MA Residential Point-of-Sale Modeling: FINAL Report

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Prepared for:

The Electric and Gas Program Administrators of Massachusetts

Part of the Residential Evaluation Program Area

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Executive Summary

Introduction and Research Goals

This report summarizes the findings of the Massachusetts (MA) Point-of-Sale (POS) modeling research. NMR, as a subcontractor on the Cadmus-led MA Residential Research Area evaluation team (the Team), performed this research and developed this report for the Massachusetts Program Administrators (PAs) and Energy Efficiency Advisory Council (EEAC) Consultants. In addition, Cadmus performed quality control.

The purpose of the POS modeling research was to inform two major studies in the MA 2013 Residential cycle: the Saturation Stagnation investigation and the Multistage Lighting Net-to-Gross (NTG) research. The modeling lends itself to the former by investigating potential reasons for the lack of gains in efficient bulb saturation in MA between 2009 and 2012, and to the latter by providing MA-specific NTG estimates for CFLs and LEDs (and both bulb types combined) by leveraging nationwide sales data. These sales data, the first of their kind to be utilized for residential lighting program evaluation, were purchased through LightTracker, an initiative of the Consortium for Retail Energy Efficiency Data (CREED) and represent bulb purchase data captured at the point-of-sale for select retail channels for 44 states across five years (2009-2013).[1] A shortcoming of the sales data is the absence of home improvement and hardware retail channels, both of which can account for substantial statewide bulb sales. The Team estimates that the POS data capture roughly one-quarter of both MA market-level sales and MA program-level sales. We discuss this shortcoming in more detail in the Threats to Validity section. The Team also collected an extensive set of model inputs including statewide program activity, demographics, and presence/absence of major retailers reporting to CREED to run a series of regression models predicting the proportion of statewide bulb sales that were efficient. In this way, the Team sought to identify those model inputs that had the greatest impact upon the sales of CFLs and LEDs.

The present research examines the influence of all the input variables—but most importantly program activity—in order to determine whether residential lighting programs have an important impact on CFL and LED sales. If the programs do not have such an impact, this may suggest that it is time to exit the market or to shift strategies. If they do have a significant impact, this suggests that residential lighting programs should remain a part of Program Administrators' portfolios. Alternatively, if program activity has a differential influence depending on which bulb type is being considered, this would indicate that program funds may be better utilized to reduce the price of CFLs *or* LEDs, rather than both.

Data

As mentioned above, the Team collected several model inputs for the POS modeling, all of which were utilized to predict the proportion of statewide efficient bulbs sales, which served as the dependent

[1] The information contained herein is based in part on data reported by IRI through its Advantage service for, and as interpreted solely by LightTracker Inc. Any opinions expressed herein reflect the judgment of LightTracker Inc. and are subject to change. IRI disclaims liability of any kind arising from the use of this information.

variable in all models. This information was garnered from the POS data that the Team purchased through CREED. This extensive bulb sales dataset included information for all available states and retail channels by bulb type from the years 2009 to 2013. Of particular importance for predicting efficient bulb sales were statewide program activity, statewide demographics, and the presence of retailers both reporting sales data and not reporting sales data to CREED. The program activity variable was defined as a particular state's lighting program budget, which the Team conducted extensive background research to quantify. This was a continuous variable, defined as a particular states' annual residential lighting program budget.[2]

Along with the program activity input, the Team also collected statewide demographic variables that could potentially influence or help explain lighting purchases, and researched the number and size of various light bulb retailers to calculate the square footage of those retailers per household in each state. The dependent variables included the percentage of all bulb sales in a particular state that were energy efficient (*i.e.*, [CFL+LED Sales]/All Bulb Sales), the percentage of all bulb sales that were CFLs-only, and the percentage of all bulb sales that were LEDs-only, which were all calculated from the POS data.

Findings

The Team fit models utilizing the continuous program budget variable for each of the three dependent variables: proportion of all efficient bulbs types (CFLs + LEDs), proportion of CFLs only, and proportion of LEDs only. In all models the Team controlled for the change in the proportion of efficient bulb sales purchased in non-program states, so that extraneous factors influencing efficient sales would not be confounded with the influence of program activity.

When considering the dependent variable *proportion of all efficient bulb types*, the Team found that increases in a state's lighting program budget are significantly associated with increases in efficient bulb sales. Model results suggested that every $1,000 increase in the square root of a state's lighting program budget was associated with an expected increase of 5.5% in the proportion of efficient bulb sales. For Massachusetts, this translates to a program impact elasticity of roughly 0.2.

The Team then considered the dependent variable *proportion of CFL sales*. Across the full range of the POS data (all states and years available), CFLs comprised almost all of the efficient bulbs sales (accounting for over 99% of all efficient bulb sales between 2009 and 2013). As such, the CFL-only model behaved almost identically to the overall CFL + LED model.

The LED-only models also demonstrated that program budget influenced the proportion of statewide sales. Also of note was the steady increase over time in the proportion of LED sales. Sales of this new technology were over 22 times higher in 2013 than in 2009. CFLs, conversely, saw their proportion of sales peak between 2011 and 2012. By 2013, the proportion of CFL sales was no different than it had been in 2009. It is important to note, of course, that increases in sales of LEDs—and any efficient bulb

2 The Team also considered utilizing a categorical program budget variable gleaned from the ENERGY STAR® Summary of Lighting Programs. However, the continuous program budget variable proved to be a much more successful model input. We discuss this in more detail, and provide the categorical results, in Appendix E.

type for that matter—are due not solely to program activity impacts but also to numerous other factors including changes in the technology and price drops not related to lighting program incentives.

The Team utilized the model results to calculate NTG ratios for CFLs, LEDs, and both bulb types combined. Necessary inputs for the NTG calculations included the results of the regression models discussed above (which were used to estimate a MA counterfactual), the POS data, and MA program-tracking databases, which the Team used to estimate program sales through retailers reporting to the POS data collection vendor. The Team derived the NTG ratios by subtracting the counterfactual estimates (the number of efficient bulbs sold assuming no program activity) gleaned from the models from the number of efficient bulbs sold under the program. The Team then divided this number by the total number of program bulbs sold, as follows:

$$NTG = \frac{(\#\ bulbs\ sold\ with\ program - \#\ bulbs\ sold\ with\ no\ program)}{\#\ of\ program\ incented\ bulbs\ sold}$$

The models resulted in a 2013 NTG ratio of 45.4% for all efficient bulbs, 43.9% for CFLs only, and 97.9% for LEDs only (Table 1). [3]

Table 1: MA NTG Values

Bulb Type	NTG
All Efficient Bulbs	45.4%
CFLs Only	43.9%
LEDs Only	97.9%

The Team discusses these values in much more detail in the NTG Estimates section of the report. It is important to remember, however, that the NTG estimates from the current research represent only one mode of estimation, to be used in conjunction with the complementary methodologies the Team is developing on behalf of the MA PAs and EEAC consultants. Also imperative to understand is that the data used to develop these models only cover those retailer channels represented by the POS data. The other approaches to estimate NTG include a demand elasticity model, supplier interviews, and saturation estimates from comparison areas which are meant to reflect the MA program as a whole. The PAs will ultimately use an aggregated NTG ratio estimate resulting from all these efforts to assess the upstream lighting program's net savings.

Conclusions

Program activity, as defined by program budget measures, showed a consistently positive and significant relationship to the proportion of CFLs and LEDs sold across all available states and retail channels.

[3] The NTG estimates in this report represent the sales-weighted average net-to-gross across channels in the POS dataset.

The research also sheds light on the confounding finding in prior MA saturation studies that increases in CFL sales are not necessarily accompanied by increases in CFL saturation. It may be that saturation gains take longer to materialize than previously expected. Being able to observe this relationship, however, relies on the ability to control for intervening factors for which prior methods and exploratory analyses were unable to account.

Introduction

This document presents the results of the Massachusetts (MA) Point-of-Sale (POS) Modeling research, an investigation utilized to inform both the MA Multistage Lighting Net-to-Gross (NTG)[4] and Saturation Stagnation[5] studies. This draft report was developed for the MA Program Administrators (PAs)[6] and the Energy Efficiency Advisory Council (EEAC) consultants. NMR, as a subcontractor on the Cadmus-led MA Residential Research Area evaluation team (the Team), performed the modeling, while Cadmus performed Quality Control.

The purpose of the POS Modeling research was to explore possible explanations for the stagnation of efficient bulb saturation in MA, calculate NTG ratios[7] for CFLs and LEDs in MA for 2013, and understand the influence of various predictors on the sales of efficient bulb types across the nation, especially the impact of program activity. Given the rapid and widespread changes to the lighting market in the United States, including the increased lighting efficiency standards stemming from the Energy Independence and Security Act of 2007 (EISA) that should phase-out general service incandescent bulbs, many have begun questioning whether residential lighting programs continue to impact efficient bulb sales. The introduction of general service light-emitting diode (LED) and halogen bulbs also intended to replace incandescents only complicates the matter further. To assess the continued impact of lighting programs on efficient bulb sales, this research determines the influence of lighting program activity on the percentage of efficient bulbs sold at the state level, while controlling for other potentially biasing factors.

The results of the POS Modeling research inform the NTG and Saturation Stagnation research by presenting estimates of statewide bulb sales, potential counterfactuals to MA (by investigating states with no program activity and those that dropped their programs), and carefully examining if and how differences in program support (along with other potential predictors) influenced the sales in each area examined.

To get at potential reasons for the stagnation in efficient bulb saturation that MA experienced from 2009 to 2012, the Team had initially planned for a more descriptive analysis, looking at bulb sales and pricing trends between MA and other similar program states and comparison non-program states. We planned to focus this analysis on MA, three program states (California, Connecticut, and Georgia as a

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4 NMR, Cadmus, DNV GL, and Tetra Tech. *Multistage Lighting Net-to-Gross Assessment: Work Plan.* Final delivered to the PAs and EEAC Consultants on April 3, 2014.

5 NMR, Cadmus, DNV GL, and Tetra Tech. *Lighting Saturation Stagnation Assessment: Evaluation Plan.* Final delivered to the PAs and EEAC Consultants on January 13, 2014.

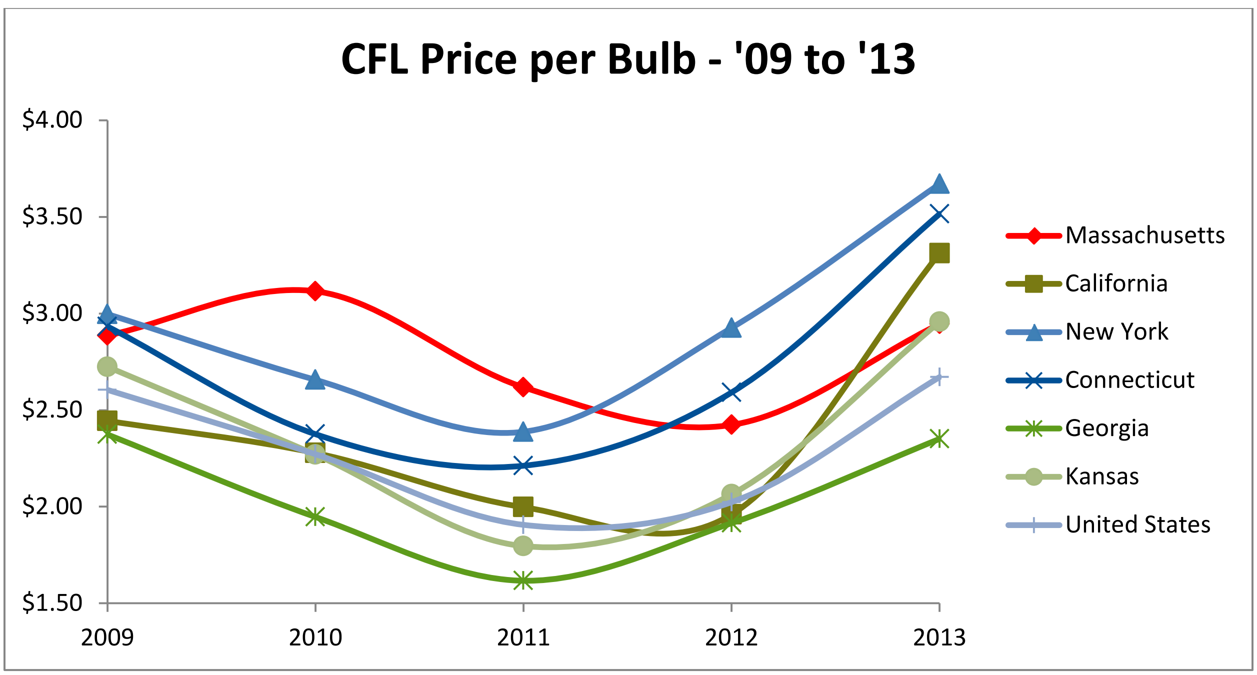
6 The Team uses *PAs* when referring exclusively to the MA Program Administrators but uses *program administrators* when referring more generally to companies or organizations that may sponsor lighting incentive programs.

7 These NTG ratios are not meant to be applied retrospectively, but instead are meant to inform NTG ratios for the next planning cycle (*i.e.,* prospective NTG). The Team will prepare an overall report that brings together the NTG findings from the current research together with the demand elasticity approach, the supplier Interviews, and comparison area research to inform a prospective estimate of NTG.

recent program state), one non-program state (Kansas), and one former program state (New York). The Team focused on Georgia and Kansas because of concurrent onsite saturation work and New York because it made for an ideal comparison area; New York previously maintained strong lighting programs until dropping support for standard CFLs. By examining the proportion of efficient sales in those areas, as well as bulb pricing trends and actual saturation estimates, the Team had hoped to identify potential reasons for the lack of saturation gains in MA and explore potential solutions.

However, the results of that preliminary exploratory analysis revealed several unusual and seemingly inexplicable findings. These descriptive graphs raise many questions: What is the role of cost of living? Electricity price? Demographics? Program activity? It is precisely such questions—and their resistance to simple, straightforward explanations—that led us to recommend the modeling approach described in this report. Therefore, these graphs should pique your interest in the data and the modeling exercise, but the explanations arise through the modeling exercise and are not addressed here.[8] For example, as shown in Figure 1, when examining CFL pricing trends, states with active lighting programs (like MA, CA, and CT) did not tend to show lower CFL prices than states with no programs.

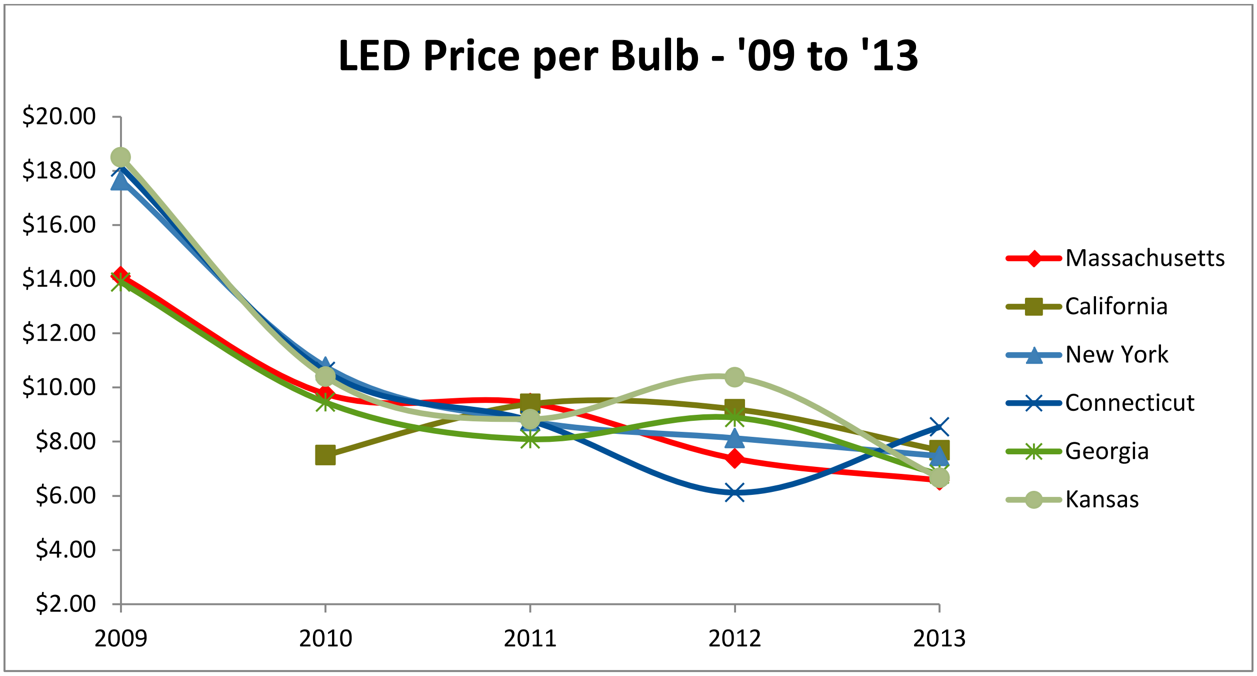
Figure 1: CFL Pricing Trends



[8] One caveat to keep in mind regarding the following figures is that the POS data does not allow for isolating standard vs specialty CFLs, and that difference may be driving some of the year to year fluctuations in pricing.

The Team found a similarly odd set of results when examining LED pricing trends. As shown in Figure 2, all states considered in the initial exploratory descriptive analyses had converging LED prices, despite program states specifically focusing on bringing the shelf price of LEDs (and CFLs) down to be competitive with that of incandescents.

Figure 2: LED Pricing Trends



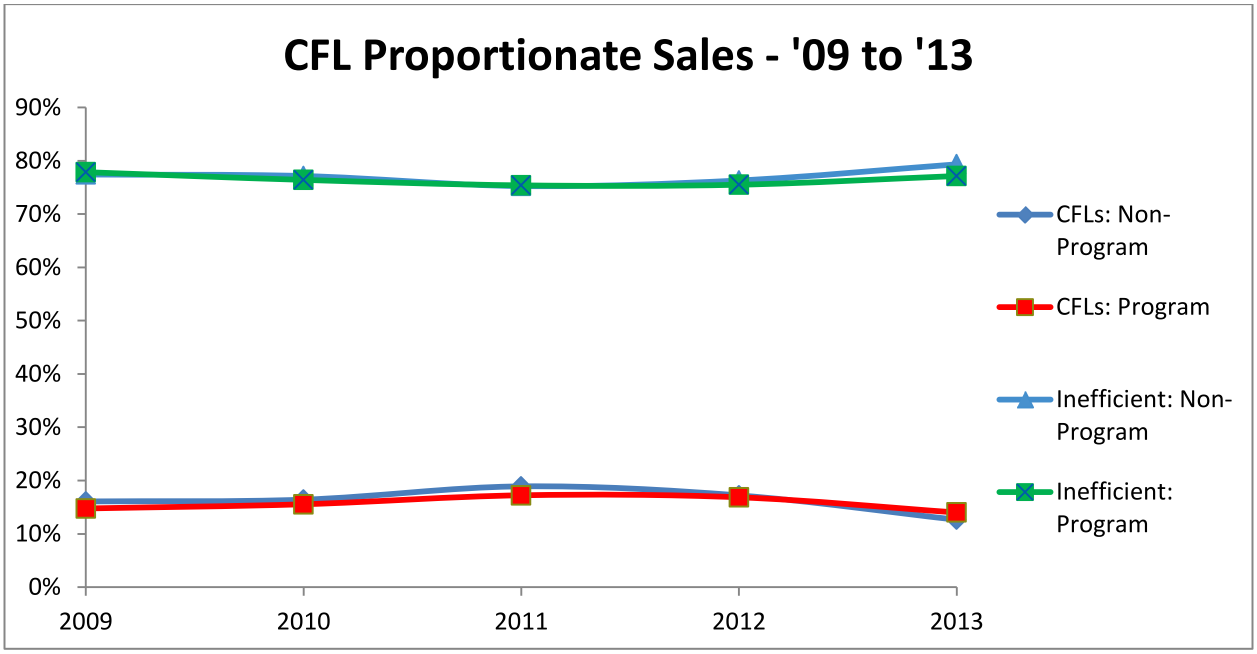
Along with the unexpected findings related to pricing trends, the Team was also confounded by the preliminary results related to bulb sales across territories, particularly as they related to the proportion of efficient sales. Consider, for example, Table 2 below, which provides estimates of CFL saturation over time for the original six states involved in the analysis. Although saturation studies are not conducted every year, the trends in CFL saturation from 2009 to 2014 show consistent increases over time. In fact, almost every state shows at least one large increase in saturation at some point. As such, when looking at sales data for those states, one would expect to see an increase in the *proportion* of CFL sales equivalent, or at least similar, to that trend.

Table 2: CFL Saturation over Time by State

State	2009	2010	2011	2012	2013	2014
MA	26%	26%	-	27%	28%	33%
CA	22%	-	-	30%	-	-
NY (Upstate)	19%	24%	-	-	25%	-
NY (Downstate)	21%	31%	-	-	29%	-
CT	24%	-	-	26%	32%	-
GA	16%	-	-	-	-	19%
KS	21%	19%	-	-	-	29%

However, when examining CFL sales in the POS data, there was no increase in the proportion of CFLs sold over the years examined (Figure 3). The bottom two lines of the graph in Figure 3 display the proportion of all bulb sales that were CFLs in both program (red line) and non-program (blue line) states. For the program states (MA, CA, CT, GA, and NY) and the non-program state (KS), CFLs continued to make up only a small (roughly 13%-18%) and non-increasing proportion of all bulb sales.

Figure 3: Proportion of All Bulb Sales that are CFLs



However, when looking at the percentage of efficient bulb sales over time for program and non-program states on a finer scale, and utilizing the full POS data sample (rather than the initial 6-state analysis), the Team did observe potentially important differences based on programmatic activity. Consider Figure 4 through Figure 6, which show the proportion of all bulb sales that are efficient, CFLs, and LEDs between program and non-program states for the full sample.[9] These figures indicate that program states do show differences from non-program states when considering more of the POS data than the preliminary analyses, and when looking on a finer scale.

[9] Research does indicate that prior saturation levels can influence efficient bulb sales (longer lifetimes for efficient bulbs leads to fewer bulbs of all types being sold) which should be kept in mind when examining the current figures.

Figure 4: Proportion of All Bulb Sales that are Efficient across Larger Sample

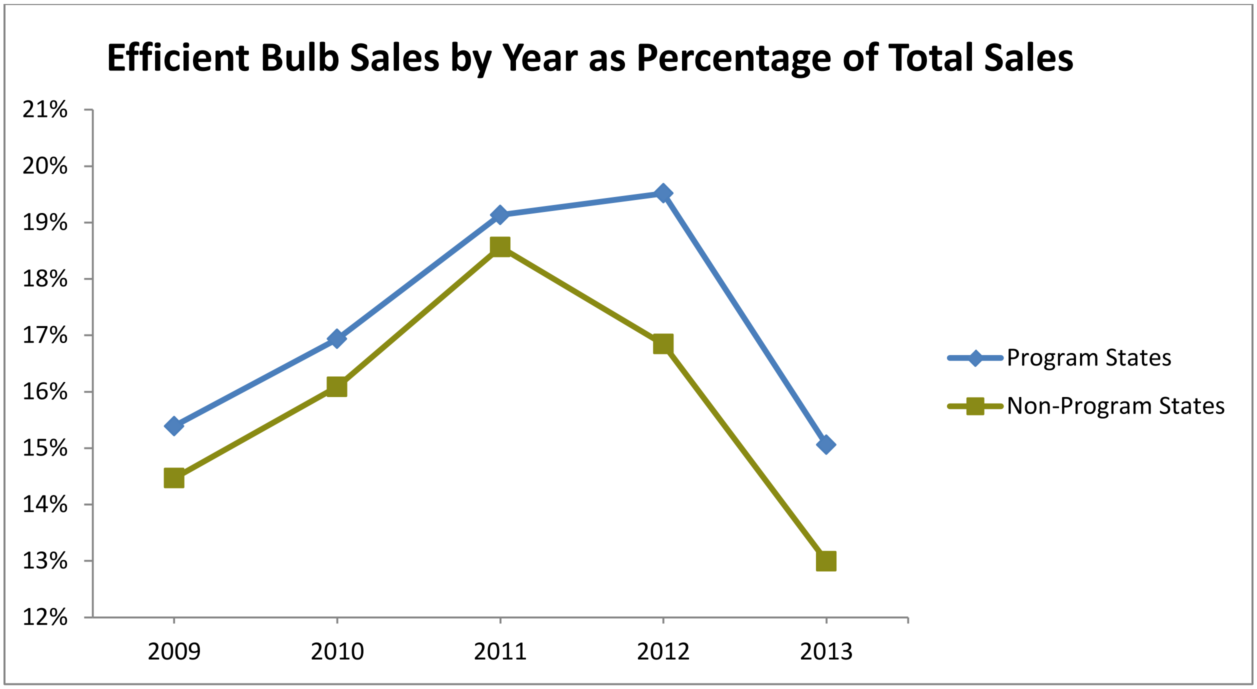


Figure 5: Proportion of All Bulb Sales that are CFLs across Larger Sample

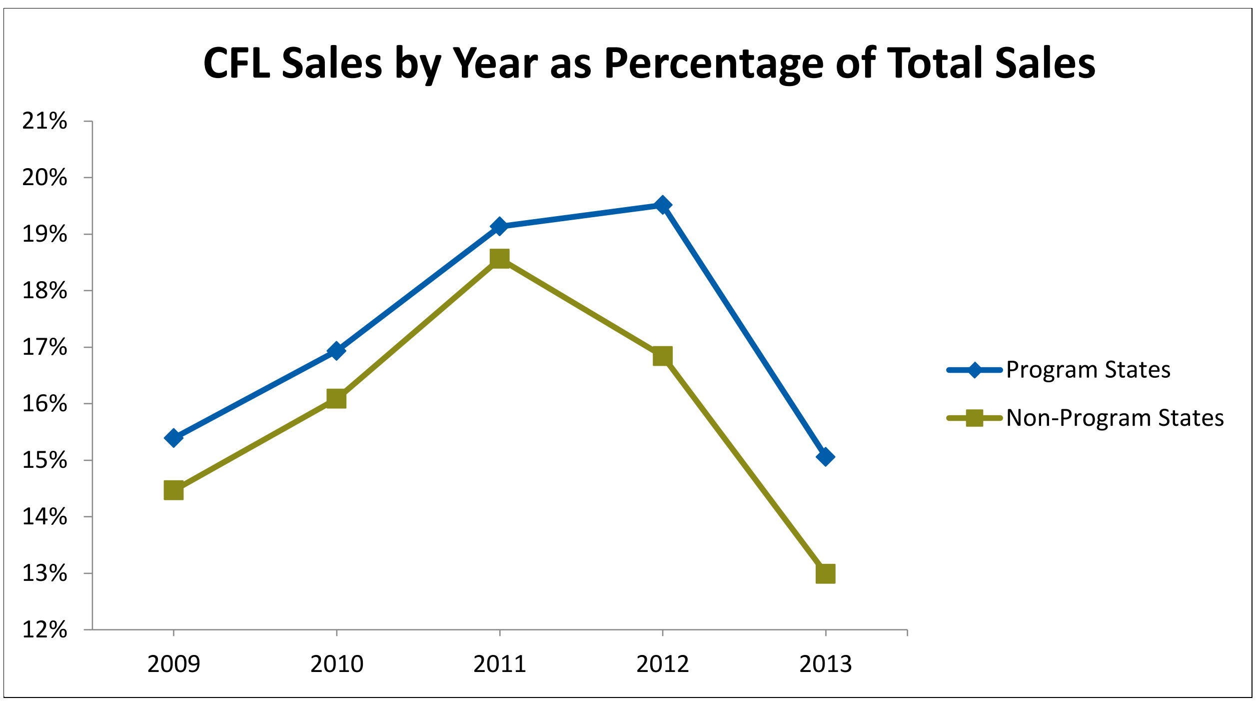
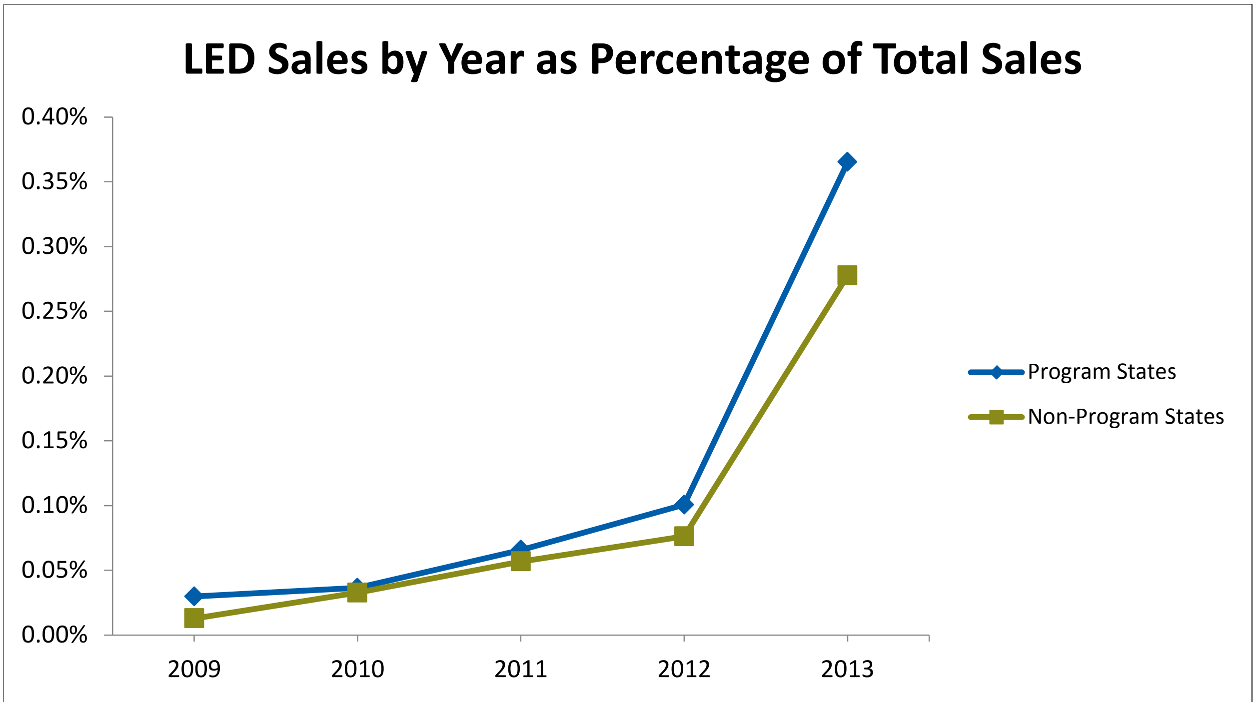


Figure 6: Proportion of All Bulb Sales that are LEDs across Larger Sample



Ultimately, the preliminary six-state analysis, which was meant to explore and understand the potential reasons for the saturation stagnation in MA, left the Team with more questions than answers. Although the proportion of CFL sales in MA did not show increases over the examined periods, thus providing evidence for the stagnation, this same trend held true for all six states the Team examined. Despite the observed increases in CFL saturation achieved between 2009 and 2013 for most of the six states, these increases were not accompanied by any growth in the proportion of statewide CFL sales in the POS data. Further, program states did not show lower pricing trends for efficient bulbs than did non-program states. The team surmised that the simplistic graphs and exploratory analyses conducted only on the initial 6 states in the POS data likely hid the impact of intervening factors, which a larger model might be able to take into account. The difference seen in the proportionate efficient bulb sales over time between all program and non-program states (in the entire sample) also provided support for an analysis considering this broader sample. For these reasons, the Team turned to a more nuanced approach to explore the true influence of program activity on bulb sales. Utilizing a more sensitive and expansive modeling approach, the Team could control for external factors with the potential to bias the exploratory analyses and could more accurately explore the reasons for stagnation in MA while also providing the necessary inputs for calculating NTG values.

Overall Research Goals

The goal of the research was to explore possible explanations for the stagnation of efficient bulb saturation in MA, calculate net-to-gross (NTG) ratios for CFLs and LEDs in MA for 2013, and understand the influence of various predictors on the sales of efficient bulb types across the nation, especially the impact of program activity. More specifically, the research sought to accomplish the following:

- Track sales of all major bulb types in the 44 states reporting to the data collection vendor
- Model the impact of program activity and state-level demographics on efficient bulb sales statewide
- Develop one "leg" of the 2013/2014 MA NTG ratio for CFLs and LEDs
- Determine whether lighting program activity is still a driver of efficient bulb sales and saturation, thereby providing insight into whether states should maintain their residential lighting programs

Data Sources

Point-of-Sale Data

The Team purchased the POS data through LightTracker, an initiative of the Consortium for Retail Energy Efficiency Data (CREED), who worked closely with the data collection vendor to deliver a comprehensive data set for energy efficiency program administrators, implementers, and evaluators. Although data could be purchased for specific states, bulb types, and periods, the Team, along with the MA PAs and EEAC consultants, deemed the Universal Dataset (UDS) Report to be the most appropriate option for the current effort because it included data for all available territories, bulb types, and years of reporting. More specifically, this data set includes lighting sales data for grocery, drug, dollar, club, and mass market distribution channels.[10] Unfortunately, the POS data represent only approximately one-quarter of MA sales of light bulbs, and a comparable amount of MA program bulbs. To the extent that these channels are representative of the market in each of the states then there is no bias in the results of the analyses. The section on threats to validity more thoroughly assesses and discusses this issue. Key aspects of the UDS Report include:

- Sales volume and pricing from 2009 to 2013 for CFLs, LEDs, halogens, and incandescent bulbs for all channels combined
- Data reporting by state (with 44 states included) and bulb type
- Inclusion of all bulb styles and controls

More detailed information on the UDS Report is provided in Appendix B.

[10] The POS data do not include the home improvement and hardware retail channels, which can account for a substantial amount of statewide bulb sales. Utilizing statewide market-level estimates from the most recent MA onsite study, the Team estimates that the POS data capture roughly one-quarter of MA market-level bulb sales. The Team discusses this shortcoming in more detail in the Threats to Validity section.

For the purposes of the modeling, the Team utilized the POS data to create the dependent variable for all models, defined as the percentage of all bulb sales in a particular state that were energy efficient. All model inputs described below attempted to predict the percentage of statewide efficient bulb sales, defined as (CFL+LED Sales)/All Bulb Sales.

Program Activity

Because the program activity model input variables were central to the Team's efforts, researching the presence of a program and the extent to which that program aimed to incentivize efficient bulbs was a key aspect of the background research. The Team relied on a three-pronged approach to researching program activity: utilizing the internal resources of each sub-contractor on the project (thereby also utilizing any internal evaluation results that were available for a specific state or territory), conducting a literature review of publically available reports found on the internet or provided by program administrators or their evaluators,[11] and reaching out to local utilities in each given area when reports with the relevant information were not available. Appendix A presents the data collection form for this effort.

As seen on the data collection form, the first piece of information the team gathered was simply whether a particular state had a lighting program in place for any year between 2009 and 2013. If there was evidence of a program (either through internal evaluation work or a literature review), the next step was to search for more detailed program information—in particular, the lighting program budget. The Team researched and aggregated all this program activity information into two main program activity predictors to utilize as the main model inputs of interest. These included a simple yes/no predictor of whether a particular state had a program in a given year and a continuous predictor variable represented by the more detailed information the Team gathered on program budgets.

Presence and Absence of Retailers Reporting to Vendor

The Team conducted secondary internet research in order to determine the number of store locations in each state and the total square footage of those stores per state for both the retail channels reporting to the data collection vendor and those channels not reporting.[12] In MA, the team estimates that approximately 22% of program bulb sales, and 23% of market-level bulb sales, are represented by the channels reporting to the data collection vendor. The purpose of this background research, and the eventual model inputs resulting from it, was not only to assess the influence of stores' presence or absence on bulb sales, but also to utilize these data as control variables such that any significant impacts of other model inputs would not be a result of a particular state simply having greater or fewer stores in the channels whose bulb sales were reported. In other words, the Team wanted to ensure that any

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11 In particular, the Team began by searching the www.dsireusa.org website and program activity information cited through the ENERGY STAR® Summary of Lighting Programs http://www.energystar.gov/ia/partners/downloads/2013_ENERGY_STAR_Summary_of_Lighting_Programs.pdf

12 Per the contractual agreements between the Team and the data collection vendor, the Team is unable to report the names of any retail chains either reporting or not reporting to the vendor.

significant findings were over and above the influence of the particular retail channels included in the data.

Some of the retail stores within the represented channels include the locations, numbers, and average square footages on their company websites. In these cases, Team members entered the relevant information into the database as it appeared on the website. Further, when store square footage was not available, the Team estimated this using a variety of journalistic and industry sources, including the Business Journals (www.bizjournals.com), the business section of *Time* magazine (business.time.com), the Institute for Local Self-Reliance (www.ilsr.org), and CSI Market (www.csimarket.com).

State-Level Demographics

The Team also gathered state-level demographic data from the American Community Survey (ACS, www.factfinder2.census.gov), including annual state-level data for the population, total number of households, household tenure, count of homes built before 1980, categorical education, median income, and average number of rooms in the home. These variables served as model inputs and, in the case of statewide population and households, were utilized to create the per-capita and per-household square footage rates of the retailer channels that do or do not report to the data collection vendor. The rationale for gathering the demographic data was to control for non-program factors that could possibly impact the number of efficient bulbs sold in a state and to reduce variation in the model.

Program-Tracking Data

The Team also utilized the MA program-tracking database provided by the fulfillment contractor, Parago, as a key input in developing the 2013 NTG estimates (described in detail in the NTG Estimate section). This dataset lists the number and type of program-supported bulbs sold through each retailer by location. The Team was able to narrow down the bulb sales information from the program-tracking data to only those retail channels represented by the POS data collection vendor. In this way, the Team could calculate necessary inputs to the NTG calculation.

Findings

Model Design and Inputs

To determine the influence of state-level program activity, presence/absence of reporting retail channels, and state-level demographics on percentage of efficient bulb sales (also at the state level), the Team fit a series of robust random-effects regression models[13] of the following form:

$$\begin{aligned}\log(\%efficient.sales_{i,j}) \\ &= \alpha + \beta_{0,i} + \beta_1 \log(cr.sqft_{i,j}) + \beta_2 \log(noncreed.sqft_{i,j}) \\ &+ \beta_3 avg.electric.price_{i,j} + \beta_4 cost.of.living_i + \sum_{k=1}^{p} \gamma_k dem.var_{i,j,k} \\ &+ \theta prog_{i,j} + \tau_j + \epsilon_{i,j}\end{aligned}$$

Where:

$\%efficient.sales_{i,j}$ = Proportion of total CREED-reported bulb sales that were efficient bulbs in state *i* and year *j*. Calculated as $(\#CFL_{i,j} + \#LED_{i,j})/(total\ bulb\ sales_{i,j})$.

$cr.sqft_{i,j}$ = Number of square feet of major CREED-reporting retailer channels in state *i* and year *j.*

$noncreed.sqft_{i,j}$ = Number of square feet of major non-CREED-reporting retailer channels in state *i* and year *j.*

avg.electric.price = Average cost of electricity in state *i* and year *j.*

cost.of.living = Average cost of living index in state *i.*

$dem.var_{i,j,k}$ = One of *p* demographic variables for state *i*, at time *j*, with $k \in (1, \ldots, p)$. The following state-level demographic variables were considered: number of households, % of homes built before 1980, % of renters who pay their own utilities, median income, % owner-occupied households, education level, and population. The Team determined which demographic variables to include in each model by selecting the covariate pattern yielding the highest adjusted R^2.

$prog_{i,j}$ = Program activity variable for state *i* in year *j*, defined as the lighting program budget in state *i* in year *j*, as gathered through published reports, internet searches, internal evaluations, or provided directly by Utilities. It should be noted that the program budget variable includes

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13 The Team deemed the random-effects models appropriate after Hausman tests comparing the results from these models to analogous fixed-effects models failed to reject the hypothesis that the estimates obtained from the random-effects model were inconsistent. See, for example, Oscar Torres-Reyna, *Getting Started in Fixed/Random Effects Models using R*, Princeton University Data & Statistical Services, Fall 2010, http://www.princeton.edu/~otorres/Panel101R.pdf, Accessed October 22, 2014.

program activity even if it was in retail channels not represented by the POS data. The square root of program-related budgets was used in the models in order to adjust for the skewedness in the distribution of that variable.

τ_j = Average proportion of efficient bulb sales across states that had no program activity for the entire study period, 2009 to 2013. Including this term allows the model to account for naturally occurring, non-program influenced, "baseline" trends in efficient bulb sales during the study period, which in turn helps to isolate the effect of program activity on efficient bulb sales as opposed to other outside factors.

α = Overall model intercept term.

$\beta_{0,i}$ = Subject-specific deviation from overall-level intercept, α, as estimated by random-effects specification.

β_1, β_2, γ_k, ϑ = Regression coefficients to be estimated by the model.

$\epsilon_{i,j}$ = Error term.

The Team calculated the dependent variable in the model as the proportion of all bulbs sold in each state that were energy-efficient bulbs, or (CFL sales + LED sales)/All Sales. This approach (instead of the absolute count) recognizes that the state population would heavily influence absolute counts of sales. This allowed the model to control for factors besides the number of households, such as average hours of use, average home size (sq. ft.), and any climate-related or other regional differences across states that could also have an impact on the absolute number of state-level bulb sales.

The random-effects models account for any potential correlation among the multiple observations in each state through the random intercept terms $\beta_{0,i}$. Additionally, the models estimate the program effect using both within-state and between-state variability, thereby using more information. Specifically, while fixed-effects models are more common in energy efficiency evaluation (e.g. billing analyses), such models only utilize within-subject variability to estimate program impacts. Given the relatively short-time period investigated in the present research and the limited within-state variability in the variable of interest – program budget – over that time, the random effects specification is a preferable alternative as it utilizes both within-state and between-state variability to inform the estimate of program impact on efficient bulb sales. The random-effects model is also able to use information from all available states. The main parameter of interest in all three models is ϑ, which quantifies the impact of state-level program activity as defined by each of the specifications of $prog_{i,j}$ discussed above. The Team used natural logarithms of the dependent variable and several control variables in the model to adjust for the skewed distributions of those variables on their original scales and reduce the impact of outlying observations.

After fitting these models, the Team then considered two additional sets of models: those using only the proportion of CFL bulb sales and those using only the proportion of LED bulb sales as the dependent

variable. In this way, the Team was able to compare the impact of program activity on each of those technologies separately and determine whether either bulb type was benefiting more than the other from state-level program activity.

Model Results

All Efficient Bulb Types

Table 3 below shows the results of the model using the proportion of *total* efficient bulb sales as the dependent variable. The table summarizes the estimated regression coefficients across the model. Increased program activity, as measured by the $prog_{i,j}$ variable, is positively and significantly associated with increases in efficient bulb sales at the 90% confidence level. The results demonstrate that increases in a state's lighting program budget are associated with increases in efficient bulb sales. Specifically, for every $1,000 increase in the square root of a state's lighting program budget, there is an expected increase of 5.5% in the proportion of efficient bulb sales. To simplify interpretation of the model, this relationship can also be quantified as a program expenditure elasticity. Consider a $1M increase in program budget: Based on this model, such an increase would lead to a 0.36% increase in efficient bulb sales in MA, yielding an elasticity of 0.2 (Table 3).

Table 3: State-Level Model Results for All Efficient Bulbs

Variable	Level	Model Results
Intercept	--	1.6392 (1.3456)
log(cr.sqft)	Continuous	0.1794* (0.0747)
log(noncreed.sqft)	Continuous	-0.1378* (0.0545)
% built pre-1980	Continuous	-1.0199† (0.5972)
% renters paying utilities	Continuous	-2.3382 (1.5922)
Median # rooms per home	Continuous	--
Electric Price	Continuous	0.0149** (0.0054)
Cost of Living Index	Continuous	-0.0083** (0.0028)
Program Budget	Continuous	5e-05*** (2e-05)
log(non-program eff. sales trend)	Continuous	0.6934*** (0.0925)

Additional Details		
Number of States		27
Number of Observations		94
R^2		0.663

Coefficient estimates presented with standard errors in parentheses beneath them.
log(covariate) indicates the natural logarithm of that covariate.
Note: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

CFL-only Results

Next, the Team considered the dependent variable of CFL sales (the proportion of all statewide sales that were CFLs). Across all years and all states in the POS data, however, the average proportion of total efficient bulb sales was 17.03%, and the average proportion of CFL bulb sales was 16.91%. As such, across all states, CFLs accounted for over 99% of all efficient bulb sales between 2009 and 2013. Unsurprisingly, then, the CFL-only model behaved nearly identically to the overall CFL + LED model. The CFL-only model results are shown in Appendix C.

LED-only Results

In contrast to CFLs, the proportion of LED sales nationwide remains small, thereby contributing very little to the combined CFL + LED analysis. Considering only the proportion of LED sales—as opposed to combined CFL and LED sales or CFLs sales only, then, brings about different results. This also allows us to have a separate estimate of net-to-gross for LEDs. LED-only regression results are summarized in Table 4 below. Of note, the LEDs-only model is able to explain almost all of the variation in LED sales as a proportion of all bulbs purchases having an R^2 of over 0.9.

Table 4 : State-Level Model Results, LEDs Only

Variable	Level	Model Results
Intercept	--	-1.1557 (0.9101)
log(cr.sqft)	Continuous	0.3886* (0.1677)
log(noncreed.sqft)	Continuous	0.2062 (0.1997)
Median income	Continuous	0.0196* (0.0090)
log(# of households)	Continuous	-0.5984** (0.2066)
% own	Continuous	--
% built pre-1980	Continuous	--
Electric Price	Continuous	-0.0047 (0.0104)
Cost of Living Index	Continuous	-0.0012 (0.0059)
Program Indicator	Yes	--
	No	--
Program Budget	Continuous	7e-05* (3e-05)
log(non-program LED sales trend)	Continuous	1.0607*** (0.0278)

Additional Details		
Number of States		27
Number of Observations		94
R^2		0.956

Coefficient estimates presented with standard errors in parentheses beneath them.
log(covariate) indicates the natural logarithm of that covariate.
Note: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

NTG Estimates

All Efficient Bulbs

Using the results of the regression models discussed above, the POS data on efficient bulb sales, and the program-tracking databases described in Program-Tracking Data section, the Team estimated NTG ratios for all efficient bulbs (CFLs + LEDs), CFLs-only, and LEDs-only in 2013. As outlined in previous work,[14] these NTG ratios were derived by subtracting a counterfactual estimate (the number of efficient bulbs sold assuming no program activity), as estimated via modeling, from the number of efficient bulbs sold under the program. This number was then divided by the total number of program bulbs sold, as follows:

$$NTGR = \frac{(\#\ bulbs\ sold\ with\ program - \#\ bulbs\ sold\ with\ no\ program)}{\#\ of\ program\ incented\ bulbs\ sold}$$

It is important to note that the number of bulbs sold with the program (first numerator input) and the number of program-incented bulbs (denominator) come directly from the POS dataset, and therefore represent only the channels reporting to the data collection vendor. As such, all subsequent NTG calculations and estimates are only meant to represent those channels captured by the POS data, and not the MA program as a whole. The Team provides a NTG estimate for each of the bulb types described above (all efficient bulbs, CFLs-only, and LEDs-only).

As discussed above, it was not necessary for the Team to estimate the first input to the NTG equation (# of bulbs sold with program) because those bulb sales were readily available as the actual number of CFL and LED sales in the POS data set. Based on the model results the proportion of efficient bulbs sold was $(e^{7,505*5e\text{-}05}\text{-}1) \approx 49.4\%$ higher than what would have been expected in the absence of a program. The total number of program-incented bulbs sold was derived from the program-tracking data. In the case of all efficient bulb types, the Team simply summed the total number of program-supported CFL and LED sales at all retailer channels in MA represented by the data.

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14 NMR Group, Inc., KEMA Inc., The Cadmus Group, Inc., and Tetra Tech. *Massachusetts ENERGY STAR Lighting Program: 2010 Annual Report, Volume 1.* Prepared for the Energy Efficiency Advisory Council Consultants, among others. June, 2011.

The total number of efficient bulbs sold at MA retailers reporting to the data collection vendor in 2013 was 1,844,827, and the total number of program-supported bulbs sold at retailers reporting to the data collection vendor in the program-tracking database was 1,345,263. The estimated number of bulbs sold in the absence of the program is equal to 1,234,531 (or 1,844,827 ÷ 1.494). This results in a 2013 NTG estimate of 45.4% for all efficient bulbs. Again, it is imperative to note that this estimate relates only to the retailer channels represented by the POS data, which the Team estimates to encapsulate 22% of full MA program sales. Table 5 below provides a full breakdown of the estimates utilized for the NTG calculation.

Table 5: All Efficient Bulbs Net-to-Gross Calculation

Total CFLs + LEDs in POS Data	Estimated CFLs + LEDs Sold in Absence of Program	Total CFLs + LEDs in POS Data – Estimated CFLs + LEDs Sold in Absence of Program	Total Program CFLs + LEDs Through POS Retailer Channels in Program-Tracking Records	NTG
1,844,827	1,234,531	610,296	1,345,263	45.4%

CFL NTG

For CFLs-only, the Team again calculated a NTG ratio using the results which are presented in Appendix C. The total number of CLFs sold at MA retailers reporting to the data collection vendor in 2013 was 1,778,740, and the total number of program-supported bulbs sold at retailers reporting to the data collection vendor in the program-tracking database was 1,317,218. The estimated number of bulbs sold in the absence of the program is 1,200,402. This results in a 2013 NTG of 43.9% for CFLs in MA in the represented retailer channels (Table 6).

Table 6: CFL-Only Net-to-Gross Calculation

Total CFLs in POS Data	Estimated CFLs Sold in Absence of Program	Total CFLs in POS Data – Estimated CFLs Sold in Absence of Program	Total Program CFLs Through POS Retailer Channels in Program-Tracking Records	NTG
1,778,740	1,200,402	578,338	1,317,218	43.9%

LED NTG

The Team also calculated a NTG ratio for LEDs, using the model presented in Table 4. The total number of LEDs sold at MA retailers reporting to the data collection vendor in 2013 was 66,087, and the total number of program-supported bulbs sold at retailers reporting to the data collection vendor in the program-tracking database was 28,045. The estimated number of LEDs sold in the absence of the program is 38,644 (66,087 ÷ 1.710). This results in a 2013 NTG of 97.9% for LEDs in MA in the represented retailer channels (Table 7).

Table 7: LED-Only Net-to-Gross Calculation

Total LEDs in POS Data	Estimated LEDs Sold in Absence of Program	Total LEDs in POS Data – Estimated LEDs Sold in Absence of Program	Total Program LEDs Through POS Retailer Channels in Program-Tracking Records	NTG
66,087	38,644	27,443	28,045	97.9%

For more information on the reported NTG values, along with alternative calculations, please see Appendix E.

Threats to Validity

The model results and the NTG estimates provided in this report are not without limitations. First and foremost is the issue of generalizability. As discussed, the sales data that serve as the dependent measure for all models and factor heavily into the NTG estimates do not represent full, market-level sales in MA or nationwide. Although many program and non-program bulbs sell through the retail channels included in the POS dataset, the absence of home improvement and hardware channels means that many bulb sales are not accounted for in the models. Based on the assessment of market-level bulb sales in MA calculated during the most recent onsite saturation study, the Team estimates that the POS data represents roughly one-quarter of all MA sales, and 22% of MA program sales.

This is not to discount the importance and quality of the data that are available—residential lighting program evaluators and implementers have been working for years to obtain actual bulb data captured at the point of sale for *any* retail channels, and the current POS data set represents the best of what is available. However, it should not be viewed as perfectly representative of the entire lighting market.

Further, with regard to the present NTG analyses, the counterfactual estimates of bulb sales in MA are based not just on data from that state, but also on data from the 26 other states that contributed to the regression model. Because of the state-level nature of the data, the NTG estimates lack the specificity that might be obtained from research conducted on a finer scale using data only from MA or data that could also track sales to specific retail locations (which the POS data cannot). NMR also found in previously conducted Multistate Modeling[15] research that prior saturation can negatively influence current sales. The Team cannot take that into account in the current research because many of the 27 states in the analysis do not have saturation estimates. This effect would mean that, if anything, the current models would tend to underestimate program influence and NTG, although utilizing proportionate sales as opposed to absolute counts helps accounts for decreases in bulb sales. For these

[15] NMR, *Results of the Multistate CFL Modeling Effort.* Final delivered to the New York State Energy Research and Development Authority on September 25, 2011.

reasons, the Team suggests (and intends to provide) a triangulation of NTG estimates derived from a variety of measurements, including demand elasticity modeling, supplier self-reports, and comparison-area on-site research. The results of all such investigations are forthcoming in separate reports, as is the finalized NTG for the 2013 program, which will weigh all methods and estimations.

Conclusions

The results of the modeling efforts conducted in the present research suggest that lighting programs continue to have an influence on the lighting market, even in the years following EISA implementation. Across the three separate bulb-proportion dependent variables (all efficient bulbs, CFLs only, and LEDs only) the model demonstrated the positive and significant influence of program activity on the percentage of energy-efficient bulbs purchased statewide. Results suggest that as the lighting market continues to progress, programs focusing on LEDs are likely to have greater relative impacts, evidenced by the higher NTG values for LEDs than CFLs (Table 8).

Table 8: MA NTG Values

Bulb Type	NTG
All Efficient Bulbs	45.4%
CFLs-Only	43.9%
LEDs-Only	97.9%

The modeling also reveals that more simplistic approaches to understanding the lighting market, considering only factors such as bulb pricing trends or the number of efficient bulbs sold, often fall short of being able to explain or account for the many interceding dynamics in the market. The models presented here provide evidence that lighting programs matter, but the preliminary exploratory analyses and graphs of MA vs. the nation and program states vs. non-program states hid the impact of intervening factors. The modeling allowed the Team to control for many of those factors and therefore see that MA really does continue to move forward with energy-efficient bulb sales.

The Team does not offer any recommendations or considerations at this time, as they will fit best within overall reports for the Saturation Stagnation and NTG studies. The various tasks within these larger studies must be taken as a whole when making suggestions about how to move forward with the Residential Lighting Program at this time, although the present research does suggest that lighting programs continue to impact sales, especially when considering LEDs.

Appendix A: Program Activity Data Collection Form

State, Utility name	Program variable	Presence of lighting program according to internal sources	Presence of lighting program according to www.dsireusa.org	Presence of lighting program according to EnergyStar http://www.energystar.gov/ia/partners/downloads/2013_ENERGY_STAR_Summary_of_Lighting_Programs.pdf	Number of CFLs incented by the program	Number of LEDs incented by the program	Lighting Program Budget	Lighting Program incentive budget	Age of lighting program
	Collection metric	(Yes/No followed by explanatory notes)	(Yes/No followed by explanatory notes)	(Yes/No followed by explanatory notes)	(Count)	(Count)	($)	($)	(Years)
Year	2009								
	2010								
	2011								
	2012								
	2013								

Program Data Collection Instructions and Suggestions:

1. It may be that there are multiple utilities within a state that have major lighting programs. If so, please copy and paste the table below and give each major utility its own table.

2. The grey shaded columns are program data we would like to have but which may not be readily available.

Appendix B: Universal Dataset Report Information

Detailed aspects of the Universal Dataset include:

Products

- Light Bulb Category

Measures

- Type of Light (e.g., Incandescent, Halogen, CFL, LED)
- Unit Sales (Number of Unique bulbs)
- Dollar Sales (Total Value of Dollar Sales)

Time Periods

- Calendar Year 2013
- Calendar Year 2012
- Calendar Year 2011
- Calendar Year 2010
- Calendar Year 2009

Geographies

- All Available States Multi-Outlet
- All Available States Drug
- All Available States Food

Appendix C: Detailed Model Results – CFLs Only

Variable	Level	Model Results
Intercept	--	1.6686 (1.3443)
log(cr.sqft)	Continuous	0.1764^{*} (0.0750)
log(noncreed.sqft)	Continuous	-0.1365^{*} (0.0549)
% built pre-1980	Continuous	-0.9818 (0.5996)
% renters paying utilities	Continuous	-2.3068 (1.6035)
Median # rooms per home	Continuous	--
Electric Price	Continuous	0.0147^{**} (0.0054)
Cost of Living Index	Continuous	-0.0083^{**} (0.0028)
Program Indicator	Yes	--
	No	--
Program Budget	Continuous	$5e\text{-}05^{***}$ (2e-05)
log(non-program CFL sales trend)	Continuous	0.7166^{***} (0.0877)

Additional Details		
Number of States		27
Number of Observations		94
R^2		0.666

Coefficient estimates presented with standard errors in parentheses beneath them.
log(covariate) indicates the natural logarithm of that covariate.
Note: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Appendix D: POS Modeling and Interpretation Details

The Team fit several regression models to determine the impact of EE program activity on efficient bulb sales across 44 states from 2009 to 2013. The models fitted were state-level robust random-effects regression models of the following form:

$$\log(\%efficient.sales_{i,j}) = \alpha + \beta_{0,i} + \beta_1 \log(cr.sqft_{i,j}) + \beta_2 \log(noncreed.sqft_{i,j}) + \beta_3 avg.electric.price_{i,j} + \beta_4 cost.of.living_i + \sum_{k=1}^{p} \gamma_k dem.var_{i,j,k} + \theta prog_{i,j} + \tau_j + \epsilon_{i,j}$$

Where:

$\%efficient.sales_{i,j}$ = Proportion of total CREED-reported bulb sales that were efficient bulbs in state *i* and year *j*. Calculated as $(\#CFL_{i,j} + \#LED_{i,j})/(total\ bulb\ sales_{i,j})$.

$cr.sqft_{i,j}$ = Number of square feet of major CREED-reporting retailer channels in state *i* and year *j.*

$noncreed.sqft_{i,j}$ = Number of square feet of major non-CREED-reporting retailer channels in state *i* and year *j.*

avg.electric.price = Average cost of electricity in state *i* and year *j.*

cost.of.living = Average cost of living index in state *i.*

$dem.var_{i,j,k}$ = One of *p* demographic variables for state *i*, at time *j*, with $k \in (1, \ldots, p)$. The following state-level demographic variables were considered: number of households, % of homes built before 1980, % of renters who pay their own utilities, median income, % owner-occupied households, education level, and population. The Team determined which demographic variables to include in each model by selecting the covariate pattern yielding the highest adjusted R^2.

$prog_{i,j}$ = Program activity variable for state *i* in year *j*, indicating the lighting program budget in state *i* in year *j*, as gathered through published reports, internet searches, internal evaluations, or provided directly by Utilities. It should be noted that the program budget variable includes program activity even if it was in retail channels not represented by the POS data. The square root of program-related budgets was used in the models in order to adjust for the skewedness in the distribution of that variable.

τ_j = Average proportion of efficient bulb sales across states that had no program activity for the entire study period, 2009 to 2013. Including this term allows the model to account for naturally

occurring, non-program influenced, “baseline” trends in efficient bulb sales during the study period, which in turn helps to isolate the effect of program activity on efficient bulb sales as opposed to other outside factors.

α = Overall model intercept term

$\beta_{0,i}$ = Subject-specific deviation from overall-level intercept, α, as estimated by random-effects specification

β_1, β_2, γ_k, ϑ = Regression coefficients to be estimated by the model

$\epsilon_{i,j}$ = Error term

Of primary importance is the interpretation of the coefficient ϑ, which quantifies the impact of program related activity in these models. In the models presented in the report (see Model Results section) state-level programmatic activity, is associated with increased overall efficient bulb sales (Table 3), with increased CFL sales, and increased LED sales (Table 4). It is important to remember that all models are fitted at the state level, and the reported regression coefficients indicate state-level (not individual-level) associations. To interpret these findings at the individual level would be to commit the ecological fallacy.

Appendix E: NTG Details and Alternative Calculations

The 2013 NTG calculations for MA were estimated using the following equation:

$$NTGR = \frac{(\#\ bulbs\ sold\ with\ program - \#\ bulbs\ sold\ with\ no\ program)}{\#\ of\ program\ incented\ bulbs\ sold}$$

For each of the calculations presented in the report, the Team used the actual observed number of program bulbs sold with the program and the actual number of program incented bulbs sold, and used the appropriate coefficient from the regression models to estimate the counterfactual number of bulbs sold assuming no program based on the observed data.

Note, however, that another approach for estimating the NTG ratio involves predicting both quantities in the numerator above using the regression model. That is, rather than using the observed number of bulbs sold with the program, it is not uncommon to instead predict that value based on the regression model so that both quantities in the numerator are predictions (as opposed to one prediction and one observed value). The Team ultimately chose not to use this approach, because the denominator used in the NTG formula is a fixed quantity, obtained from an external data source that was not subject to any modeling. The *predicted* number of bulbs sold with the program in 2013 for MA was slightly biased downward for all three models – CFL + LED, CFL only, and LED only – compared to the observed value. Therefore, the obtained NTG values when using this method were also biased downward because the denominator is a fixed (not estimated) quantity. Had the denominator also been modeled, and it too was proportionately biased downward, then there would be no issue. However, in order to make an "apples-to-apples" comparison between the numerator and denominator, the Team chose the method presented in the body of the report.

Further, the Team also had to decide which program budget variable to utilize in the models and the NTG calculations. The decision ultimately came down to using the detailed program expenditure data collected by the Team, or the categorical program data provided by the ENERGY STAR Summary of Lighting Programs. The only advantage of using the ENERGY STAR categorical expenditures is that they capture more states (44 as opposed to 27). There are also several disadvantages of that data however, including extremely large budget bins by state (categories of $1-$10 million and $10-$25 million for example), which make it difficult to isolate true program spending. A state could double or even triple its lighting budget between years, but still remain in the same category. Nevertheless, the Team chose to run the models and NTG values using the categorical data as well, and found that it did not perform as well as the reported models which utilized continuous program budgets. Table 9 below, provides the R^2 and NTG values obtained from using the categorical expenditures, along with those presented in the report.

Table 9: Reported and Alternative NTG and R^2 Values

	All Efficient Bulbs	CFLs-Only	LEDs-Only
Reported NTG (and R^2)	45.4% (0.663)	43.9% (0.666)	97.9% (0.956)
NTG (and R^2) Utilizing Categorical Program Variable	25.3% (0.430)	23.5% (0.419)	176.6% (0.600)