Shedding a Cool New Light on a Heated Topic: Verifying Interactive Effects for Retail Lighting Retrofit Participants Using Monthly and AMI Bills

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ABSTRACT

Lighting interactive effects refer to the indirect effect on HVAC energy usage due to the installation of energy efficient lighting measures. The decline in heat emitted from high efficiency lighting may lead to an increase in heating requirements and a decrease in cooling requirements. For utilities where lighting interactive effects are applied, the potential increased heating requirements can result in significant reductions in gas energy efficiency savings leading to difficulty meeting gas goals. There have been few empirical analyses designed to directly measure lighting interactive effects and the findings have been inconclusive. Previous attempts to analyze the existence and size of interactive effects have focused on the residential sector.

This paper seeks to determine if interactive effects can be observed and reliably quantified in the non-residential sector using measure installation information, engineering estimates of interactive effects, and monthly and advanced metering infrastructure (AMI) billing data. This research focuses on small and medium sized retail business that participated in extensive lighting retrofits. In the retail segment, lighting usage forms a relatively high proportion of electric consumption, which increases the likelihood of observing the direct impact of lighting retrofits in electric consumption and the indirect interactive effects on electric and gas consumption. This research adds to our understanding of interactive effects by expanding the limited empirical analyses and extending the analyses to the non-residential sector. The findings from this paper are informative for all lighting retrofit program administrators as well as any utility currently implementing or considering implementing gas efficiency savings reductions due to interactive effects.

Introduction

This study was developed to determine if interactive effects can be observed and reliably quantified in the non-residential sector using measure installation information, engineering estimates of interactive effects, and monthly and advanced metering infrastructure (AMI) billing data. High efficiency lighting measures transform a larger share of energy into light, emitting substantially less heat than inefficient lighting measures. The decline in heat emitted from these lighting measures may lead to an increase in the heating usage and a decrease in the building's cooling usage. These impacts will be referred to as lighting interactive effects (IE).

This work was commissioned by the California Public Utility Commission (CPUC) and focused on California retail customers having participated in a downstream high efficiency lighting retrofit in the years 2011-2013. Prior methods used to identify and quantify IE include building simulation, engineering spreadsheet analysis, field measurement, and utility billing analysis modeling (CPUC 2012; Sezgen 1998; NPCC 2011; Parekh et al. 2005; Brunner et al. 2010). This study used utility billing analysis modeling and expanded upon the previous billing analysis by extending to the non-residential sector and using building simulation results to estimate IE. This approach has the advantage of using these simulation results as well as information from actual participants, but has the challenge of identifying a relatively small impact within noisy data.

This paper attempts to respond to three main questions. First, for which end-use impacts in the retail sector is a billing analysis approach appropriate? Second, in the cases where it is appropriate, were the impacts reliably observed? Lastly, when observed, what was the magnitude of the impacts?

Data Sources

We relied mainly on four[1] different sources of data to perform the study. The first and most crucial source was that of the CPUC Energy Efficiency (EE) program tracking data from 2010-2014. These data include ex-ante[2] and ex-post[3] impact savings values, installation dates, some customer characteristics and additional data.

Weather data files containing hourly temperature reads for 20 weather stations across California were the second main data source used in this study. These data were obtained through Schneider Electric. The hourly temperatures were used to calculate daily heating and cooling degree days (HDD and CDD) by weather station from January 2009 through December 2014.

The third data source of interest was participant consumption data. As part of the 2010-2012 and 2013-2015 CPUC impact evaluations, Itron manages the non-residential data including monthly bills and the aforementioned program tracking data. Monthly bills contain records with customer-level consumption for a provided number of days ending on a given meter read date. The number of days is typically near 30, but this and the day of the month of the read date can vary substantially from customer-to-customer and month-to-month. These data are calendarized to create consistent calendar months for a billing analysis. Itron also requested AMI data from each utility, which allowed us to develop monthly billing series more reliably. However, limited availability of interval data made it necessary to make use of both the AMI and monthly bills in the analysis.

The final data source was interactive effects from building simulation results and corresponding population weights. These were provided to Itron by the CPUC Ex-Ante team. IE factors were developed from these data, separately, for gas heating units, units providing air conditioning and units with only electric heating. These HVAC specific factors were applied to the direct lighting savings to calculate customer specific interactive effects for gas heating, electric heating and air-conditioning.

Population Development

The results presented in this paper are based on several groups of electric and gas sites. The purpose of the discussion below is to explain how we arrived at the various analysis populations and characterize them in terms of attributes relevant to the analysis.

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[1] This study also made use of utility Customer Information Systems (CIS) data.
[2] Estimates of expected measure implementation savings used for program planning and contracting purposes.
[3] Impact evaluation estimates of actual energy savings that can be documented after measure implementation.

Initial Population

We started the site identification process using the high efficiency (HE) lighting retrofit participants in the four investor owned utilities in California – Pacific Gas & Electric (PG&E), Southern California Edison (SCE), Southern California Gas Company (SCG) and San Diego Gas & Electric (SDG&E) – from the program tracking data. The definition of HE lighting for this analysis was restricted to the general measures: indoor CFLs, indoor LEDs and indoor linear fluorescents. Sites were allowed to have installed multiple HE lighting measures in 2011-2013, but were removed from consideration if non-HE lighting measures were installed during the years 2010-2014 or if HE lighting measures were installed in 2010 or 2014.

The definition of a retail site uses the Database for Energy Efficient Resources (DEER) building type from program tracking data and the North American Industry Classification System (NAICS) code provided in CIS. Size definitions for small to medium were defined by the restriction that a site must have had less than 1.75 GWh of usage and an annual maximum demand of less than 500 kW. The application of each criterion listed above and the associated site counts are listed in Table 1 below.

Table 1. Identification of Initial Population from Program Tracking Data

	PG&E	SCE	SDG&E	ALL
Non-Res 2010-2014 EE Participants	169,527	124,961	22,706	317,194
Which Installed Lighting During 2011-2013	18,690	62,188	9,517	90,395
Which Installed Nothing Else	4,843	15,950	2,995	23,788
Which are Retail Establishments	1,983	3,899	1,790	7,672
Which have data and are Small - Medium	1,969	3,866	1,772	7,607
Electricity				
Which have electricity billing data	1,569	3,125	1,545	6,239
Gas				
Which have natural gas account(s)	1,021	1,097[4]	576	2,694
Which have natural gas billing data	1,012	844[5]	574	2,430

One of the main aspects of this study differentiating itself from prior studies is the use of non-residential participants. Indoor linear fluorescent measures are much more common in the non-residential sector. Table 2 below demonstrates by utility how the 6,239 electric sites' participation is distributed amongst the three measure types allowed in the study.

[4] The count of SCE sites identified with having natural gas accounts was a result of a merge between SCE sites and SCG sites as noted below.
[5] Natural gas billing data for SCE sites were provided by SCG for those accounts requested by Itron. In many cases, data were not provided for accounts requested.

Table 2. Initial Population Distribution amongst Measure Types Installed

Utility	CFLs Only	LEDs Only	CFLs and LEDs	Linears Only	CFLs and Linears	LEDs and Linears	All HE Lighting Measures
PG&E	4%	24%	1%	53%	13%	3%	2%
SCE	1%	15%	1%	36%	18%	25%	5%
SDG&E	2%	7%	0%	47%	35%	6%	4%
ALL	2%	15%	1%	43%	21%	15%	4%

We see that the vast majority of sites installed some type of linear fluorescent measure and, in fact, around 40% of sites installed only linear fluorescent measures.

Another aspect of a non-residential study that differentiates it from a residential study is the definition of a site. In contrast to single family homes in the residential sector, the notion of a site is not as clear for the non-residential population. For the purposes of this paper, a site is most accurately defined as a best estimate of a self-contained portion of a structure or structures having a similar business activity with a single energy use decision maker. With this definition a retail site is most often a single unit within a building housing multiple units with varying business activities or a stand-alone retail establishment owned or rented by the energy consumption and equipment manager. A single site typically contains multiple accounts.

Data Attrition

Having identified a population of participants appropriate for the study, the next step was to collect and compile the data necessary to conduct the analysis. Numerous data anomalies were identified during this process that led to the removal of participants from the initial population, which is referred to as data attrition. The process of participant attrition from the analysis dataset was carefully considered and reviewed to ensure that no bias was introduced to the analysis.

It is critical that each participant in the study have sufficient billing data in both the pre- and post-install periods to model the impacts. Considering the constrained number of participants, a threshold of 10 months was applied. Given this threshold and the importance of seasonality on HVAC usage, a minimum number of calendar months and billing days in the winter and summer periods was required.

Anomalies such as missing or excessively low values for consumption, large gaps between the end date of one bill record and the start date of the next, or extreme variation in consumption during the analysis period were considered. However, no minimum bill usage amount was set for natural gas due to the nature of its use in the summer months. For each site the coefficient of variance of monthly bills was required to be below 100 for electricity and 200 for natural gas consumption.

Sites were removed if they had savings values considered to be statistical outliers. The statistic in question is the ratio of ex-ante impacts to consumption. Thresholds were set at 75% for direct lighting savings and 35% for other IE effects. Each of these thresholds was set after reviewing the quartiles of these ratios.

Myriad issues arise when attempting to group accounts. Sites were removed if it appeared as though an account that should have been grouped with the site was not. In a mirroring fashion, sites were removed if accounts were grouped together that should not have been. Additionally, sites were removed if the building type of certain accounts grouped in the site did not use energy in a way consistent with a retail establishment. Lastly, sites were removed from the analysis population because the number of active accounts adding consumption to the site in the pre- versus post-install period varied drastically.

Impact Specific Populations

A key step in establishing the analysis populations was identifying participants appropriate for modeling the different effects. It does not make sense to either include a site without air conditioning in the electric model or to apply that particular interactive effect. Unfortunately, it is not always obvious when a participant has air conditioning, electric heating, or gas heating.

As a means of identifying which participants should be associated with the different heating and cooling effects, Itron relied on an analysis of the partial correlations[6] between usage and HDD/CDD. The criteria for each population is listed below:

- AC: positive correlation between *kWh* and CDD and a p-value of at least 10%.
- Elec. heating: positive correlation between *kWh* and HDD and a p-value of at least 10%.
- Gas heating: positive correlation between *thm* and HDD with a p-value of at least 10%.

Data Attrition Summary

Below, we review the effect of the attrition rules discussed above on the populations for natural gas and electricity and then how the application of the end use specific criteria affects each. Table 3 summarizes the number of natural gas sites lost due to each attrition criteria.

Table 3. Natural Gas Population Attrition and Final Population Counts by Utility

	PG&E	SCE	SDG&E	ALL
Initial Gas Population	1,012	844	574	2,430
Sites w/ Insufficient Usage Data	-99	-219	-147	-465
Sites w/ Billing Data Anomalies	-305	-184	-160	-649
Sites w/ Impact Data Anomalies	-198	-30	-62	-290
Sites w/ Site Aggregation Issues	-77	-11	-68	-156
Final Gas Population	333	400	137	870

We see that insufficient billing data and billing data anomalies led to the removal of the largest number of sites. It is worth noting, however, the relatively large number of sites eliminated due to impact data anomalies in the natural gas population for PG&E.

Table 4 below summarizes the overall loss due to attrition from the natural gas population. Also, Table 4 shows the final number of sites determined to have gas heating, using the criterion mentioned above, and how these numbers compare to the number of sites in the natural gas population after attrition.

[6] A partial correlation means the relationship between two variables when controlling for the influence of a third. In this case, the third variable was HDD when looking at the correlation of CDD and usage and CDD when looking at the correlation of HDD and usage.

Table 4. Natural Gas End Use Specific Population and Percent of Appropriate Population

Utility	Initial	Natural Gas	% after Attrition	Gas Heating	% with Gas Heating
PG&E	1,012	333	33%	322	97%
SCE	844	400	47%	333	83%
SDG&E	574	137	24%	109	80%
ALL	2,430	870	36%	764	88%

Moving forward these 764 sites in the column headed "Gas Heating" will be referred to as the gas heating population.

In Table 5, we review the attrition criteria effects on the electricity population. Here we see significant losses due to each criterion. Specifically, we note the large loss due to site aggregation issues. This was mainly due to the number of electricity accounts typically associated with a site and difficulty of maintaining reliable data for each of them.

Table 5. Electricity Population Attrition and Final Population Counts

	PG&E	SCE	SDG&E	ALL
Initial Electricity Population	1,569	3,125	1,545	6,239
Sites w/ Insufficient Usage Data	-69	-569	-88	-726
Sites w/ Billing Data Anomalies	-293	-214	-105	-612
Sites w/ Impact Data Anomalies	-238	-187	-115	-540
Sites w/ Site Aggregation Issues	-233	-475	-347	-1,055
Final Electricity Population	736	1,680	890	3,306

Table 6 below summarizes the overall loss due to attrition from the electric population. Also, Table 6 shows the final number of sites determined to have each of the IE end uses and how these numbers compare to the number of sites in the lighting population after attrition.

Table 6. Electricity Impact Population Counts and Percent of Parent Population

Utility	Initial Population	Lighting Population	Percent After Attr.	AC	Percent w/ AC	Elec. Heating	Percent w/ Heating
PG&E	1,569	736	47%	382	52%	230	31%
SCE	3,125	1,680	54%	1,032	61%	383	23%
SDG&E	1,545	890	58%	429	48%	238	27%
ALL	6,239	3,306	53%	1,843	56%	851	26%

The site counts summarized in this table will hence forth be referred to by their column headings. For example, the 1,843 sites counted in the column entitled "AC" will be called the AC population.

Since the IE factor used to calculate gas heating IE is applied to direct lighting savings, it was important to be able to model the direct lighting savings and gas heating IE for the same population. This population contains exactly the 488 sites in both the 3,306 sites from the lighting population and the 764 sites from the gas heating population. The breakdown by utility of each final analysis population is provided in Table 7.

Table 7. Final Impact Specific Analysis Population Counts

Utility	Lighting Population	AC Population	Electric Heating	Gas Heating Population	Direct Comparison
PG&E	736	382	230	322	229
SCE	1,680	1,032	383	333	188
SDG&E	890	429	238	109	71
ALL	3,306	1,843	851	764	488

Population Characteristics

The average consumption, the average effects of weather, and the average impact of savings or increases in consumption each have a fairly large effect on the billing analysis method. These characteristics and their differences in the pre- and post-install period are summarized for the model populations below.

Table 8 lists the annual average electricity usage and degree day variables in the pre- and post-install periods. This gives a view of the amount of energy consumed in each population, the amount of weather effect expected and whether or not these factors were drastically different before and after the measures were installed.

Table 8. Pre- and Post-Install Annual Consumption and Degree Days for Electric Populations

Model Population	Sites	Average Pre kWh	Average Post kWh	Average Pre CDD	Average Post CDD	Average Pre HDD	Average Post HDD
Lighting	3,306	36,014	32,966	843	1,028	1,664	1,463
Air Conditioning	1,843	38,695	36,253	1,080	1,307	1,651	1,448
Elec Heating	851	21,571	20,068	758	945	1,785	1,566

The rather consistent drop in heating degree days and increase in cooling degree days indicates that the post-install period was on average warmer than the pre-install period. However, on the whole, the pre- and post-install period consumption and degree days are comparable.

Table 9 presents the ex-ante impacts for the electricity population as they compare to consumption. Each of these percentages is the average of the annual ex-ante impact taken as a portion of the pre-install kWh.

Table 9. Ex Ante Electricity Impacts as Percent of Pre-Installation Electricity Consumption

Model Population	# Sites	Average Pre kWh	Ex-Ante Lighting Savings	Ex-Ante IE - AC	Ex-Ante IE - Heat
Lighting	3,306	36,014	13.8%	1.2%	0.2%
AC	1,843	38,695	12.6%	2.1%	0.2%
Electric Heating	851	21,571	17.4%	1.5%	1.3%

The most telling information from Table 9, is the relative ratio of the ex-ante IE for AC and electric heating to pre-install consumption. Even within the overall AC population, the IE from AC accounts for only 2% of consumption making the observation of this effect in a billing analysis very difficult. However, the ex-ante impact of direct lighting is on average around 10-15% of consumption.

Table 10 gives a summary of annual natural gas consumption and heating degree days in the pre- and post-install periods. The data includes the full gas heating population as well as those sites for which both the gas heating and direct lighting models were estimated.

Table 10. Pre- and Post-Install Annual Consumption and Degree Days for Gas Populations

Model Population	# Sites	Average Pre thm	Average Post thm	Average Pre HDD	Average Post HDD
Gas Heating	764	738	706	2,034	1,830
Direct Comparison	488	603	568	2,060	1,837

Heating degree days, by in large, decrease from the pre-install period to the post-install period. There is a decline in average natural gas consumption, though the magnitudes are still comparable across pre- and post-install periods and this is likely due to the decline in HDD.

A similar comparison of annual pre-install natural gas consumption to the average annual ex-ante IE increase is provided in Table 11. The IE of heating is about 5-6% of average consumption. This puts the effect within a range that makes finding reliable model results much more likely than the ex-ante IE electric impact of approximately 1% of consumption.

Table 11. Consumption and Ex Ante IE Gas Impact Natural Gas Population

Model Population	# Sites	Average Annual Pre thm	Average Ex-Ante Annual IE Increase from Gas Heating	Ex-Ante IE from Heat over Pre thm
Gas Heating	764	738	47.3	6.40%
Direct Comparison	488	603	29.0	4.81%

Model Specifications

Both the electric and natural gas analyses were based on a panel data structure where a series of up to 12 months of pre-installation and 12 months of post-installation consumption data (normalized to a 30.4 day month) for each participant is lined up with explanatory variables (weather, calendar variables, and the savings and/or interactive effects). The electric and gas billing models were estimated separately. The billing analysis for each was conducted using a cross-sectional, time-series regression to estimate the impacts of interest. In each case, a fixed effects model was used to address the energy-related characteristics of the business that do not change over time, such as, the size of the business, the business hours of the retail establishment, and the presence of major electric or gas appliances and heating equipment.

Natural Gas Model

We estimated a natural gas model of the following form:

$$thm_{it} = \alpha_i + \gamma_1 \cdot Year_t + \gamma_2 \cdot Month_t + \delta_i(\alpha_i \cdot HDD_{it}) + \beta \cdot IEHtg_{it} + \varepsilon_{it}$$

Where thm_{it} is the monthly gas consumption, measured in *thm*, for site *i* in month *t*, α_i is the fixed effect vector for site *i*, and $Year_t$ and $Month_t$ are time fixed effect vectors for each calendar month and each calendar year.

The variable $IEHtg_{it}$ is the ex-ante estimated increase in gas consumption following the lighting installation. This variable is site-specific and the annual value given by ex-ante estimates is distributed to the 12-month post-period and zero prior to a participant's installation. The impacts are distributed to months using the normalized average HDD, in month *t*, over the past 20 years. HDD_{it} is the heating degree days for site *i* in month *t*, which is interacted with the site-specific fixed effect. Finally, ε_{it} is the random disturbance term to be minimized.

The coefficient of primary interest is β, which represents the average realization rate of the engineering estimated monthly increase in heating usage.

Electricity Model

The general form of the electricity model we estimated was as follows:

$$kWh_{it} = \alpha_i + \gamma_1 \cdot Year_t + \gamma_2 \cdot Month_t + \delta_i(\alpha_i \cdot HDD_{it}) + \phi_i(\alpha_i \cdot CDD_{it}) + \beta_1 \cdot Ltg_{it} + \beta_2 \cdot IEAC_{it} \cdot ACFlg_i + \beta_3 \cdot IEHtg_{it} \cdot HtgFlg_i + \varepsilon_{it}$$

Here, Ltg_{it} is the ex-ante monthly savings directly from lighting, which is zero in the pre-installation period and positive in the post-installation 12 months. This is calculated as the site specific annual direct lighting savings multiplied by a monthly load factor for lighting usage taken from the approved cost-effectiveness calculator for the California utilities.

$IEAC_{it}$ and $IEHtg_{it}$ are the ex-ante indirect monthly impacts on AC and heating usage as a result of installing high efficiency lighting. They are calculated by multiplying site specific annual direct lighting savings by the IE factor for AC/electric heating and distributed to months using a monthly load factor. For AC this factor is taken from the approved cost-effectiveness calculator for the California utilities. For heating the monthly load factor is created using the 20 year monthly average percent of heating degree days. $ACFlg_i$ and $HtgFlg_i$ are binary – 1 or 0 – indicator flags for the AC and electric heating populations.

The β coefficients are of primary interest, as they determine whether or not IE was observable in this billing analysis model. Each is the slope coefficient on the corresponding impact. They represents realization rates on these ex-ante impacts. Since the direct lighting savings variable is positive, β_1 is expected to be negative. Since the indirect AC savings variable is positive and the IE for AC is an additional reduction, β_2 is expected to be negative. Since $IEHtg_{it}$ is positive and the IE from heating is an increase in consumption, β_3 is expected be positive.

Model Specification Variations

In addition to varying which sites and accompanying time periods were included in each model estimation, the model specifications and variable constructions were attempted in multiple manners. We review here four main variations. Each of which was explored in combination with each other, leading to a very large number of permutations.

Different approaches were explored for how to use separately or combine the monthly and AMI data. The AMI data were not regularly available for both the 12-month pre- and post-installation periods necessary for the model. However, these data are more reliable and desirable for use in the model estimation. Models were estimated for calendarized monthly bills and where available calendar AMI data separately. Finally, the "hybrid" approach of creating a single usage series that takes AMI data when available and calendarized monthly data otherwise was used.

The simulation data provided by the CPUC DEER team allowed for the creation of annual estimates of IE for each consumption end use modeled. For modeling purposes, these annual values needed to be distributed amongst the post-period months. This analysis employed two different approaches to develop monthly IE series. The first was to take the annual interactive effects and allocate them to monthly values based on the share of HDD or demand load shapes.[7] The second approach was to use the annual value in the model and interact it with the actual HDD or CDD in the model estimation.

Controlling for participant response to weather is the single most important factor in isolating the savings and/or IEs associated with the installation of lighting measures. This study looked at the multiple approaches for incorporating the effects of weather in the model. The first approach used a single HDD and/or CDD variable in the model specification. Within this approach, we looked at different thresholds for calculating degree days and/or the inclusion of a quadratic term to capture non-linear relationships. Next, we considered separate slopes for HDD and/or CDD. This refers to the interaction of the site specific fixed effect with each degree day variable in the model specification. Lastly, a Princeton Scorekeeping Method (PRISM) was incorporated. This approach uses a single degree day series where the degree day threshold is participant specific. An analysis to determine the HDD/CDD thresholds that have the highest correlation with monthly usage during the pre-installation period was performed to select the site specific threshold.

Every model specification estimated included a fixed effect for the participant, but in addition there were different ways to include fixed effects for time. Three methods were explored in detail. The first and simplest was to include a time fixed effect only for each calendar year. The second was the inclusion of a time fixed effect for each calendar month. The final time fixed effect employed was that of separate fixed effects for the month and the year.

Final Model Selection

The final models for both electricity and gas were modeled statewide. Any stratification would have resulted in too few participants in the models. The final models were based on separate analysis populations for each of the different IE impacts. The basis for this approach was that it would help to isolate the effects in question and reliably estimate the associated parameters.

The usage series was based on a “hybrid” version, where data based on interval data was used when available but was supplemented by calendarized monthly bills when necessary. A large analysis population is highly desirable for this type of study, and using the hybrid series allowed for the inclusion of many more participants. Also, while the usage based on interval data is better, our analysis showed that the calendarized monthly bills were a very good approximation and their conclusion would not jeopardize the analysis.

The representation of all impacts was based on the version where the ex-ante annual values were allocated to calendar months using degree day or DEER end use load shape proportional shares. In addition to generating very similar results to the interacted version, this approach had the advantage of having more easily interpreted parameter estimates.

[7] See the section on Model Specifications for an explanation of this distribution.

Time fixed effects were based on separate effects for year and month as opposed to a strict time series effect based on the year and month combined. This was virtually inconsequential in the model results, but it was determined that the separate year and month effects might do a better job of capturing calendar effects irrespective of the participation date.

Finally, the representation of weather effects was based on separate slope models with a linear degree days series calculated using a base temperature of 65 degrees Fahrenheit. The representation of weather did result in more substantial differences in the model results, so the justification for this approach deserves more scrutiny. The decision to go with participant-specific slopes was based on two key considerations. The first is that at numerous points in this analysis it was abundantly clear that there is substantial variability across participants in the relationship between consumption and temperatures. The second reason is that this approach resulted in more stable and intuitive parameter estimates for the impacts of interest.

Results

The results for the two gas analysis populations are presented in Table 12. The parameter estimates for IE gas heating are positive and statistically significantly different from zero[8] for both groups. Though markedly closer to a realization rate of X%[9] for the subset of directly comparable participants, the result for the full set of gas participants should be considered the more accurate estimate. In addition to the intuitive idea that a larger population produces more reliable results, the standard error of the estimate for this model is much smaller than for the directly comparable participant subset. With respect to the direct lighting savings, the parameter estimate of X is statistically significant and the right sign. Viewed together, these results tell us that for this set of comparable participants, the HE lighting produced roughly half the expected energy savings, which resulted in around X% of the estimated increase in gas heating.

Table 12. Natural Gas Population - Model Estimate Results for IE Gas Heating

		IE - Gas Heating					Direct Lighting Savings				
Analysis Population	# Sites	R^2	Est.	Std. Err	t-Val	Pr > |t|	R^2	Est.	Std. Err	t-Val	Pr > |t|
Gas Heating	764										
Directly Comparable	488										

The results for the electric heating and AC IEs are presented in Table 13 and Table 14. The direct lighting savings are the correct sign and statistically significant, indicating realized lighting savings of around X% and X% for the two analysis populations. With respect to the IEs, however, neither parameter estimate is the correct sign or statistically significant. What these results suggest is that in spite of clear energy savings from HE lighting – though lower than expected – the analysis did not generate any evidence of the expected electric IEs.

[8] For this study, any p-value less than or equal to 0.05 was considered to be statistically significant.
[9] At this stage, results for this study are not publicly available and the client has asked that they be redacted at this point. Results will be final within a few months.

Table 13. Electric Heating Population – Model Estimate Results for IE Electric Heating

			IE - Electric Heating				Direct Lighting Savings			
Analysis Population	# Sites	R^2	Est.	Std. Err	t-Value	Pr > |t|	Est.	Std. Err	t-Value	Pr > |t|
Elec. Heating	851									

Table 14. AC Population – Model Estimate Results for IE AC

			IE - AC				Direct Lighting Savings			
Analysis Population	# Sites	R^2	Est.	Std. Err	t-Value	Pr > |t|	Est.	Std. Err	t-Value	Pr > |t|
AC	1,843									

These results are not altogether surprising in hindsight. Given the small percent of electricity consumption represented by the IE impacts, observing the effects through a billing analysis was unlikely. There is also an important issue with multicollinearity, perhaps due to the likelihood of AC and heating use for general space conditioning within retail establishments.

As a result of the inability to stratify, the basis for consistency is hidden in these results. This basis is found, though, in all the different modeling approaches that were explored during the analysis. For the gas heating IEs, the models generated positive and statistically significant parameter estimates with very high consistency. The only notable difference was that when the single HDD representation of weather was used, substantially higher estimates for the IEs were generated. No other approaches provided drastically differing results. And, further, within a particular approach for weather representation, the estimated effects were very stable. However, for the electric IEs, the models were highly inconsistent both within and across modeling approaches.

Conclusions and Recommendations

At the outset of this study, the stated objective was to estimate the observable interactive effects of lighting retrofits on non-residential energy efficiency program participants. Upon completion, however, proper consideration of the results called for addressing three related but separate questions. First, is the billing analysis approach used for this study an appropriate way of estimating IEs? Second, if the method is appropriate, are the interactive effects statistically significantly different from zero? And third, if so, what are they? This summary of results and findings will revolve around the answers to the questions.

With respect to whether the methods used to estimate the observable interactive effects was appropriate, the answer is both yes and no. While this is unsatisfying, the results revealed clear conditions where the method is likely to succeed or fail. For the gas heating IEs, where the effect sizes are more substantial, this study's results suggest that the methods applied are valid for generating reliable estimates of the IEs. In contrast, for the electric IEs, even after taking many different approaches to isolate a population where the models would more easily identify the effects, the evidence was limited and not as consistent. In general for the electric models, there are likely issues with multicollinearity that make it difficult, if not impossible, for a statistical model of this nature to parse and estimate the separate impacts.

With respect to the gas results, the answer to the question of whether the IEs are statistically significantly different from zero is yes. The gas heating IE results conformed to expectations and were consistently estimated, which is a convenient segue to the final question.

For the gas heating analysis population, the approach was clearly appropriate and the estimated heating IEs were statistically significantly different from zero with a consistency conferring reliability. Given that we believe these results are valid, what do they say about the IEs? The models do not provide IEs per se. Rather, they produce realization rates for the ex-ante IEs. These results are for just small retail establishments and there is no reason to believe they apply equally to other business types. As such, we believe that as strong as the evidence is, these results should be used as impetus to look more closely at the combination of the ex-ante lighting savings and IEs jointly. If the ex-ante lighting savings are higher than they should be – which this study's results suggested – then it could very well be that the estimates in this study are actually consistent with the engineering-based effects.

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