Igniting the Pilot Light: Impact Evaluation Methods for Time-of-Replacement Gas Heating and Water Heating Programs

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ABSTRACT

Throughout the United States, gas utilities offer heating rebate programs to encourage customers to install higher-efficiency units when purchasing new gas heating and water heating equipment. Though many have evaluated these programs, few studies have attempted to estimate savings for time-of-replacement gas heating and water heating measure rebate programs. In November 2010, the NMR Group and the Cadmus Group, Inc. (the NMR Group Team) completed an evaluation that calculated savings for energy-efficient gas heating and water heating measures. Utilizing billing data from participants and comparable nonparticipants, the study used a variety of regression models to determine more accurate and reliable savings estimates for gas efficiency programs targeting the time-of-replacement market. These improved savings estimates for heating and water heating measures currently are being used to analyze program cost-effectiveness and to help guide program design.

Using six primary modeling approaches, the analysis triangulated actual savings results by program measure category: a post, PRISM-like, annual census approach (Model 1); a pre/post, PRISM-like, annual census approach (Model 2); a monthly pre/post approach (Model 3); a PRISM-like, annual participant and nonparticipant modeling approach (Model 4); a monthly participant and nonparticipant modeling approach (Model 5); and a monthly participant and nonparticipant model, utilizing demographic characteristics from customer surveys (Model 6).

This paper presents the study's final results and details the methods used to derive the savings. Additionally, the paper compares results across the examined methods to determine the best modeling approaches for estimating measure-level savings for energy-efficient gas heating and hot water heating measures.

Introduction

The NMR Group Team's study analyzed a rebate program designed to encourage installation of boilers, furnaces, and water heaters. The program's rebates helped customers offset investment costs for high-efficiency heating and water heating equipment. From May 2007 through December 2009, customers purchased 11,984 boilers, 10,185 furnaces, 11,291 water heaters, and 418 combo units through the program.

Focusing on the 2007–2008 program year, the study conducted an impact evaluation using six billing analysis models to estimate savings for each program measure. As each model had notable advantages and disadvantages, model savings results were averaged to obtain a final, per-unit, gross savings estimate.

Methodology

The billing analysis models developed for the impact evaluation examined customers installing gas equipment during 2007–2008, including those installing high-efficiency equipment (participants) and those installing standard-efficiency equipment (nonparticipants). Table 1 presents measures installed through the program and their respective rebate incentive levels.

Table 1. Summary of Evaluated High-Efficiency Gas Heating and Water Heating Measures

Measure Type Summary	Rating	Incentive
Furnaces (forced hot air)	AFUE 92% or greater	$100
Furnaces (forced hot air with ECM)	AFUE 92% or greater	$400
Boilers (forced hot water)	AFUE 90% or greater	$1,000
Boilers (forced hot water)	AFUE 85% or greater	$500
Boilers (steam with electronic ignition)	AFUE 82% or greater	$200
Indirect water heaters (attached to an ENERGY STAR hot water boiler)		$300
On-demand tankless water heaters (with electronic ignition)	EF > 0.82	$300

Data Preparation

The NMR Group Team received participant billing data from multiple utilities as well as additional billing data for nonparticipants (customers installing standard-efficiency equipment through a nearby utility's oil-to-gas conversion program). We matched each billing period's heating degree days (base 65) to the nearest weather station for each home. Given the May 2007 through December 2008 program evaluation period, we defined 2009 as the post period year used in all proposed savings analyses. Though nearly all participants had data for 2009, data for the pre period was very limited: only two utilities could provide more than 24 months of billing data.

Employing automated queries of public assessors' records, we obtained square footage for each home. This allowed us to normalize usage between participants and nonparticipants; thus, modeling approaches comparing participants and nonparticipants would not be limited to survey respondents' small sample sizes. We obtained square footage information for approximately 85% of the homes.

We also collected efficiency ratings and sizes for new equipment installed, based on model numbers available through manufacturers' Websites and other publicly available databases. This information allowed us to develop equipment run-time estimates and to account for equipment heating capacity differences between participant/nonparticipant models.

Modeling

The six billing analysis models used to determine program savings utilized three differing methodologies. Model 1 used the Princeton Scorekeeping Method (PRISM)[1] methodology, which calculated baseline energy consumption for each measure category, and then employed an engineering ratio formula to estimate savings. Models 2 and 3 were pre/post models, based on billing data for all program participants. Models 4 through 6 were participant/nonparticipant models, based on billing data

[1] PRISM uses statistical modeling to obtain weather-normalized usage from billing data, actual weather data, and weather normals. Our SAS modeling method operates much like running PRISM with a heating degree base 65.

for all program participants and nonparticipants. Table 2 summarizes and describes these six models' characteristics.

Table 2. Summary Overview of Models and Data Sources

Model Type Summaries and Descriptions			Description	Participants		Nonparticipants	
				Billing Data	Survey Data	Billing Data	Survey Data
Model 1	Post Only	PRISM	Post only annual PRISM model with engineering ratio adjustment.	Yes	No	Yes	No
Model 2	Pre/Post	PRISM	Pre/Post annual PRISM usage difference model.	Yes	No	No	No
Model 3		Fixed Effects	Pre/Post monthly weather normalization difference model.	Yes	No	No	No
Model 4	Participant vs. Nonparticipant	PRISM	Post only participant/ nonparticipant PRISM-based differences in annual usage.	Yes	No	Yes	No
Model 5		CSA	Post only participant/ nonparticipant pooled conditional savings (CSA) model, based on differences in monthly usage.	Yes	No	Yes	No
Model 6		Enhanced CSA	Model 5, enhanced with survey data on house and behavioral characteristics.	Yes	Yes	Yes	Yes

Model 1's results strongly resembled savings estimated solely based on post usage and an engineering formula. The method, only using post period billing data, did not employ a nonparticipant group; rather, it used a simple engineering ratio method to obtain a proxy of savings. This savings estimate assumed each participant would save energy, and accounted neither for pre/post adjustments nor for a nonparticipant group. Consequently, when calculating a final average gross savings estimate across the various models, we chose not to include Model 1.

Models 2 and 3 allowed development of usage and savings estimates for each of seven program measure categories. Moreover, both pre/post modeling approaches accounted for differences in heating degree days across utilities, and allowed savings to be determined for normalized weather conditions (not limiting the model to only actual weather data, which can be more mild or extreme than 30-year normal, 1971–2000 heating degree day averages, available from the National Climatic Data Center).

Models 4 and 5 used both participant and nonparticipant data. Model 6, an enhanced monthly participant and nonparticipant model, incorporated survey-based household characteristics and behaviors to control for differences between participants and nonparticipants. Models 4, 5, and 6 yielded reliable savings estimates for some (but not all) of the seven measure categories.

Models 2 and 3 utilized an alternate approach for estimating savings with pre and post billing data: savings estimated from replacing an existing system with a new, high-efficiency system were adjusted—based on the new, standard-efficiency baseline rather than actual, replaced efficiency—using a formula. The alternate method estimated efficiencies and sizes for the replaced equipment, with savings directly proportional to the delta of the efficiency and size of the replaced units. This alternate approach allowed a more robust savings analysis and triangulation of savings estimates. However, it also required more than two years of billing data, as one year of pre and one year of post installation data were desirable for each participant. As the tracking system did not contain the efficiencies of replaced units, questions in the installation contractor surveys obtained estimates of ages and efficiencies of replaced systems for each measure group.

PRISM Modeling Methodology Overview. We used the PRISM modeling methodology to weather normalize usage for each participant and nonparticipant, allowing development of total weather-normalized annual consumption (NAC).

Gas usage was weather normalized using a fixed reference temperature PRISM equivalent approach, with a fixed heating reference temperature of 65 degrees Fahrenheit. For this modeling approach, we ran account-level models for both the participant census and nonparticipant census. The model used the specification below, which was analyzed for the post period only in the base methodology (Model 1), and for both pre and post periods in our alternate methodology (Model 2). For each customer i and month t,

$$\boldsymbol{ADC_{it} = \alpha_i + \beta_1 AVGHDD_{it} + \varepsilon_{it}}$$

Where,

- α_i is the intercept for each participant, representing the daily base load (non-heating usage) in the pre or post period (for the standard methodology, only post usage was calculated).
- β_1 is the heating slope in the pre and post period.
- ADC_{it} is average daily therm consumption during the pre or post program period.
- $AVGHDD_{it}$, is average daily heating degree days (base 65) for the pre or post period, based on home location.
- ε_{it} is the error term.

From this model, the weather NAC for the pre or post period was computed as follows:

$$\boldsymbol{NAC_i = \alpha_i * 365.25 + \beta_1 LRHDD_i}$$

Where, for each customer i,

- $LRHDD_i$, is the annual, long-run, normal, 1971–2000 heating degree days (base 65), based on home location.
- $\beta_1 LRHDD_i$, is the annual, weather-sensitive component of NAC (also known as *HEATNAC*). This translated to the total non-base load, space heating or water heating component of usage.

This method used only post-period NAC, while our first proposed alternate method estimated unadjusted savings (*DHEATNAC*) as the difference between pre-period heating consumption (*HEATNAC*) and post-period *HEATNAC*.

Post Only PRISM Model (Model 1). We calculated annual full-load equivalent hours (EFLH) utilizing the PRISM methodology, using the post period, weather-normalized therms and the manufacturers'

rated capacity (determined up by model number). Equipment savings were determined using the following formula:

$$Savings = \frac{(AFUE_{ee} - AFUE_b)}{AFUE_{ee}} \times Capacity \times EFLH = \frac{(AFUE_{ee} - AFUE_b)}{AFUE_{ee}} \times POST\_HEATNAC$$

Where,

- $AFUE_{ee}$ is the energy-efficient equipment's efficiency.
- $AFUE_b$ is the new standard-efficiency baseline.
- *Capacity* is the capacity of the equipment in therms per hour.
- *EFLH* is Equivalent Full Load Hours.

In our approach, *EFLH* was directly calculated by dividing post-heating NAC (temperature dependent NAC - *HEATNAC*) by the input capacity in therms/hour (*Capacity*).

Table 3 summarizes participants' and nonparticipants' general characteristics and usage information. These characteristics generally were quite similar, though, for the furnace group, the square footage of nonparticipant homes was considerably higher than for participants. As expected, participants installing furnaces had smaller homes than participants installing boilers.

Table 3. Equipment Efficiencies, Capacities, and Square Footage Summary

Efficiency, Capacity, and Square Footage Characteristics of Participants and Nonparticipants	**N**	**Average Efficiency**	**Heating Capacity BTU/hr**	**Average Square Footage**
PARTICIPANTS				
Furnaces: AFUE 92% or greater	2,462	92%	82,521	1,914
Furnaces: AFUE 92% or greater with ECM	2,790	95%	84,824	2,005
Boilers: AFUE 90% or greater	3,421	93%	129,507	2,288
Boilers: AFUE 85%-89%	2,128	85%	129,582	2,059
Boilers Steam: AFUE 82% or greater	1,036	82%	141,514	2,086
Indirect water heaters	3,632	91%	NA	2,236
Tankless water heaters: EF>0.82	1,114	82%	NA	2,009
OIL TO GAS CONVERSION NONPARTICIPANTS				
Furnaces: Nonparticipants	199	80%	94,171	2,240
Boilers: Nonparticipants	1,808	80%	129,459	2,114
Boilers Steam: Nonparticipants	974	80%	131,106	2,103

Table 4 summarizes average total and heating post usage, the equipment's input capacity, and equipment run-time hours. Run-times were determined by dividing therm heating usage by the input heating capacity. The nonparticipant run-times were slightly higher.

Table 4. Post Usage and Run-time Summary

Post Usage, Input Capacity, and Run-time Summary for Participants and Nonparticipants	N	Total Usage (Annual Therms)	Heating Usage (Annual Therms)	Input Heating Capacity (BTU/hr)	Input Heating Capacity (Therms/hr)	Heat Run-time (hours)
PARTICIPANTS						
Furnaces: AFUE 92% or greater	2,462	924	776	82,521	0.825	955
Furnaces: AFUE 92% or greater with ECM	2,790	988	824	84,824	0.848	982
Boilers: AFUE 90% or greater	3,421	1,273	1,083	129,507	1.295	851
Boilers: AFUE 85%-89%	2,128	1,216	1,031	129,582	1.296	809
Boilers Steam: AFUE 82% or greater	1,036	1,442	1,276	141,514	1.415	915
Indirect water heaters	3,632	1,001	844	NA		
Tankless water heaters: EF>0.82	1,114	1,195	958	NA		
OIL TO GAS CONVERSION NONPARTICIPANTS						
Furnaces: Nonparticipants	199	1,090	956	94,171	0.942	1,036
Boilers: Nonparticipants	1,808	1,298	1,091	129,459	1.295	854
Boilers Steam: Nonparticipants	974	1,323	1,132	131,106	1.311	874

Table 5 summarizes estimated annual savings from the post only PRISM Model 1 methodology for each program measure category. The formula's savings adjustment factor was:

$$\frac{(AFUE_{ee} - AFUE_{b})}{AFUE_{ee}}$$

Where,

- $AFUE_{ee}$ is efficiency for the energy-efficient equipment.
- $AFUE_{b}$ is the new, standard-efficiency baseline. We multiplied this factor by the NAC to obtain the post only engineering savings estimate.

Table 5. Post Only PRISM Ratio Model 1 Savings Results

Engineering Based Ratio Savings Adjustment Summary	N	Weather-Normalized Heating Post Usage (Therms)	Average Percent Savings Adjustment Factor[2]	Annual Savings Therms
Furnaces: AFUE 92% or greater	2,462	776	16%	134
Furnaces: AFUE 92% or greater with ECM	2,790	824	18%	160
Boilers: AFUE 90% or greater	2,128	1,083	14%	168
Boilers: AFUE 85%-89%	1,808	1,031	6%	72
Boilers Steam: AFUE 82% or greater	1,036	1,091	9%	123
Indirect water heaters	3,632	237	38%	82
Tankless water heaters: EF>0.82	1,114	157	30%	47

[2] Averages of adjustment factors for each measure categories. As these factors were calculated for each participant (each with separate efficiencies), average annual savings could not be directly calculated from the average savings adjustment factor.

Overview of Participant Only Pre/Post Models (Models 2 and 3). As Model 1 estimated annual measure savings only based on post participation participant usage, we ran a PRISM and fixed effects analysis for participants using both pre and post periods. Unfortunately, most utilities could only provide 24 months of billing data, with very little pre period data available. Billing data, however, could be found from January 2008 to December 2009, and the program participation period ranged from May 2007 to December 2008.

In the subset of participant billing analysis, where pre data were available, we selected the period from April 2007 through March 2008 as having the best data quality. Consequently, only participants from April 2008 or later with sufficient pre billing data could be used in the pre/post analysis; remaining participants did not have sufficient billing data. Due to this limited pre period billing data availability, only about 15% of participant accounts could be used in the pre/post analysis.

For Models 2 and 3, the following formula provided adjusted savings above minimum AFUE standards for new equipment (code):

$$\textbf{\textit{Adjusted Savings}} = \frac{\left(\frac{1}{AFUE_b} - \frac{1}{AFUE_{ee}} \right)}{\left(\frac{1}{AFUE_{replaced}} - \frac{1}{AFUE_{ee}} \right)} \times (PRE\_HEATNAC - POST\_HEATNAC)$$

Where,

- *Adjusted Savings* is the adjusted difference between pre and post NAC usage.
- $AFUE_{ee}$ is the efficiency of the energy-efficient equipment.
- $AFUE_b$ is the new, standard-efficiency baseline.
- $AFUE_{replaced}$ is the efficiency of replaced equipment.
- *PRE_HEATNAC* is pre period heating NAC.
- *POST_HEATNAC* is post-period heating NAC.

This adjustment formula discounted savings based on the pre/post difference, as that difference was based on installing new equipment, compared to the existing baseline (which was always lower than the actual minimum efficiency standards). The lower the efficiency of replaced equipment compared to the minimum efficiency standards, the greater the downward adjustment on pre/post savings necessary to obtain the required estimates of savings above minimum efficiency standards.

As the efficiency of replaced equipment was not available from the tracking database, it was estimated from efficiency levels reported in the contractor survey, which asked contractors the base efficiencies for equipment they replaced. This provided a reasonable estimate of how much lower existing equipment efficiency was compared to code efficiency. We averaged survey responses to obtain efficiency level estimates for the replaced equipment.

Table 6 summarizes average ages and average pre-efficiency levels for equipment from the contractor survey, and the corresponding code prevailing at time of purchase. The average pre level estimates were used in the formula above, and applied to Models 2 and 3.

Table 6. Replaced Equipment Efficiency and Age

Replaced and Code Efficiency Levels and Age of Equipment	Average Pre Efficiency	Average Code Efficiency	Average Age of the Equipment
Furnaces: AFUE 92% or greater	72.5%	78%	22
Furnaces: AFUE 92% or greater with ECM	72.5%	78%	22
Boilers: AFUE 90% or greater	72.7%	80%	26
Boilers: AFUE 85% or greater	72.7%	80%	26
Boilers Steam: AFUE 82% or greater	68.6%	75%	36
Indirect water heaters	52.5%	57.5%	12
Tankless water heaters: EF>0.82	52.5%	57.5%	12

Pre/Post PRISM Model (Model 2). For this model, we applied the PRISM methodology from Model 1 when both pre and post period data were available. Unadjusted savings equaled weather-adjusted pre and post differences in consumption. We calculated savings above minimum AFUE standards for new equipment by applying the adjustment formula, based on the average code efficiencies shown in Table 6.

Fixed Effects Model (Model 3). We also used fixed effects models to estimate differences between pre and post as unadjusted savings by measure category. This modeling method used pooled monthly time-series panel billing data, and attempted to correct for differences between pre and post weather as well as differences between participants' usage magnitudes. The fixed effects component was characterized by normalization of variations across the range of participants, accomplished by including a separate intercept for each participant.

We used the following model specification to estimate savings for each separate heating measure for the census of participants:

$$ADC_{it} = \alpha_i + \beta_1 AVGHDD_{it} + \beta_2 POST_t * AVGHDD_{it} + \varepsilon_{it}$$

For the water heating measures, we obtained savings from the following, simpler model, which controlled for differences in pre and post weather, without interacting savings with weather:

$$ADC_{it} = \alpha_i + \beta_1 AVGHDD_{it} + \beta_2 POST_t + \varepsilon_{it}$$

Where, for each customer i and month t,

- α_i is the intercept of each customer i, part of the fixed effects specification.
- ADC_{it} is the average daily therm consumption during the pre and post program periods.
- $AVGHDD_{it}$, is the average daily heating degree days (base 65), based on home location.
- $POST_t$ is a dummy variable of 1 in the post period and 0 otherwise.
- $POST_t * AVGHDD_{it}$ is an interaction of $POST_t$ and $AVGHDD_{it}$.
- β_2 is the average daily therm participant savings per heating degree day for heating measures, or the average daily savings (in the case of the water heating measures).

After obtaining unadjusted pre/post savings from the model, we applied the adjustment factor formula to obtain corrected savings.

PRISM Model (Model 4). Using the PRISM methodology, we developed the following annual model, which combined participants and nonparticipants for each measure group. This model included the square footage of homes and heating capacity of the heating equipment as a means for controlling for differences between participants and the nonparticipants:

$$\boldsymbol{HEATNAC_i = \alpha + \beta_1 PART_i + \beta_2 ANNHDD_i + \beta_3 SQFT_i + \beta_4 HEATCAP_i + \varepsilon_i}$$

Where, for customer i,

- α is the intercept.
- $HEATNAC_i$ is the total annual weather-normalized heating usage derived from the PRISM methodology.
- $PART_i$ is a dummy variable of 1 for participants, and 0 for nonparticipants.
- *ANNHDDi* is the annual normal heating degrees (base 65), based on home location.
- $SQFT_i$ is the home's square footage, based on home location, controlling for differences in square footage between participants and nonparticipants.
- $HEATCAP_i$ is the heating capacity associated with the equipment in BTUs, controlling for differences in heating capacity between participants and nonparticipants.
- β_1 is the annual heating savings associated with the measure.

We estimated this model using only post period annual data. While the model attempted to control for differences between participants and the nonparticipants, some differences occurred that could only be captured through the survey. This method yielded models with large standard errors and unreasonable results when compared to some of the other models.[3] When we compared Model 4 results to the monthly models including survey data (Model 6), results were in line with the other models, with reasonable precision levels only for boilers with 85% efficiency or higher.

CSA Model (Model 5) Specification. We also developed a CSA (conditional savings) model using monthly data for participants and nonparticipants for each measure group. For this modeling method, savings were obtained by comparing participant and nonparticipant post usage, while accounting for square footage and capacity differences between the groups. While pre/post models obtained savings only for participants, the CSA method obtained savings by comparing differences between participants and nonparticipants.

As in Model 4, we controlled for home square footage and heating capacities of heating equipment to control for differences between participants and nonparticipants.

$$\boldsymbol{ADC_{it} = \alpha + \beta_1 PARTHDD_{it} + \beta_2 AVGHDD_{it} + \beta_3 SQFT_i + \beta_4 HEATCAP_i + \varepsilon_{it}}$$

Where, for customer i and month t,

- α is the intercept.

[3] The furnace AFUE 92% model had a statistical precision level of over 60%. In the furnace 92% model with ECM, the survey-based model (Model 6) showed savings were unreliable without including key survey variables corrected for differences between the two groups. For boilers with AFUE 90% or higher, the models had large precision levels over 50%, and a savings estimate very low compared to the other model. For the steam boilers model, savings were negative and not statistically significant.

- ADC_{it} is the average daily therm consumption during the post program period.
- $PARTHDD_{it}$ is an interaction of heating degrees and a participant flag.
- $AVGHDD_{it}$ is the average daily heating degree days (base 65), based on home location.
- $SQFT_i$ is the square footage of the home, included to control for differences in square footage between participants and nonparticipants.
- $HEATCAP_i$ is the heating capacity associated with the equipment in BTUs, included to control for differences in heating capacity between participants and nonparticipants.
- β_1 is the average savings per heating degree associated with the measure installation.

CSA Model with Survey Data (Model 6). For Model 6, we augmented the CSA (conditional savings) monthly methodology from Model 5 by including the survey variables. In each measure category, we included different survey variables useful in controlling for differences between participants and nonparticipants. We estimated the following monthly model specifications using all participants and those nonparticipants installing standard-efficiency measures for each measure group. As in Models 4 and 5, we controlled for home square footage and equipment heating capacities to control for differences between participants and nonparticipants. Additionally, we ran models covering a range of survey variables, including: square footage additions, number of occupants, number of bedrooms, heating setpoints, age of home, number of rooms, number of bathrooms, home type, presence of other natural gas equipment, and use of programmable thermostats.

Due to small participant survey sample sizes, many of these variables had incorrect signs on the coefficients,[4] were collinear with other independent variables included in the model, and did not improve the precision around the savings estimate (suggesting they added no explanatory power).

The analysis yielded the following final model specifications for each measure:

Furnaces AFUE>92%:

$$ADC_{it} = \alpha + \beta_1 PARTHDD_{it} + \beta_2 AVGHDD_{it} + \beta_3 SQFT_i + \beta_4 HEATCAP_i + \beta_5 SF_i + \beta_6 WHNG_i + \varepsilon_{it}$$

Furnaces AFUE>92% with ECM**:**

$$ADC_{it} = \alpha + \beta_1 PARTHDD_{it} + \beta_2 AVGHDD_{it} + \beta_3 SQFT_i + \beta_4 HEATCAP_i + \beta_5 EE_i + \beta_6 BATH_i + \beta_7 WHNG_i + \varepsilon_{it}$$

Hot Water Boilers AFUE>90%**:**

$$ADC_{it} = \alpha + \beta_1 PARTHDD_{it} + \beta_2 AVGHDD_{it} + \beta_3 SQFT_i + \beta_4 HEATCAP_i + \beta_5 SF_i + \varepsilon_{it}$$

Where, for customer i and month t,

- α is the intercept.
- ADC_{it} is the average daily therm consumption during the post program period.
- $PARTHDD_{it}$ is an interaction of heating degrees and a participant flag.
- $AVGHDD_{it}$ is the average daily heating degree days (base 65), based on home location.
- $SQFT_i$ is the home square footage, based on home location, controlling for square footage differences between participants and nonparticipants.
- $HEATCAP_i$ is the input heating capacity associated with the equipment in BTUs, controlling for differences in heating capacity between participants and nonparticipants.
- SF_i is a survey variable of 1 if a detached single-family home, 0 otherwise, controlling for differences between a detached single-family mix of homes between participants and nonparticipants.
- EE_i is a survey variable of 1 if additional energy efficiency actions were taken, 0 otherwise.

[4] For example, negative coefficients on number of occupants or square footage.

- $BATH_i$ is a survey variable representing the number of bathrooms in the home, controlling for differences in the number of bathrooms between participants and nonparticipants.
- $WHNG_i$ is a survey variable of 1 if water heating with natural gas, 0 otherwise, controlling for water heating saturation differences between participants and nonparticipants.
- β_1 is the average savings per heating degree associated with the measure.

Results

Table 7 summarizes savings, 90% relative precision levels, and model sample sizes used for each measure-level model.

Table 7. Model Results Summary

Measure-Level Savings, Model Precision Levels, and Sample Sizes		**1. Post Only PRISM Model Annual Savings (Therms)**	**2. Pre/ Post PRISM Model Annual Savings (Therms)**	**3. Pre/ Post Fixed Effects Model Annual Savings (Therms)**	**Participants vs. Nonparticipants**		
					4. PRISM Model Annual Savings (Therms)	**5. CSA Model Annual Savings (Therms)**	**6. CSA Model with Survey Data Annual Savings (Therms)**
Furnaces: AFUE 92% or greater	Savings	134	116	132		99	125
	Precision	1%	10%	10%		17%	33%
	N	2,462	358	347		2,470	174
Furnaces: AFUE 92% or greater with ECM	Savings	160	131	147			102
	Precision	1%	7%	5%			40%
	N	2,790	686	663			126
Boilers: AFUE 90% or greater	Savings	168	153	182		105	108
	Precision	2%	8%	5%		8%	20%
	N	3421	729	705		3,821	179
Boilers: AFUE 85%-89%	Savings	72	65	64	87		
	Precision	1%	18%	15%	22%		
	N	2,128	162	160	2,547		
Boilers Steam: AFUE 82% or greater	Savings	123	96	122			
	Precision	3%	19%	15%			
	N	1,036	130	122			
Indirect water heaters	Savings	82	70	89	NA	NA	NA
	Precision	3%	27%	36%	NA	NA	NA
	N	3,632	178	177	NA	NA	NA
Tankless water heaters: EF>0.82	Savings	47	82	111	NA	NA	NA
	Precision	3%	12%	16%	NA	NA	NA
	N	1,114	320	261	NA	NA	NA

We averaged the savings results from models presented in Table 7 to obtain the final per-unit gross savings estimate. As noted, results from the Post Only PRISM Model 1 were not included in the average, and only Models 2 through 6 were included in the final savings estimate.

Table 8 shows the final average, estimated, overall program per-unit gross savings. Program-level savings estimates were based on the weighted average of the relative proportions of installations per measure. Estimated gross per-unit savings for the 2007–2008 program years ranged between 72 therms (for boilers with 85% to 89% AFUE) to 137 therms (for boilers with 90% or greater AFUE). When comparing model results to the original deemed savings, model estimates were in line for the boilers and instantaneous water heaters, lower for the furnaces, and higher for the indirect water heaters.

Table 8. Program Savings Summary

Program Savings Measure Level Summary	**Number of Installations**	**Savings per Unit (Therms)**			**Model Savings Range**
		Post Only PRISM Savings	**Average Model Savings**	**Deemed Savings**	**Savings Range**
Furnaces: AFUE 92% or greater	4,491	134	118	211	99–132
Furnaces: AFUE 92% or greater with ECM	3,563	160	127	196	102–147
Boilers: AFUE 90% or greater	4,520	168	137	150	105–182
Boilers: AFUE 85%–89%	4,549	72	72	80	64–87
Boilers Steam: AFUE 82% or greater	1,817	123	109	123	96–122
Indirect water heaters	4,785	82	80	40	70–89
Tankless water heaters: EF>0.82	1,621	47	97	78	82–111
Overall Program	25,346	116	105	127	NA

Conclusions

This paper presents various regression modeling techniques for obtaining measure-level savings estimates. Each of these, in context, offers advantages and disadvantages; therefore, an average of various savings estimates was used to determine the best savings estimate. This method demonstrates reliable savings estimates for gas heating and water heating measures can be obtained, even with limited data availability. Generally, using a fixed effects pre and post monthly approach, with both participants and nonparticipants, offers the most reliable billing analysis approach. In actual program evaluations, however, one often must work with the data available, despite possible limitations.