

# PY2011 Energy Savings Assistance Program Impact Evaluation Final Report

**STUDY ID: SDG0273.01** 

August 30, 2013

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# **Executive Summary**

The Energy Savings Assistance (ESA) Program, formerly referred to as the Low Income Energy Efficiency (LIEE) Program, provides energy efficiency measures and services at no cost to qualifying low-income customers of California's four investor-owned utilities (IOUs), Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), Southern California Gas Company (SoCal Gas), and the San Diego Gas and Electric Company (SDG&E). The ESA Program is administered by the IOUs in their respective service areas. This report presents the findings of the impact evaluation of the ESA Program for Program Year 2011 (PY2011) conducted by Evergreen Economics, CIC Research, and Michaels Energy.

# **ESA Program Delivery Overview**

Initially established by the California Public Utilities Commission (CPUC) in the early 1980s,¹ low-income energy efficiency programs provided a channel for low-income customers to receive services similar to those provided by the energy efficiency programs instituted in response to the energy crisis of the 1970s. Subsequent legislation through the early 2000s continued to allow for the provision of energy efficiency measures to low-income customers in California.² Following the 2001 California energy crisis and an unanticipated increase in energy prices in 2005, the CPUC took increasingly aggressive approaches to low-income efficiency programs, expanding services and marketing activities, funding and income eligibility levels.³

In D. 07-12-051, the CPUC committed to expanding low-income programs by making them available to more customers, improving their cost effectiveness and designing them in ways to make them a reliable energy resource. To achieve these objectives, it adopted a programmatic initiative to provide all eligible low-income customers the opportunity to participate in the ESA Program and to offer those who wish to participate all cost-effective energy efficiency measures in their residences by 2020. The IOUs' 2009-11 ESA programs were to be treated as resource programs by focusing on energy savings, while improving the customers' quality of life. Budgets were also increased substantially in order to treat 25 percent of the overall 2020 goals within the 2009-11 program period.

Both home owners and renters may participate in the ESA Program if they have an account with an IOU offering the ESA Program and meet low-income qualifications. Eligibility for the ESA Program is determined by income-level and household-size guidelines established by the CPUC, which are updated annually to account for inflation. As indicated above, in 2005's Decision 05-10-044, the CPUC expanded the criteria for low-income program eligibility to include customers at or below 200 percent (an increase from 175 percent) of the Federal Poverty Level guidelines, regardless of elderly or disability status.

Customers may also be eligible to participate in the ESA Program if they have already been enrolled in one of the following low-income programs that require income verification:

PY2011 ESA Program Impact Evaluation

<sup>&</sup>lt;sup>1</sup> See CPUC D.92653, D.82-02-135, D.82-11-019 and D.82-11-086.

<sup>&</sup>lt;sup>2</sup> See Pub. Util. Code § 2790, Pub. Util. Code § 382, SB 845, AB 1890, AB 1393 and SBX15.

<sup>&</sup>lt;sup>3</sup> See CPUC D.01-05-033, D.01-08-065, D.05-10-044, D.06-12-036 and D.06-12-038.

- Bureau of Indian Affairs General Assistance
- CalFresh/Supplemental Assistance Program (SNAP)
- CalWORKS/Temporary Assistance for Needy Families (TANF)
- Head Start income Eligible (Tribal Only)
- Healthy Families A&B
- Low Income Home Energy Assistance Program (LIHEAP)
- Medicated/Medi-Cal
- National School Lunch Program (NSLP)
- Supplemental Security income (SSI)
- Tribal TANF
- Women, Infants, and Children Program (WIC)

# **Evaluation Objectives**

The PY2011 ESA Impact Evaluation is one of four low-income program studies that the CPUC directed the IOUs to undertake in Decision 12-08-044. In this Decision, the CPUC directs the IOUs to conduct an impact evaluation of the ESA Program. To this end, the primary objective for the impact evaluation is to estimate first-year gas and electric energy savings, and coincident peak demand reduction attributable to the PY2011 ESA Program. The RFP issued for this study specifically directed that the energy impact estimates be provided in the following manner:

- In aggregate;
- By IOU service area;
- By average participant household;
- By measure and/or measure group; and
- Where possible and appropriate, by climate zone and housing type (multifamily, single family and mobile homes).

In addition to providing impact results, additional research goals were developed as part of the study's Final Research Plan to address issues that arose during the two prior impact evaluations of the ESA Program (covering PY2005 and PY2009), some of which were discussed as part of CPUC A.11-05-017 et al. Specific issues addressed in the current evaluation include the following:

1. **Data Screening.** For the PY2009 impact evaluation, data screens were used to remove those observations that represented either erroneous data entries or abnormally high usage points that would bias the billing model results. Although some data screening is necessary to estimate a billing model, concern was raised during the previous evaluation that the data screening process excluded too many high usage customers, and, had these observations been retained, ESA Program impacts would have increased substantially.<sup>4</sup> The issue was addressed in the PY2009 evaluation by re-estimating the billing regression model with less stringent

<sup>&</sup>lt;sup>4</sup> See comments filed June 17, 2011 on the draft PY2009 impact evaluation by the CPUC Department of Ratepayer Advocates (DRA), The East Los Angeles Community Union (TELACU) and other community based organizations at <a href="http://docs.cpuc.ca.gov/efile/P/138446.pdf">http://docs.cpuc.ca.gov/efile/P/138446.pdf</a>.

screens, and these results were reported to CPUC Energy Division and the IOUs in a memo and included as an appendix in the final PY2009 impact evaluation report.<sup>5</sup>

As discussed below, the PY2011 ESA Program impact evaluation uses a less stringent data screening process that only eliminates a small number of outlier observations.

- 2. **Savings estimates over time.** An important finding from the last several evaluations of the ESA Program is that savings tend to fluctuate over time. The fact that there are valid reasons why estimates might vary from year to year needs to be communicated better in the evaluation reports, and the reasons for these fluctuations better understood. The distribution of measures across customer usage groups and weather zones in a given year will change average savings levels, for example. This issue was explored in the PY2009 evaluation by examining changes in participation across usage categories and weather zones, and using information from phone surveys and on-sites. In the current evaluation, we provide a comparison of PY2011 impact estimates to the results from prior program year evaluations, as well as comparisons with both the *ex ante* and DEER savings values. Possible reasons for discrepancies across these sources are also discussed.
- 3. Weather zones. The PY2009 evaluation found that ESA participation had shifted to more moderate climate zones for some of the large weather-dependent measures. This led to lower impact estimates for these measures and resulted in a recommendation to focus ESA Program installation for these measures in the harsher climate zones. In the current evaluation, we continue to examine weather effects by analyzing how weather-normalized energy consumption changes between the pre-participation and post-installation periods for PY2011.
- 4. **Survey results.** The PY2009 impact evaluation included extensive phone survey and on-site data collection efforts, which provided some important insights into how customers use energy and the measures installed through the ESA Program. For instance, the surveys revealed that 34 percent of customers were not operating their evaporative coolers properly,<sup>6</sup> which helped explain why the impact estimates were lower than expected in the billing regression. For the current evaluation, a smaller and more targeted participant phone survey effort was conducted. The survey sample targeted customers who saw an increase in energy use after participating in the ESA Program, and questions explored possible reasons for the increase.

A Research Plan that addresses these issues was developed at the beginning of the PY2011 ESA Program Impact Evaluation. A Draft Research Plan was first posted on the CPUC website and a public workshop was held in San Francisco to present the plan and answer questions. Once the comment period ended, the plan was revised to address comments and a Final Research Plan was posted to the CPUC Energy Division website<sup>7</sup> on March 18, 2013.

<sup>&</sup>lt;sup>5</sup> See Appendix E of *Impact Evaluation of the 2009 Low-Income Energy Efficiency Program*. Prepared for SCE and the CPUC by ECONorthwest (June 16, 2011), available on www.calmac.org.

<sup>&</sup>lt;sup>6</sup>Impact Evaluation of the 2009 Low-Income Energy Efficiency Program. Prepared for SCE and the CPUC by ECONorthwest (June 16, 2011), p. 34.

<sup>&</sup>lt;sup>7</sup> http://www.energydataweb.com/cpuc/home.aspx

# **Analysis Methods**

There are two primary analysis components of this impact evaluation:

- 1. A fixed effects billing regression model was used to develop energy savings estimates (both kWh and therms) at the measure level for each IOU. The billing regression model relied on detailed information regarding which measures were installed through the ESA Program, combined with weather data and monthly energy consumption for both gas and electricity. All of this information was supplied to the evaluation team by the IOUs.
- 2. A phone survey was conducted on a sample of 602 participants that exhibited an increase in usage in the period directly after program participation. The goal of this survey was to collect information on customer behavior that would help illuminate why energy use was increasing.

Details on both of these evaluation components (and related analysis tasks) are included in the main body of this report.

#### **Evaluation Results**

The results of the regression models are used to calculate impacts for each measure group by IOU, house type and (where possible) climate zone.

Energy savings values were assigned to a measure group from the billing regression models using the following algorithm:

- 1. If the 95 percent confidence interval of the impact estimate from the Basic Model included the *ex ante* savings value, then the estimate from the Basic Model was used.
- 2. If the confidence interval for Basic Model estimate did not include the *ex ante* value, then evaluator judgment was used to assign an impact value from among the Basic Model, Measure Model, or *ex ante* values.
- 3. In a couple of instances, an engineering estimate was assigned when the *ex ante* values appeared to be unusually high and neither of the regression models could provide a reasonable result.

The impact estimates using these assignments are discussed below by fuel type. In most cases, the impact estimate from the Basic Model was used whenever possible.

# **Electric Impact Estimates**

Table ES-1, Table ES-2, and Table ES-3 show the electric impacts by measure group. For each measure, the *ex ante*, Basic Model and Measure Model estimates are provided, along with information on the impact estimates from the PY2009 ESA Program evaluation. Note that in cases where the regression models estimate zero or negative savings (e.g., an increase in usage rather than a decrease), the estimated impact has been set to zero in the table. Our engineering team reviewed those measures where the algorithm assigned the *ex ante* values to assess if the *ex ante* values appeared reasonable. In the case of the SCE values for AC Tune-up and Pool Pumps, an alternative value was calculated based on engineering estimates for these measures.

The final impact number assignment is shown in the highlighted column of each table. Using the final assigned values, the total average household savings is shown at the bottom of the table for each IOU. The far right column of the tables also shows the impact estimates from the PY2009 evaluation, both at the measure-group and household level. Note that impacts on a per unit level (rather than per household, where multiple units may be installed) are shown in the detailed impacts estimates provided in Appendix D.

Once the final savings values are assigned and the whole house savings calculated, the aggregated effect increases total household savings slightly from the PY2009 evaluation for SCE, while SDG&E and PG&E both experience decreases relative to the previous evaluation estimates.

Table ES-1: SDG&E Electric Impact Estimates (kWh)

	Households Receiving	Basic	Measure	Average <i>Ex</i>	Final		PY2009 Savings
Measure	Measure	Model	Model	Ante Savings	Assignment	Final Source	Estimate
Room AC	305	27.40	99.88	42.11	27.40	Basic Model	50
Central AC	30	N/A	N/A	38.66	38.66	Ex ante	50
AC Tune-up	59	N/A	N/A	229.13	229.13	Ex ante	326
CFLs	16,434	N/A	N/A	112.11	112.11	Ex ante	93
Ducts	937	55.72	1.36	0.00	55.72	Basic Model	-
Clothes Washer	1,667	123.05	86.94	528.57	123.05	Basic Model	788
Hardwired lighting	6,623	34.61	0.00	115.05	115.05	Ex ante	100
Insulation	800	85.53	359.74	94.90	85.53	Basic Model	104
Lighting	20,825	36.99	30.35	60.48	36.99	Basic Model	346
Microwave	1,852	0.00	66.52	175.91	66.52	Measure Model	-
Refrigerator	1,808	640.42	399.40	722.11	640.42	Basic Model	697
HW Conservation	1,334	85.19	60.30	172.03	172.03	Ex ante	24
WH Repair/Replace	5	0.00	0.00	0.00	0.00	Ex ante	-
Weatherization	16,703	0.00	0.00	49.59	49.59	Ex ante	63
Average household savings		119.71	92.92	346.35	278.57		303

Table ES-2: PG&E Electric Impacts (kWh)

	Households Receiving	Basic	Measure	Average Ex	Final		PY2009 Savings
Measure	Measure	Model	Model	Ante Savings	Assignment	Final Source	Estimate
Central AC	79	141.04	116.53	317.35	141.04	Basic Model	50
AC Tune-up	12,143	0.00	0.00	230.04	230.04	Ex ante	326
CFLs	99,402	0.00	0.00	75.29	75.29	Ex ante	
Ducts	3,007	112.26	10.59	94.33	112.26	Basic Model	
Evaporative Cooler	5,841	0.00	0.00	262.15	262.15	Ex ante	502
Hardwired lighting	87,276	1.85	0.00	145.74	145.74	Ex ante	100
Insulation	6,290	145.41	0.00	46.69	145.41	Basic Model	104
Lighting	26,414	0.75	0.00	140.47	140.47	Ex ante	346
Refrigerator	16,773	655.36	427.92	766.89	655.36	Basic Model	697
HW Conservation	11	0.00	0.00	273.30	273.30	Ex ante	24
Weatherization	64,837	3.51	0.00	9.99	3.51	Basic Model	63
Room AC	3,175	0.00	0.00	111.56	111.56	Ex Ante	50
Average household savings		113.11	64.47	381.46	366.90		402

Table ES-3: SCE Impact Estimates (kWh)

	Households Receiving	Basic	Measure	Average <i>Ex</i>	Final		PY2009 Savings
Measure	Measure	Model	Model	Ante Savings	Assignment	Final Source	Estimate
Room AC	927	0.00	57.51	69.47	57.51	Measure Model	50
Central AC	4,869	309.18	160.69	150.41	160.69	Measure Model	-
AC Tune-up	32	0.00	0.00	1265.00	257.00	Engineering Est.	326
CFL	67,872	71.25	82.25	25.44	71.25	Basic Model	93
Central Heat Pumps (CHP)	137	N/A	N/A	695.24	695.24	Ex ante	-
Ducts	4,490	0.00	20.65	0.00	20.65	Measure Model	-
Evaporative Cooler	15,928	239.16	448.48	481.87	448.48	Measure Model	502
Evaporative Cooler Tune-up	9	N/A	8236.20	37.13	37.13	Ex ante	-
Lighting	3,390	38.73	145.09	161.33	145.09	Measure Model	346
Pool Pump	1,908	0.00	0.00	1686.00	1088.00	Engineering Est.	-
Refrigerator	16,714	773.99	768.14	704.03	773.99	Basic Model	697
HW Conservation	505	720.97	1255.32	83.00	83.00	Ex ante	24
Weatherization	722	0.00	0.00	51.14	51.14	Ex ante	63
Average household savings	230.31	270.46	253.38	279.26		247	

# **Gas Impact Estimates**

The gas impact estimates are shown in Table ES-4, Table ES-5 and Table ES-6, and use the same savings assignment algorithm discussed above for the electric measures. Note that in cases where the Basic or Measure Model resulted in negative savings (an increase in usage), a savings value of zero is assigned to that measure for that model. At the household level, average household savings increased substantially for all three utilities relative to the PY2009 evaluation.

Table ES-4: SDG&E Gas Savings (therms)

	Households Receiving		Measure	Average Ex			PY2009 Savings
Measure	Measure	Basic Model	Model	Ante Savings	<b>Final Assignment</b>	<b>Final Source</b>	Estimate
Ducts	930	14.54	13.48	0.00	14.54	Basic Model	-
Furnace Repair/Replace	3,666	0.00	0.00	0.00	0.00	Ex Ante	-
Furnace Clean & Tune	6,551	9.81	4.02	0.00	9.81	Basic Model	
Clothes Washer	1,585	15.88	14.42	35.88	15.88	Basic Model	-
Insulation	732	26.66	5.35	9.17	26.66	Basic Model	10
Pilot Light Change Out	985	15.10	18.50	11.85	15.10	Basic Model	-
HW Conservation	11,125	0.00	0.00	15.49	15.49	Ex ante	7
WH Repair/Replace	1,236	6.80	0.00	0.00	6.80	Basic Model	-
Weatherization	9,113	3.24	0.85	5.01	3.24	Basic Model	4
Average household savi	ngs	13.14	6.87	21.99	26.06		8

Table ES-5: PG&E Gas Savings (therms)

	Households Receiving		Measure	Average Ex			PY2009 Savings
Measure	Measure	Basic Model	Model	Ante Savings	Final Assignment	Final Source	Estimate
Ducts	3,578	17.17	12.10	32.75	17.17	Basic Model	0
Furnace Repair	2,197	0.00	0.00	3.21	3.21	Ex ante	0
Furnace Replace	1,218	0.00	0.00	3.31	3.31	Ex ante	0
Insulation	7,165	44.50	22.13	61.05	44.50	Basic Model	10
HW Conservation	80,871	0.00	0.00	13.92	13.92	Ex ante	7
WH Repair/Replace	1,326	5.58	0.00	11.68	5.58	Basic Model	0
Weatherization	69,656	0.00	0.00	9.46	9.46	Ex ante	4
Average household savi	ngs	3.82	1.99	23.29	21.50		9

Table ES-6: SoCal Gas Savings (therms)

Measure	Households Receiving Measure	Basic Model	Measure Model	Average Ex Ante Savings	Final Assignment	Final Source	PY2009 Savings Estimate
Ducts	2,629	15.37	0.00	0.00	15.37	Basic Model	-
Furnace Repair/Replace	15,644	0.00	0.00	0.00	0.00	Ex ante	-
Furnace Clean & Tune	20,016	5.65	15.55	2.70	5.65	Basic Model	-
Clothes Washer	4,648	30.88	30.96	27.30	30.88	Basic Model	-
Insulation	8,225	26.51	17.49	7.76	26.51	Basic Model	10
Pilot Light Conversion	109	N/A	N/A	44.31	44.31	Ex ante	
HW Conservation	113,312	3.31	5.43	7.00	5.43	Measure Model	7
WH Repair/Replace	1,812	3.52	1.30	0.00	3.52	Basic Model	-
Weatherization	108,402	3.98	2.74	4.00	3.98	Basic Model	4
Average household savi	ngs	11.31	12.90	12.58	13.40		11

# **Impact Results Discussion**

Despite the variation in impact estimates across program years and utilities, the current evaluation impact estimates are relatively close to the original *ex ante* values. Table ES-7 shows the realization rates at the household level, which is simply the estimated household savings using the current evaluation estimates divided by the estimated *ex ante* household savings. With the exception of the SDG&E electric measures, in general the evaluation estimates are reasonably consistent with the *ex ante* values. The realization rate metric is somewhat misleading in this application, however, as some of the evaluation assigned values were in fact the *ex ante* values, which move the realization rate closer to 1.0. Therefore, the realization rate as calculated here should not be interpreted as a confirmation of the *ex ante* values, as several of the *ex ante* values are used in the calculation. Nevertheless, the realization rate metric does show that the savings values recommended by the evaluation team are fairly close to the original savings estimates provided by the IOUs.

**Table ES-7: ESA Impact Evaluation Realization Rates** 

	Evaluation Savings	Ex Ante Savings	Realization Rate
Electricity (kWh)			
SDG&E	278.57	346.35	0.80
PG&E	366.90	381.46	0.96
SCE	279.26	253.38	1.10
Gas (therms)			
SDG&E	26.06	21.99	1.19
PG&E	21.50	23.29	0.92
SoCal Gas	13.40	12.58	1.07

While there is some consistency with current evaluation savings estimates and the *ex ante* values at the household level, there are some obvious differences in savings estimates for individual measures. The electric impact models provide a range of savings estimates – some of which have internal consistency while other measures show significant variation across utilities, previous evaluation results, and individual *ex ante* values. While we attempted to explore reasons for these differences, it was not possible with the current budget and timeline to explore in-depth all the possible reasons for variations across models, utilities, and the results from the previous evaluation.

It is also important to note that – as discussed in the previous impact evaluation – there are legitimate reasons for savings numbers to vary both across time and utilities. In particular, with regard to comparing evaluation estimates across time, one must not conclude from these differences that one set of estimates is 'correct' or 'more accurate' than the other; the estimates may be equally accurate but reflect different baseline, program, or market conditions inherent in the different evaluation periods.

Table ES-8 shows the current PY2011 impact estimates compared with the whole house savings estimates from prior evaluation years. Since 2000, there has been a wide range of savings estimates for both gas and electricity at the household level. For electricity, the current impact estimates are lower than those from PY2009 and PY2005, but in line with estimates from PY2000 thru PY2002. For gas, the current impact estimates are significantly higher than those from PY2009 and generally consistent with impacts from earlier evaluations.

**Table ES-8: Impact Estimate Comparison with Prior Evaluations** 

	PY2011 Evaluation	PY2009 Evaluation	PY2005 Evaluation	PY2002 Evaluation	PY2001 Evaluation	PY2000 Evaluation
Electric Savings (kWh)						
PG&E	367	402	433	399	236	240
SCE	279	247	435	286	203	153
SDG&E	279	303	342	370	215	89
Gas Savings (therms)						
PG&E	21	9	19	9	18	28
SDG&E	26	8	14	4	13	13
SoCal Gas	13	11	17	17	20	26

There are a multitude of factors that can result in different levels of savings across program years and utilities, and some of the more prevalent influences are discussed below.

**Energy consumption.** Households that use more energy may have the potential for greater energy savings, depending on what end uses are driving energy consumption. Differences in household energy use across both utilities and evaluation periods may account for some of the differences observed in the estimated energy savings. Additionally, it is not just the levels of energy use that are important, but also the degree to which energy consumption changes between pre-participation and post-participation periods. Changes in energy use between these two periods (and the degree to which this inter-period change differs from changes in other utilities and time periods) will also result in different impact estimates.

**Household composition and home characteristics.** One of the most important factors determining energy use is the number of occupants within a home. Those households with more people typically use more energy (all else equal). Similarly, differences in the household structures themselves will lead to differences in energy impacts. Homes with larger or older structures will likely have a greater potential for energy savings, as will homes in disrepair (requiring more energy to heat and cool) or older appliances (requiring more energy to run).

**Weather.** Weather has an important influence on energy savings, particularly for those measures where energy use and savings will vary with changes in temperature. In the current evaluation, weather is incorporated directly into the savings calculations for those measures where we can reasonably expect savings to vary with changes in temperature. The discussion later in this report illustrates how weather has changed between the current and prior evaluations, both in terms in the amount of heating degree and cooling degree days, as well as the distribution of participants across climate zones. Also note that – while the climate zones have been defined to have similar weather within each zone – there is still often significant variation in temperatures within a climate zone, particularly for those zones that include the hottest and coldest areas.

**Measure mix.** The amount of total household savings will vary by the types and quantity of measures installed. This is important to remember when considering that many of the savings estimates from the regression models are for groups of measures, such as weatherization and hot water conservation. While these are by necessity modeled as a single group in the regression (to mitigate the estimation problems associated with collinearity), customers may have different amounts of individual measure components installed within each measure group. These differences in measure group composition will lead to differences in savings estimates across utilities and across evaluations.

Different estimation methods. For the current evaluation, we have used the same model specification and data screening process for each utility, so different analysis methods will not explain differences in the current estimates across utilities. The current models, however, are different than what were used in the previous two impact evaluations (PY2009 and PY2005), which in turn were different than the models used in the earlier evaluations (PY2000, PY2001, PY2002). We attempted to develop impact estimates in the current evaluation using the same model specification from the 2009 evaluation, but this was abandoned due to high collinearity issues and because many of the measure-level impact estimates were showing either no energy savings or increased energy use. While we believe that the current models are an improvement over earlier evaluations, the different specifications will result in different energy savings estimates.

Savings small relative to overall energy consumption. For many of the measures installed in the ESA program, the amount of savings expected is small relative to overall household consumption. This is particularly true for some of the most common measures such as CFLs, lighting, weatherization, and hot water conservation. Given the small amount of savings, it is challenging to develop rigorous estimates that are consistent across utilities and evaluations from prior years – even when the exact same model specifications are used. The small amount of savings involved, combined with a lack of information on other influencing factors (discussed above) can result in the ESA savings being overwhelmed in the regression model by these other forces.

#### **Conclusions and Recommendations**

General conclusions that can be drawn from the impact analysis results include the following.

**Savings from the ESA Program measures is a small fraction of overall household energy consumption.** Savings from the ESA program on average ranges from three to nine percent of overall energy consumption. This low level of savings makes developing savings estimates (particularly at the measure level) particularly challenging. These challenges are compounded by the wide array of external factors that can influence energy use. As discussed throughout the report, the small amount of program savings is sometimes overwhelmed by these other non-program factors in the billing regression and result in estimates of no savings or increased energy use for some measures.

The final impact estimates are generally consistent with the *ex ante* savings values. The final recommended impact values for both electric and gas measures resulted in total household savings that were fairly close to the original *ex ante* savings values. For electricity, household realization rates ranged from 80 to 110 percent of *ex ante* savings. For gas, realization rates ranged from 92 to 119 percent. Note that this consistency with the *ex ante* values is due in part to how the final impact numbers were assigned from either the regression models or *ex ante* values. Since the *ex ante* values were used as the final impact estimates in cases where the regression models did not produce a reliable estimate, the potential for differences with the *ex ante* values was naturally reduced.

The impact estimates deviate from the previous evaluation and from DEER values. For electric measures, estimated savings in the current evaluation are lower than estimates from PY2009, while gas estimates in the current evaluation are significantly higher. In the case of the gas savings, this may be due to significantly more heating degree days in the current evaluation relative to the last. The current impact estimates are within the range of those observed in previous evaluations going back to 2001, however, as there is substantial variation in household savings estimates over the years. The current evaluation estimates were also different from DEER values for the same measures, although no trend of being consistently higher or lower than DEER at the measure level was observed.

Impact estimates will naturally vary across years due to a variety of factors. Differences across customer groups in terms of energy use, geographic location, measure mix, demographics, economic situation, and condition of the home will all lead to differences in impact estimates for the ESA Program. We should not expect these estimates to be the same across time or across service territories due to the large number of potential influencing factors. In the current evaluation, differences from the prior evaluation may also be due to the utilization of a different regression model and data screening process. While identifying these influencing factors is straightforward, determining the relative importance of each of these factors on the change in savings values between years is not possible without significantly more evaluation resources being devoted to making a

detailed comparison of participation patterns between years. Given that the primary objective of this impact evaluation is to develop impact estimates for the current program year, a more detailed analysis was not attempted beyond the comparisons presented earlier in this report.

A significant number of ESA participant households are using more energy after participation. Despite the new measures and energy education received through the program, a significant number of households were found to be consuming more energy after participation. For electricity, more than half all of all participants exhibited weather-normalized increases in energy use during either heating or cooling periods. Similarly, approximately 60 percent of gas participants increased their gas consumption in the post-participation period. Because this increase appears to be independent of weather, it is especially challenging to address in the billing regression and may lead to biased impact estimates. The phone survey did not provide any additional information as to what might be causing this increase in energy use. Since the vast majority of participants were already on the CARE rate prior to ESA enrollment, it is unlikely that the lower CARE rate is a factor in increased energy use for the time period examined.

Whole house impacts estimated from the household-level regression models produced lower estimates. The results from the Whole House fixed effects models that estimate total savings (rather than savings for individual measures) produced generally lower house-level savings values than simply aggregating up the measure-level savings from the Basic and Measure Models. This is due in part to the ability with the Basic/Measure models to remove impact estimates showing an increase in energy use and replacing them with the *ex ante* values, which by definition will increase the overall savings estimate. Since measure-level detail is not available in the Whole House model, it is not possible to make these types of post-model adjustments.

While it was hoped that having a whole house variable for savings would help address the possibility of collinearity among the measure variables, this advantage appears to have been outweighed by a lower ability to disentangle the program effects from other factors influencing energy consumption. This is particularly challenging given the number of homes observed to have an increase in energy use in the post-participation period (particularly with PG&E). Given this context, it is not surprising that the Whole House model (which utilizes less program information) produces lower savings estimates than the Basic Model that utilizes more information on what was installed through the program.

Customers may be unaware that they are using more energy. The phone survey targeting households with increased energy use did not provide any clear answers on what might be driving the higher consumption. Respondents generally reported that they were using their heating and cooling systems about the same as they did prior to participation. For those that said they used the systems more, the most common reason for using heating and cooling systems more had to do with changes in weather (e.g., hotter or cooler weather). As shown in the analysis of weather-normalized energy use, changes in weather are not sufficient to explain all of the increase in usage. Other factors, such as having more people home during the day, did not appear to be a significant factor in explaining increased use. While participants have been adding new appliances to their homes, these appear mostly to be replacing older units and therefore should be using less energy. These findings raise the possibility that – despite the new measures and energy education – consumers are using more energy and (perhaps more importantly) they are unaware that they are consuming more energy. The issue of whether they were truly unaware was not explored directly in the phone survey, however.

From the evaluation conclusions, we offer the following recommendations for the ESA Program.

**Continue using billing regression to estimate program impacts.** Despite some of the challenges discussed in this report, we recommend that the fixed effects billing regression model continue to be used to estimate impacts for the ESA Program using data from the participant population. The fixed effects model provides a means for producing statistically reliable and unbiased estimates of savings that account for both differences across households and time periods.

**For future impact evaluations utilizing a billing regression, developing multiple model specifications provides more flexibility.** If billing regression is to be used in future ESA Program evaluations, we recommend an approach that combines results from the Basic and Measure Model specifications presented here. While this does rely on evaluator judgment to make some impact assignments, the approach is ultimately more flexible than relying on the results of a single model. In the current evaluation, having multiple models resulted in impact estimates for some measures that could not have been provided using the Basic Model alone.

If variations in impact estimates over time are not acceptable, consider using DEER deemed values to estimate savings. The wide swings in savings estimates – both across utilities and evaluation time periods – has raised concern among some reviewers. Possible reasons for these discrepancies have been discussed in the last two impact evaluations, and variations will continue in the future. It is also stressed again here that the exact cause of these differences will likely remain unknowable without an enormous data collection effort that collects statistically representative data on home and customer demographics within each utility service territory by housing type, climate zone, and possibly additional household characteristics such as family size and home vintage. Short of a massive data collection effort, the root causes of energy savings variation across utilities and program years will likely remain unknowable.

As argued in this report, we do not believe that the variation in savings estimates is necessarily a bad thing. Nevertheless, if more consistency in the impact estimates is desired, then using deemed savings values from DEER in place of a billing regression should be considered. This deemed approach will reduce uncertainty with respect to savings estimates across utilities within a program year, as well as produce more stable savings estimates across program years. Using DEER, however, does not allow for the possibility that the low-income population is significantly different in terms of energy savings relative to the general population. While testing this theory is beyond the scope of this project, it may be worth reducing the uncertainty in savings estimates by using DEER even if that database is not an entirely accurate representation of the savings achieved in the low-income sector.

Weather variables should be calculated using hourly (rather than daily) temperature data. The calculations of CDD and HDD using hourly temperature data allow for a more accurate representation of days that heating or cooling equipment might be used. In this evaluation, the hourly method resulted in significantly more cooling degree days and only slightly more heating degree days then the traditional daily method. Given that the hourly method is more accurate and easy to calculate, we recommend that it be used for future impact evaluations of this program.

**Allow more time for the impact evaluation**. The time allocated for this evaluation was very short (five months), with a research plan finalized on March 1 and a final report produced by August 31. For comparison, the previous impact evaluation took 20 months. While the current impact evaluation

was completed in the time allotted, this was accomplished by having a very focused approach that did not allow for exploring additional research questions when they arose. For example, more time might have allowed for additional analysis of the survey data, or even a short follow up survey to explore other aspects of energy use that might have shed more light on increased energy consumption. Similarly, there was not enough time to conduct a more in-depth comparison of the impact estimates between the 2009 and 2011 evaluations to determine how changes in participation patterns, measure mix, and weather might have contributed to differences in impact estimates between the two years. Adding three to six months to the impact evaluation timeline would allow for a more in-depth and flexible approach that provides more insights into the ESA Program savings estimates.

Conduct a more rigorous analysis of participation patterns across evaluation years. As mentioned above, the current evaluation did not have enough time to conduct a rigorous comparison of participation patterns between PY2009 and PY2011. While this evaluation did provide some information on weather conditions and participation across climate zones between the two evaluation years, the primary focus was in developing defensible savings estimates for the current evaluation year. Additional analysis on changes in participation patterns in terms of measure mix, housing type, energy use, weather conditions, and geographic distribution would likely provide additional insights as to the factors driving the variation in savings estimates across program years. We recommend additional time and budget be allocated for this analysis in the next ESA Program impact evaluation.

Continue with current evaluation cycle timing. The last several impact evaluations have focused on a single program year and have occurred every 2-3 years, and we recommend that this cycle continue. Given that the savings levels will change regularly due to weather, measure mix, and participant characteristics, the evaluation should also be conducted at regular intervals in order to reflect this variation. This is especially important when the impact evaluation results are used to set the *ex ante* savings values for future program years. If impact evaluations are done less often, or are done for multiple evaluation years combined, then some of the inherent variability will be lost due to the timing and structure of the evaluation cycle. This may result in less accurate impact estimates moving forward, particularly if the market is shifting and the programs are locked in to using fixed impact estimates for a longer period of time until a new impact evaluation can be completed. Having the evaluations done more often (instead of every five years, as has been suggested) will provide flexibility to adjust the energy savings estimates as needed to reflect changing demographics and market conditions.

**Remember lessons from previous evaluations.** Finally, reviewers raised a couple of issues that relate to analysis methods that were explored in the previous impact evaluation. These are methods that were recommended by reviewers of this current report as possible methods to consider in the future:

• **Billing regression using additional survey data.** A common approach for obtaining additional customer information for use in a billing model is to conduct a phone survey of program participants that asks detailed questions about their home and factors that may have changed since participating in the program. This approach was used in the PY2009 ESA impact evaluation but did not yield useful results for the impact analysis. While in theory it might be valuable to have survey data that provide additional explanatory variables in the billing regression, in practice this did not result in an improved billing model in the PY2009 evaluation. Consequently, we do not recommend this approach for the billing regression in

future evaluations and instead recommend that the billing models rely on the ESA participant population.

- **Billing regression using on-site data.** Customer on-sites can be used to collect additional information on home characteristics that can be used as additional variables in a billing regression model. This method was also used in the PY2009 impact evaluation and did not provide credible impact estimates. The on-sites are also expensive to conduct, especially if a large enough sample is needed to be representative for a billing regression. We also do not recommend conducting on-sites in future ESA Program evaluation if their primary purpose is to collect data to support a billing regression. The on-sites may be useful for other purposes, however, such as providing additional information on baseline conditions, customer attitudes toward efficiency and energy use, whether or not installed equipment is being used properly, and other factors that affect energy consumption.
- Billing regression using a control group of non-participants. The PY2009 evaluation also developed a billing regression that utilized a control group of low-income non-participants, where the PY2010 participants were used as a non-participant control group for PY2009. The theory underlying this method is that the control group customers will have similar patterns of energy use as participants and therefore will control for external events such as economic conditions within the model.8 Selecting a well-matched control group is challenging at best, however, and particularly difficult in the low-income population given the variability across program years. Using the control group did not produce useful billing regression results in the previous evaluation, and we are not optimistic that these challenges can be overcome in future evaluations without significantly more resources being devoted to identifying an appropriate control group. Despite these concerns, future evaluations may want to explore the potential benefits of using a control group if there is a way to ensure that the control group matches the participant population on key demographic variables (e.g., home type, energy use, geographic location, vintage, etc.). Exploring the use of several alternative control groups in the billing regression may also prove useful, as this was not attempted in the previous impact evaluation.

<sup>&</sup>lt;sup>8</sup> The control group also helps account for free ridership in the model, which is less of a concern with the low-income population where free ridership rates are likely very low.



#### 1 Introduction

The Energy Savings Assistance (ESA) Program provides energy efficiency measures and services at no cost to qualifying low-income customers of California's four investor-owned utilities (IOUs), Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), Southern California Gas Company (SoCal Gas), and the San Diego Gas and Electric Company (SDG&E). The ESA Program is administered by the IOUs in their respective service areas. This report presents the findings of the impact evaluation of the ESA Program for Program Year 2011 (PY2011) conducted by Evergreen Economics, CIC Research, and Michaels Energy.

# 1.1 Program Background

Initially established by the California Public Utilities Commission (CPUC) in the early 1980s, low-income energy efficiency programs provided a channel for low-income customers to receive services similar to those provided by the energy efficiency programs instituted in response to the energy crisis of the 1970s. Subsequent legislation through the early 2000s continued to allow for the provision of energy efficiency measures to low-income customers in California. Following the 2001 California energy crisis and an unanticipated increase in energy prices in 2005, the CPUC took increasingly aggressive approaches to low-income efficiency programs, expanding services and marketing activities, funding and income eligibility levels.

With the 2008 adoption of the *California Long-Term Energy Efficiency Strategic Plan*<sup>12</sup> the approach to low-income programs again shifted. Per CPUC Decision 08-11-031<sup>13</sup> the PY2011 Program is intended to meet the objectives of a major new policy direction for low-income programs as set forth by the CPUC in Decision 07-12-051.<sup>14</sup> More specifically, these programs, in addition to promoting the quality of life of eligible customers, should serve as resource programs, designed to save energy, limit the need for new power plants, and curb greenhouse gas emissions. Low-income efficiency programs are to provide an energy resource for California, consistent with the state's established "loading order" that sets energy efficiency as its first priority, while reducing low-income customers' bills and improving their quality of life.

In D. 07-12-051, the CPUC committed to expanding low-income programs by making them available to more customers, improving their cost effectiveness and designing them in ways to make them a

<sup>&</sup>lt;sup>9</sup> See CPUC D.92653, D.82-02-135, D.82-11-019 and D.82-11-086.

<sup>&</sup>lt;sup>10</sup> See Pub. Util. Code § 2790, Pub. Util. Code § 382, SB 845, AB 1890, AB 1393 and SBX15

<sup>&</sup>lt;sup>11</sup> See CPUC D.01-05-033, D.01-08-065, D.05-10-044, D.06-12-036 and D.06-12-038.

<sup>&</sup>lt;sup>12</sup> California Long-Term Energy Efficiency Strategic Plan, (August 2008), available at http://www.californiaenergyefficiency.com/index.shtml

<sup>&</sup>lt;sup>13</sup> CPUC, D.08-11-031 in A.08-05-022, "Decision on Large Investor-Owned Utilities' 2009-11 Low Income Energy Efficiency (LIEE) and California Alternate Rates for Energy (CARE) Applications," (November 2008), available

at: http://docs.cpuc.ca.gov/PublishedDocs/WORD\_PDF/FINAL\_DECISION/93648.PDF

<sup>&</sup>lt;sup>14</sup> CPUC D. 07-12-051 in R.07-01-042, ""Decision Providing Direction for Low-Income Energy Efficiency Policy Objectives, Program Goals, Strategic Planning and the 2009-2011 Program Portfolio and Addressing Renter Access and Assembly Bill 2140 Implementation," (December 2007), available at <a href="http://docs.cpuc.ca.gov/word\_pdf/FINAL\_DECISION/77082.pdf">http://docs.cpuc.ca.gov/word\_pdf/FINAL\_DECISION/77082.pdf</a>



reliable energy resource. To achieve these objectives, it adopted a programmatic initiative to provide all eligible low-income customers the opportunity to participate in the ESA program and to offer those who wish to participate all cost-effective energy efficiency measures in their residences by 2020. The IOUs' 2009-11 ESA programs were to be treated as resource programs by focusing on energy savings, while improving the customers' quality of life. Budgets were also increased substantially in order to treat 25 percent of the overall 2020 goals within the 2009-11 program period.

Both home owners and renters may participate in the ESA Program if they have an account with an IOU offering the ESA Program and meet low-income qualifications. Eligibility for the ESA Program is determined by income-level and household-size guidelines established by the CPUC, which are updated annually to account for inflation. As indicated above, in 2005's Decision 05-10-044, the CPUC expanded the criteria for low-income program eligibility to include customers at or below 200 percent (an increase from 175 percent) of the Federal Poverty Level guidelines, <sup>15</sup> regardless of elderly or disability status.

Customers may also be eligible to participate in the ESA Program if they have already been enrolled in one of the following low-income programs that require income verification:

- Bureau of Indian Affairs General Assistance
- CalFresh/Supplemental Assistance Program (SNAP)
- CalWORKS/Temporary Assistance for Needy Families (TANF)
- Head Start income Eligible (Tribal Only)
- Healthy Families A&B
- Low-income Home Energy Assistance Program (LIHEAP)
- Medicated/Medi-Cal
- National School Lunch Program (NSLP)
- Supplemental Security income (SSI)
- Tribal TANF
- Women, Infants, and Children Program (WIC)

#### 1.1.1 Program Measures

While each IOU, with approval from the CPUC, determines the specific offerings of its ESA Program, all include weather-sensitive and non-weather-sensitive measures, as well as energy education. The utilities have coordinated to offer many of the same measures, and in those areas where gas and electric service are provided by different utilities, they have aligned efforts so that one contractor provides ESA measures and services for both IOUs.<sup>16</sup>

<sup>&</sup>lt;sup>15</sup> These poverty guidelines are updated periodically in the Federal Register by the U.S. Department of Health and Human Services (HHS) under the authority of 42 U.S.C. 9902(2) and are available at <a href="http://aspe.hhs.gov/poverty/11poverty.shtml">http://aspe.hhs.gov/poverty/11poverty.shtml</a>

<sup>&</sup>lt;sup>16</sup> In areas served by different investor-owned gas and electric utilities (e.g., the SoCal Gas/SCE overlap area) the fuel source for the dwelling's space heat determines which utility will be the primary provider of weatherization services to the dwelling.



The ESA Program guidelines call for the installation of all eligible measures that are feasible. In effect, no household or measure-level cost-effectiveness criteria are applied on a per-participant basis. Nonfeasibility criteria are provided in the ESA Program Policy and Procedures Manual (P&P Manual) for all measures. Generally measures are considered non-feasible when they are already present, are refused by the customer, cannot be physically installed, would create a safety hazard or violate code, or cannot meet the modified three measure rule. When necessary to complete the installation of eligible measures, contractors are also allowed to provide minor home repairs. To ensure that equipment installations are installed properly, the applicable IOU (or designated agent) provides inspection services.

Figure 1 shows a mapping of the 16 climate zones in California. The eligible measures by climate zone are included in the detailed impact tables provided in Appendix D, along with the number of each measures installed for PY2011.

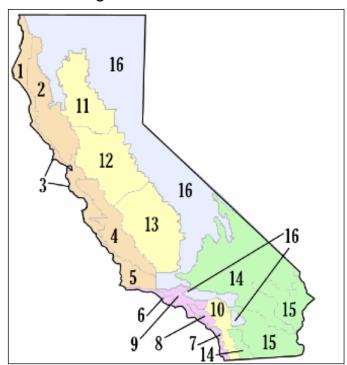


Figure 1. CEC Climate Zones

# 1.1.2 Program Services

In addition to the equipment measures described above, the ESA Program offers information services and an energy education component. The P&P Manual provides guidelines regarding what information should be provided to low-income households during the initial home visit. In particular, the ESA Program outreach representative must provide a description of the following:

• The ESA Program, including program goals, eligibility requirements, eligible measures, and procedures. This must include energy education, available energy efficiency services and minor home repairs, general installation procedures, inspection procedures, and, if applicable, natural gas appliance testing procedures; and



- Other programs, including:
  - The existence of other separate programs designed to repair or replace furnaces or install other energy efficiency measures;
  - The California Alternate Rates for Energy (CARE) Program, along with assistance in enrolling the customer in CARE if the customer chooses to participate in it;
  - Other utility programs designed to provide services to low-income customers, including level-payment programs, medical baseline programs, and other energy efficiency programs for which the customer may be qualified; and
  - Similar programs offered by the local Department of Community Services and Development (DCSD) agencies and other known energy-related programs.

The Program's energy education component provides guidance on the following:

- General levels of energy usage associated with specific end uses and appliances;
- Impacts on energy usage of individual energy efficiency measures offered through the ESA Program or other programs offered to low-income customers by the utility;
- Practices that diminish the savings from individual energy efficiency measures, as well as the
  potential cost of such practices;
- Ways of decreasing usage through changes in practices;
- Information on CARE, the Medical Baseline Program, and other available programs;
- Appliance safety information;
- How to read a utility bill; and
- Procedures used to conduct natural gas appliance testing (if applicable).

The effectiveness of the ESA Program energy education component is being evaluated under a separate study and, consequently, is not addressed in the PY2011 ESA Impact Evaluation.

# 1.2 Evaluation Background

The PY2011 ESA Impact Evaluation is one of four low-income program studies that the CPUC directed the IOUs to undertake in Decision 12-08-044<sup>17</sup>. In this Decision, the CPUC directs the IOUs to conduct an impact evaluation of the ESA Program to estimate energy savings. The RFP issued for this study specifically directed that the energy impact estimates be provided in the following manner:

- In aggregate;
- By IOU service area;
- By average participant household;

<sup>&</sup>lt;sup>17</sup> CPUC, D.12-08-044 in A.11-05-017 et al., "Decision on Large Investor-Owned Utilities' 2012-2014 Energy Savings Assistance (ESA) (Formerly Referred to as Low Income Energy Efficiency or LIEE) and California Alternative Rates for Energy (CARE) Application," (August 2012), available at <a href="http://www.liob.org/docs/ACF265.pdf">http://www.liob.org/docs/ACF265.pdf</a>



- By measure and/or measure group; and
- Where possible and appropriate, by climate zone and housing type (multifamily, single family and mobile homes).

In addition to this primary objective, additional research goals were developed as part of the study's Final Research Plan to address issues that arose during the two prior impact evaluations of the ESA Program (covering PY2005 and PY2009), some of which were discussed as part of CPUC A.11-05-017 et al. Specific issues addressed in the current evaluation include the following:

1. **Data Screening.** For the PY2009 impact evaluation, data screens were used to remove those observations that represented either erroneous data entries or abnormally high usage points that would bias the billing model results. Although some data screening is necessary to estimate a billing model, concern was raised during the previous evaluation that the data screening process excluded too many high usage customers, and, had these observations been retained, ESA Program impacts would have increased substantially. The issue was addressed in the PY2009 evaluation by re-estimating the billing regression model with less stringent screens, and these results were reported to CPUC Energy Division and the IOUs in a memo and included as an appendix in the final PY2009 impact evaluation report.

As discussed below, the PY2011 ESA Program impact evaluation uses a less stringent data screening process that only eliminates a small number of outlier observations.

- 2. **Savings estimates over time.** An important finding from the last several evaluations of the ESA Program is that savings tend to fluctuate over time. The fact that there are valid reasons why estimates might vary from year to year needs to be communicated better in the evaluation reports, and the reasons for these fluctuations better understood. The distribution of measures across customer usage groups and weather zones in a given year will change average savings levels, for example. This issue was explored in the PY2009 evaluation by examining changes in participation across usage categories and weather zones, and using information from phone surveys and on-sites. In the current evaluation, we provide a comparison of PY2011 impact estimates to the results from prior program year evaluations, as well as comparisons with both the *ex ante* and DEER<sup>20</sup> savings values. Possible reasons for discrepancies across these sources are also discussed.
- 3. **Weather zones.** The PY2009 evaluation found that ESA participation had shifted to more moderate climate zones for some of the large weather-dependent measures. This led to lower impact estimates for these measures and resulted in a recommendation to focus Program

<sup>&</sup>lt;sup>18</sup> See comments filed June 17, 2011 on the draft PY2009 impact evaluation by the CPUC Department of Ratepayer Advocates (DRA), The East Los Angeles Community Union (TELACU) and other community based organizations at http://docs.cpuc.ca.gov/efile/P/138446.pdf.

<sup>&</sup>lt;sup>19</sup> See Appendix E of *Impact Evaluation of the 2009 Low-Income Energy Efficiency Program*. Prepared for SCE and the CPUC by ECONorthwest (June 16, 2011), available on <a href="https://www.calmac.org">www.calmac.org</a>.

<sup>&</sup>lt;sup>20</sup> The Database for Energy Efficient Resources (DEER) is a California Energy Commission and CPUC sponsored database designed to provide well-documented estimates of energy and peak demand savings values, measure costs, and effective useful life (EUL) all with one data source. DEER has been has been designated by the CPUC as its source for deemed and impact costs for program planning and is available at <a href="www.deeresources.com">www.deeresources.com</a>



installation for these measures in the harsher climate zones. In the current evaluation, we continue to examine weather effects by analyzing how weather-normalized energy consumption changes between the pre-participation and post-installation periods for PY2011.

4. **Survey results.** The PY2009 impact evaluation included extensive phone survey and on-site data collection efforts, which provided some important insights into how customers use energy and the measures installed through the ESA Program. For instance, the surveys revealed that 34 percent of customers were not operating their evaporative coolers properly,<sup>21</sup> which helped explain why the impact estimates were lower than expected in the billing regression. For the current evaluation, a smaller and more targeted participant phone survey effort was conducted. The survey sample targeted customers who saw an increase in energy use after participating in the ESA Program, and questions explored possible reasons for the increase.

A Research Plan that addresses these issues was developed at the beginning of the PY2011 ESA Program Impact Evaluation. A Draft Research Plan was first posted on the CPUC website and a public workshop was held in San Francisco to present the plan and answer questions. Once the comment period ended, the plan was revised to address comments and a Final Research Plan was posted to the CPUC Energy Division website<sup>22</sup> on March 18, 2013.

# 1.3 Organization of Report

The remainder of this report is divided into the following five chapters.

- **Chapter 2: Research Methods** describes the regression model specifications and phone survey methods.
- **Chapter 3: Model Results** presents the basic model output from the billing regression.
- **Chapter 4: Impact Estimates** discusses the impact estimates (kWh, therm and kW) derived from the billing regression model. A comparison of the impact estimates with the *ex ante* and DEER values is also provided.
- **Chapter 5: Phone Survey Results** presents selected findings from the participant phone surveys relating to how energy use changed between the pre-participation and post-participation periods.
- Chapter 6: Conclusions and Recommendations discusses overall conclusions and recommendations derived from the impact analysis.

Included with the main report are the following appendices:

- Appendix A: Phone Survey Instruments
- Appendix B: Complete Phone Survey Result Tabulations
- Appendix C: Detailed Regression Results
- Appendix D: Detailed Impact Tables

<sup>&</sup>lt;sup>21</sup>Impact Evaluation of the 2009 Low-Income Energy Efficiency Program. Prepared for SCE and the CPUC by ECONorthwest (June 16, 2011), p. 34.

<sup>&</sup>lt;sup>22</sup> http://www.energydataweb.com/cpuc/home.aspx



#### 2 Research Methods

# 2.1 Conformity with the California Evaluation Protocols

The evaluation team designed the PY2011 ESA Program Impact Evaluation to be consistent with the *California Energy Efficiency Evaluation Protocols: Technical, Methodological, and Reporting Requirements for Evaluation Professionals,* adopted by the CPUC on June 19, 2006 (Protocols).<sup>23</sup> The estimates of gross demand savings meet the standard for basic rigor and gross energy savings are consistent with the enhanced rigor criteria set forth therein. Adherence to the Protocols is demonstrated by the following characteristics of the analysis:

- Estimates of energy savings are primarily based on a fixed effects regression model, with twelve months of pre- and post-installation billing data.
- Factors that change over time, such as weather, were evaluated and included in the model as indicated.
- Rigorous diagnostics of the regression model were conducted, and adjustments to the model were made accordingly.

Additional components of the evaluation were designed to minimize the possibility of bias and ensure that the process and results are objective and defensible.

# 2.2 Regression Models

#### 2.2.1 Basic Model Specification

The electric and gas impacts are estimated using a fixed effects billing regression model, with separate models run by IOU for each fuel type. The general specification of the fixed effects model for the electric measures is as follows:

$$KWH_{NORM_{it}} = \alpha_i + \sum_{k=1}^{K} \beta_k POST_{ikt} + \beta_2 HDD_{it} + \beta_3 CDD_{it} +$$

$$\sum\nolimits_{k = 1}^K {{{\beta _k}POS{T_{ikt}} * HD{D_{it}}} } + \sum\nolimits_{k = 1}^K {{{\beta _k}POS{T_{ikt}} * CD{D_{it}}} + {v_i} + {\epsilon _{it}}$$

Where:

*KWH*<sub>NORM</sub>= Normalized household monthly energy usage (kWh)

POST = Vector of N indicator variables equal to 0 for months prior to installation of respective measure and equal to 1 for months after installation of measure

<sup>&</sup>lt;sup>23</sup> California Energy Efficiency Evaluation Protocols: Technical, Methodological, and Reporting Requirements for Evaluation Professionals. Prepared for the CPUC by the TecMarket Works Team (April 2006), available at <a href="http://www.cpuc.ca.gov/PUC/energy/Energy+Efficiency/EM+and+V/">http://www.cpuc.ca.gov/PUC/energy/Energy+Efficiency/EM+and+V/</a>.



*HDD* = Total heating degree days during month

CDD = Total cooling degree days during month

i = Index for households (i = 1, 2, ..., I)

t = Index for monthly time period (t = 1, 2, ..., T)

k = index for measure (K different measures; k = 1, ..., K)

 $[\alpha, \beta_1, ..., \beta_K] =$ Coefficients to be estimated in the model

 $v, \varepsilon = \text{Random error terms}$  assumed to be normally distributed

A similar fixed effects model is used to estimate savings for the gas measures:

$$THERM_{NORM_{it}} = \alpha_i + \sum_{k=1}^{K} \beta_k POST_{ikt} + \beta_2 HDD_{it} + \sum_{k=1}^{K} \beta_k POST_{ikt} * HDD_{it} + v_i + \epsilon_{it}$$

Where:

*THERM*<sub>NORM</sub>= Normalized household monthly gas usage (therms)

POST = Vector of N indicator variables equal to 0 for months prior to installation of respective measure and equal to 1 for months after installation of measure

HDD = Total heating degree days during month

i = Index for households (i = 1, 2, ..., I)

t = Index for monthly time period (t = 1, 2, ..., T)

k = index for measure (K different measures; k = 1, ..., K)

 $[\alpha_l,\beta_1$  , ... ,  $\beta_N] = \text{Coefficients}$  to be estimated in the model

 $v, \varepsilon = \text{Random error terms}$  assumed to be normally distributed

# 2.2.2 Measure Model Specification

A variation of the Basic Model, the Measure Model, was also estimated in an attempt to isolate the savings that could be attributed to each individual measure group. In particular, some measures, such as CFLs and weatherization, were installed in a high percentage of homes, leading to possible



collinearity with the other Program measures.<sup>24</sup> In some cases, this resulted in estimates of either no energy savings or increased energy usage associated with the measure.

To mitigate this problem, separate models were estimated for each measure group using a sample customers who only received that particular measure. If these customers had received additional measures, this information was incorporated into the Measure Model as additional explanatory variables. The additional measure variables were not used to calculate savings.

The Basic Model and Measure Model used the same model specifications and data screens, it is only the sample for each model that was changed. Detailed results for each Measure Model (by measure and utility) are provided in Appendix C.

#### 2.2.3 Whole House Model Specification

In addition to the Basic Model and Measure Model, a Whole House Model was also estimated to develop house-level savings estimates for all measures combined. The fixed effects specification is again used to estimate the model for each household:

$$\begin{aligned} KWHNorm_{it} &= \alpha_i + \beta_1 POST_{it} + \beta_2 CDD_{it} + \beta_3 HDD_{it} + \beta_4 POST_{it} * CDD_{it} + \beta_5 POST_{it} * HDD_{it} \\ &+ \sum_{j=1}^{11} \beta_j MONTH_j + \epsilon_{ijt} \end{aligned}$$

Where:

*KWHNorm* = Normalized household monthly energy usage (KWH)

POST = Indicator variable equal to 0 for months prior to ESA participation and equal to 1 for months after ESA participation

CDD = Total cooling degree days per month

*HDD* = Total heating degree days per month

i = Index for household (i = 1, 2, ..., I)

t = Index for monthly time period (t = 1, 2, ..., T)

j = Index for calendar month (j = 1, 2, ..., 11), one month dropped to avoid perfect collinearity with constant term

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<sup>&</sup>lt;sup>24</sup> Collinearity (or multicollinearity) is a condition occurring when two or more independent variables in the same regression model contain high levels of the same information and, consequently, are strongly correlated with one another. When significant collinearity is present, the coefficient estimates of the independent variables in the regression model can be unstable, and even the signs of these coefficients estimates may change when different variables are included, making it difficult to interpret the regression coefficient estimates. In addition, standard errors may be inflated, resulting in insignificant t-statistics and incorrect conclusions regarding the statistical significance of the coefficient estimates.



 $[\alpha_i, \beta_1, ..., \beta_5] = \text{Coefficients to be estimated in the model}$ 

 $\varepsilon = \text{Random error term}$ , assumed to be normally distributed

A similar model was estimated for household gas savings. Both the electric and gas Whole House Models were estimated separately for single family, multi-family and mobile homes.

#### 2.2.4 Additional Regression Models

A wide variety of other model specifications were explored during this evaluation in addition to the Basic and Measure Models that were finally adopted. These other models were eventually eliminated as viable options as they generally did not produce reliable or consistent results. In many cases, the alternative models produced reasonable impact estimates for only a few measures, while the remaining measures had estimates of no savings or even increased energy usage for individual measures. None of the alternative models explored provide any benefit over the Basic and Measure Model specifications.

Specific model variations that were explored are discussed below.

**PY2009 impact evaluation models.** The basic models from the PY2009 impact evaluation were estimated for both the gas and electric measures. The PY2009 models involved assigning customers into measure groups based on the primary measures installed as well as interacting the measure terms by energy use categories. In the current application, the PY2009 model specification resulted in high levels of collinearity in the variables, which in some cases prevented the models from being estimated at all. For many of the measures, the PY2009 model specification resulted in estimates of zero savings or increased energy use. For these reasons, the PY2009 model specifications were abandoned in favor of the Basic and Measure Models.

**Data screens.** To explore the potential benefit of screening some outlier observations to make the analysis dataset more homogenous in terms of energy use, the Basic, Measure and Whole House models were estimated with more stringent data screens. This included screens based on the following criteria:

- Requiring a minimum number of months of billing data (both 6 and 10 month minimums were tried)
- Eliminating households with large changes in energy use between the pre-participation and post-participation periods (increases greater than 100 percent and reductions greater than 50 percent).
- Removing observations and households with consumption more than three standard deviations from the mean for that house type
- Dropping households that had a furnace repair or replacement, as these are expected to increase in energy use in the post-participation period.

It was hoped that these screens might produce savings estimates for some measures where an increase in usage was shown in the Basic or Measure Models. That is, by screening out some of the households that might be contributing to the overall 'noise' in the analysis dataset, the measure-level savings effects might be isolated and a reasonable impact estimate obtained. Unfortunately, none of these screens resulted in consistent improvements to the measure impacts, as the



screened data models produced similar estimates to the same models without these data screens. Because there was little added benefit, these additional screens were not used for the final models.

**Measure group models.** In an effort to mitigate some of the collinearity problem between measures, the Basic Model was estimated with all the measures aggregated into three or four larger measure groups. By creating larger measure group categories, savings estimates for measure groups would allow the savings to be parsed out post-model by using the *ex ante* savings values to determine the share of savings attributable to each of the individual measures within a group. While in theory this approach seemed reasonable, in practice this specification resulted in erratic savings estimates across utilities, with some measure groups resulting in estimates of increased energy use. This indicates that the loss of information resulting from combining measures was not enough to overcome the collinearity problems associated with including the individual measures separately. Since each group covered multiple measures (e.g., even more measures included within a group than with the Basic Model), a positive savings value for a measure group meant that an even larger number of measures could not be assigned savings values from the regression models. For this reason, the measure group models were not used in the final impact analysis.

**Logged variables.** The Basic Model was estimated using a natural log transformation of the dependent variable to see if the Basic Model might fit the transformed data better and produce more reliable savings estimates. In the initial runs, this model produced similar results to the Basic Model. Since the log-transformed model has a less intuitive interpretation and did not provide any additional benefit, it was abandoned in favor of the Basic Model specification.

# 2.2.5 Measure Groupings

Because some measures are often installed together, individual variables representing separate installations of each measure will be highly collinear in the regression model, which results in the model being unable to attribute energy savings to the individual measures. An example of this is faucet aerators and low-flow showerheads, which are usually installed together in eligible households. It is difficult or even impossible for the model to develop reasonable estimates of savings for each of these measures since they are almost always installed simultaneously. For other individual measures with low expected savings, it is unlikely that a household-level billing regression model will be able to provide reliable savings estimates.

To address the issue of small savings and collinearity across similar measures, some individual measures were combined into a single measure group for use in the regression models in place of the individual measure variables. This approach was used in the prior two impact evaluations and we have attempted to use the same measure groupings wherever possible.

The individual measures that comprise the measure groups are shown in the following table for both gas and electric measures. More detail on the measure group assignments by IOU is included at the end of Appendix D.



**Table 1: Measure Groupings Used for Billing Regressions** 

Measure Group for Model	IOU Measure Name
Central AC	Central AC
Central AC Tune-Up	Maintain Central AC
Central Heat Pump	Central Heat Pump
Clothes Washer	High Efficiency Clothes Washer
CFL	CFL
Ducts	Duct Test and Seal
Evaporative Cooler	Evaporative Cooler
Evaporative Cooler Tune-Up	Maintain Evaporative Cooler
Furnace Repair/Replace	Forced Air Furnace
Hard Wired Lighting	Hard Wired Lighting
Hot Water Conservation	Faucet Aerators
Hot Water Conservation	Low-Flow Showerhead
Hot Water Conservation	Shower Hardware
Hot Water Conservation	Pipe Insulation
Hot Water Conservation	Thermostatic Shower Valve
Hot Water Conservation	Water Heater Blanket
Hot Water Conservation	Water Heater Pipe Wrap
Insulation	Attic Insulation
Lighting	Light Fixture
Lighting	Occupancy Sensor
Lighting	Torchiere
Other	Attic Ventilation
Other	Microwaves
Other	FAU Stand Pilot / Change Out
Other	Programmable Control
Other	Thermostat
Pool Pump	Pool Pump
Refrigerator	Refrigerator
Room AC	Room Air Conditioner
Weatherization	Attic Access Door Installation
Weatherization	Attic Access Weather-stripping
Weatherization	Casing
Weatherization	Caulking
Weatherization	Door Assembly
Weatherization	Door Hardware
Weatherization	Door Replacement
Weatherization	Envelope & Air Sealing
Weatherization	Exhaust Fan Vent Repair
Weatherization	Evaporative Cooler Cover
Weatherization	Glass
Weatherization	Outlet Cover Plate Gaskets
Weatherization	Vent Cover
Weatherization	Wall/Floor Repair
Weatherization	Weather-stripping
Weatherization	Window Replace
Weatherization	Window Repair



#### 2.2.6 Weather Variables

In prior evaluations of the ESA Program, the weather variables (CDD and HDD) were calculated on a daily basis using a fixed base temperature (65° F). While this is a standard approach, a potential shortcoming of this method is that using a daily (rather than hourly) value might mask some heating or cooling loads on days with large temperature swings. For example, if a day starts out cool and then warms up to the point where some air conditioners are used, there will be some cooling load and, consequently, some potential for some energy savings during the warm hours of the day. When the cool morning temperatures are combined with the warm afternoon temperatures, however, they may cancel each other out when averaging over the entire day, giving the appearance that this was not a cooling degree day when in fact some cooling did occur.

To address this issue and help ensure that all heating and cooling activity is reflected in the model, we developed HDD and CDD variables based on hourly rather than daily temperature fluctuations.

To calculate the hourly CDD and HDD variables, a dataset of hourly weather conditions recorded at various weather stations was obtained for each IOU included in our analysis. <sup>25</sup> Matching the hourly data to each customer billing record was accomplished using the following steps:

- 1. First, heating degree hours (HDH) and cooling degree hours (CDH) were calculated using a base temperature of 65° F;
- 2. Next, the hourly data were aggregated into a set of daily observations that included HDD and CDD. HDD and CDD were computed as the mean of twenty-four HDH and CDH observations for each day in the three-year study period;
- 3. Following this aggregation, the daily weather dataset was matched to the set of billing records using the weather station and billing period end date as identifiers;
- 4. The total HDD and total CDD corresponding to each billing record were then computed using a set of lagged, daily weather values with the lag number set equal to the number of days in the billing period,<sup>26</sup> This allowed us to create a custom set of HDD and CDD values for each customer record;
- 5. Finally, in order to weigh all observations equally in the analysis, each set of HDD and CDD values were normalized by calculating the average value of each value within the billing period (computed as total HDD/CDD divided by number of billing days) and multiplying by the average number of days in a month (30.4375).

This combination of using hourly information and customizing each set of weather values to fit the corresponding billing period allowed the evaluation team to include a more accurate representation of each customer's weather conditions in the regression models.

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<sup>&</sup>lt;sup>25</sup> SCE weather data were used to assign hourly temperature data for the SoCal Gas models based on zip codes. <sup>26</sup>For example, if a customer billing record was from January 1, 2010 to February 2, 2010, the weather data values for all days from February 2, 2010 back to January 1, 2010 (33 days) were summed to compute billing period HDD and CDD.



Figure 2 and Figure 3 show the difference in the weather variables for each climate zone using both the hourly and traditional daily calculations. As Figure 2 shows, the hourly method results in a greater number of cooling degree days compared to the daily average. There is also an increase in heating degree days with the hourly method, but here the increase is less pronounced. These differences had relatively little effect on the regression results when tested using the Basic Model. Nevertheless, we believe that the hourly calculation method is a more accurate representation of weather conditions and therefore should be used in future evaluations of the ESA program. Additionally, even though the effect is small in the current evaluation, larger differences may appear in future years and given the importance of weather in the regression models, these differences should be incorporated into the analysis. The hourly values are also not difficult to calculate, so the cost of incorporating them into the evaluation analysis is minimal.

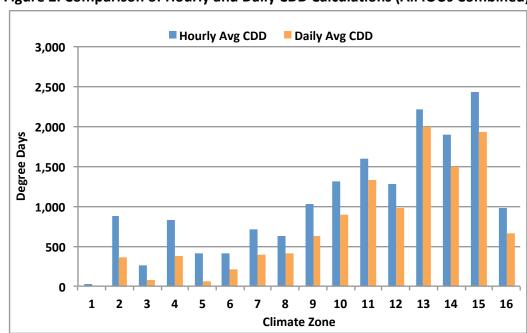


Figure 2: Comparison of Hourly and Daily CDD Calculations (All IOUs Combined)



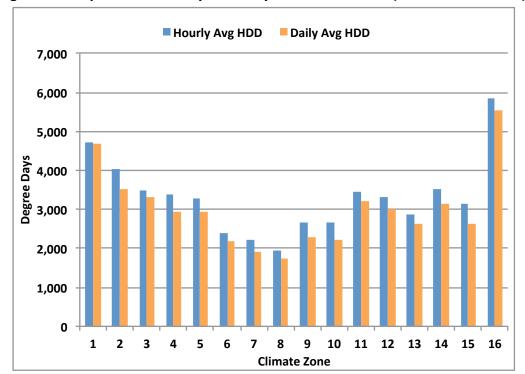


Figure 3: Comparison of Hourly and Daily HDD Calculations (All IOUs Combined)

# 2.3 Demand Impacts

In addition to estimating energy impacts, a separate evaluation task was to estimate demand impacts (kW) for each of the electric measures. The energy-to-demand conversion factors used in this evaluation were taken from the E3 Calculator developed for the CPUC by Energy Environment Economics, Inc.<sup>27</sup> The IOUs use the E3 Calculator to calculate the cost-effectiveness of energy efficiency programs, and, consequently, the kW conversion factors are used in the ESA Program impact evaluation in order to be consistent with the cost-effectiveness analyses to the extent possible.

The E3 Calculator contains a set of coincident peak conversion factors at the measure level for each IOU. An important part of this task was to match the ESA measures to those in the E3 Calculator spreadsheets as closely as possible. Where a direct match could not be made, the next most similar measure was chosen. In the event that a match could not be found for a specific measure within an IOU, the measure was assigned a conversion factor from a different utility that had the same measure. The measures where assignments were made from similar measure or utilities are displayed in Table 2.

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<sup>&</sup>lt;sup>27</sup> More detail on the E3 Calculator is available at the Energy Environment Economics, Inc. website at <a href="http://ethree.com/public\_projects/cpuc4.php">http://ethree.com/public\_projects/cpuc4.php</a>



**Table 2: Coincident Peak kW Conversion Factor Indirect Matches** 

Utility	Measure Category	Source Value			
PG&E	Insulation	PG&E Weatherization			
PG&E	Lighting	PG&E Indoor CFL			
PG&E	Room AC	PG&E Central AC			
SCE	Central AC Tune-Up	SCE; Central AC			
SCE	Evap Cooler	SCE; Central AC			
SCE	Evap Cooler Tune-Up	SCE; Central AC			
SCE	Furnace Repair/Replace	SDG&E Residential Space Heating			
SCE	Lighting	SCE; Indoor CFL			
SCE	Other	SCE; Residential Building Shell Insulation			
SCE	Room AC	SCE; Central AC			
SCE	Weatherization	SCE; Residential Building Shell Insulation			
SDG&E	Central AC Tune-Up	SDG&E Central AC			
SDG&E	FAU Standing Pilot Light Conversion	SDG&E Space Heating			
SDG&E	Microwaves	PG&E Residential Cooking			
SDG&E	Room AC	SDG&E Central AC			
SDG&E	Weatherization	SDG&E Duct Sealing			

Once the matching was completed at the measure level, the conversion factors were averaged within each measure group to obtain a single conversion factor for each respective measure group. Ultimately, this matching procedure ensured that each measure category was assigned the most representative coincident peak conversion factor.

Once the conversion factors were determined, the demand savings were estimated directly by applying the conversion factors to the kWh impacts for each measure group for each IOU.

The demand-to-energy savings conversion factors for each measure category are shown in Table 3.



Table 3: Coincident Peak kW Conversion Factors by Measure and IOU

IOU	Measure Category	kWh-to-kW Conversion Factor				
PG&E	Central AC & Tune-Up	0.00018				
PG&E	CFL	0.00013				
PG&E	Ducts	0.00016				
PG&E	Evaporative Cooler	0.00032				
PG&E	Furnace Repair/Replace	0.00005				
PG&E	Hardwired Lighting	0.00013				
PG&E	Insulation	0.00019				
PG&E	Lighting	0.00013				
PG&E	Microwaves	0.00020				
PG&E	Refrigerator	0.00014				
PG&E	Room AC	0.00018				
PG&E	Water Heater Repair/Replace	0.00015				
PG&E	Weatherization	0.00019				
PG&E	Water Heating Conservation	0.00015				
SCE	Central AC / Room AC & Tune-Up	0.00015				
SCE	Central Heat Pump	0.00045				
SCE	CFL	0.00013				
SCE	Ducts	0.00016				
SCE	Evaporative Cooler	0.00015				
SCE	Evaporative Cooler Tune-Up	0.00015				
SCE	Furnace Repair/Replace	0.00005				
SCE	Insulation	0.00012				
SCE	Lighting	0.00013				
SCE	Other	0.00012				
SCE	Pool Pump	0.00005				
SCE	Refrigerator	0.00012				
SCE	Room AC	0.00015				
SCE	Weatherization	0.00012				
SCE	Water Heating Conservation	0.00012				
SDG&E	Central AC / Room AC & Tune-Up	0.00019				
SDG&E	CFL	0.00012				
SDG&E	Clothes Washer	0.00013				
SDG&E	Ducts	0.00021				
SDG&E	FAU Standing Pilot Light Conversion	0.00005				
SDG&E	Furnace Repair/Replace	0.00005				
SDG&E	Hardwired Lighting	0.00007				
SDG&E	Insulation	0.00019				
SDG&E	Lighting	0.00012				
SDG&E	Microwaves	0.00020				
SDG&E	Refrigerator	0.00012				
SDG&E	Water Heater Repair/Replace	0.00012				
SDG&E	Weatherization	0.00012				
SDG&E	Water Heating Conservation	0.00012				



# 2.4 Data Screening

To estimate the fixed effects models, several data screens were applied to remove extreme outlier observations and/or observations that were clearly data entry errors. Per the related discussion above, we kept these screens to the bare minimum and focused primarily on those that removed individual observations rather than entire households. This allowed us to retain as much usable data as possible – and significantly more than in previous evaluations.

A variety of relaxed and stricter data screens were explored, but we ultimately settled on a set that removed single observations in the billing data based on monthly energy usage. Specific screening criteria included the following:

- Removing master-metered customers where these could be easily identified;
- Removing monthly observations that had electricity consumption greater than 10,000 kWh;
- Removing monthly observations that had electricity consumption less than 100 kWh; and
- Removing monthly observations that had gas consumption greater than 5,000 therms.

The number of monthly observations and households dropped due to these screens is shown in Table 4 and Table 5. Neither SDG&E nor SoCal Gas had any observations removed from its gas account data based on the above criteria. The screen of 5,000 therms per month removed 391 observations and two households from the PG&E gas dataset, which may have been unidentified master-metered accounts.

A relatively small percentage of observations and households were removed from the electric account data. The cutoff points of 100 kWh and 10,000 kWh per month affected electric billing data for all IOUs, with SCE losing the most observations and households. However, this still amounted to less than two percent of households and less than three percent of the total monthly observations for that utility.

**Table 4: Electric Model Data Screening** 

		# obs	% obs				% of	
	Starting # of	screened	screened	# obs used in	Starting # of	# households	households	# households
	obs	out	out	model	households	screened out	screened out	used in model
PG&E Electric	3,318,940	63,294	2%	3,255,646	112,565	602	1%	111,963
SDG&E Electric	610,728	17,672	3%	593,056	21,846	83	0%	21,763
SCE	3,172,228	92,468	3%	3,079,760	103,869	1,475	1%	102,394

**Table 5: Gas Model Data Screening** 

		# obs	% obs				% of	
	Starting # of	screened	screened	# obs used in	Starting # of	# households	households	# households
	obs	out	out	model	households	screened out	screened out	in model
PG&E Gas	2,941,844	391	0%	2,941,453	101,568	2	0%	101,566
SDG&E Gas	378,850	0	0%	378,850	13,336	0	0%	13,336
SCG	3,652,191	0	0%	3,652,191	117,386	0	0%	117,386

An additional screen involved manually removing master-metered accounts for two primary reasons:



- 1. Master-metered accounts are problematic in a billing regression. The aggregation of data to the master-metered level removes much of the variation needed to develop robust impact estimates in a billing regression model.
- 2. The IOUs have few master-metered accounts in the ESA Program, representing only a small fraction of overall participation. For the PY2011 Program, the number of such accounts by utility are approximately:

PG&E: 9,728SCE: 2,700SCG: 670SDG&E: 330

Given the difficulties in modeling this population with a billing model, the low numbers for these accounts, and limited project budget and time, these customers were excluded from the billing regression analysis in order to focus evaluation resources on areas of higher priority.

## 2.5 Phone Survey

As mentioned above, the phone survey of ESA Program participants fielded as part of the PY2011 ESA Impact Evaluation was a smaller and more targeted effort than in past studies. For the survey, the Research Plan called for the sample to target 600 customers, distributed evenly across IOUs, who saw an increase in energy use after participating in the ESA Program. Questions were developed to explore possible reasons for the increase. To identify which customers had an increase in usage, we normalized the pre-installation and post-installation data based on HDD and CDD. The result was a measure that identifies households that had an increase in energy use while controlling for changes in average weather conditions between the two periods (pre- and post-participation). Table 6 lists the phone survey sample sizes.

Table 6: Phone Survey Sample Sizes by IOU and CDD/HDD

Utility	HDD-based Increased Users (Top 33%)	CDD-based Increased Users (Top 33%)	Totals
PG&E	75	75	150
SCE	75	75	150
SDG&E	75	75	150
SCG	75	75	150
Totals	300	300	600

CIC Research fielded the survey in April 2013, completing 602 surveys. Table 7 shows the final call disposition.



**Table 7: Phone Survey Call Disposition** 

	Number	Percentage
Live Numbers		
No Answer	500	10.9%
Answering Machine	1217	26.6%
Busy Number	28	0.6%
Callback	242	5.3%
Dead Numbers		
Respondent Never Available	15	0.3%
Number not in Service	466	10.2%
Business/Fax/Modem	42	0.9%
Refused/Mid-Term Refusal	369	8.1%
Wrong Number	224	4.9%
Spanish	589	12.9%
Other Language	84	1.8%
No Longer at That Address	57	1.2%
No Awareness of Program	63	1.4%
Did Not Participate In Program	34	0.7%
Pre-Test Interviews Deleted	47	1.0%
Completed Interviews	602	13.1%
Total	4579	100.00%



# 3 Regression Model Results

## 3.1 Participant Data Analysis

#### 3.1.1 Participation Patterns Across Climate Zones

Prior to discussing the regression model results and savings estimates, it is useful to have a broader understanding of the ESA participant population, including participation trends and how energy consumption has changed between the pre-participation and post-participation periods. To facilitate this, Table 8 shows the number of households participating in the program for PY2011, which was used as the basis for all of the regression modeling and impact analysis.<sup>28</sup>

**Table 8: PY2011 ESA Impact Evaluation Participation Counts** 

IOU	Electric Participants	Gas Participants
PG&E	112,565	101,566
SDG&E	21,846	13,336
SCE	103,869	
SoCal Gas		117,386

For the common service territory covered by both SoCal Gas and SCE, a list of overlapping accounts was provided to the evaluation team by SoCal Gas. These accounts were then merged against the SCE participant and billing data to obtain a dataset with the appropriate SoCal Gas and SCE account data combined. Weather data from SCE were then also assigned to SoCal Gas customers in this manner.

The primary research question of this impact evaluation is to determine how much energy savings was achieved by the measures installed through the ESA Program. While the measures themselves will save energy, they are just one of many possible influences that affect energy use over the same period. The challenge of any impact evaluation is to isolate the measure influences and disentangle their effect from the other influencing factors.

Weather is an important driver for both energy use and potential energy savings, and examining the distribution of ESA participants can help us understand the magnitude of savings achieved. In general, if ESA participants tend to be located in the hotter or colder areas, then (all else equal) we can expect greater savings than if participants are clustered in the milder climates.

Figure 4 shows the number of cooling degree and heating degree days by climate zone for the current evaluation. While the weather data are analyzed by individual climate zone in the impact calculations, they are grouped into three climate zone categories for ease of presentation. It also allows us to

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<sup>&</sup>lt;sup>28</sup> Note that the participation counts are calculated based on the PY2011 ESA Program tracking data provided by the IOUs in response to a data request submitted by the evaluation team. Given that this was a separate data request exercise, there may be discrepancies between the numbers reported here and those reported in the ESA Program Annual Reports, which are compiled separately. These numbers also reflect the total number of participants that could be matched to billing data for each IOU.



present some comparisons with the previous evaluation, which utilized the same climate zone groupings.

For cooling degree days, there is a trend toward warmer weather in the higher numbered climate zones, with climate zones 1-5 having the fewest cooling degree days and climate zones 11-16 having the most over the evaluation analysis period. Other things equal, we would then expect those weather-sensitive measures (e.g., AC installations and tune ups, Room ACs, evaporative coolers) installed in the higher numbered climate zones to achieve more savings than those installed in the more moderate climate zones with fewer cooling degree days.

A less pronounced trend is shown for heating degree days, where more heating days are observed for climate zones 1-5 and zones 11-16 relative to the middle zones 6-10. Measures installed in those zones with higher amounts of heating degree days should result in higher levels of savings.

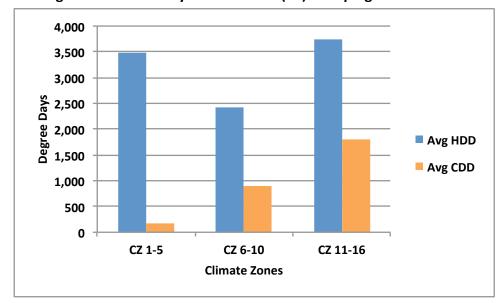


Figure 4: Average CDD and HDD by Climate Zone (CZ) Grouping for the Current Evaluation

For comparison, Figure 5 shows the analogous graph from the previous (PY2009) ESA impact evaluation. When comparing Figure 5 with Figure 4, we can see that the current evaluation has more heating degree days across all three of the climate zone groupings. The current evaluation also has slightly lower cooling degree days across all three of the climate zone groupings. Given the importance of weather in the impact calculations, these differences are likely a significant contributor explaining some the differences in energy impacts between the two evaluations.



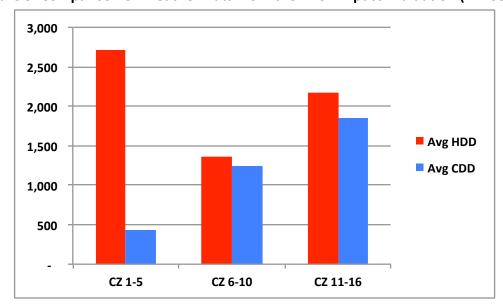


Figure 5: Comparison of Weather Data from the Prior Impact Evaluation (PY2009)<sup>29</sup>

From the weather data alone shown in Figure 4, we would want heating-related measures to focus on the colder climate zones (zones 1-5 and 11-16) while cooling-related measures should be targeted more in climates zone 11-16. The following graphs show how well the actual PY2011 measure installations followed these weather patterns. Note, however, that there are other factors such as home owner eligibility that also determine which measures get installed in which areas, and consequently the ESA participation cannot just target areas with the most extreme weather conditions. This evaluation did not investigate the factors driving participation trends across climate zones or the reasons why these may have shifted relative to PY2009.

Finally, the following graphs show the distribution of participating households by climate zone, for both electricity and gas measures. In general, the electric customer participants are somewhat evenly distributed across climate zones, with no clear tendency toward the more extreme weather areas for either heating or cooling.

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<sup>&</sup>lt;sup>29</sup> Impact Evaluation of the 2009 Low-Income Energy Efficiency Program, p. ES-8.



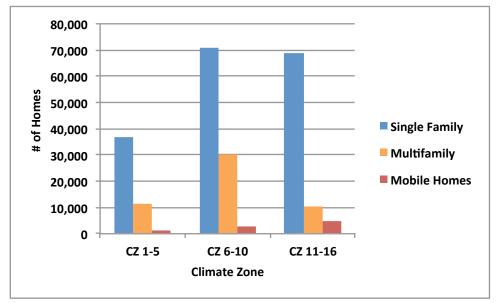
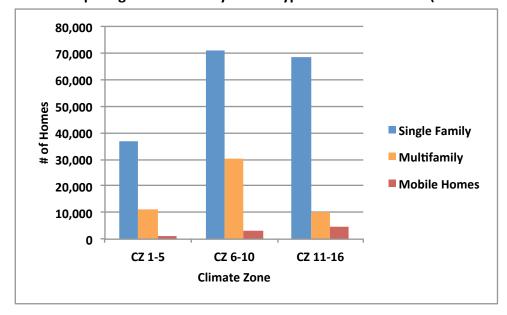


Figure 6: Participating Households by Home Type and Climate Zone (Electric Measures)





#### 3.1.1.1 Electric Measures

Figure 8 shows the distribution of all electric measures installed in ESA PY2011 (all utilities combined). A slight majority is installed in climate zones 11-16, which also have the largest amount of both heating degree and cooling degree days.



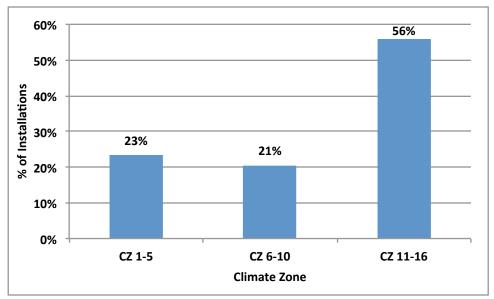


Figure 8: Electric Measure Distribution Across Climate Zones (All Utilities)

Figure 9 shows the share of installation of just cooling measures (Central AC, Room AC, AC Tune Up, Evaporative Cooler) across the same climate zones. With the cooling measures, the trend toward climate zones 11-16 even more pronounced. This trend of having more installations in the higher numbered climate zones is consistent with the trend shown earlier in Figure 4, where more cooling degree days are also occurring in the higher numbered climate zones. This indicates (at least for this program year) that the ESA cooling measure installations are being done in warmer climate zones where energy savings impacts will be greater.

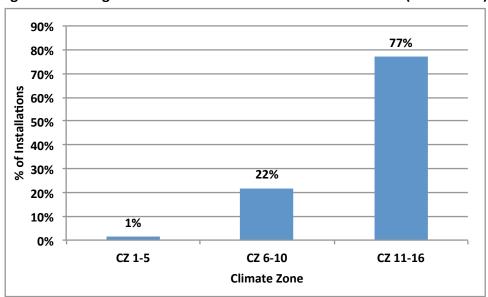


Figure 9: Cooling Measure Installations Across Climate Zones (All Utilities)



Figure 10 shows the distribution for the weatherization, insulation, and duct measures (the remaining weather-sensitive measures for electricity). Here we see a more even distribution across climate zones, with climate zones 11-16 still receiving the highest share.

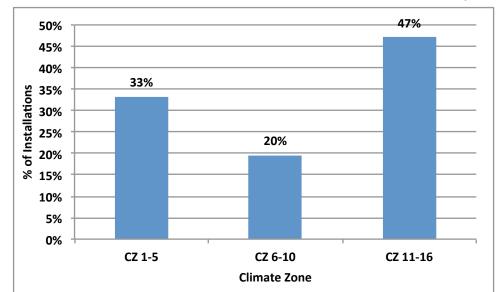


Figure 10: Weatherization/Insulation/Duct Measures Across Climate Zones (All Utilities)

#### 3.1.1.2 Gas Measures

The same analysis was conducted for the gas measures, and in this case we have the distribution from the pervious PY2009 evaluation for comparison (this comparison was not done previously for the electric measures).

Figure 11 shows the overall distribution of gas measures installations for PY2011, for all utilities combined. Recall from Figure 4 that climate zones 1-5 and 11-16 had the most heating degree days, and consequently we would like to see most of the gas measures installed in these zones to maximize the potential for energy savings. As shown in the graph below, however, the middle climate zones 6-10 are receiving the most gas measures, suggesting that the savings realized for these measures are lower than they might be if they had been installed in the other climate zones with more heating degree days.



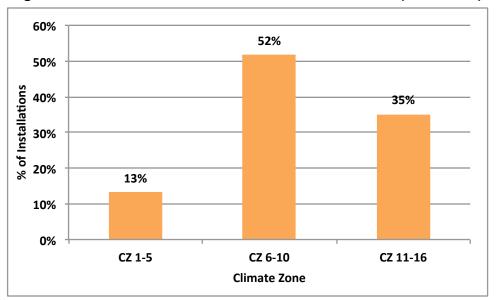


Figure 11: Gas Measure Distribution Across Climate Zones (All Utilities)

Figure 12 shows the distribution of furnace measures installed by climate for PY2011 along with the comparison with the previous evaluation of PY2009. Both years show the vast majority of installations falling in the milder 6-10 climate zones, although PY2011 is showing a shift to the cooler 11-16 climate zones. This suggests that the energy savings for these measures might be lower than they would have been had they been installed in the colder climate zones, although weather is just one of several factors determining energy savings.

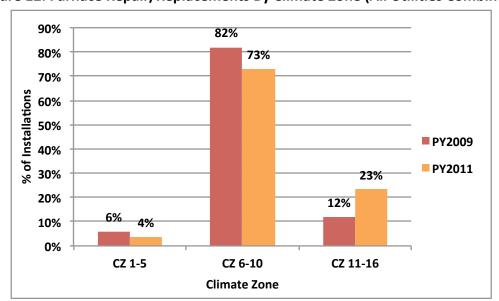


Figure 12: Furnace Repair/Replacements By Climate Zone (All Utilities Combined)

Figure 13 shows the insulation installations by climate zone. For this measure, there has been a distinct trend toward more installations in climate zone 11-16 relative to PY2009, although possible



reasons for this shift were not explored as part of this evaluation. This trend toward the cooler climate zones should result in greater average savings for these gas measures (all else equal).

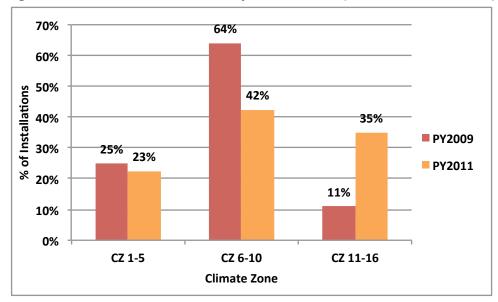


Figure 13: Insulation Installations By Climate Zone (All Utilities Combined)

A similar trend is observed for weatherization installations, as shown in Figure 14. For this measure, there is a marked increase in installations in climate zones 11-16 relative to the prior evaluation, which should also increase the average savings estimates for these measures.

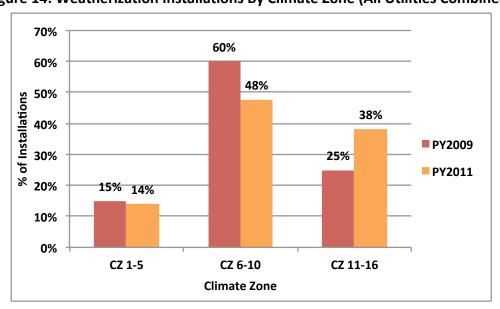


Figure 14: Weatherization Installations By Climate Zone (All Utilities Combined)



#### 3.1.2 Analysis of Participation Energy Consumption

While weather conditions are important for determining impacts, they are only one of several important influences. As discussed throughout this report, there are a myriad of other factors impacting the energy savings estimates, and the trends discussed here from the weather data are sometimes overwhelmed by these other forces.

As the following graphs show, isolating the effect of the measures on overall household energy consumption has been particularly challenging in this evaluation, as energy use among participants has generally increased between the pre-participation and post-participation periods.

A simple measure of this trend is shown in Figure 15. In this graph, the energy use in the period after ESA Program participation is divided by energy use in the pre-participation period. If nothing else changes between the two periods, we would expect that the installation of the ESA measures would cause a decrease in energy use in the post-participation period, and the ratio would be less than 100 percent. For electricity, all of the IOUs showed a slight increase in energy use between the two periods, as demonstrated by the ratio values greater than 100 percent. For gas, consumption was approximately unchanged between the two periods.

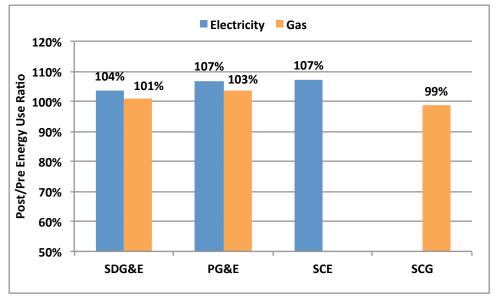


Figure 15: Post-Participation Energy Use as a Percentage of Pre-Participation Use

If the increase in energy use is primarily due to increases in weather (either CDD or HDD), then the increasing consumption can be controlled for in the model through the inclusion of weather variables, which we have done in our model specifications. To determine if there are additional factors affecting energy use, we have developed a metric to determine how much energy consumption changes while holding the effect of weather constant. This was done by dividing energy consumption by cooling degree days to obtain the average kWh used per CDD for both the pre-participation and post-participation periods. A similar calculation was done using HDD for both electricity and gas consumption. Changes in these weather-normalized variables between the two periods indicates the degree to which factors other than weather are affecting energy use for ESA participants.



Figure 16 shows the percentage of households that have weather-normalized electricity use (measured as kWh consumption divided by CDD or HDD) increasing in the post-participation period. For days with heating (the orange bars), there were a significant number of households in each utility that had an increase in weather-normalized electricity use, with over 60 percent of the households in SDG&E and SCE having an increase in the period directly after participating in the ESA Program. This affect was less pronounced for the cooling (the blue bars), with PG&E having over 60 percent of households with an increase in weather-normalized electricity use after participating in the ESA Program. This indicates that there are a substantial number of households that have an increase in energy use after participating in the ESA Program, and that this increase cannot be explained entirely by changes in weather alone.

Figure 16: Percentage of Households with Weather-normalized Energy Use Increasing After ESA Participation (Electricity)

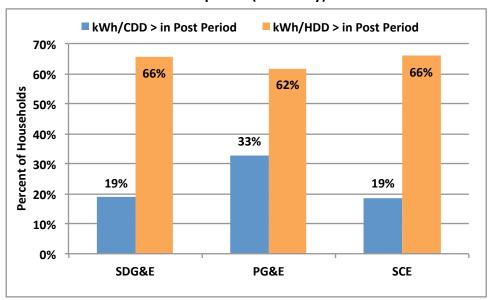


Figure 17 shows the analogous information for gas usage. In this case, all of the utilities had approximately 60 percent of participants increasing their weather-normalized gas consumption in the post-participation period.



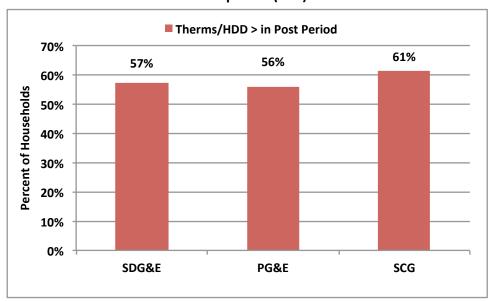


Figure 17: Percentage of Households with Weather-normalized Energy Use Increasing After ESA Participation (Gas)

The trend toward more energy use (both electricity and gas) represents a challenge for the billing regression. In the case where the post-installation energy usage is greater than the pre-installation usage, energy savings from the measures installed through the ESA program are masked by other changes that occur in the home that have lead to an overall increase in energy consumption. Given the nature of the fixed effects model run on the participant population, there is limited information available to control for these other effects. There are indicator variables for both individual household characteristics and time trends, which will control for some of the factors leading to increased energy use. Variables in the model for cooling degree and heating degree days will control for weather effects, although the preceding graphs indicate that there is a substantial amount of increased energy consumption that is due to factors other than weather. To the extent that there is a significant amount of increased energy use that is not controlled for in the model, this will bias downward the impact estimates derived from the measure variable coefficients.

The remainder of this chapter presents the fixed effects regression model results for the Basic Model by utility for each fuel type. Additional model results showing the Measure Model and Whole House regression output are provided in Appendix C.

## 3.2 Electric Models (Basic Model Specification)

Table 9, Table 10, and Table 11 show the regression estimation model results for the Basic Model specification for electric measures included in the PY2011 ESA Program. Models were estimated separately for each IOU, with coefficients for each of the measure groups that had significant amounts of participation.

In general, the estimation results were as expected, with most of the coefficient estimates statistically significant at the five percent level. For the measure coefficients, a negative value indicates a decrease in usage (i.e., savings) in the post-participation period. Note that savings cannot be calculated from



the measure coefficients alone, as the coefficients for the measure/weather interaction terms (along with the average weather values) need to be included in the calculation.

Table 9: SDG&E Electric Regression Results (Basic Model)

	Coefficient	Standard			Variable
Variable Name	Estimate	Estimate Error		P-value	Mean
HDD	0.34	0.00	129.12	0.00	179.08
CDD	0.80	0.01	129.90	0.00	70.56
RoomAC	-8.33	3.62	-2.30	0.02	0.01
DuctTestSeal	-20.88	3.92	-5.32	0.00	0.03
ClothesWasher	-10.25	1.32	-7.78	0.00	0.04
HardwiredLighting	-2.88	0.77	-3.72	0.00	0.16
Insulation	-23.10	4.99	-4.63	0.00	0.02
Lighting	-3.08	0.70	-4.39	0.00	0.48
Microwave	3.29	1.07	3.09	0.00	0.04
Refrigerator	-53.37	1.30	-41.10	0.00	0.04
HWConservation	-7.10	1.30	-5.47	0.00	0.41
WHRepairReplace	0.87	1.46	0.60	0.55	0.03
Weatherization	7.95	1.60	4.96	0.00	0.39
RoomAC*CDD	0.06	0.02	3.16	0.00	0.70
DuctTestSeal*CDD	0.23	0.02	9.97	0.00	2.11
DuctTestSeal*HDD	0.00	0.01	0.18	0.86	4.20
Insulation*CDD	0.05	0.03	1.79	0.07	1.69
Insulation*HDD	0.07	0.02	3.73	0.00	3.46
Weatherization*CDD	0.01	0.01	0.68	0.49	32.08
Weatherization*HDD	0.00	0.00	0.46	0.65	64.18
Adjusted R-squared	0.80				



Table 10: PG&E Electric Model Results (Basic Model)

	- ••				
	Coefficient	Standard			Variable
Variable Name	Estimate	Error	t statistic	P-value	Mean
HDD	0.65	0.00	465.37	0.00	235.37
CDD	1.26	0.00	705.99	0.00	112.20
CentralAC	49.86	12.00	4.16	0.00	0.00
CentralACTuneUp	-31.02	0.94	-33.18	0.00	0.05
CFL	7.66	0.69	11.17	0.00	0.45
Ducts	-15.88	1.27	-12.48	0.00	0.02
EvaporativeCooler	-27.44	1.57	-17.53	0.00	0.03
HardwiredLighting	-0.15	0.60	-0.26	0.80	0.40
Insulation	-0.79	2.04	-0.39	0.70	0.03
Lighting	-0.06	0.54	-0.12	0.91	0.12
Refrigerator	-54.61	0.68	-79.80	0.00	0.07
RoomAC	50.82	2.01	25.26	0.00	0.01
HWConservation	2.38	0.56	4.27	0.00	0.35
Weatherization	45.06	0.87	52.01	0.00	0.30
CentralAC*CDD	-0.30	0.04	-8.45	0.00	2.57
CentralACTuneUp*CDD	0.32	0.00	96.42	0.00	9.29
Ducts*CDD	0.08	0.01	9.55	0.00	3.27
EvaporativeCooler*CDD	0.19	0.00	44.67	0.00	5.71
Insulation*CDD	-0.09	0.01	-11.07	0.00	3.06
Insulation*HDD	-0.01	0.01	-2.17	0.03	6.56
RoomAC*CDD	-0.28	0.01	-43.96	0.00	2.47
Weatherization*CDD	-0.08	0.00	-29.27	0.00	36.14
Weatherization*HDD	-0.16	0.00	-69.20	0.00	64.71
Adjusted R-squared	0.79				



Table 11: SCE Electric Model Results (Basic Model)

	Coefficient	Standard			Variable
Variable Name	Estimate	Error	t statistic	P-value	Mean
CDD	1.26	0.00	800.97	0.00	126.32
HDD	0.47	0.00	396.84	0.00	183.32
RoomAC	54.68	3.16	17.32	0.00	0.00
CentralAC	-41.42	5.38	-7.71	0.00	0.03
CFL	-5.94	0.28	-20.88	0.00	0.35
Ducts	-19.71	6.23	-3.17	0.00	0.02
EvaporativeCooler	-7.84	0.87	-9.01	0.00	0.08
Lighting	-3.23	1.23	-2.62	0.01	0.02
PoolPump	-40.74	2.91	-14.02	0.00	0.01
Refrigerator	-64.50	0.55	-116.72	0.00	0.08
HWConservation	-60.08	7.21	-8.33	0.00	0.00
Weatherization	-62.70	7.71	-8.13	0.00	0.00
CentralACTuneUp	-16.59	17.30	-0.96	0.34	0.00
RoomAC*CDD	-0.24	0.01	-24.64	0.00	0.92
CentralAC*CDD	0.09	0.01	8.01	0.00	6.12
Ducts*CDD	0.02	0.01	1.88	0.06	5.55
Ducts*HDD	0.16	0.01	21.55	0.00	4.61
EvaporativeCooler*CDD	-0.07	0.00	-24.19	0.00	16.41
PoolPump*CDD	0.41	0.01	43.69	0.00	1.99
Weatherization*CDD	-0.23	0.02	-9.64	0.00	0.55
Weatherization*HDD	0.59	0.02	24.48	0.00	0.62
CentralACTuneUp*CDD	0.19	0.04	5.26	0.00	0.06
Adjusted R-squared	0.77				

## 3.3 Gas Models (Basic Model Specification)

Table 12, Table 13 and Table 14 show the analogous regression results for PY2011 ESA Program gas measures, by utility and using the Basic Model specification. As with the electric models, the estimation results for the gas models are as expected, with most coefficient estimates statistically significant at the five percent level. Negative coefficient estimates reflect savings and the impact estimates are calculated based on the measure coefficient estimate combined with the coefficient estimates and average values for the measure/HDD interaction terms.



Table 12: SDG&E Gas Model Results (Basic Model)

	Coefficient	Standard			Variable
Variable Name	Estimate	Error	t statistic	P-value	Mean
HDD	0.07	0.00	322.74	0.00	177.79
Ducts	-3.80	0.22	-17.45	0.00	0.04
FurnaceRepairReplace	-0.08	0.13	-0.57	0.57	0.14
FurnaceCleanTune	-4.52	0.12	-36.67	0.00	0.26
ClothesWasher	-1.32	0.12	-10.89	0.00	0.06
Insulation	-4.19	0.25	-16.94	0.00	0.03
FurnacePilotLight	-1.26	0.16	-8.08	0.00	0.03
HWConservation	0.51	0.12	4.31	0.00	0.44
WHRepairReplace	-0.57	0.14	-4.02	0.00	0.05
Weatherization	2.28	0.15	15.16	0.00	0.39
Ducts*HDD	0.01	0.00	16.88	0.00	6.58
FurnaceRepairReplace*HDD	0.01	0.00	11.90	0.00	22.95
FurnaceCleanTune*HDD	0.02	0.00	41.97	0.00	42.74
Insulation*HDD	0.01	0.00	11.16	0.00	5.22
Weatherization*HDD	-0.01	0.00	-33.81	0.00	64.97
Adjusted R-squared	0.65				

Table 13: PG&E Gas Model Results (Basic Model)

	Coefficient	Standard			Variable
Variable Name	Estimate	Error	t statistic	P-value	Mean
HDD	0.11	0.00	1078.89	0.00	232.38
Ducts	-8.34	0.17	-48.22	0.00	0.02
FurnaceRepair	3.20	0.19	16.87	0.00	0.01
FurnaceReplace	3.42	0.25	13.77	0.00	0.01
Insulation	-5.37	0.12	-44.69	0.00	0.04
HWConservation	0.30	0.05	6.52	0.00	0.41
WHRepairReplace	-0.46	0.31	-1.51	0.13	0.01
Weatherization	1.40	0.06	21.51	0.00	0.36
Ducts*HDD	0.03	0.00	57.27	0.00	4.35
FurnaceRepair*HDD	0.00	0.00	0.52	0.61	2.61
FurnaceReplace*HDD	0.00	0.00	-1.89	0.06	1.56
Insulation*HDD	0.01	0.00	19.51	0.00	8.36
Weatherization*HDD	-0.01	0.00	-31.13	0.00	78.56
Adjusted R-squared	0.81				



Table 14: SoCal Gas Model Results (Basic Model)

	Coefficient	Standard			Variable
Variable Name	Estimate	Error	t statistic	P-value	Mean
HDD	0.10	0.00	1197.08	0.00	177.35
Ducts	-4.37	0.15	-28.87	0.00	0.01
FurnaceRepairReplace	2.40	0.06	41.25	0.00	0.06
FurnaceCleanTune	-3.98	0.05	-72.76	0.00	0.09
ClothesWasher	-2.57	0.10	-26.45	0.00	0.01
Insulation	-3.40	0.08	-40.73	0.00	0.04
HWConservation	-0.28	0.05	-5.76	0.00	0.50
WHRepairReplace	-0.29	0.18	-1.61	0.11	0.01
Weatherization	2.13	0.05	39.25	0.00	0.47
Ducts*HDD	0.02	0.00	29.05	0.00	1.80
FurnaceRepairReplace*HDD	0.01	0.00	27.79	0.00	9.35
FurnaceCleanTune*HDD	0.02	0.00	95.64	0.00	15.30
Insulation*HDD	0.01	0.00	21.37	0.00	5.98
Weatherization*HDD	-0.01	0.00	-111.63	0.00	77.42
Adjusted R-squared	0.67				

#### 3.4 Measure and Whole House Models

In addition to the Basic and Measure Model specifications, we also developed a Whole House model that estimates energy savings at the household level. With this model, savings are estimated as a total value for the entire house and are not broken out by measure group. The regression results for the Whole House models are provided in Appendix C, which includes 27 different models covering each IOU, fuel, and home type.

Additional regression results for each of the Measure Models (by IOU) for the electric and gas measures are also provided in Appendix C.

The estimated energy savings calculated from the Measure and Whole House models are discussed with the Basic Model estimates in the next chapter.



## 4 Impact Estimates

The results of the regression models were used to calculate impacts for each measure group by IOU, house type and climate zone. The impact results by IOU are discussed in this chapter, with more detailed impact results, including those by house type and climate zone, provided in Appendix D.

Energy savings values were assigned to a measure group using the following algorithm:

- 1. If the 95 percent confidence interval of the impact estimate from the Basic Model included the *ex ante* savings value, then the estimate from the Basic Model was used.
- 2. If the confidence interval for Basic Model estimate did not include the *ex ante* value, then evaluator judgment was used to assign an impact value from among the Basic Model, Measure Model, or *ex ante* values.
- 3. In a couple of instances, an engineering estimate was assigned when the *ex ante* values appeared to be unusually high and neither of the regression models could provide a reasonable result.

The impact estimates using these assignments are discussed below by fuel type. In most cases, we assigned the value from the Basic Model as often as possible.

## 4.1 Electric Impact Estimates

Table 15, Table 16 and Table 17 show the electric impacts by measure group. For each measure, the *ex ante*, Basic Model and Measure Model estimates are provided, along with information on the impact estimates from the PY2009 ESA Program evaluation. Note that in cases where the regression models estimate an increase in energy use, the estimated impact has been set to zero in the table.

The source of the final impact number assignment is shown in the highlighted column of each table. Using the final assigned values, the total average household savings is shown at the bottom of the table for each IOU. The far right column of the tables also shows the impact estimates from the PY2009 evaluation, both at the measure-group and household level. Note that impacts on a per unit level (rather than per household, where multiple units may be installed) are shown in the detailed impacts estimates provided in Appendix D.

As can be seen from these tables, there is a significant amount of variation on how well the current impact estimates (from either the Basic or Measure Model) match the *ex ante* values. In some cases, such as refrigerators, they are similar, while in others the regression estimates are substantially different from the *ex ante* savings values.

Our engineering team reviewed those measures where the algorithm assigned the *ex ante* values to assess if the *ex ante* values appeared reasonable. In the case of the SCE values for AC Tune-up<sup>30</sup>, an alternative value was calculated based on engineering estimates for these measures.

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<sup>&</sup>lt;sup>30</sup> The new AC Tune Up value is assumes a 3-ton unit installed in single family and mobile homes, and a 2-ton unit for multifamily. Savings estimate is based on DEER values using the refrigerant charge, airflow adjustment measures (weighted equally).



For SCE Pool Pumps, an alternative value was also calculated based on an engineer review of the available literature. The savings for the SCE pool pump measure were reduced from the claimed savings of 1,686 kWh per year to 1,088 kWh per year based on this analysis. The 1,088 kWh per year savings value is consistent with the expected savings presented in a Residential Pool Pump Measure Revisions document presented to the California Energy Commission by PG&E in 2008.<sup>31</sup> To verify this value, the savings were also calculated using information presented in a recent Residential Pool Pumps and Motors response by the IOUs to the California Energy Commission.<sup>32</sup> Based on this document, the majority of California pool pumps are between one and 1.5 horsepower. Using an average value of 1.25 HP, and the hours of operation for single and multiple speed pumps (as indicated in the same document) the resulting savings are approximately 1,088 kWh annually.

Once the final savings values are assigned and the whole house savings calculated, the aggregated effect increases total household savings slightly from the PY2009 evaluation for SCE, while SDG&E and PG&E both experience decreases relative to the previous evaluation estimates.

Table 15: SDG&E Electric Impact Estimates (kWh)

Measure	Households Receiving Measure	Basic Model	Measure Model	Average Ex Ante Savings	Final Assignment	Final Source	PY2009 Savings Estimate
Room AC	305	27.40	99.88	42.11	27.40	Basic Model	50
Central AC	30	N/A	N/A	38.66	38.66	Ex ante	50
AC Tune-up	59	N/A	N/A	229.13	229.13	Ex ante	326
CFLs	16,434	N/A	N/A	112.11	112.11	Ex ante	93
Ducts	937	55.72	1.36	0.00	55.72	Basic Model	-
Clothes Washer	1,667	123.05	86.94	528.57	123.05	Basic Model	788
Hardwired lighting	6,623	34.61	0.00	115.05	115.05	Ex ante	100
Insulation	800	85.53	359.74	94.90	85.53	Basic Model	104
Lighting	20,825	36.99	30.35	60.48	36.99	Basic Model	346
Microwave	1,852	0.00	66.52	175.91	66.52	Measure Model	-
Refrigerator	1,808	640.42	399.40	722.11	640.42	Basic Model	697
HW Conservation	1,334	85.19	60.30	172.03	172.03	Ex ante	24
WH Repair/Replace	5	0.00	0.00	0.00	0.00	Ex ante	-
Weatherization	16,703	0.00	0.00	49.59	49.59	Ex ante	63
Average household savings		119.71	92.92	346.35	278.57		303

http://www.energy.ca.gov/appliances/2013rulemaking/documents/responses/Residential\_Pool\_Pumps\_and\_Replacement\_Motors\_12-AAER-

<sup>&</sup>lt;sup>31</sup> http://www.energy.ca.gov/appliances/2008rulemaking/documents/2008-05-

 $<sup>15\</sup>_workshop/other/PGE\_Updated\_Proposal\_Information\_Template\_for\_Residential\_Pool\_Pump\_Measure\_Revisions.pdf.$ 

<sup>32</sup> 

<sup>&</sup>lt;u>2F/California\_IOUs\_Response\_to\_the\_Invitation\_to\_Participate\_for\_Residential\_Pool\_Pumps\_and\_Motors\_2013-05-09\_TN-70822.pdf.</u>



Table 16: PG&E Electric Impacts (kWh)

	Households Receiving	Basic	Measure	Average Ex	Final		PY2009 Savings
Measure	Measure	Model	Model	Ante Savings	Assignment	Final Source	Estimate
Central AC	79	141.04	116.53	317.35	141.04	Basic Model	50
AC Tune-up	12,143	0.00	0.00	230.04	230.04	Ex ante	326
CFLs	99,402	0.00	0.00	75.29	75.29	Ex ante	
Ducts	3,007	112.26	10.59	94.33	112.26	Basic Model	
Evaporative Cooler	5,841	0.00	0.00	262.15	262.15	Ex ante	502
Hardwired lighting	87,276	1.85	0.00	145.74	145.74	Ex ante	100
Insulation	6,290	145.41	0.00	46.69	145.41	Basic Model	104
Lighting	26,414	0.75	0.00	140.47	140.47	Ex ante	346
Refrigerator	16,773	655.36	427.92	766.89	655.36	Basic Model	697
HW Conservation	11	0.00	0.00	273.30	273.30	Ex ante	24
Weatherization	64,837	3.51	0.00	9.99	3.51	Basic Model	63
Room AC	3,175	0.00	0.00	111.56	111.56	Ex Ante	50
Average household savings		113.11	64.47	381.46	366.90		402

Table 17: SCE Impact Estimates (kWh)

	Households Receiving	Basic	Measure	Average Ex	Final		PY2009 Savings
Measure	Measure	Model	Model	Ante Savings	Assignment	Final Source	Estimate
Room AC	927	0.00	57.51	69.47	57.51	Measure Model	50
Central AC	4,869	309.18	160.69	150.41	160.69	Measure Model	-
AC Tune-up	32	0.00	0.00	1265.00	257.00	Engineering Est.	326
CFL	67,872	71.25	82.25	25.44	71.25	Basic Model	93
Central Heat Pumps (CHP)	137	N/A	N/A	695.24	695.24	Ex ante	-
Ducts	4,490	0.00	20.65	0.00	20.65	Measure Model	-
Evaporative Cooler	15,928	239.16	448.48	481.87	448.48	Measure Model	502
Evaporative Cooler Tune-up	9	N/A	8236.20	37.13	37.13	Ex ante	-
Lighting	3,390	38.73	145.09	161.33	145.09	Measure Model	346
Pool Pump	1,908	0.00	0.00	1686.00	1088.00	Engineering Est.	-
Refrigerator	16,714	773.99	768.14	704.03	773.99	Basic Model	697
HW Conservation	505	720.97	1255.32	83.00	83.00	Ex ante	24
Weatherization	722	0.00	0.00	51.14	51.14	Ex ante	63
Average household savings		230.31	270.46	253.38	279.26		247

## **4.2** Gas Impact Estimates

The gas impact estimates are shown in Table 18, Table 19 and Table 20, and use the same savings assignment algorithm discussed above for the electric measures. Note that in cases where the Basic or Measure Model resulted in estimates of increased energy use, a savings value of zero is assigned to that measure. At the household level, average household savings increased substantially for all three utilities relative to the PY2009 evaluation.



Table 18: SDG&E Gas Savings (therms)

	Households Receiving		Measure	Average Ex			PY2009 Savings
Measure	Measure	Basic Model	Model	Ante Savings	<b>Final Assignment</b>	<b>Final Source</b>	Estimate
Ducts	930	14.54	13.48	0.00	14.54	Basic Model	-
Furnace Repair/Replace	3,666	0.00	0.00	0.00	0.00	Ex Ante	-
Furnace Clean & Tune	6,551	9.81	4.02	0.00	9.81	Basic Model	
Clothes Washer	1,585	15.88	14.42	35.88	15.88	Basic Model	-
Insulation	732	26.66	5.35	9.17	26.66	Basic Model	10
Pilot Light Change Out	985	15.10	18.50	11.85	15.10	Basic Model	-
HW Conservation	11,125	0.00	0.00	15.49	15.49	Ex ante	7
WH Repair/Replace	1,236	6.80	0.00	0.00	6.80	Basic Model	-
Weatherization	9,113	3.24	0.85	5.01	3.24	Basic Model	4
Average household savi	ngs	13.14	6.87	21.99	26.06		8

Table 19: PG&E Gas Savings (therms)

Measure	Households Receiving Measure	Basic Model	Measure Model	Average Ex Ante Savings	Final Assignment	Final Source	PY2009 Savings Estimate
Ducts	3,578	17.17	12.10	32.75	17.17	Basic Model	0
Furnace Repair	2,197	0.00	0.00	3.21	3.21	Ex ante	0
Furnace Replace	1,218	0.00	0.00	3.31	3.31	Ex ante	0
Insulation	7,165	44.50	22.13	61.05	44.50	Basic Model	10
HW Conservation	80,871	0.00	0.00	13.92	13.92	Ex ante	7
WH Repair/Replace	1,326	5.58	0.00	11.68	5.58	Basic Model	0
Weatherization	69,656	0.00	0.00	9.46	9.46	Ex ante	4
Average household savi	ings	3.82	1.99	23.29	21.50		9

**Table 20: SoCal Gas Savings (therms)** 

	Households			A 5			PY2009
	Receiving		Measure	Average Ex			Savings
Measure	Measure	Basic Model	Model	Ante Savings	Final Assignment	Final Source	Estimate
Ducts	2,629	15.37	0.00	0.00	15.37	Basic Model	-
Furnace Repair/Replace	15,644	0.00	0.00	0.00	0.00	Ex ante	-
Furnace Clean & Tune	20,016	5.65	15.55	2.70	5.65	Basic Model	-
Clothes Washer	4,648	30.88	30.96	27.30	30.88	Basic Model	-
Insulation	8,225	26.51	17.49	7.76	26.51	Basic Model	10
Pilot Light Conversion	109	N/A	N/A	44.31	44.31	Ex ante	
HW Conservation	113,312	3.31	5.43	7.00	5.43	Measure Model	7
WH Repair/Replace	1,812	3.52	1.30	0.00	3.52	Basic Model	-
Weatherization	108,402	3.98	2.74	4.00	3.98	Basic Model	4
Average household savi	ngs	11.31	12.90	12.58	13.40		11

# 4.3 Impact Results Discussion

When reviewing the impact estimates, it is important to place the relative magnitude of the expected savings within the context of overall household energy consumption. Table 21 provides this comparison by utility for both electricity and gas. In each case, the expected savings is a relatively small fraction of annual energy consumption, ranging from three to nine percent. Even if the *ex ante* savings or impact estimates from the PY2009 evaluation were used in the comparison, the savings are



still only a small portion of overall energy consumption. This small amount of savings increases the challenges of isolating the effect of the ESA Program from the other factors influencing energy use.

**Table 21: Comparison of Annual Savings and Energy Consumption** 

			Savings as %
	Evaluation	Annual	of Annual
	Savings	Consumption	Consumption
Electricity (kWh)			
SDG&E	278.57	4,897	6%
PG&E	366.90	7,132	5%
SCE	279.26	6,276	4%
Gas (therms)			
SDG&E	26.06	288	9%
PG&E	21.50	450	5%
SoCal Gas	13.40	388	3%

It should also be noted that, despite the variation in impact estimates across program years and utilities, the current evaluation impact estimates are relatively close to the original *ex ante* values. Table 22 shows the realization rates at the household level, which is simply the estimated household savings using the current evaluation impact estimates divided by the estimated household savings using the *ex ante* savings values. With the exception of the SDG&E electric measures, in general the evaluation estimates are reasonably consistent with the *ex ante* values. The realization rate metric is somewhat misleading in this application, however, as some of the evaluation assigned values were in fact the *ex ante* values, which move the realization rate closer to 1.0. Nevertheless, the realization rate metric does show that the savings values recommended by the evaluation team are fairly close to the original savings estimates provided by the IOUs.

**Table 22: ESA Impact Evaluation Realization Rates** 

	Evaluation Savings	Ex Ante Savings	Realization Rate
Electricity (kWh)			
SDG&E	278.57	346.35	0.80
PG&E	366.90	381.46	0.96
SCE	279.26	253.38	1.10
Gas (therms)			
SDG&E	26.06	21.99	1.19
PG&E	21.50	23.29	0.92
SoCal Gas	13.40	12.58	1.07

While there is some consistency with current evaluation savings estimates and the *ex ante* values at the household level, there are some obvious differences in savings estimates for individual measures. The electric impact models provide a range of savings estimates – some of which have internal consistency while other measures show significant variation across utilities, the previous evaluation



results, and individual *ex ante* values. While we attempted to explore reasons for these differences, it was not possible with the current budget and timeline to explore in-depth all the possible reasons for variations across models, utilities, and the results of the previous evaluation.

It is also important to note that – as discussed in the previous impact evaluation – there are legitimate reasons for savings numbers to vary both across time and utilities. In particular, with regard to comparing evaluation estimates across time, one must not conclude from these differences that one set of estimates is 'correct' or 'more accurate' than the other; the estimates may be equally accurate but reflecting different market conditions inherent in two different evaluation periods.

Table 23 shows the current PY2011 impact estimates compared with the whole house savings estimates from prior evaluation years. Since 2000, there has been a wide range of savings estimates for both gas and electricity at the household level. For electricity, the current impact estimates are lower than those from PY2009 and PY2005, but in line with estimates from PY2000-PY2002. For gas, the current impact estimates are significantly higher than those from PY2009 and generally consistent with impacts from earlier evaluations.

PY2009 PY2005 PY2002 PY2001 PY2000 PY2011 Evaluation **Evaluation Evaluation Evaluation** Evaluation **Evaluation Electric Savings (kWh)** PG&E 402 399 240 367 433 236 SCE 279 247 435 286 203 153 SDG&E 279 303 342 370 215 89 Gas Savings (therms) PG&E 9 9 19 28 21 18 SDG&E 26 8 14 4 13 13 SoCal Gas 13 11 17 17 20

**Table 23: Impact Estimate Comparison with Prior Evaluations** 

There are a multitude of factors that can result in different levels of savings across program years and utilities, and some of the more prevalent influences are discussed below.

**Energy consumption.** Households that use more energy may have the potential for greater energy savings, depending on what end uses are driving energy consumption. Differences in household energy use across both utilities and evaluation periods may account for some of the differences observed in the estimated energy savings. Additionally, it is not just the levels of energy use that are important, but also the degree to which energy consumption changes between pre-participation and post-participation periods. Changes in energy use between these two periods (and the degree to which this inter-period change differs from changes in other utilities and time periods) will also result in different impact estimates.

**Household composition.** One of the most important factors determining energy use is the number of occupants within a home. Those households with more people typically use more energy (all else equal). Similarly, differences in the household structures themselves will lead to differences in energy impacts. Homes with larger or older structures will likely have a greater potential for energy savings, as will homes in disrepair (requiring more energy to heat and cool) or containing older appliances (requiring more energy to run).



**Weather.** Weather has an important influence on energy savings, particular for 'weather sensitive' measures where use and energy savings will vary directly with changes in weather. In the current evaluation, weather is incorporated directly into the savings calculations for those measures where we can reasonably expect savings to vary with changes in temperature. The discussion earlier in this report illustrates how weather has changed between the current and prior evaluations, both in terms in the amount of heating degree and cooling degree days, as well as the distribution of participants across climate zones. Also note that – while the climate zones have been defined to have similar weather within each zone – there is still often significant variation in temperatures within a climate zone, particularly for those zones that include the hottest and coldest areas.

**Measure mix.** The amount of total household savings will vary by the type and quantity of measures installed. This is important to remember when considering that many of the savings estimates from the regression models are for groups of measures, such as weatherization and hot water conservation. While these are by necessity modeled as a single group in the regression (to mitigate collinearity), customers may have different amounts of the individual measure components installed within each group. These differences in measure group composition will lead to differences in savings estimates across utilities and across evaluations.

Different estimation methods. For the current evaluation, we have used the same model specification and data screening process for each utility, so different analysis methods will not explain differences in the current estimates across utilities. The current models, however, are different than what were used in the previous two impact evaluations (PY2009 and PY2005), which in turn were different than the models used in the earlier evaluations (PY2000, PY2001, PY2002). We attempted to develop impact estimates in the current evaluation using the same model specification from the 2009 evaluation, but this was abandoned due to high collinearity issues and because many of the measure-level impact estimates were showing an increase in energy use for some measures. While we believe that the current models are an improvement over earlier evaluations, the different specifications will result in different energy savings estimates.

Savings small relative to overall energy consumption. Finally, it should be noted that for many of the measures installed in the ESA program, the amount of savings expected is small relative to overall household consumption. This is particularly true for some of the most common measures such as CFLs, lighting, weatherization, and hot water conservation. Given the small amount of savings, it is challenging to develop rigorous estimates that are consistent across utilities and evaluations from prior years – even if the exact same model specifications are used. The small amount of savings involved, combined with a lack of information on other influencing factors (discussed above) can result in the ESA Program savings being overwhelmed in the regression model by these other forces.

## **4.4 Demand Impact Estimates**

As discussed in the Research Methods chapter, the demand impacts are calculated by applying the kWh-to-kW conversion factors from Table 3 to the kWh impacts shown in Table 15, Table 16 and Table 17. Detailed demand impacts by housing type and climate zone are presented in Appendix D.



## **4.5** Whole House Impact Estimates

#### 4.5.1 Electric Impacts

The Whole House regression models were also estimated in an attempt to estimate whole house savings without parsing savings into the individual measures. The estimates for whole house savings are shown for electricity in Table 24 for all home types. As can be seen from these results, the Whole House model produced impact estimates that vary significantly both across utilities and housing types.

Table 24: Whole House Model Impact Estimates (kWh)

	Single Family	Multi-family	Mobile Home
SDG&E	157.53	42.99	196.59
PG&E	35.68	70.38	-27.17
SCE	266.57	307.56	273.53

Table 25 shows the comparison of the Whole House Model for just Single Family, compared with the assigned values from the Basic/Measure Models and the household estimate from the PY2009 evaluation (which used a similar assignment method to the current Basic/Measure Model approach).

The lower savings values from the Whole House Model are due in part to the significant number of households that had an increase in energy usage in the post-installation period, which had an overall dampening effect on energy savings. Another important factor is that the Whole House model does not allow us to isolate those measures that are showing an increase in energy use in the regression model. For these cases in the Basic Model, the positive savings values were set to zero and the *ex ante* value assigned in its place to calculate the whole house savings. This post-model adjustment is not possible in the Whole House Model, which results in a lower overall savings estimate.

Table 25: Single Family Whole House Impact Estimates (kWh)

	Whole		
	House	Basic/Measure	PY2009
	Model	<b>Model Results</b>	Estimate
SDG&E	157.53	278.57	303.00
PG&E	35.68	366.90	402.00
SoCal Gas	266.57	279.26	247.00

## 4.5.1 Gas Impacts

Whole house savings estimates for gas were also obtained using the Whole House Model specification, and these are shown by housing type in Table 26. These estimates are somewhat more consistent across utilities, although the model was unable to produce an estimate for mobile homes for PG&E.



Table 26: Whole House Model Impact Estimates (therms)

	Single Family	Multi-family	Mobile Home
SDG&E	8.13	5.57	14.71
PG&E	7.64	3.79	-0.80
SCG	9.47	3.31	14.90

Table 27 shows the comparison of the single family gas impact estimates. As with electricity, the Whole House Model produced much lower gas savings estimates than either the Basic/Measure model assignments.

Table 27: Single Family Whole House Impact Estimates (therms)

	Whole House Model	Basic/Measure Model Results	PY2009 Estimate
SDG&E	8.13	26.06	8.00
PG&E	7.64	21.50	9.00
SCG	9.47	13.40	11.00

## 4.6 Impact Estimate Comparison with DEER Values

After estimating energy savings impacts (kWh and therms), the PY2011 evaluation savings estimates were compared to the appropriate impact values in DEER.<sup>33</sup> Given the wide variation in impact estimates observed over the past few ESA Program evaluations, a comparison with DEER values is appropriate to determine if the latest savings estimates are significantly different from them, even though the DEER values are estimated from the general customer population and not limited to just low income households.

Many of the measures listed in the DEER are delineated by efficiency rating and assumed base case equipment. Additionally, within each DEER measure, the savings values provided are broken out by utility and climate zone. This required that the evaluation team review a wide range of detailed DEER savings values and match the appropriate values to the more aggregated estimates obtained from the billing regressions. The values used for comparison are the "Whole Building Above Customer-Average Impacts." These DEER values reflect the savings using the existing home conditions as the baseline, as opposed assuming a standard efficiency replacement value equal to code. Because the existing conditions are also what are utilized in the billing regression to estimate savings, choosing the analogous values in DEER enables a more consistent basis for comparison.

In order to compute a single value for each utility and measure category, the DEER data were compiled, assigned a measure category, and aggregated based on measure category and utility. The resulting compilation produced a single set of average energy savings values (kWh and therms) for each utility and measure category. Using this method, we were able to match 91 percent of the

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<sup>&</sup>lt;sup>33</sup> The DEER database can be accessed at www.energy.ca.gov/deer/.



electric measures and 70 percent of the gas measures installed through the ESA Program with similar measures in the DEER database.

Comparisons of the relevant DEER, evaluation and *ex ante* savings values are presented below by utility, measure category and fuel type. Additionally, the number of ESA Program participants installing at least one measure in a given measure category are included in the tables below as well.

Table 28 and Table 29 show the comparison of the PY2011 evaluation savings estimates with the corresponding DEER values. Note that the evaluation and *ex ante* savings values are per household and the DEER values are per unit, so it is not entirely a consistent comparison. The DEER database does provide a range of savings values by home size, and the savings values for smaller home sizes in DEER might match more closely with the estimates for the ESA Program participants, who are often in smaller homes. We did not attempt to explore this issue further in the current evaluation, however. Notable discrepancies between the DEER and evaluation savings values include the much higher *ex ante* values for AC tune-up, particularly for the SCE *ex ante* value. The DEER values for insulation are negative, due presumably to interactive or snapback effects incorporated into the DEER values, which are not included in the evaluation savings values. Refrigerator savings estimates from the evaluation are consistently higher than the DEER values, which may be reflecting an older stock of existing refrigerators in low-income households relative to the general population.



Table 28: Comparison of PY2011 Evaluation, DEER and Ex Ante Impact Estimates (kWh)

-			DEER	Evaluation	Ex Ante
Utility	Measure Category	Number of Participants	kWh Savings (per unit)	kWh Savings (per household)	kWh Savings (per household)
PG&E	Central AC	79	192.22	141.04	317.35
PG&E	Central AC Tune-Up	12,143	95.46	230.04	230.04
PG&E	CFL	99,402	16.56	75.29	75.29
PG&E	Ducts	3,007	97.30	112.26	94.33
PG&E	Evaporative Cooler	5,841	292.29	262.13	262.15
PG&E	Insulation	6,290	-47.13	145.41	46.69
PG&E	Refrigerator	16,773	178.79	655.36	766.89
PG&E	Weatherization	64,837	0.51	3.51	9.99
SCE	Central AC	4,869	219.63	160.69	150.41
SCE	Central AC Tune-Up	32	107.51	257.00	1265.00
SCE	CFL	67,872	17.63	71.25	25.44
SCE	Ducts	4,490	121.38	20.65	-
SCE	Evaporative Cooler	15,928	398.88	448.48	481.87
SCE	Refrigerator	16,714	199.70	773.99	704.03
SCE	Weatherization	722	0.64	13.00	13.00
SDG&E	Ducts	937	76.21	55.72	-
SDG&E	Insulation	800	-48.90	85.53	94.90
SDG&E	Refrigerator	1,808	192.97	640.42	722.11
SDG&E	Weatherization	16,703	0.46	49.59	49.59



Table 29: Comparison of PY2011 Evaluation, DEER and Ex Ante Impacts Estimates (therms)

			DEER	Evaluation	Ex Ante
Utility	Measure Category	Number of Participants		therm Savings (per household)	therm Savings (per household)
PG&E	Ducts	3,578	17.79	17.17	32.75
PG&E	Furnace Repair	2,197	0.57	3.21	3.21
PG&E	Furnace Replace	1218	0.57	3.31	3.31
PG&E	Insulation	7,165	22.29	44.50	61.05
PG&E	Water Heater Repair/Replace	1,326	21	4.69	4.69
PG&E	Weatherization	69,656	0.11	9.46	9.46
SoCal Gas	Ducts	2,629	16.39	15.37	-
SoCal Gas	Furnace Repair/Replace	15,644	0.54	-	-
SoCal Gas	Insulation	8,225	13.79	26.51	7.76
SoCal Gas	Weatherization	108,402	0.14	3.98	4.00
SDG&E	Ducts	930	15.13	14.54	-
SDG&E	Furnace Repair/Replace	3,666	0.52	-	-
SDG&E	Insulation	732	9.71	26.66	9.17
SDG&E	Water Heater Repair/Replace	1,236	19.29	6.80	-
SDG&E	Weatherization	9,113	0.14	3.24	5.01



## 5 Phone Survey Results

## 5.1 Phone Survey Sample Design

A separate analysis component of the impact evaluation involved administering a phone survey to a sample of PY2011 ESA Program participants. The Research Plan called for the completion of 600 participant phone surveys, with these surveys targeting those customers that experienced an increase in energy use after participating in the ESA Program. To identify which customers had an increase in usage, we normalized the pre-installation and post-installation data based on HDD and CDD. The result was a measure that identifies households that increase in energy use while controlling for changes in average weather conditions between the two periods.

Table 30 shows the results for the highest 33 percent of those customers experiencing an increase in usage between the pre and post periods based on electricity consumption. Table 31 provides similar information for increases in gas consumption. The left half of the table shows the number of households that are in the top third of increased users, while the right part of the table shows the lower bound for the increase in usage. For example, for PG&E there were 8,830 customers that had at least an 18.83 percent increase in energy usage (based on HDD) between the pre and post-installation periods. These 8,830 customers represent the top 33 percent (i.e., largest increases) of those customers that had an increase in energy usage over the same time period.

Table 30: Number of Customers (Top 33%) Increasing Energy Use (kWh)

	HDD-based	CDD-based	HDD	CDD
	Increased Users	<b>Increased Users</b>	Top 33%	Top 33%
Utility	(Top 33%)	(Top 33%)	Cutoff	Cutoff
PG&E	8,830	6,311	+18.83%	+20.60%
SCE	10,570	4,502	+22.97%	+14.53%
SDG&E	1,594	631	+23.00%	+18.00%
SoCal Gas				

Table 31: Number of Customers (Top 33%) Increasing Energy Use (therms)

Utility	HDD-based Increased Users (Top 33%)	CDD-based Increased Users (Top 33%)	HDD Top 33% Cutoff	CDD Top 33% Cutoff
PG&E	948	516	+18.83%	+20.60%
SCE				
SDG&E	958	446	+26.00%	+24.00%
SoCal Gas	8,582	5,745	+31.57%	+23.76%

Within this group of increased consumption customers, we next examined whether or not there was any particular measures that occurred more frequently for these customers relative to the entire population of ESA participants. The rationale is that the installation of certain measures like furnace repair might spur an increase in energy use in the post-installation period. The results of this analysis found generally that there were not significant deviations among measures between the increased



energy users and the participant population for each utility. The following tables show the specific measures examined for each utility, and the frequency in which these measures were installed in homes where there was an increase in energy use.

Table 32: PG&E Distribution of Measures for Increased Energy Users (kWh)

	HDD-based	CDD-based
Measure Name/Category	<b>Increased Users</b>	<b>Increased Users</b>
AC	0.4%	0.3%
Caulking	7.9%	8.0%
CFL	14.4%	14.4%
Ducts	0.2%	0.2%
DWH	0.3%	0.3%
Faucet Aerator	8.3%	8.6%
Furnace	0.0%	0.0%
Furnace Repair	0.1%	0.1%
Gaskets	7.8%	7.8%
HWD Lights	17.9%	18.0%
Lighting	2.1%	2.0%
Other	4.7%	4.1%
Refrigerator	0.6%	0.6%
Shower head	7.9%	8.3%
Vent	0.3%	0.3%
Water Heater Blanket	1.7%	1.9%
Weatherization	17.2%	17.1%
Weatherstripping	7.9%	8.0%



Table 33: PG&E Distribution of Measures for Increased Energy Users (Therms)

	HDD-based	CDD-based
Measure Name/Category	<b>Increased Users</b>	<b>Increased Users</b>
AC	0.0%	0.0%
Caulking	13.9%	9.5%
CFL	0.4%	4.8%
Ducts	0.0%	0.2%
Faucet Aerator	14.3%	14.3%
Furnace	0.1%	0.2%
Furnace Repair	0.4%	0.5%
Gaskets	13.6%	13.7%
Shower head	12.9%	12.7%
Vent	0.3%	0.3%
Water Heater Blanket	3.1%	3.0%
Water Heater Repair	0.2%	0.2%
Weatherization	26.7%	26.5%
Weatherstripping	13.9%	13.9%

Table 34: SDG&E Distribution of Measures for Increased Energy Users (kWh)

	HDD-based	CDD-based
Measure Name/Category	<b>Increased Users</b>	Increased Users
AC	0.4%	0.1%
CFL	17.2%	18.0%
Ducts	1.0%	1.3%
Furnace Repair	8.8%	9.7%
High Efficiency Clothes Washer	2.0%	2.2%
Insulation	0.9%	1.1%
Lighting	23.0%	22.2%
Miscellaneous Controls	4.7%	5.1%
Other	1.5%	0.7%
Refrigerator	1.3%	1.0%
Water Heater Conservation	19.3%	18.8%
Water Heater Repair	1.6%	1.6%
Weatherization	18.3%	18.1%



Table 35: SDG&E Distribution of Measures for Increased Energy Users (Therms)

	HDD-based	CDD-based
Measure Name/Category	<b>Increased Users</b>	<b>Increased Users</b>
AC	0.2%	0.2%
CFL	16.0%	16.1%
Ducts	1.6%	1.9%
Furnace Repair	12.5%	13.9%
High Efficiency Clothes Washer	2.5%	2.5%
Insulation	1.0%	1.2%
Lighting	20.5%	19.8%
Refrigerator	2.7%	2.7%
Water Heater Conservation	17.8%	17.4%
Water Heater Repair	2.1%	2.1%
Weatherization	16.1%	16.2%

Table 36: SCE Distribution of Measures for Increased Energy Users (kWh)

	HDD-based	CDD-based
Measure Name/Category	<b>Increased Users</b>	<b>Increased Users</b>
AC	1.9%	1.9%
Caulking	0.1%	0.1%
CFL	23.5%	22.2%
Ducts	1.5%	1.4%
DWH	0.0%	0.0%
Evaporative Cooler	5.1%	4.7%
Faucet Aerator	0.1%	0.1%
Furnace	0.0%	0.0%
Gaskets	0.1%	0.1%
Heat Pump	0.0%	0.0%
Lighting	1.0%	1.1%
Pool Pump	0.7%	0.8%
Refrigerator	2.4%	2.3%
Showerhead	0.1%	0.1%
Water Heater Blanket	0.0%	0.0%
Weatherization	0.1%	0.1%
Weatherstripping	0.2%	0.1%



Table 37: SoCal Gas Distribution of Measures for Increased Energy Users (Therms)

	HDD-based	CDD-based
Measure Name/Category	<b>Increased Users</b>	<b>Increased Users</b>
Clothes Washer	0.3%	0.5%
Ducts	0.3%	0.3%
Furnace	6.7%	8.1%
Furnace Repair	1.8%	1.6%
Insulation	0.8%	0.8%
Water Heater Replace	0.2%	0.2%
Weatherization	69.0%	68.3%
Water Heating Conservation	20.8%	20.2%

Since there were no obvious measures to target that were related to increased energy use, the final phone survey sample was evenly distributed across utilities and households that experienced an increased in normalized energy use for either CDD or HDD (Table 38). In the hopes of identifying behaviors and trends that lead to increased energy use, the sample was further restricted to those customers showing the large increase in energy use between the two periods (i.e., the top 33 percent). The participants were randomly sampled without any specific quotas set for specific measures beyond those shown below.

Table 38: Phone Sample Sizes by Utility and CDD/HDD

Utility	HDD-based Increased Users (Top 33%)	CDD-based Increased Users (Top 33%)	Totals
PG&E	75	75	150
SCE	75	75	150
SDG&E	75	75	150
SoCal Gas	75	75	150
Totals	300	300	600

## **5.2** Phone Survey Results

This section presents selected results from the participant phone survey, with complete survey response tabulations provided in Appendix B. As noted above, the evaluation Research Plan included a goal of 600 participant phone surveys targeting those customers who experienced an increase in energy use after participating in the PY2011 ESA Program. CIC Research fielded the survey in April 2013, completing 602 surveys. Table 39 shows the number of survey respondents by IOU.

Table 39: PY2011 Program Participant Phone Survey Respondent Count by IOU

PG&E	SCE	SCG	SDG&E	Total
150	150	151	151	602



Below is a summary of selected participant responses to the survey.

#### 5.2.1 Home Characteristics

Figure 18 displays the percentage of respondents by housing type by IOU. Between 85 and 90 percent of respondents were from single-family households, except for SDG&E (65 percent). Likewise, multifamily homes were responsible for between 5 and 10 percent of all phone surveys, except for SDG&E (26 percent), with mobile home respondents providing the rest of the responses.

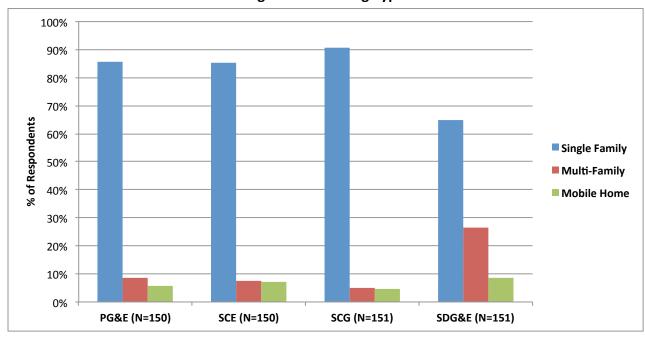


Figure 18: Housing Type



To determine whether or not landlords (rather than the participants themselves) were responsible for paying the utility bills, several questions were asked regarding home ownership and bill payment. If landlords are paying the utility bills rather than the tenants, then participants that are renters will have little incentive to conserve energy and might be more likely to increase energy consumption after participating in the ESA Program.

To explore this possibility, participants were first asked if they rent or own their homes, and more than 70 percent of respondents stated that they own their home. Of those respondents who rent, almost 95 percent said their landlords do not pay utilities. These responses together indicate that having landlords (rather than tenants) paying the utility bills is not especially prevalent in the ESA participant population that experienced increases in energy use. Consequently, having landlords paying the utility bills is unlikely to be a factor in the increased energy use observed in the post-participation period. See Figure 19 and Table 40 for more detail on responses to these questions.

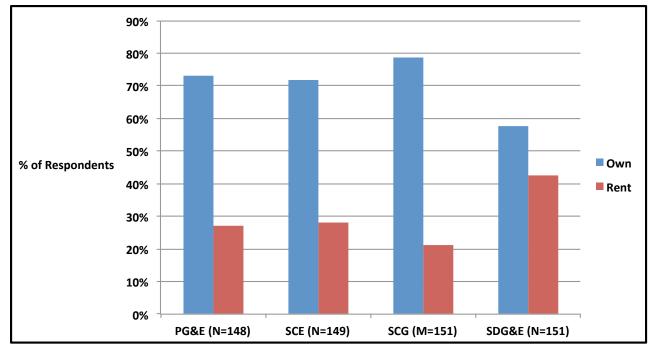


Figure 19: Responses to "Do you own or rent your home?"

Table 40: Responses to "Does your landlord pay for any portion of the electric and gas utilities?" (asked of renters only)

	PG&E (N=40)	SCE (N=42)	SCG (N=32)	SDG&E (N=63)	Total (N=177)
Yes	5%	7%	6%	5%	6%
No/Other	95%	93%	94%	95%	94%

Figure 20 displays the average response for when homes where built. The majority of homes were built between 1950 and 1989, with less than 10 percent of the response for any decade outside of this



range. PG&E customers had the oldest homes, 16 percent built before 1940, while SDG&E respondents tended to have the newest, 60 percent of homes built after 1970.

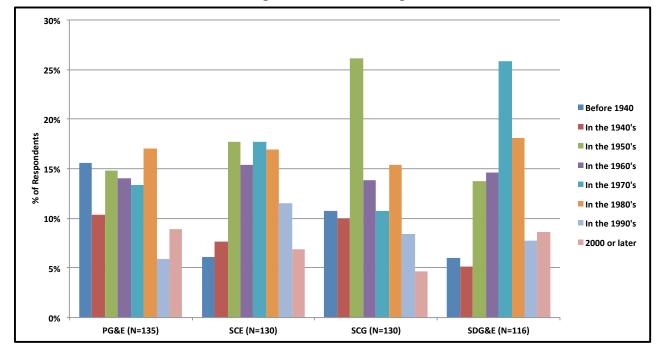


Figure 20: Home Vintage

As illustrated in Figure 21, most homes are between 1,000 and 1,500 square feet (38 percent) and this size distribution is fairly consistent across IOUs. Less than 15 percent of respondents live in homes that are smaller than 500 square feet or homes that are greater than 2,000 square feet.



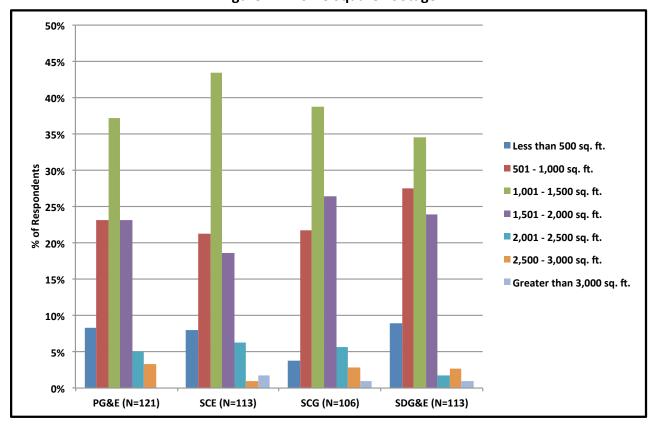


Figure 21: Home Square Footage



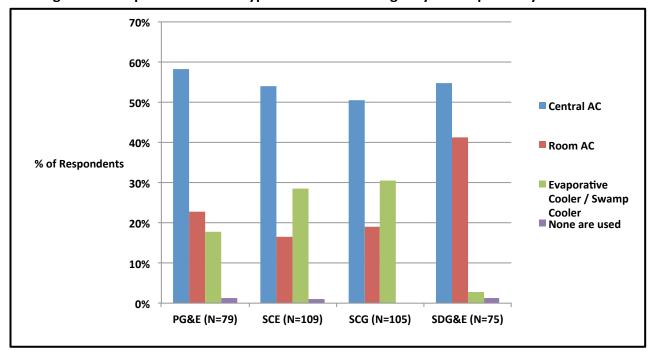
### **5.2.2 Home Cooling**

A series of questions were asked about cooling to determine whether or not increases in home cooling might be driving the overall increase in energy use. Table 41 illustrates that, of those surveyed, 61 percent stated they have an air conditioner or an evaporative cooler in their home. These respondents were then asked a follow-up question on the primary type of air-conditioning they use. As shown in Figure 22, the majority of these responses (54 percent) use central air conditioning as their primary source, with lesser numbers reporting using evaporative coolers or room air conditioners.

Table 41: Responses to "Do you have an air conditioner, evaporative cooler or swamp cooler in your home?"

	PG&E (N=150)	SCE (N=150)	SCG (N=151)	SDG&E (N=151)	Total (N=602)
Yes	53%	73%	70%	50%	62%
No/Other	47%	27%	30%	50%	38%

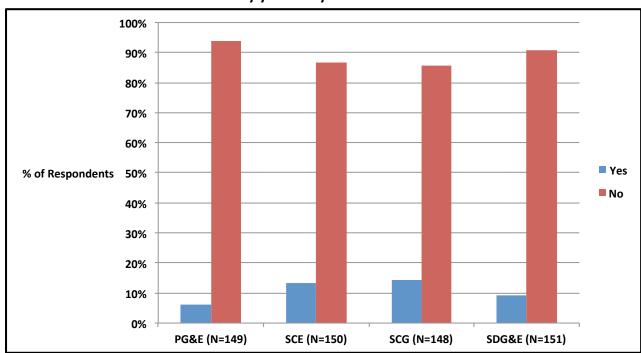
Figure 22: Response to "What type of air conditioning do you use primarily?"





When asked if participation in the ESA Program caused a change in the way they cool their home, only 11 percent of respondents said "Yes," as illustrated in Figure 23. It would appear, then, that while energy usage may have changed after ESA Program participation, the primary equipment used for cooling largely did not. The majority of participants continued to use the same primary method of air conditioning to cool their home, even if new equipment was installed through the ESA Program.

Figure 23: Responses to "Did your participation in the ESA Program cause you to change the way you cool your home?"





In addition to continuing to use the same method for cooling their homes, Figure 24 shows that the majority of respondents stated that they cool their homes either the same amount or less than before participating in the ESA Program. Because each of those surveyed had increased energy usage after participation, we assume that this increase is not due to changes in participant home cooling.<sup>34</sup>

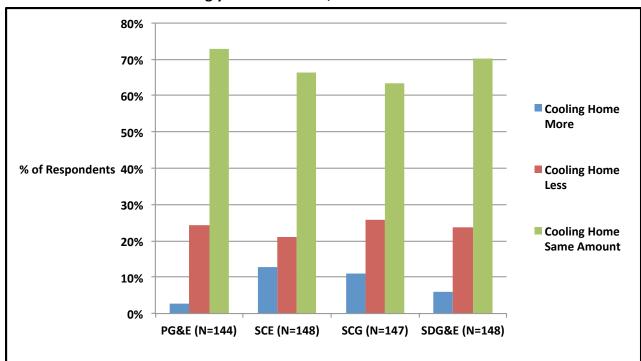


Figure 24: Responses to "Since you participated in the ESA program, would you say you are cooling your home more, less or the same?"

Of the small percentage of participants who claimed to be cooling their home more since participating in the ESA Program, half say they are doing so because of warmer weather. Other responses included that, they had a new child or pet in their home, or they simply wanted their house cooler. Some claimed it was because the new cooling system was more cost efficient.

For those respondents that indicated that they cooled their home more since participating in the ESA program, very few received cooling measures through the ESA Program. Of the 26 respondents (four percent of the total survey sample) that indicated that they cooled their home more, only one respondent received a cooling measure (e.g., Central AC, Room AC, Evaporative Cooler) through the ESA Program, based on analysis of program tracking data for these customers. This suggests that receiving a cooling measure through the ESA Program by itself is unlikely to be a significant driver in

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<sup>&</sup>lt;sup>34</sup> The survey respondents' monthly energy use was also examined to determine if the increase in energy use after program participation was seasonal in nature. After comparing the month-over-month energy use for the survey sample, there was no discernable seasonal pattern that would indicate the change in use was due to increased heating or cooling. This finding is consistent with the survey responses regarding heating and cooling behavior since participating in the program.



the observed increase in energy consumption. The sample size for this question is very small, however, and these results are not statistically significant.

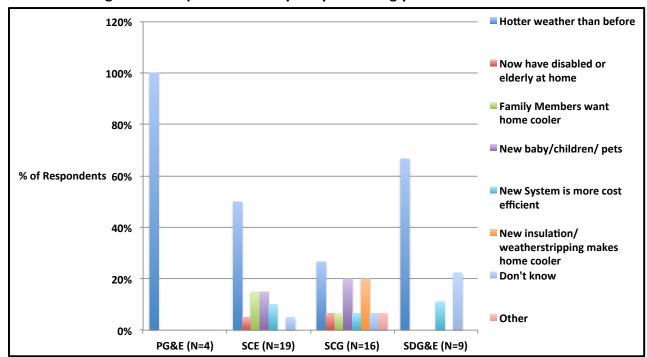


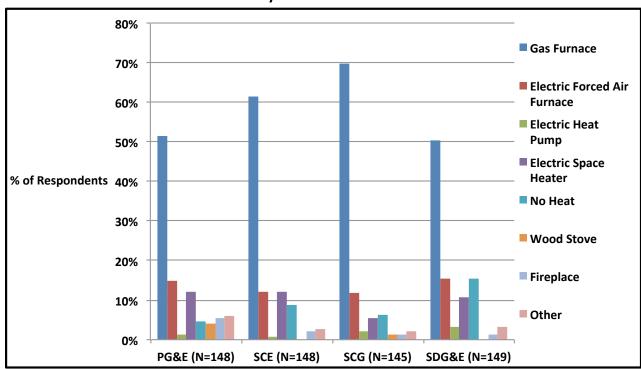
Figure 25: Responses to "Why are you cooling your home more now?"



### 5.2.3 Home Heating

Participants were also asked about the primary method used to heat their home. As shown in Figure 26, 58 percent of survey respondents named a gas furnace as the primary source of home heat, 14 percent an electric forced air furnace, and 10 percent an electric space heater.

Figure 26: Responses to "Which of the following best describes the primary way you heat your home?"



As was true for home cooling, the majority of participants (88 percent) stated that they did not change the way they heat their home as a result of participation in the ESA Program (see Table 42). This indicates that energy usage increases were generally not caused by changes in participant home heating.

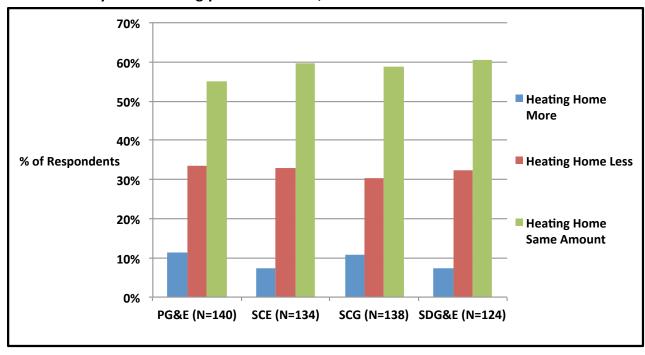


Table 42: Responses to "Did your participation in the ESA Program cause you to change the way you heat your home?"

	PG&E (N=142)	SCE (N=135)	SCG (N=142)	SDG&E (N=128)	Total (N=547)
Yes	13%	13%	11%	10%	12%
No/Other	87%	87%	89%	90%	88%

As shown in Figure 27, the vast majority of participants (91 percent) claim to heat their home either less or about the same as before ESA Program participation.

Figure 27: Responses to "Since you participated in the ESA Program, would you say you are heating your home more, less or about the same?"





Of the 48 respondents who claimed to be heating their home more now than before participating in the Program, the largest group (44 percent) said that they are running their furnace more often. Others say they are using space heaters more often (31 percent) or have increased the base temperature on their home thermostat (15 percent). Figure 28 shows the breakout of all responses by IOU. This subsample of respondents is small, however, and these results are not statistically significant.

70% Running furnance more often 60% Increased the 50% temperature on thermostat 40% Using space heaters more often % of Respondents 30% ■ Wasn't heating before / Heater 20% didn't work Other 10% 0% PG&E (N=16) SCG (N=14) SCE (N=9) SDG&E (N=9)

Figure 28: Responses to "How are you primarily heating your home more?"



As seen in Figure 29, among those 48 respondents who claimed to heat their home more post-participation, the largest group (44 percent), attribute this behavior to colder weather. Others suggested that their old equipment was not in working condition, family members just want their home warmer, or that they needed a warmer home as they aged. Again, these responses are from a very small sample size and are not statistically significant. However, they do provide anecdotal evidence that there is not a single factor driving the increase in heating for these customers.

For the fraction of respondents that indicated that they heated their home more since participating in the ESA program, only a few received heating measures through the ESA Program. Of the 50 respondents that said that they were heating their home more since participating in the program (eight percent of the total survey sample), only 16 respondents also received a heating measure (e.g., furnace repair, replacement, or tune-up) through the ESA Program. This suggests that using a program-supplied heating measure is unlikely to be a major driver of the observed increase in energy consumption.

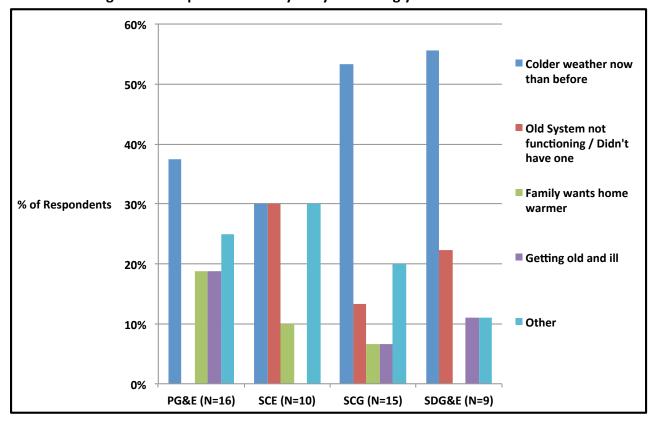


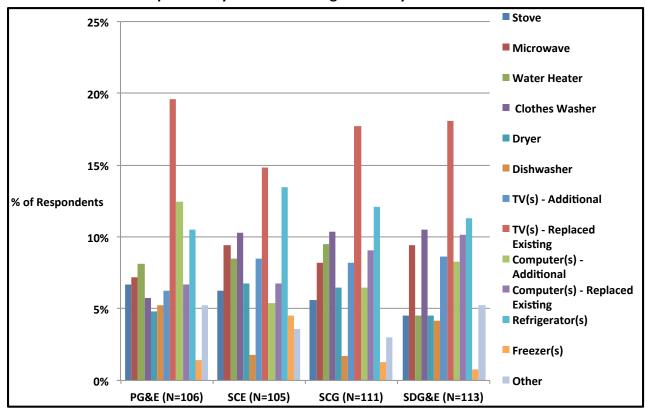
Figure 29: Responses to "Why are you heating your home more now?"



# 5.2.4 Added or Replaced Items in Home

To better understand why their energy usage changed after the participation in the ESA Program, survey respondents were asked what equipment was either added to or replaced in their homes since Program involvement. As shown in Figure 30, the most common new equipment added or replaced by participants were stoves, microwaves, water heaters, clothes washers, dryers, TVs, computers and refrigerators.

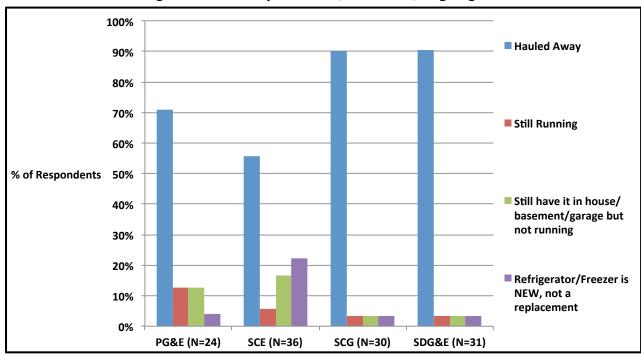
Figure 30: Responses to "Since your involvement with the ESA program, have you added or replaced any of the following items to your home?"





For those who had installed new refrigerators/freezers, a follow up question was asked to determine what was done with the old appliance. As shown in Figure 31, 76 percent of participants who replaced their refrigerators/freezers stated that the equipment was hauled away and no longer running in their homes. Having the old equipment removed is a requirement for the ESA Program, but it is possible that these respondents had their equipment replaced outside the program. The small number reporting that they kept their old appliance suggests that adding a new refrigerator or freezer and keeping the old one is unlikely to be a factor driving the increase in energy consumption.

Figure 31: Responses to "Did your old Refrigerator / Freezer get hauled away, or is it still running somewhere in your house, basement, or garage?"





### 5.2.5 Change in Number of People in Home

Several questions were also asked about the number of people living in the home, as occupancy is a key determinant of energy use, and increases in occupancy could be an important cause of increased energy use. Based on the survey responses, the average household surveyed had 3.2 people living in their home at the time of the interview. Figure 32 displays the number of people in each household by utility. Aside from SCE respondents, most homes are occupied by one or two people.

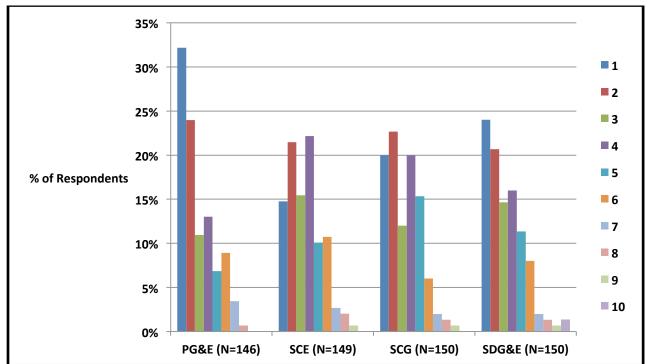
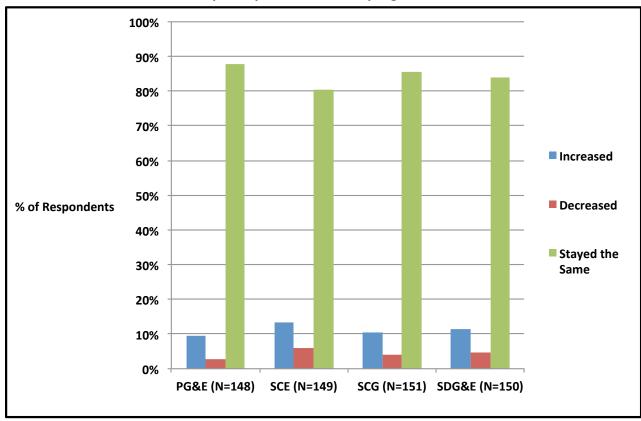


Figure 32: Responses to "How many people currently live in your home?"

Respondents were asked if the number of people living in their homes had changed since participating in the ESA Program. As shown in Figure 33, the majority of participants stated that the number of people in their home had stayed the same (85 percent), while only about 10 percent indicated that the number of people living in the home had increased.



Figure 33: Responses to "Has the number of people living in your home changed since you participated in the ESA program?"



Of those respondents who stated there was a change in the number of people living in their homes, over 85 percent said the change was by only one or two people. Note that of those who stated a change (16 percent of the entire survey sample), 72 percent said they had an increase in the number of people in the household and 28 percent said the number had decreased. See Figure 34 for additional detail by utility.



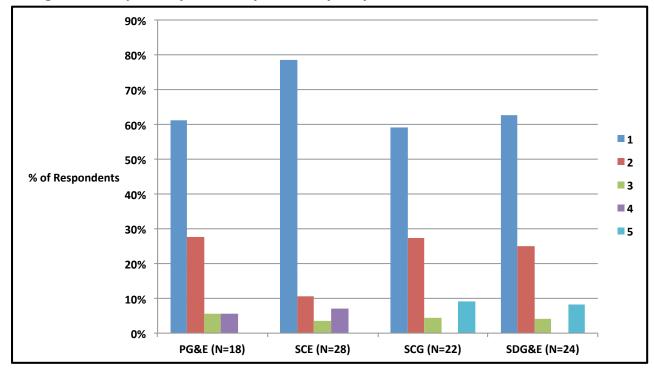


Figure 34: Response by IOU to "By how many did your household increase/decrease?"

Respondents were asked if the number of people who stay home during the day had changed, as this can have a significant impact on energy use. Most respondents indicated that the number home during the day had either stayed the same (86 percent) or decreased (4 percent). For the 10 percent of the survey sample that said there was an increase in the number of people at home during the day, most said the change was only by one or two people. Figure 35 and Figure 36 illustrate these responses.



Figure 35: Response by IOU to "Has the number of people that stay at home during the day changed since you participated in the ESA Program?"

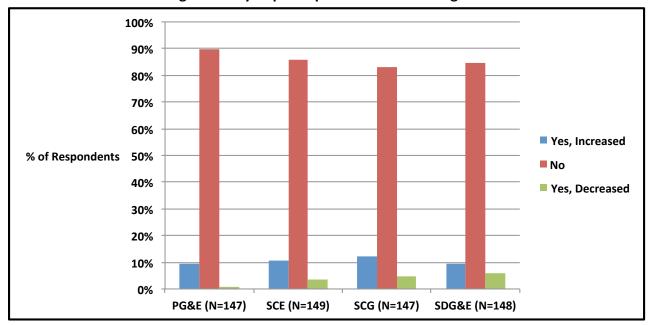
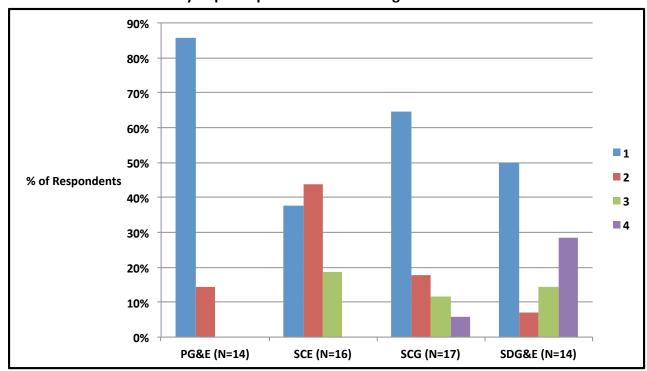


Figure 36: Response by IOU to "How many more people stay at home during the day since you participated in the ESA Program?"





# **5.3** Phone Survey Results Summary

Despite covering all of the topics that would reasonably be expected to contribute to an increase in energy use, the survey was unable to identify a clear driver for increased energy use. General findings from the phone survey include the following:

- Respondents indicate that there is generally no increase in the amount of cooling in their homes. About 92 percent indicated that there was no change in how much they cooled their home (or that they cooled their home less) after they participated in the program.
- Similarly, respondents indicated that there was no increase in how much they heated their home. When asked the same question regarding heating, 91 percent of respondents indicated that there was no change in how much they heated their home (or that they heated their home less) since they participated in the program.
- **Increases in heating or cooling attributed to weather.** For the small fraction of respondents that indicated they increased their heating or cooling, the most common reason given was due to weather (50 percent for hotter weather, 44 percent for colder weather). Note that weather is the one factor that we can control for in the billing regression model. The remaining responses were distributed across multiple reasons, with no clear trends apparent.
- Vast majority of respondents pay their own utility bills. Most of the respondents own their home, and among the remaining renters 95 percent pay their own utility bills. This indicates that having the landlord (rather than the tenants) paying the utility bills is unlikely to be a cause of the increased energy use.
- Heating and cooling measures obtained through the ESA Program do not seem to be contributing to increased energy use. Of the small subsample that indicated an increase in heating or cooling use, only a small fraction of this group received heating and cooling measures through the program. Given these small numbers, it does not appear that increased use of measures obtained through the ESA Program is a significant factor in the increase in energy use observed in the post participation period.
- Additional appliances added to homes, but unlikely to be a significant driver in increased energy use based on the types of appliances added. The majority of respondents (72 percent) indicated that they had added at least one new appliance to their household, although some of these were installed through the program and therefore would be expected to save energy (assuming that they were replacing a functioning existing unit). The most commonly cited appliance addition was a new TV that replaced an existing TV (37 percent). Other frequently mentioned appliances included refrigerators (25 percent), clothes washers (20 percent), computer (17 percent), and water heater (16 percent). Given that these measures are likely replacing existing measures that presumably are less efficient, it is unlikely that the new appliance purchases can explain the increased energy use observed in these homes.
- Little change in occupancy among surveyed homes. Across utilities, only 11 percent of respondents indicated that the number of people in the household had increased since participating in the program. Among these households, the majority (66 percent) only had one additional person staying in their home, and 22 percent had two additional people. Similar responses were observed for questions relating to changes in how many people remained home during the day. The low occurrence of additional people suggests that this is unlikely a significant factor in the increase in energy use observed for the ESA participant population.



The overall conclusion to be drawn from the survey results (and the examination of energy use trends discussed earlier) is somewhat disappointing; households often appear to be using more energy after participating in the ESA program, but it is unclear why this increase is occurring. While respondents indicate that increases to heating and cooling use are due to changes in weather, the fact that usage has increased even when weather has been accounted for (e.g., usage for the survey sample is examined on a per-CDD and per-HDD basis to take into account changes in temperature) indicates that something else is occurring that drives energy consumption.



# **6** Conclusions and Recommendations

Based on the ESA Program impact evaluation for PY2011, the evaluation team offers the following analysis conclusions and recommendations.

#### **6.1 Conclusions**

General conclusions that can be drawn from the impact analysis results include the following.

Savings from the ESA Program measures is a small fraction of overall household energy consumption. Savings from the ESA program on average ranges from three to nine percent of overall energy consumption. This low level of savings makes developing savings estimates (particularly at the measure level) particularly challenging. These challenges are compounded by the wide array of external factors that can influence energy use. As discussed throughout the report, the small amount of program savings is sometimes overwhelmed by these other non-program factors in the billing regression and result in estimates of no savings or increased energy use for some measures.

The final impact estimates are generally consistent with the *ex ante* savings values. The final recommended impact values for both electric and gas measures resulted in total household savings that were fairly close to the original *ex ante* savings values. For electricity, household realization rates ranged from 80 to 110 percent of *ex ante* savings. For gas, realization rates ranged from 92 to 119 percent. Note that this consistency with the *ex ante* values is due in part to how the final impact numbers were assigned from either the regression models or *ex ante* values. Since the *ex ante* values were used as the final impact estimates in cases where the regression models did not produce a reliable estimate, the potential for differences with the *ex ante* values was naturally reduced.

The impact estimates deviate from the previous evaluation and from DEER values. For electric measures, estimated savings in the current evaluation are lower than estimates from PY2009, while gas estimates in the current evaluation are significantly higher. In the case of the gas savings, this may be due to significantly more heating degree days in the current evaluation relative to the last. The current impact estimates are within the range of those observed in previous evaluations going back to 2001, however, as there is substantial variation in household savings estimates over the years. The current evaluation estimates were also different from DEER values for the same measures, although no trend of being consistently higher or lower than DEER at the measure level was observed.

Impact estimates will naturally vary across years due to a variety of factors. Differences across customer groups in terms of energy use, geographic location, measure mix, demographics, economic situation, and condition of the home will all lead to differences in impact estimates for the ESA Program. We should not expect these estimates to be the same across time or across service territories due to the large number of potential influencing factors. In the current evaluation, differences from the prior evaluation may also be due to the utilization of a different regression model and data screening process. While identifying these influencing factors is straightforward, determining the relative importance of each of these factors on the change in savings values between years is not possible without significantly more evaluation resources being devoted to making a detailed comparison of participation patterns between years. Given that the primary objective of this impact evaluation is to develop savings estimates for the current program year, this more detailed analysis was not attempted beyond the comparisons presented earlier in this report.



#### A significant number of ESA Program households are using more energy after participation.

Despite the new measures and energy education received through the program, a significant number of households were found to be consuming more energy after program participation. For electricity, more than half all of all participants exhibited weather-normalized increases in energy use during either heating or cooling periods. Similarly, approximately 60 percent of gas participants increased their gas consumption in the post-participation period. Because this increase appears to be independent of weather, it is especially challenging to address in the billing regression and may lead to biased impact estimates. The phone survey did not provide any additional information as to what might be causing this increase in energy use. Since the vast majority of participants were already on the CARE rate prior to ESA enrollment, it is unlikely that the lower CARE rate is a factor in increased energy use for the time period examined.

Whole house impacts estimated from the household-level regression models produced lower estimates. The results from the Whole House fixed effects models that estimate total savings (rather than savings for individual measures) produced generally lower house-level savings values than simply aggregating up the measure-level savings from the Basic and Measure Models. This is due in part to the ability with the Basic/Measure models to remove impact estimates showing an increase in energy use and replacing them with the *ex ante* values, which by definition will increase the overall savings estimate. Since measure-level detail is not available in the Whole House model, it is not possible to make these post-model adjustments.

While it was hoped that having a whole house variable for savings would help address the possibility of collinearity among the measure variables, this advantage appears to have been outweighed by a lower ability to disentangle the program effects from other factors influencing energy consumption. This is particularly challenging given the number of homes observed to have an increase in energy use in the post-participation period (particularly with PG&E). Given this context, it is not surprising that the Whole House model (which utilizes less program information) produces lower savings estimates than the Basic Model that utilizes more information on what was installed through the program.

Customers may be unaware that they are using more energy. The phone survey targeting households with increased energy use did not provide any clear answers on what might be driving the increased consumption. Respondents generally reported that they were using their heating and cooling systems about the same as they did prior to participation. For those that said they used the systems more, the most common reason for using heating and cooling systems more had to do with changes in weather (e.g., hotter or cooler weather). As shown in the analysis of weather-normalized energy use, changes in weather are not sufficient to explain all of the increase in usage. Other factors, such as having more people home during the day, did not appear to be a significant factor in explaining increased use. While participants have been adding new appliances to their homes, these appear mostly to be replacing older units and therefore should be using less energy. These findings raise the possibility that – despite the new measures and energy education – consumers are using more energy and (perhaps more importantly) they are unaware that they are consuming more energy. The issue of whether they were truly unaware was not explored directly in the phone survey, however.

#### **6.2 Recommendations**

From the evaluation conclusions, we offer the following recommendations for the ESA Program.



**Continue using billing regression to estimate program impacts.** Despite some of the challenges discussed in this report, we recommend that the fixed effects billing regression model continue to be used to estimate impacts for the ESA Program using data from the participant population. The fixed effects model provides a means for producing statistically reliable and unbiased estimates of savings that account for both differences across households and time periods.

For future impact evaluations utilizing a billing regression, developing multiple model specifications provides more flexibility. If billing regression is to be used in future ESA Program evaluations, we recommend an approach that combines results from the Basic and Measure Model specifications presented here. While this does rely on evaluator judgment to make some impact assignments, the approach is ultimately more flexible than relying on the results of a single model. In the current evaluation, having multiple models resulted in impact estimates for some measures that could not have been provided using the Basic Model alone.

If variations in impact estimates over time are not acceptable, consider using DEER deemed values to estimate savings. The wide swings in savings estimates – both across utilities and evaluation time periods – has raised concern among some reviewers. Possible reasons for these discrepancies have been discussed in the last two impact evaluations, and variations will continue in the future. It is also stressed again here that the exact cause of these differences will likely remain unknowable without an enormous data collection effort that collects statistically representative data on home and customer demographics within each utility service territory by housing type, climate zone, and possibly additional household characteristics such as family size and home vintage. Short of a massive data collection effort, the root causes of energy savings variation across utilities and program years will likely remain unknowable.

As argued in this report, we do not believe that the variation in savings estimates is necessarily a bad thing. Nevertheless, if more consistency in the impact estimates is desired, then using deemed savings values from DEER in place of a billing regression should be considered. This deemed approach will reduce uncertainty with respect to savings estimates across utilities within a program year, as well as produce more stable savings estimates across program years. Using DEER, however, does not allow for the possibility that the low-income population is significantly different in terms of energy savings relative to the general population. While testing this theory is beyond the scope of this project, it may be worth reducing the uncertainty in savings estimates by using DEER even if that database is not an entirely accurate representation of the savings achieved in the low-income sector.

Weather variables should be calculated using hourly (rather than daily) temperature data. The calculations of CDD and HDD using hourly temperature data allow for a more accurate representation of days that heating or cooling equipment might be used. In this evaluation, the hourly method resulted in significantly more cooling degree days and only slightly more heating degree days then the traditional daily method. Given that the hourly method is more accurate and easy to calculate, we recommend that it be used for future impact evaluations of the ESA Program.

Allow more time for the impact evaluation. The time allocated for this evaluation was very short (six months), with a research plan finalized on March 18 and a final report produced by August 31. The previous impact evaluation, by comparison, required 20 months to complete. While the impact evaluation was completed in the time allotted, this was accomplished by having a very focused approach that did not allow for exploring additional research questions when they arose. For example, more time might have allowed for additional analysis of the survey data, or even a short



follow up survey to explore other aspects of energy use that might have shed more light on increased energy consumption. Similarly, there was not enough time to conduct a more in-depth comparison of the impact estimates between the 2009 and 2011 evaluations to determine how changes in participation patterns, measure mix, and weather might have contributed to differences in impact estimates between the two years. Adding three to six months to the impact evaluation timeline would allow for a more in-depth and flexible approach that provides more insights into the ESA Program savings estimates.

Conduct a more rigorous analysis of participation patterns across evaluation years. As mentioned above, the current evaluation did not have enough time to conduct a rigorous comparison of participation patterns between PY2009 and PY2011. While this evaluation did provide some information on weather conditions and participation across climate zones between the two evaluation years, the primary focus was in developing defensible savings estimates for the current evaluation year. Additional analysis on changes in participation patterns in terms of measure mix, housing type, energy use, weather conditions, and geographic distribution would likely provide additional insights as to the factors driving the variation in savings estimates across program years. We recommend additional time and budget be allocated for this analysis in the next ESA Program impact evaluation.

Continue with current evaluation cycle timing. The last several impact evaluations have focused on a single program year and have occurred every 2-3 years, and we recommend that this cycle continue in future years. Given that the savings levels will change regularly due to weather, measure mix, and participant characteristics, the evaluation should also be conducted at regular intervals in order to reflect this variation. This is especially important when the impact evaluation results are used to set the *ex ante* savings values for future program years. If impact evaluations are done less often, or are done for multiple evaluation years combined, then some of the inherent variability will be lost due to the timing and structure of the impact evaluation. This may result in less accurate impact estimates moving forward, particularly if the market is shifting and the programs are locked in to using fixed impact estimates for a longer period of time until a new impact evaluation can be completed. Having the evaluations done more often (instead of every five years, as has been suggested) will provide flexibility to adjust the energy savings estimates as needed to reflect changing demographics and market conditions.

**Remember lessons from previous evaluations.** Finally, a couple of issues were raised by reviewers relating to analysis methods that were explored in the previous impact evaluation. These are methods that were recommended by reviewers of this current report as possible methods to use in the future:

• Billing regression using additional survey data. A common approach for obtaining additional customer information for use in a billing model is to conduct a phone survey of program participants that asks detailed questions about their home and factors that may have changed since participating in the program. This approach was used in the PY2009 ESA impact evaluation but did not yield useful impact results. While in theory it might be valuable to have survey data that provides additional explanatory variables in the billing regression, in practice this did not result in an improved billing model in the PY2009 evaluation.

Consequently, we do not recommend this approach for the billing regression in future evaluations and instead recommend that the billing models rely on the ESA participant population.



- **Billing regression using on-site data.** Customer on-sites can be used to collect additional information on home characteristics that can be used as additional variables in a billing regression model. This method was also used in the PY2009 impact evaluation and did not provide credible impact estimates. The on-sites are also expensive to conduct, especially if a large enough sample is needed to be representative for a billing regression. We also do not recommend conducting on-sites in future ESA Program evaluation if their primary purpose is to collect data to support a billing regression. The on-sites may be useful for other purposes, however, such as providing additional information on baseline conditions, customer attitudes toward efficiency and energy use, whether or not installed equipment is being used properly, and other factors that affect energy consumption.
- Billing regression using a control group of non-participants. The PY2009 evaluation also developed a billing regression that utilized a control group of low-income non-participants, where the PY2010 participants were used as a non-participant control group for PY2009. The theory underlying this method is that the control group customers will have similar patterns of energy use as participants and therefore will control for external events such as economic conditions within the model.<sup>35</sup> Selecting a well-matched control group is challenging at best, however, and particularly difficult in the low-income population given the variability across program years. Using the control group did not produce useful billing regression results in the previous evaluation, and we are not optimistic that these challenges can be overcome in future evaluations without significantly more resources being devoted to identifying an appropriate control group. Despite these concerns, future evaluations may want to explore the potential benefits of using a control group if there is a way to ensure that the control group matches the participant population on key demographic variables (e.g., home type, energy use, geographic location, vintage, etc.). Exploring the use of several alternative control groups in the billing regression may also prove useful, as this was not attempted in the previous impact evaluation.

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<sup>&</sup>lt;sup>35</sup> The control group also helps account for free ridership in the model, which is less of a concern with the low-income population where free ridership rates are likely very low.



# 7 Appendices

The report appendices (provided as a separate volume) include the following:

Appendix A: Phone Survey Instruments

Appendix B: Complete Phone Survey Result Tabulations (by IOU)

Appendix C: Detailed Regression Model Results

Appendix D: Detailed Impact Estimate Tables