between the two service areas, and when excluding particularly high water and gas users in the commercial and multifamily residential classes. Only the results from all Fontana and LAC premises combined and all residential premises combined are reported, since this allows for the most robust interpretation, given the sample size issue. There are relatively few non-residential premises in the sample, yet these tend to be very high water and gas users. Thus, it is important to characterize the results for a representative sample of all SGVWC 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 treatment effects are summarized in the panels in Figure 16. 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), 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 models applied to all premises and on the right, for models applied only to residential premises. 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 15. The results of this model are interpreted below.

The top two panels show the treatment effects for water models. The one on the left uses W_{it} as the dependent variable, and the average treatment effect on the treated is on the y-axis in terms of percentage points. The panel on the right uses lnw_{it} as the dependent variable, with the y-axis in terms of percent (divided by 100). For the models for W_{it}, Model 3 estimates a positive effect of AMI on water consumption of about 2.5% for the premises including non-residential premises, a counter-intuitive result. The effect is -1% for residential premises only. This suggests that certain non-residential users measured large increases in water consumption before and after AMI. It is possible that this effect was caused by the replacement of potentially under-registering meters with new meters, rather than representing additional water consumption. However, the AMI effect on water consumption is not statistically significant in either case.

In the right panel, for lnw_{it}, Model 3 estimates effects very close to 0, and the results are not noticeably different when using all premises or only residential premises. This indicates that the lnw_{it} specification may indeed have been dampening the effect of high water use changes among commercial and multifamily premises, while the W_{it} specification did not. Overall, we accept the null hypothesis that the water AMI program has not affected water consumption.

The middle two panels show the treatment effects for the gas consumption models, and is laid out in the same manner as the water models. Here, the treatment effects estimated by Model 3 for G_{it} are positive 1.3%, and for lng_{it} are positive 1.8%, although neither are statistically significant. Again, we accept the null hypothesis that the AMI program had no significant effect on gas consumption.

The bottom two panels show treatment effects for monthly algorithm leak flags in the left column and combined monthly and AMI algorithm leak flags in the right column. The y-axis is the treatment effect in percentage points (divided by 100). Among all premises, the Model 3 estimates a positive effect on the prevalence of monthly water leak flags of about 0.1%. However, the estimated effect for residential premises is -0.5%. This is a similar discrepancy as in the models for W_{it}. It is likely that very large, non-residential premises have had more monthly leak flags due to increased meter accuracy, while in residential premises the pattern is more consistent with increased AMI leak flags resulting in faster leak fixes and thus in fewer leaks detected by algorithms relying on monthly data. Neither of the estimated effects are statistically different from zero, and so the null hypothesis is again accepted. For the monthly and hourly AMI flags considered together, the estimated effect for all models and data subsets is generally in increase of about 1%, indicating that the AMI program was indeed flagging 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 is 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 merely verifies that leak detection algorithms based on water AMI data do result in more leak flags then 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 non-significant evidence that AMI analytics reduces monthly leak flags in residential premises, indicating that leaks duration may be reduced through AMI analytics and notification.

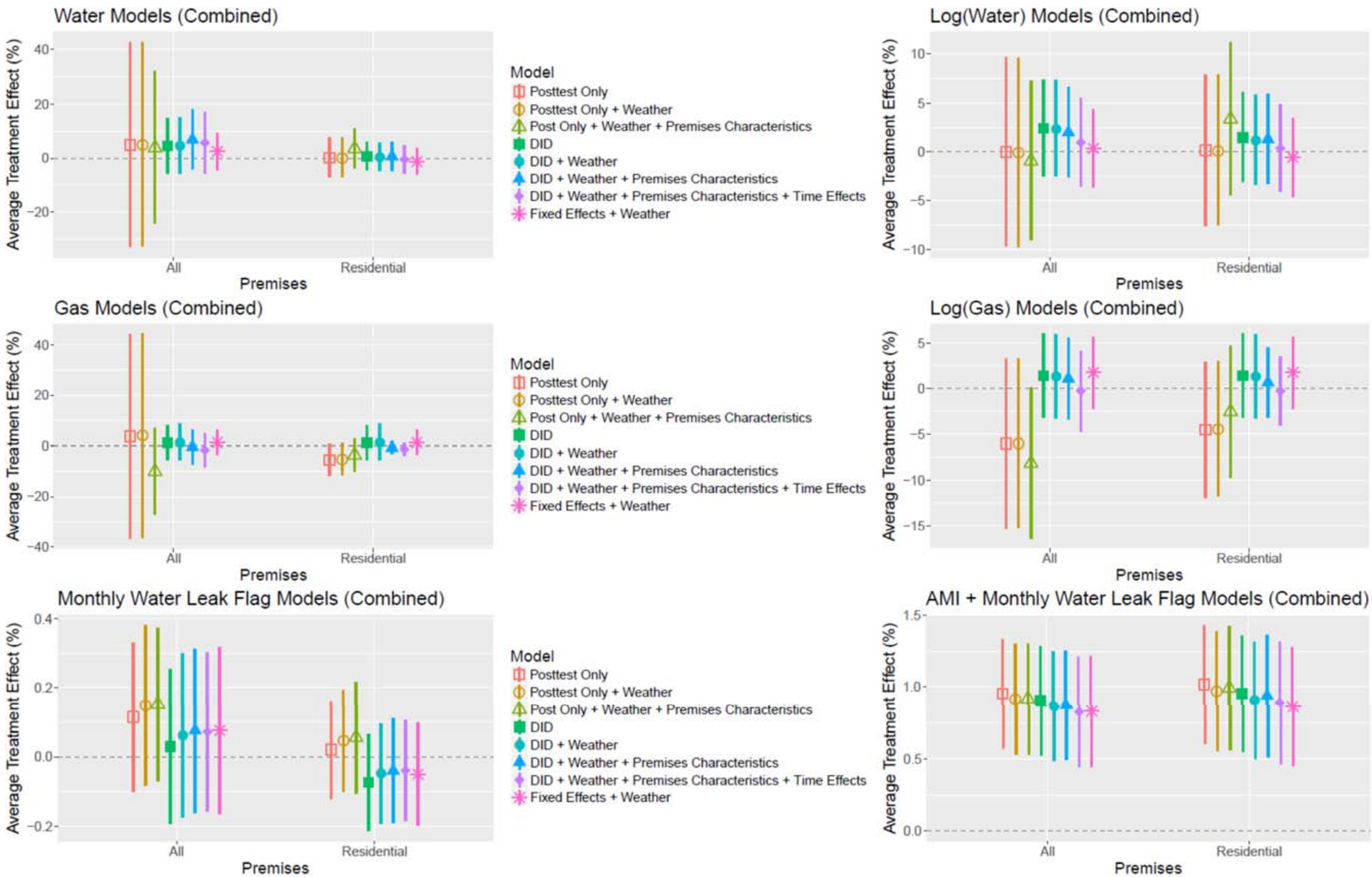

Figure 16: Estimated average treatment effects with 95% confidence intervals

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 SGWVC offers a unique randomly selected 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 17 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.

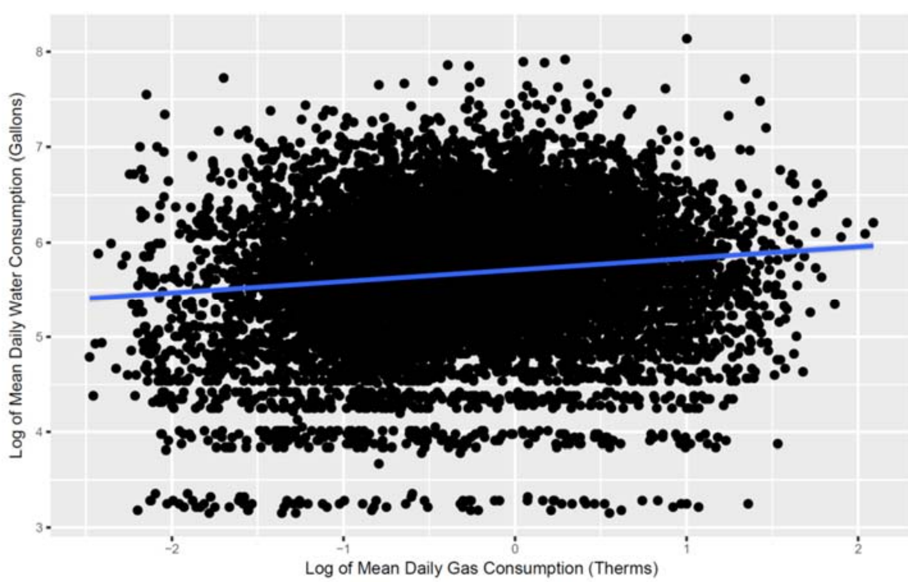

Figure 17: Average daily water consumption vs. average daily gas consumption, 2015-2017

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 18 plots the average daily water and gas consumption of all of the treatment premises between June 2015 (when gas consumption data are reasonably representative) and September 2017 (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-February, and peak water consumption July-September. Thus, a failure to control for seasonality would be expected to produce an underestimate of the average relationship between water and gas consumption.

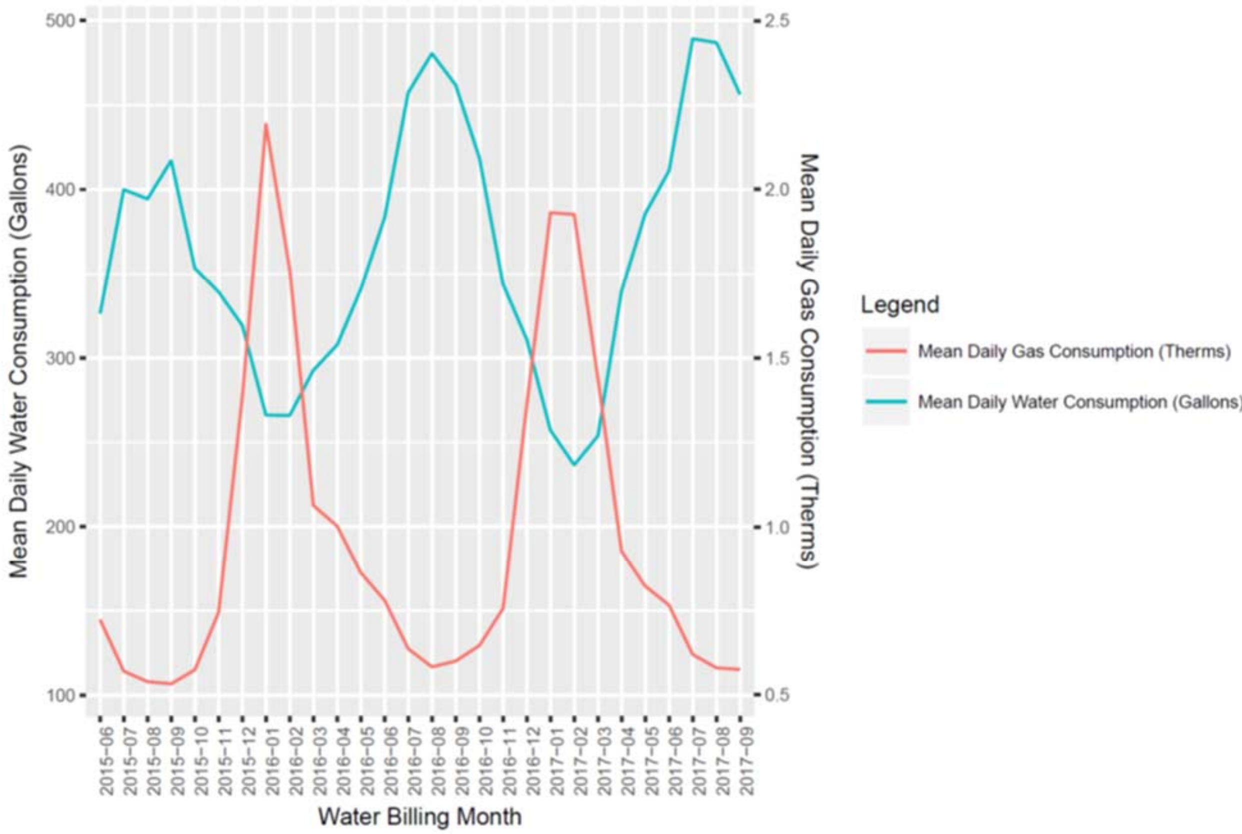

Figure 17: Mean Daily Water Consumption and Mean Daily Gas Consumption over time, June 2015 - October 2017

Figure 19 separates out Figure 17 by each water billing month in the study period. It is seen that by controlling for seasonality through the simple technique of considering the data on a month-by-month data, 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.

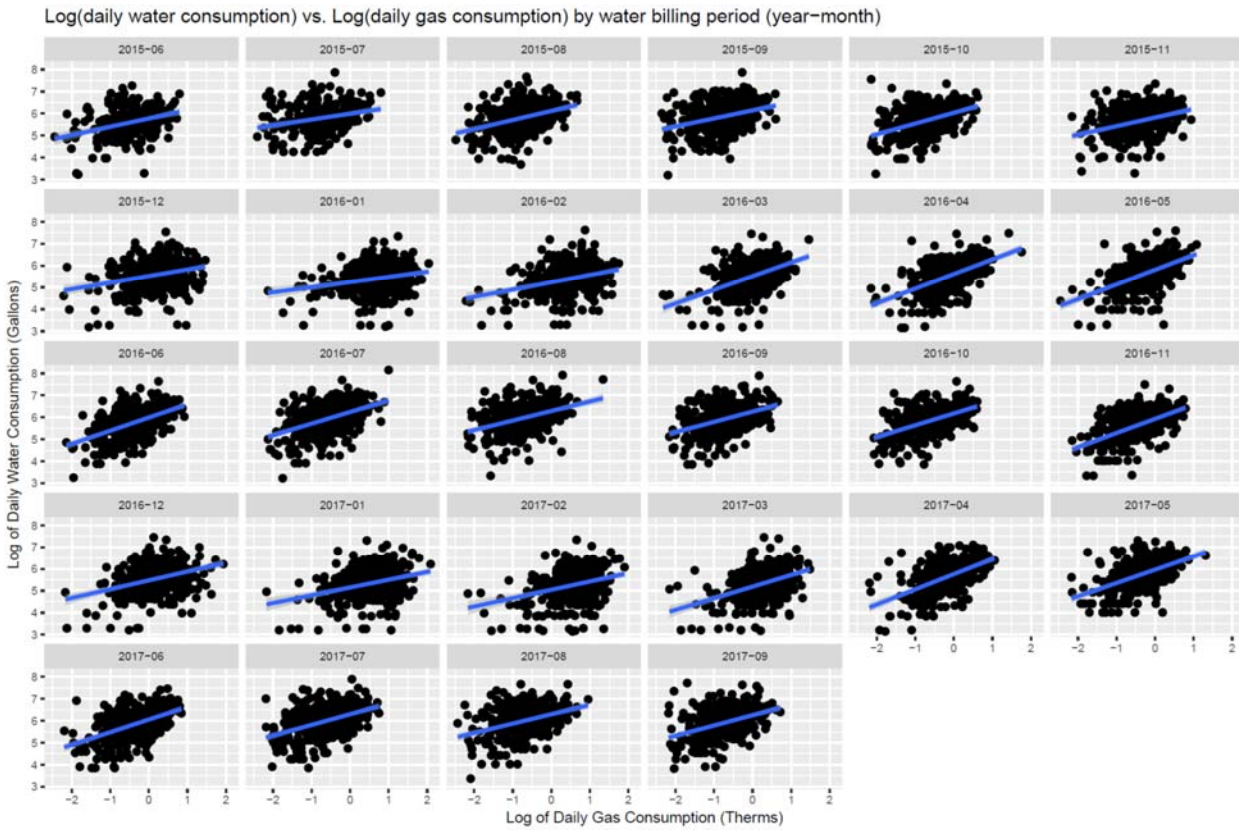

Figure 18: Average daily water consumption vs. average daily gas consumption by water billing period

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
- 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 LA County or San Bernardino 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
- MeterSize' – A dummy variable for each water meter size
- Customer Type – A dummy variable for each premises water customer classification (commercial, multi-family residential, single-family residential)
- Fontana – A dummy variable indicating whether the premises is in Fontana or LAC

- τ – A dummy variable for each water billing period, controlling for events over time common to all of the premises that are not covered by temperature and precipitation, such as state-level economic conditions and policies.

$$
\begin{aligned}
(A)\ \ln(w_{it}) = {} & \beta \ln(g_{it}) + \gamma AMI_{it} + \delta_1 HDD_{it} + \delta_2 CDD_{it} + \delta_3 PRCP_{it} + \delta_4 bathrooms_i \\
& + \delta_5 bedrooms_i + \delta_6 taxAssessment_i + \delta_7 irrigableArea_i + \delta_8 SqFt_i \\
& + \boldsymbol{\rho}' MeterSize_i + \boldsymbol{\sigma}' CustomerType_i + Fontana_i + \tau_t + \epsilon_{it}
\end{aligned}
$$

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. 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 water billing period separately. 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 compare this model with a version without gas consumption. This allows for an evaluation of the extent to which accounting for gas consumption improves the prediction of water consumption.

Table 14 shows the regression result. 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. A negative effect of Heating Degree Days and precipitation, and a positive effect of Cooling Degree Days is consistent with water use being higher during hotter, dryer weather. The coefficient on tax assessed value is significant, and indicates that on average, a difference in premises tax value of $100,000 is associated with a difference in water consumption of about 8%. The coefficients on the other household characteristics are small and statistically insignificant.

The coefficient on gas consumption is significant with a p-value less than 0.01. It indicates that a difference between premises gas consumption of 1% is associated with a 0.47% difference in water consumption over the study period. Comparing Model 1 to Model 2, the R^2 increases from 0.193 to 0.333 with the inclusion of gas consumption, indicating that gas consumption explains an additional 14% of the variance in water consumption.

Table 14: Regression results for water and gas consumption correlation analysis

	Dependent Variable: log (Ave. Daily Water Consumption))	
	Month Effects	Month Effects-With Gas

	(1)	(2)
$\ln(g_{it})$		0.469^{***}
		(0.039)
AMI	-0.143^{**}	-0.093^{*}
	(0.063)	(0.056)
HDD.mean	-0.035^{***}	-0.067^{***}
	(0.006)	(0.007)
CDD.80.mean	0.062^{***}	0.053^{***}
	(0.017)	(0.016)
prcp_days.mean	-0.100	-0.077
	(0.100)	(0.098)
taxAssessment ($ 100,000s)	0.077^{***}	0.080^{***}
	(0.00000)	(0.00000)
finishedSqFt	0.0001	0.00005
	(0.0001)	(0.0001)
bathrooms	-0.019	-0.025
	(0.055)	(0.045)
bedrooms	0.055	0.029
	(0.039)	(0.035)
irrigable	0.00001	0.00001
	(0.00001)	(0.00000)
Fontana	0.313^{***}	0.373^{***}
	(0.061)	(0.052)
factor(Meter_Size)3/4 INCH	0.289^{*}	0.215^{*}
	(0.150)	(0.115)
factor(Meter_Size)5/8 INCH	0.071	0.004
	(0.075)	(0.061)
Constant		
Observations	10,082	10,082
Adjusted R^2	0.193	0.333
Residual Std. Error	0.620 (df = 10042)	0.564 (df = 10041)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Robust Standard Errors Clustered by Premises

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.

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 SGVWC/SoCalGas WEN engagement.

While considering AMI's impact on water and gas consumption, we recommend using the study results with caution. The study used a randomized experimental design to evaluate a potential program, which is a laudable, if relatively rare undertaking in evidence-based policymaking. 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 171 water leaks and two hot water leaks.

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 randomized experiments will likely need to be at least four times larger in sample size, and non-randomized experiments will need to be at least six times larger, to confidently determine plausible effects of AMI 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.

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Appendix 1: SGVWC Data Exclusions Process. Updated and shared with SGVWC in February 2017.

Usage File

152,912 accounts in all (2011-2015 by BillingDate)

Note: In what follows, accounts are referred to as tuples of the form (Division, Office, Book, Sequence, SeqExtn, CustomerCount)

Account status

We want to make sure that all accounts we are considering are currently active and have been active since at least 2013 for the purposes of our study.

- Removed 2 accounts that were active before, and inactive later. (38 records removed)
- Removed 10 accounts that flip flopped between active and inactive multiple times. (144 records removed, associated with 10 accounts)
- Removed all records indicating inactive status (177048 records removed from 16000 accounts; of these, 3507 accounts completely removed)

Billing Information

We want to only consider accounts with billing histories with no discrepancies. This will help us benchmark against historical data.

- Removed 1 account with BillType='0' (zero -- not to be confused with an opening bill) which could not be recognized as a valid bill type. (3 records, associated with 1 account, removed -- although the single record with BillType='0' did indeed seem like an opening bill, and was therefore most likely a typo, this account would have been excluded in the upcoming steps anyway due to the low number of records associated with it)
- Removed 1,333 accounts with BillType='B' (1369 records, associated with 1333 accounts, removed)
- Removed 1 account with multiple duplicates of the combination of: account, billing date, billtype -- this combination should be unique (18 records removed, associated with 1 account)
- Removed 126 accounts with multiple bills on the same billing date. (2034 records removed, associated with 126 accounts)
- Removed 30 accounts with the same Prior and CurrentReadDates and also a positive CurrentConsumption (459 records removed, associated with 30 accounts)
- Removed any remaining records with the same Prior and CurrentReadDate--all of these have CurrentConsumption=0 (13646 records removed, associated with 122 accounts)

Meter/Customer Info

We want to only consider meters and customers whose information is clean and unambiguous for our segmentation purposes.

- Removed 254 accounts that have mixed 'Classification' (e.g. (1, 1, 1, 2160, 0, 5) has Classifications ['MULTI-FAMILY RESIDENTIAL' 'RESIDENTIAL']; (3, 5, 170, 3434, 0, 3) has Classifications ['RESIDENTIAL' 'COMMERCIAL']. (10300 records removed, associated with 254 accounts)

- Removed one account ((1, 3, 541, 1730, 0, 2)) that has a record with BillSize='NO METER/REMOVED’. (22 records removed, associated with 1 account)
- Removed 770 accounts that have more than one address, which is defined as a unique combination of (ServiceAddressNbr, ServiceAddressStreet, City). (32864 records removed associated with 770 accounts)
- Removed 2 accounts that are in the Usage file but not in the Meters file. (2 accounts removed, together with the 4 records associated with them) Meters File

For the meters file, we want to make sure we are selecting accounts in the Usage file that had clean and unambiguous customer and meter information in the Meters file as well.

- Removed 206 accounts that had at least one MeterNumber listed as ‘NO METER’. (206 accounts removed from Usage with 10172 records; 206 accounts removed from Meters with 11098 records)
- Removed 1833 accounts that had at least one MeterNumber=‘REMOVED’ (1833 accounts along with 26200 records removed from Usage; 1833 accounts along with 51842 records removed from Meters)
- Removed 127 accounts that had at least one MeterNumber=‘STOLEN’. (127 accounts along with 5736 records removed from Usage; 127 accounts along with 6164 records removed from Meters)
- Removed 538 accounts in Meters that had at least one MeterNumber=’JUMPER’. (538 accounts along with 2585 records removed from Usage; 538 accounts along with 10045 records removed from Meters) MeterDetail File

Similar to the Meters file, for the meter detail file, we want to make sure we are selecting accounts in the Usage file that had clean and unambiguous information in the MeterDetail file as well.

- Removed 12 accounts associated with meters that had a RemovedDate other than 0. (12 accounts removed along with 394 records from Usage; 12 accounts removed along with 403 records from Meters)
- Removed 46 accounts that had MeterSizeCode=0 (46 accounts along with 2174 records removed from Usage; 46 accounts along with 2310 records removed from Meters)
- Removed 1 account that had Installed_Date_Month>12 (1 account along with 60 records removed from Usage; 1 account along with 60 records removed from Meters)

Geocoding

In order to ensure that we understand the spatial extent of your data, and to ensure the accounts selected represent a good spread of your service areas, we want to select meters that can be geocoded.

- Removed accounts that could not be geocoded (71 accounts together with 3471 records removed from Usage)

Segmenting by customer behavior

In order to ensure a valid treatment and control group for this study, customer segmentation was conducted to group accounts by their customer information and use behavior.

Monthly Imputation

To compare equivalent customer use within equivalent time frames, your data was normalized to a monthly scale before conducting any customer behavior segmentation.

- Removed 48,886 accounts that did not have enough complete water use information to establish a water use pattern
- Restricted attention to accounts that existed in both the years 2013 and 2015

Segmentation

- In order to draw a sample that best represents the attributes of the underlying population, we segment customers according to the Region (either LA or Fontana), Classification, MeterSize (BillSize), and then further based on their usage, shortly described below.
- The Classification or customer types we kept were Residential, Multi-Family Residential and Commercial. All other customer types had fairly low percentages among the total population. Classification/customer types we excluded: ['PUBLIC AUTHORITY', 'DUPLEX INDIVIDUALLY METERED', 'INDUSTRIAL', 'FIRE', 'CONSTRUCTION', 'COMMERCIAL RECYCLED', 'PUBLIC AUTHORITY RECYCLED', 'PUBLIC AUTHORITY MULTI-FAMILY']
- The MeterSizes (BillSizes) considered were all the possible MeterSizes that belonged to the particular combination of (Region, Classification)
- We further segmented customers according to their baseline use and peaking values into one of four possible quadrants. The segments provided in the .xls files are marked with the letters A-D as follows:
    - Segment A: Low Users, High Peakers
    - Segment B: High Users, High Peakers
    - Segment C: Low Users, Low Peakers
    - Segment D: High Users, Low Peakers

Final number of accounts under consideration

We have selected 76,348 accounts that we checked are representative of the population and will be suitable for sampling pilot treatment and control sets. We collected a sample of 500 accounts - - roughly 250 each for LA and Fontana -- that are also representative of the underlying population. In sampling, we used the distribution of the characteristics described above for the year 2013. We chose this year as it is often considered to be the “last good year” of water use, representative of typical customer behavior before the onset of the California drought.

Since some of the percentages for the various segments (Region, Classification, Meter/BillSize, Use/Peak-quadrant) were fairly low, in drawing samples for a total sample size of 250 for each of LA and Fontana, there were some segments that should not be drawn samples for, for the simple reason that the number of samples to be picked out of that segment was rounding off to zero. We excluded such segments in the Excel file we have provided you.

In all, we generated 247 Treatment/Control pairs for LAC, and 250 Treatment/Control pairs for Fontana. Of these pairs, the following Valor IDs were removed over the course of the pilot project for various reasons: 'T-LA7', 'C-LA7', 'T-LA25', 'C-LA25', 'T-LA189', 'C-LA189', 'T-Font1', 'C-Font1', 'T-Font5', 'C-Font5'. Thus, the final list of participants 244 Treatment/Control pairs for LAC, and 248 Treatment/Control pairs for Fontana.

SGVWC Sample Size Significance

Our goal is to determine a sample size that will allow us to establish statistically significant results for an hourly AMI vs. monthly manual reads effectiveness comparison. In general, we recommend as large a sample size as possible within a practical resource budget. For the SGVWC engagement, we have used the following calculation to determine the minimal treatment group sample size:

$n = z^2(p*q)/ \delta^2$, with $z=2$, $p=0.5$, $\delta=0.05 \Rightarrow n = 400$

We require at least 400 treatment accounts in our sample size, and therefore have reasonable confidence that with a test sample size of 500, we can carry out our experiments in the right manner. It must be noted that with any statistical experiment, it is not possible to have any *a priori* determination.

In summary, we expect with our treatment sample size of 500, we can make statistically plausible inferences about results of the study across the San Gabriel Valley Water Company service areas.

Appendix 2: List of Treatment and Control Group Accounts

Double-click on embedded object to view full list

Valor ID	Customer Type	Meter Size	Municipality	Use Segment		
T-LA1	COMMERCIAL	1 INCH	LA County	A		
C-LA1	COMMERCIAL	1 INCH	LA County	A		
T-LA2	COMMERCIAL	1 INCH	LA County	B		
C-LA2	COMMERCIAL	1 INCH	LA County	B		
T-LA3	COMMERCIAL	1 INCH	LA County	C		
C-LA3	COMMERCIAL	1 INCH	LA County	C		
T-LA4	COMMERCIAL	1 INCH	LA County	D		
C-LA4	COMMERCIAL	1 INCH	LA County	D		
T-LA5	COMMERCIAL	1 INCH	LA County	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-Font155	7/29/2016 19:00	11/15/2016 22:00				
T-Font148	8/4/2016 0:00	1/16/2017 19:00				
T-Font211	10/8/2016 18:00	12/6/2016 20:00				
T-Font25	10/14/2016 3:00	10/23/2016 14:00				
T-Font178	10/20/2016 16:00	10/21/2016 6:00				
T-LA87	11/6/2016 18:00	11/11/2016 6:00				
T-Font181	11/6/2016 23:00	11/14/2016 2:00				
T-LA112	11/12/2016 21:00	12/3/2016 23:00				
T-Font155	11/16/2016 16:00	12/18/2016 18:00				