RESULTS OF THE MULTISTATE CFL MODELING EFFORT

Final

April 15, 2011

Submitted to:

National Grid

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Executive Summary

This report summarizes the analyses conducted in support of the multistate CFL modeling effort, highlighting the results as they pertain to the net-to-gross ratio (NTG) for National Grid in Rhode Island. The Sponsors of this study include the following: Ameren Illinois (Ameren IL); Ameren Missouri (Ameren MO); ComEd; Consumers Energy in Michigan (Consumers); Dayton Power and Light (DP&L); EmPower Maryland (EmPower); the five program administrators of the Massachusetts ENERGY STAR® Lighting Program (Massachusetts) which are the Cape Light Compact, NSTAR, National Grid in Massachusetts, Unitil, and Western Massachusetts Electric; National Grid in Rhode Island; the New York State Energy Research and Development Authority (NYSERDA); and the Salt River Project (SRP). This report draws on data from 15 different geographic areas in the United States, but was written specifically for National Grid in Rhode Island. The analyses draw primarily on data collected from 1,495 households that took part in onsite saturation surveys.[1] Note that the report uses the term "program administrators (PAs)" because the various parties supporting this effort include electric utilities, energy service organizations, public service commissions, and state agencies.

The key result emerging from the analysis of the models is that the NTG ratio for the eighteen-month period of January 2009 to June 2010 was 0.34. This executive summary provides an overview of the approach, methods, and findings that have led to this conclusion.

Areas Included in the Analyses

The multistate modeling effort relies on data drawn from telephone and onsite surveys conducted in areas with longstanding CFL programs, those with newer or smaller programs, and those with no CFL programs through June 2010. The ten PAs funded data collection in eleven program areas and four non-program areas (Table ES–1). The PAs and evaluators chose these four non-program areas to complement the demographic, social, and economic characteristics of the eleven program areas.

[1] We report many results for fewer than the 1,523 participants because some respondents provided unusable responses (*e.g.* failed to respond, responded "don't know", *etc.*).

Table ES–1: Participating Areas, Sample Sizes, and Survey Dates

Area	Abbreviation	Years Supporting CFLs[e]	On-Site Sample Size
Program Areas			
Ameren IL (part Illinois)	AIU	1.5	92
Ameren MO (part Missouri)	AUE	0.5	87
ComEd (part Illinois)	ComEd	5.0	98
Consumers Energy (part Michigan)[a]	Consumers	0.5	61
Dayton Power and Light (part Ohio)	DPL	1.0	72
EmPower Maryland (most Maryland)	EmPower	2.0	79
Massachusetts (entire state)[b]	MA	12.0	150
New York City[c]	NYC	11.0	100
New York State[d]	NYS	11.0	200
Rhode Island (entire state)[b]	RI	12.0	100
Salt River Project (part Arizona)	SRP	2.0	101
Non-program Areas			
Houston, Texas (Harris County)	Houston	0.0	100
Indiana (central portion)	IN	0.0	67
Kansas (entire state)	KS	0.0	95
Pennington County, SD (portion)	SD	0.0	93
TOTAL			1,495

[a] A total of 99 homes were surveyed, but the analysis excludes those households who only have natural gas service with Consumers Energy.
[b] Surveyed the entire state, even though some portions may be served by municipal utilities not taking part in the ENERGY STAR Lighting Program.
[c] Surveyed separately from the remainder of the state due to its unique demographic and economic characteristics
[d] State minus New York City and Nassau and Suffolk Counties
[e] At the beginning of 2010

Development of Program Variables

The program variables were the key components of the statistical models guiding the calculation of the NTG ratios. The team began development of these variables by reviewing CFL program plans and documents, prior evaluation reports, and program summaries compiled by the Consortium for Energy Efficiency (CEE), the US Department of Energy (DOE), and ENERGY STAR in order to locate CFL programs in each state and gather information on CFL program activity through 2010 in each area. Specifically, we searched for: data on the program budgets; the number of CFLs incented; the percentage of the budget allocated to incentives, marketing and advertising, and overhead; the percentage of CFLs that had specialty features, and the method of support (*e.g.*, retail coupons, catalog, and/or upstream approaches).[2] The team successfully collected this information for all programs for 2009 and 2010 and verified the data

[2] Specialty features primarily included the following: dimmable and three-way capabilities, colored bulbs, small screw bases, and shapes other than the usual spiral.

with the PAs. These data were then entered into the model as individual variables or combined in various ways to represent "composite" variables, as described in more detail in Appendix B

We also gathered information on when the current CFL program and any of its predecessor programs had been launched in order to assess the impact of prior program activity on current purchases. This variable is not considered to be descriptive of the *current* program, however, and is kept separate from variables representing program activity in a given time period. We do show the implication of this choice on NTG-ratio estimation.

Comparison of Key Variables across Areas

Many of the PAs sponsoring this effort expressed an interest in the levels of CFL purchases, use, and saturation in their areas compared to the levels in the other areas taking part in this study, and Table ES–2 presents this comparison for current saturation, current use, and purchases from January 2009 through June 2010. The shaded cells indicate areas with results above the overall average for the entire sample. The data demonstrate that program areas differed widely in their level of saturation, current use (which depends in part on the size of the home), and purchases over the study period. Moreover, the data do not point to clear delineations between program and non-program areas; non-program areas rival and often exceeded program areas in CFL saturation, use, and purchases. This is important because the modeling process seeks to isolate the net impact of programs from the impacts of other demographic, economic, and social factors that may also influence CFL purchases, use, and saturation, but the lack of a strong "signal" between program activity and CFL purchase, use, and saturation increases the challenges of finding an effect.

Table ES–2: Current CFL Saturation by State
(Collected during onsite visits; saturation = percentage of sockets)

Area	Sample Size	Current Saturation (Percentage of lighting sockets filled by CFLs)	Current Use (Mean number of CFLs installed per household)	2009 to 2010 Purchases* (Mean number of CFLs purchased)
Program Areas				
Ameren IL	92	23%	12.9	9.7
Ameren MO	87	17%	11.4	6.4
ComED	98	20%	12.5	9.0
Consumers	61	18%	7.6	5.1
DP&L	72	15%	9.2	6.8
EmPower	79	19%	10.2	4.4
Massachusetts	150	27%	11.6	6.1
New York City	100	28%	8.2	6.7
New York State	200	21%	12.6	7.5
Rhode Island	100	20%	8.8	3.8
SRP	101	23%	11.8	8.7
Non-program Areas				
Indiana	67	17%	8.7	8.4
Kansas	95	19%	11.2	7.8
Houston	100	18%	9.3	7.3
Pennington Cnty, SD	93	24%	11.6	7.1
OVERALL	**1,495**	**21%**	**10.8**	**7.1**

* January 2009 to June 2010
Shaded cells indicate areas with results above the overall average for the entire sample

Modeling Procedures

The team used a zero-inflated negative binomial (ZINB) model to predict CFL purchases. Similar to the related model, the negative binomial regression model (NBRM), the ZINB is one of the more common methods of analyzing count data (*e.g.* the number of CFLs) with many cases falling at zero and with a fair degree of variability in the data.

The ZINB distinguishes between the zeros by first running a logistic model in which it sorts out the differences underlying zero purchases during a time period. Our analysis led the multistate modeling team to conclude zeros in the data represented two separate populations:

- CFL users who happened not to have purchased during the observation time (*i.e.*, the not-always zero group); and
- Households that will likely never purchase CFLs (*i.e.*, the always zero group).

The zero-inflation portion of the model uses a logistic regression to identify persistent non-purchasers, who can be thought of as never considering a CFL purchase.[3] For those not identified as persistent non-purchasers, the probability of each possible count of CFL purchases (including zero) is modeled as a negative binomial distribution, which has more cases at smaller numbers and very few cases at larger numbers.

The team also developed statistical models to explain CFL use and saturation, but we used different model types to do so. For CFL use, we turned to a NBRM, because the modeling procedures failed to identify systematic differences between the households that did not use CFLs (*i.e.*, their use was zero). Moreover, the ZINB was not an appropriate choice to model saturation because saturation is measured as the proportion of sockets in the home filled with CFLs. For saturation, we turned to ordinary least squares regression, the most commonly used linear regression technique. We discuss these models in more detail in the full report.

The team developed models using the different program variables and other explanatory variables capturing demographic, economic, and social characteristics, the concentration of box stores, duration of household CFL use, CFL storage, and CFL use and saturation prior to the purchase period under consideration, and various measures of environmental opinions and early adoption behavior. The team excluded explanatory variables found to be excessively collinear with other explanatory variables in the model, that had little statistical effect on CFL use, saturation, and purchases, that were tautological, or that made little theoretical sense.[4,5] The models presented in Section 6 are parsimonious in that almost every variable in them has a statistically significant net effect on CFL use or purchases (at the 0.10 level of significance); removing any of the variables reduces the predictive capability of the model or its maximum likelihood R^2 statistic.[6] In short, they represent the best models yielded by the analyses.

Results: Purchase Models and NTG Estimates

After developing numerous model specifications, the team used a series of diagnostics (see the full report for more detail) to select recommended "best models" for the full eighteen month

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[3] In statistically parlance, it is most accurate to think in terms of the probability of being in the not-always zero purchasers group or the always zero purchasers group.

[4] Collinearity was determined by the tolerance statistic and the variance inflation factor.

[5] For example, the variable, "area electricity rate"—defined as average cents per kWh for the residential customer class of each program area—was found to be significant in some models, but the direction indicated that higher electricity price was associated with lower purchases. Closer examination revealed that the variable was serving as a proxy for the East Coast, where electricity rates are higher but also where programs have been operating for many years. CFL purchases tend to be lower on the East Coast because prior program activity has boosted saturation such that many households have relatively few sockets to fill with CFLs and have slowed their previously rapid purchases of the bulbs.

[6] The maximum likelihood R^2 is one of various statistics reported for non-linear regression that attempts to mimic the explained variance R^2 of OLS models. However, most statistical sources warn that its interpretation is not the same as OLS because non-linear models behave differently than linear ones. For this reason, the maximum likelihood R^2 can be understood as a method to assess a model's goodness of fit but should not be considered to be equivalent to the OLS R^2.

period running from January 2009 through June 2010 and another model that covers only January to June 2010. The models demonstrate that, after controlling for other factors, the number of CFLs supported per household had a significant and positive effect on CFL purchases in both time periods. Furthermore, CFL saturation was a significant predictor of the number of bulbs purchased in both models; this effect was negative, indicating that, the higher the rate of saturation, the fewer bulbs participants were purchasing. The most important source of variation between the two models involves a variable meant to isolate the impact of prior program support on current CFL purchases. This variable was not statistically significant in the eighteen-month model but as significant in the early 2010 model.

Using the specific models, the team used statistical software to predict purchases in the presence and absence of the program.[7] As shown in Table ES–3, for Rhode Island, the NTG ratios were 0.34 for the entire eighteen month period and 0.81 for the first half of 2010. Importantly, the estimate for the first half of 2010 assumes that the prior program support variable is *not* a measure of current program activity; the calculation of NTG, in other takes, takes the impact of prior program activity into account. However, some advisors to this project have made the argument that prior program activity should be treated as a current program variable. Table ES–4 shows the calculations which follow the same procedures described above, except that, when computing the non-program scenario, we also assume that all programs had no prior activity. This produces a NTG ratio of -9.09 (negative 9.09) for Rhode Island. The confidence intervals were developed using a bootstrap method, and their width reflects the non-linear nature of the models and the remaining uncertainty in the models.

Table ES–3: NTG Ratio Calculations*

Input	Full 18 Months	First half of 2010
A. Per-household purchases with program	5.64	2.20
B. Per-household purchases without program	5.35	2.03
C. Net program purchases per household	0.29	0.17
D. Incented CFLs per household	0.85	0.21
E. Total NTG	0.34	0.81
F. Confidence Interval	0.08 to 0.80	0.45 to 1.41

Table ES–4: Alternative 2010 NTG Ratio Calculations

Input	First half of 2010
A. Per-household purchases with program	2.20
B. Per-household purchases without program	4.15
C. Net program purchases per household	-1.95
D. Incented CFLs per household	0.21
E. Total NTG	--9.09

* Results subject to rounding error.

[7] Team members used STATA and SAS to predict these purchasers in order to confirm the reliability of the results.

Conclusions

The results of the eighteen-month CFL purchase model yield a NTG ratio for the period of January 2009 to June 2010 of 0.34, while the model limited to the first half of 2010 suggests a NTG of 0.81 when prior program support is included, and -9.08 (negative 9.09) when years of program support is set to zero. The difference in the estimates reflects economic, statistical, and programmatic factors, namely the improvement in the economy, the inclusion or exclusion of a variable that captures the impact of prior program activity, and the launch of new programs outside of Rhode Island and a program revision within Rhode Island that altered CFL purchase behavior between 2009 and early 2010.

For purposes of estimating NTG, the 2009 model is superior to the 2010 model, as evidenced by the larger maximum likelihood R^2 of 0.18 for the former compared to 0.12 for the latter. This may be at least partially because respondents could not accurately differentiate CFL purchases in 2009 from purchases in the first six months of 2010, whereas they could give more accurate estimates for the entire 18-month period.

1 Introduction

This report summarizes the analyses conducted in support of the multistate CFL modeling effort, highlighting the results as they pertain to the net-to-gross ratio (NTG) for National Grid in Rhode Island. The Sponsors of this study include the following: Ameren IU (AIU); Ameren UE (AUE); ComEd; Consumers Energy in Michigan (Consumers); Dayton Power and Light (DPL); EmPower Maryland; the five program administrators of the Massachusetts ENERGY STAR® Lighting Program (Massachusetts) which are the Cape Light Compact, NSTAR, National Grid in Massachusetts, Unitil, and Western Massachusetts Electric; National Grid in Rhode Island; the New York State Energy Research and Development Authority (NYSERDA); and the Salt River Project (SRP). This report draws on data from 15 different geographic areas in the United States, but was written specifically for National Grid in Rhode Island. The analyses draw primarily on data collected from 1,495 households that took part in onsite saturation surveys. Note that the report uses the term "program administrators (PAs)" because the various parties supporting this effort include electric utilities, energy service organizations, public service commissions, and state agencies.

Changing CFL Market and the Multistate Modeling Approach

CFL program evaluators nationwide are finding it increasingly difficult to provide valid and defensible estimates of net-to-gross (NTG) ratios for CFLs. Numerous recent studies employing various methods have struggled to provide estimates that are widely accepted as realistic and valid estimates of NTG.[8,9] The CFL program evaluation community has turned to a diverse range of methods: self-reported free ridership and spillover, comparisons of CFL sales and self-reported purchase behavior in program and non-program areas, manufacturer and retailer estimates of program-induced "lift" in sales, revealed preference models, and multistate purchase models, among others—only to be frustrated by what some reviewers saw as counterintuitive or unreliable NTG estimates. In fact, the comprehensive evaluation of the Upstream Lighting Program in California (ULP) completed in the Spring of 2010 for the California Public Utilities Commission (CPUC) assessed NTG using six different methods, with the results varying from as low as 23% to as high as 74%.[10,11] This and other recent NTG studies make clear that all

[8] For example, 1) KEMA. 2010. *Final Evaluation Report: Upstream Lighting Program*. Delivered to the CPUC February 8. 2) Summit Blue Consulting. 2009. *Energy Efficiency/Demand Response Plan Year 1 (6/1/2008-5/31/2009) Evaluation Report: Residential Energy Star Lighting*. Delivered to ComEd, November 16, 2009. 3) NMR Group, Inc. 2010. *Results of the Multistate CFL Modeling Effort*. Delivered to the Massachusetts ENERGY STAR Lighting Program Sponsors, February 4, 2010.

[9] Note that assessing validity—the knowledge that the estimate truly measures what it was supposed to measure—is not entirely possible for NTG ratio estimation as it inherently involves measuring a counterfactual, what would have happened if the program had not occurred. See NMR and Research Into Action. 2010. *Net Savings Scoping* Paper. Prepared for the Northeast East Energy Efficiency Partnerships Evaluation, Measurement, and Verification Forum. http://neep.org/uploads/EMV%20Forum/EMV%20Products/FINAL%20Net%20Savings%20Scoping%20Paper%2011-13-10.pdf

[10] KEMA. 2010, ULP.

available estimation methods have strengths and weaknesses that ultimately influence the results. Given the rapidly changing CFL market, marked by volatile sales nationwide over the past three years, former "best practices" (*e.g.*, self reports of free ridership and spillover and simple comparison-state approaches) have become increasingly problematic. Numerous circumstances underlie the struggle to provide valid estimates of NTG, but chief among these is the rapid expansion of CFL programs throughout the nation,[12] the increased availability of CFLs regardless of CFL program activity, and limited access to CFL sales data from participating and non-participating retailers in both program and non-program areas. Not only do such circumstances limit the usefulness of former best practices to estimating NTG, but no clear methodology currently presents itself as the latest best practice in NTG estimation. For this reason, many PAs across the nation are embracing innovative approaches to estimating NTG in an effort to identify new ways of determining the impact of CFL program activity on actual CFLs purchases and energy savings.

Multistate modeling is one of these approaches. Numerous PAs and their evaluators have employed multistate—really multi-area—modeling as one possible avenue for estimating NTG. In this approach, data from households in multiple PA service territories are entered into a statistical model that attempts to capture the effect of program activity on CFL purchase and use behavior, net the impact of demographic, economic, and social factors that also affect such behavior. Previous attempts to use multistate modeling to explain CFL purchases and use met with mixed success.[13] Some of the limitations of the previous efforts include inconsistency in data collection instruments and the time of year in which data collection occurred, the failure to include variables that capture a household's environmental opinions or inclination to be an early adopter of technology, and the dominance in the model of program areas with long histories of supporting CFLs, leading to limited variation in the program score from which the authors determined program effects. The 2009 effort also relied on a modeling approach that the current team members concluded was not the most appropriate choice to model CFL purchases, as explained in Section 5 of this report. The current multistate modeling effort responded directly to these shortcomings by implementing greater consistency in the instruments and methods used to collect data and the timing of data collection, adding variables that capture environmental and other opinions that may affect adoption of CFL, including programs with a wide range of histories of support for CFLs, and specifying models using a technique closely related to the one employed in the prior effort but that the team believes is more suited to the unique nature of purchase data.

The principal goals of the multistate model are to identify and examine factors associated with CFL purchases from January 2009 to June 2010 and, if possible, isolate the effect of current CFL

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[11] The NTG ratios provided for the ULP were not all measuring the same time period; some were for the entire 2006 to 2008 period and others for blocks of that time making the range.

[12] Six of the 10 PAs sponsoring this study have programs that had been existence for less than three years as of June 2010.

[13] KEMA 2010 ULP; NMR 2010 Multistate CFL Modeling.

programs on those purchases. The evaluation team uses the modeling results to estimate NTG for each PA. The team bases these estimates on a model that we believe best describe CFL purchases for the entire eighteen month period as well as a model limited to the more recent 2010 time period. The analysis draws on data gathered over the telephone or at the homes of 1,495 households (Table 1–1). Note that throughout the report, the sample size reported for each area and overall will differ across table and variables, reflecting "don't know" answer, refusals to answer the question, and other missing or unusable data.

Table 1–1: Participating Areas, Sample Sizes, and Survey Dates

Area	Abbreviation	Years Supporting CFLs[e]	On-Site Sample Size
Program Areas			
Ameren IL (part Illinois)	AIU	1.5	92
Ameren MO (part Missouri)	AUE	0.5	87
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Non-program Areas			
Houston, Texas (Harris County)	Houston	0.0	100
Indiana (central portion)	IN	0.0	67
Kansas (entire state)	KS	0.0	95
Pennington County, SD (portion)	SD	0.0	93
TOTAL			1,495

[a] A total of 99 homes were surveyed, but the analysis excludes those households who only have natural gas service with Consumers Energy.

[b] Surveyed the entire state, even though some portions may be served by municipal utilities not taking part in the ENERGY STAR Lighting Program.

[c] Surveyed separately from the remainder of the state due to its unique demographic and economic characteristics

[d] State minus New York City and Nassau and Suffolk Counties

[e] At the beginning of 2010

2 Recruitment Procedures

The data used in the modeling effort was derived largely from information collected during an onsite saturation survey in which team members counted all lighting products in the home and verified when installed and stored CFLs were purchased. Households were recruited for the onsite effort through telephone surveys. This section describes the selection of comparison areas, development of the surveys, sample designs and sampling error, and weighting schemes.

Choice of Comparison Areas

The multistate modeling effort relies on data from areas with longstanding CFL programs, those with newer or smaller programs, and those with no CFL programs through 2010. Table 1–1 lists the areas included in the study. Four of the areas—Houston, part of Indiana, all of Kansas, and Pennington County, South Dakota—serve as comparisons to the program areas. In order to select comparison areas, the PAs and the multistate modeling team examined data on household demographics, concentration of major retailers selling CFLs, and CFL programs across the nation to identify potential comparison areas lacking programs. The evaluation team experienced difficulty in finding non-program areas for two reasons. First, many formerly non-program areas have recently begun implementing programs. Second, the remaining non-program areas often differ substantially from program areas regarding characteristics shown to relate to CFL sales (*e.g.*, homeownership, socioeconomic status, cost of living including electricity costs, and access to retailers selling CFLs). The multistate modeling team confirmed that these four areas had no substantial or sustained CFL program activity as of June 2010.[14] It is worth noting that the portions of Indiana we surveyed are expected to have substantial programs by 2011.

Telephone Surveys

In order to identify households to take part in the onsite data collection needed for the multistate modeling effort, the multistate modeling team fielded telephone surveys in each of the program and non-program areas included in the analysis. In areas where the PAs serve most residents and in the comparison areas, the team conducted random digit dial (RDD) surveys of households with residential—and in Massachusetts also cell phone—numbers. In the areas where PAs served specific portions of the state, we randomly dialed residential customers of the PAs. The use of these two approaches leads to one primary difference: the RDD surveys are more likely to catch renters who live in master-metered buildings in which their landlord is listed as the customer. The team adjusts for this difference by weighting on owner/renter status in the weighting scheme, described below and presented in Appendix A.

[14] The City of Houston had a short-term bulb give-away program reaching less than 5% of the population of Harris County, and Black Hills Power in South Dakota had taken part in a *Change-a-Light Campaign* but team members confirmed via phone or email that no substantial or sustained CFL program activity existed in these areas.

Onsite Visits

The PAs and the evaluation team relied on an onsite saturation study to provide information on CFL use, storage, and purchases. The reliance on an onsite survey over a telephone survey reflected the finding in the 2009 multistate effort that telephone survey responses about use and purchases differed substantially—and not very systematically—from those verified onsite. For reasons discussed in detail in those reports, last year's multistate team concluded that the onsite data were more accurate.[15] In response, we rely only on onsite data in this current multistate modeling effort.

2.3.1 Recruiting Onsite Participants

The multistate modeling team identified onsite participants through the telephone surveys. The evaluators then randomly called each household tentatively agreeing to the onsite to set up an onsite visit. The PAs offered a $75 to $150 incentive to each homeowner, depending on the cost of living in their area, to entice customers to participate in the onsite visit. However, when calling to set up the visits, fewer respondents than expected decided to move forward with the onsite visits, reflecting difficulty with scheduling (most onsite visits were conducted during the summer), lack of familiarity with the PA (in non-program states), and distrust of letting strangers into the home. Thus, while the team originally anticipated an onsite sample size of about 1,700, the final sample size was actually 1,495.

2.3.2 Variations on the Onsite Recruitment Approach

Recruitment of onsite households varied from the approach described above in the Ameren Missouri, Consumers, and SRP service areas as well as Maryland, Massachusetts, New York City, New York State, and Houston. In the Consumers service territory, the evaluators recruited households for a comprehensive residential saturation study which addressed CFLs as well as other appliances and heating and cooling equipment. The evaluators asked some of the telephone survey questions while onsite in order to reduce the time on the phone and increase compliance with the onsite saturation study. In the SRP service territory, households had already completed telephone surveys before SRP joined the effort, but the evaluators performed follow-up surveys to make sure all relevant data were collected from SRP respondents. In Maryland and for 22 Ameren Missouri customers, the evaluators recruited households for a metering study, and only CFL users were included. Because Maryland served as a comparison area in the 2009 effort in which all homes were visited despite their stated use or non-use of CFLs, we were able to adjust the weighting scheme to reflect the sample from last year in which recruitment was random and included non-users as well as users. Similarly for the Ameren Missouri households, we based the weighting scheme for those households identified through the metering study to reflect the remaining randomly drawn sample from the service territory.

[15] For example, NMR Group, Inc. (2010) *Results of the Multistate Modeling Effort* and NMR Group, Inc. (2010) *The Market for CFLs in Connecticut*. Both available at http://www.ctsavesenergy.org/ecmb/documents.php?section=22.

In Massachusetts, New York City, New York State, and Houston, a sub-set of homes took part in the 2009 onsite efforts, and the evaluators revisited these homes in 2010 to identify any differences in use and saturation between the two visits. Each “revisit” household was paid an incentive ranging from $150 to $250 depending on their location and the number of sockets found in their home last year. Similar to Consumers’ respondents, the evaluators asked many of the telephone survey questions of these householders while onsite in order to limit the time spent on the phone during recruitment for the repeat onsite visit. We have controlled for these revisit households in the models, where appropriate.

2.3.3 Conducting the Onsite Visit

The PAs and the evaluation team cooperatively developed onsite survey instruments. As with the telephone survey questionnaires, the onsite surveys differed slightly, largely reflecting the individual preferences of the PA or data collection firm, but all PAs and evaluators worked closely to ensure comparability across the study areas. The onsite visits in every area adhered to the following procedure:

A trained technician arrived at the home at a pre-scheduled time, introduced him or herself, and asked for the contact person who had been identified when scheduling the visit. The respondent and the technician walked through each room of the home examining all lighting sockets to see if they contained a bulb and, if so, the type of lighting technology in use and the switch type; some also noted the base type. If the product was a CFL, the technician noted its manufacturer and model number and any specialty features. The technician also asked the respondent to estimate when he or she purchased that particular CFL. The technician and householder examined bulbs in storage, again noting similar detailed information on stored CFLs.

One small variation in onsite protocols, however, led to some changes in the modeling procedures. In some areas, the technicians allowed respondents to say that they “did not know” *when* they had obtained CFLs found in their homes; in other areas, they strongly encouraged the respondents to guess at when the purchase occurred, resulting in very few or even no “don’t know” responses. Table 2–1 summarizes the disposition of “don’t know” responses to this critical question of when households obtained their CFLs. Although 88% of households provided a purchase date for all CFLs in their home, the remaining 12% did not provide a date of purchase.

Table 2–1: Disposition of “Don’t Know” Responses to When Purchased CFLs*

Disposition	Percent of Cases
Sample Size	*1,495*
Provided data for all CFLs	88%
Don’t know when purchased 1% to 24% of CFLs	4%
Don’t know when purchased 25% to 74% of CFLs	2%
Don’t know when purchased 75% to 99% of CFLs	1%
Don’t know when purchased 100% of CFLs	4%

* Cases do not sum to 100% because of rounding error.

The team performed various diagnostics on the households that failed to provide purchase dates for all CFLs in their homes, and we concluded that they fell into two groups. The first group tended to have a large number of CFLs in the home and provided purchase dates for some of the CFLs but not all of them. The second group failed to provide a purchase date for any CFLs in their home, and these respondents were not concentrated in high CFL use homes.

The team then tested the impact of limiting our modeling efforts to households that did know various proportions of their CFLs. We found that the results changed little based on whether we set the cut off at knowing when 70%, 75%, or 80%—or even lower percentages—of CFLs were purchased. Given that the choice had little impact, we decided to limit the modeling procedure to households that knew the purchase data for 75% or more of their purchases. The choice is admittedly arbitrary, but we believed it represented a logical choice. Note that this decision excludes 105 (7%) of the 1,495 cases from the modeling effort. Moreover, we also include a flag for data collection protocols that allowed "don't know" responses to account for the fact that around five percent of the sample (those knowing 75% to 99% of their CFLs) would not have all of its purchases accounted for in the modeling effort.

The only other variations to the standard approach involved those places in which the technician also gathered information on home electronics, appliances, and heating and cooling technologies or installed lighting loggers. Data testing revealed no need to alter or control for these variations in the modeling process.

Weighting Scheme

In order to account for any potential bias toward CFL enthusiasts or homeowners, the evaluation team weighted the onsite sample back to the telephone survey-reported familiarity with CFLs as well as to Census data on the percentage of households that own or rent in each area.[16] In Massachusetts, Rhode Island, and Kansas, we weighted the data to the entire state, as we sampled from the entire state. Likewise, in Harris County (Houston) we sampled the entire county, while in Pennington County, SD, we sampled from the zip codes we had called for the RDD. For the remainder of the areas, we drew population data on the number of households from the American Community Survey (ACS) based on the counties represented in the telephone survey for each PA. This means that some of the estimates of households served differ from the actual population served for some PAs, but it allows for the more accurate pairing of county-level data such as unemployment and concentration of box stores (discussed below). Despite the numbers of households differing, the scheme should still reflect the general distribution of households by education and homeownership status in the service territory. (See the weighting scheme in Appendix A.)

[16] For Maryland and the 22 Ameren Missouri households in which only CFL users were sampled, we used data from other sources to determine familiarity with CFLs, as households using CFLs were all aware of CFLs and most also had relatively high levels of familiarity.

Please note that the weighting scheme used in this study differs from those used in some other reports delivered to individual PAs. The weighting schemes in other reports reflect concerns unique to individual PAs. In contrast, this effort required a consistent weighting scheme across areas. The implication is that summary statistics presented in this report will likely differ from those presented in other reports based on the same data. In many cases, the differences are slight, but sometimes they may appear more substantial. The team encourages the PAs to discuss with the evaluation team which results should be used for estimating electricity and demand savings and which to report in their regulatory filings.

3 Variable Specification

The Sponsors and the evaluation team collected nearly all of the data needed for the modeling effort through the telephone and onsite surveys, but we gathered a few variables from other sources. These include the program variables, electricity price, unemployment rates at the time of the survey, the change in the unemployment rate from January 2008 through January 2009, the concentration of various types of discount or home improvement stores (collectively called box stores), and whether the US Census Bureau classified the county as a metropolitan area, a micropolitan area, or a non-metropolitan area. We discuss the development of these other variables as well as specification of some of the survey data below.

Program variables[17]

The program variables were the key components of the statistical models guiding the calculation of the NTG ratios. The team began development of these variables by reviewing CFL program plans and documents, prior evaluation reports, and program summaries compiled by the Consortium for Energy Efficiency (CEE), the US Department of Energy (DOE), and ENERGY STAR in order to locate CFL programs in each state and gather information on CFL program activity through 2010 in each area. Specifically, we searched for data on the program budgets; the number of CFLs incented; the percentage of the budget allocated to incentives, marketing and advertising, and overhead; the percentage of CFLs that had specialty features, and the method of support (*e.g.*, retail coupons, catalog, and/or upstream approaches).[18] The team successfully collected this information for all programs for 2009 and 2010 and verified the data with the PAs. Table 3–1 summarizes the program data we gathered for each area for the three time periods: the first half of 2009, the second half of 2009, and the first half of 2010.[19] These data were then entered into the model as individual variables or combined in various ways to represent "composite" variables, as discussed in more detail in Appendix B. Ultimately, only the variables for individual components worked in the models, with the number of program supported CFLs per household serving as the consistent program variable identified across all the resulting models as discussed in Section 6.

We also gathered information on when the current CFL program and any of its predecessor programs had been launched in order to assess the impact of prior program activity on current

[17] NMR and Shel Feldman used a similar method in the appliances regression modeling approach conducted as part of the Market Progress and Evaluation Report for the Massachusetts ENERGY STAR Appliances Program. See NMR and Feldman (2005) *Statistical Analyses of Market Penetration of Energy Star-compliant Appliances*. Final delivered July 2005.

[18] Specialty features primarily included the following: dimmable and three-way capabilities, colored bulbs, small screw bases, and shapes other than the usual spiral.

[19] We show the data in these time periods to account for programs that began in the middle of 2009 or in January 2010. Some areas, however, keep data only for the entire program year. We had to allocate data to these smaller time periods, typically using the average unless the PA provided other information that indicated another appropriate allocation, such as for the programs that launched in mid-2009.

purchases. Because these variables were closely correlated, we added the scores together to yield a "prior program support" variable. This combined prior program support variable is not considered to be descriptive of the *current* program activity, however, and is kept separate from variables representing program activity in a given time period.

Table 3–1: Prior Program Support and Current Program Data by Area

Area	Years Supporting CFL	Years Buydown*	CFL Incented per Household	Budget Spent per Household	Percent of Budget for Incentives	Percent Standard CFLs
First Half of 2009						
Ameren IL	0.5	0.5	0.47	0.87	60%	87%
Ameren MO	No program in this period					
ComED	4.0	0.25	1.00	1.84	59%	67%
Consumers	No program in this period					
DP&L	0.0	0.0	0.63	1.09	75%	95%
EmPower	1.0	1.0	0.57	1.13	45%	90%
Massachusetts	11.0	6.0	0.51	1.98	71%	89%
NYSERDA**	10.0	0.0	0.15	0.22	40%	95%
Rhode Island	11.0	6.0	0.28	1.21	79%	94%
SRP	1.0	1.0	0.77	0.45	30%	55%
Houston	No program					
Indiana						
Kansas						
Pennington						
Second Half of 2009						
Ameren IL	1.0	1.0	0.43	0.95	51%	80%
Ameren MO	No program in this period					
ComED	4.5	0.75	1.39	2.13	70%	89%
Consumers	0.0	0.0	0.31	0.88	36%	86%
DP&L	0.5	0.5	2.64	4.58	75%	95%
EmPower	1.5	1.5	0.85	1.86	42%	90%
Massachusetts	11.5	6.5	0.77	1.98	71%	90%
NYSERDA**	10.5	0.5	0.23	0.93	62%	95%
Rhode Island	11.5	6.5	0.36	1.21	79%	90%
SRP	1.5	1.5	0.89	0.92	51%	48%
Houston	No program					
Indiana						
Kansas						
Pennington						

Area	Years Supporting CFL	Years Buydown*	CFL Incented per Household	Budget Spent per Household	Percent of Budget for Incentives	Percent Standard CFLs
First Half of 2010						
Ameren IL	1.5	1.5	0.39	0.95	0.51	86%
Ameren MO	0.5	0.5	1.09	2.05	0.55	89%
ComED	5.0	1.25	1.39	2.13	0.70	89%
Consumers	0.5	0.5	0.16	1.41	0.32	86%
DP&L	1.0	1.0	2.45	4.34	0.85	95%
EmPower	2.0	2.0	1.11	2.43	0.58	90%
Massachusetts	12.0	7.0	0.56	2.53	0.63	59%
NYSERDA**	11.0	1.0	0.26	0.56	0.62	95%
Rhode Island	12.0	7.0	0.21	1.32	0.40	80%
SRP	2.0	2.0	1.12	1.46	0.54	40%
Houston	No program					
Indiana						
Kansas						
Pennington						
Full Eighteen Month Period						
Ameren IL	1.5	1.5	1.14	2.45	0.54	84%
Ameren MO	0.5	0.5	1.20	4.81	0.26	89%
ComED	5.0	1.25	3.78	6.09	0.67	82%
Consumers	0.5	0.5	0.46	2.29	0.33	86%
DP&L	1.0	1.0	2.45	4.34	0.85	95%
EmPower	2.0	2.0	2.53	5.42	0.25	90%
Massachusetts	12.0	7.0	1.83	6.49	0.67	79%
NYSERDA**	11.0	1.0	0.63	1.70	0.59	95%
Rhode Island	12.0	7.0	0.84	3.73	0.65	88%
SRP	2.0	2.0	2.78	2.83	0.49	48%
Houston	No program					
Indiana						
Kansas						
Pennington						

* Refers to upstream as the dominant approach, although most areas still have some coupon, catalog, or give-away components to their programs.

** Includes both New York State and New York City

Additional Non-survey Variables

The evaluation team thought that certain external factors may have affected CFL sales and use, including the local economic conditions and the concentration of box stores.[20] Turning first to electricity price, we collected data on electricity price in 2009 and 2010, measured as cents per kilowatt hour, from the Energy Information Administration at the state level for all areas in the analysis. We supplemented these data with information on electricity rates in New York and Illinois to distinguish between the higher rates in the New York City and Chicago areas compared to the remainders of the state.

For economic conditions, the team focused on unemployment rates due to the inability to locate reliable and comparable data on foreclosure rates across all areas in the study.[21] We gathered unemployment data from the US Bureau of Labor Statistics (BLS).[22] The analyses included two different measure of unemployment, both collected at the county level. The first was the county unemployment rate during the month the telephone survey was fielded. The second was the change in the county unemployment rate from January 2008 to January 2009. The first approach provides a snapshot of the economic conditions in the county, while the second captures the relative change in the economic conditions. Both high unemployment rates and large changes in unemployment rates could affect purchasing behavior of CFLs, among other products.

The models also tested three different variables to capture the concentration of big box stores, specifically Home Depot, Lowes, Menards, and Wal-Mart (including Sam's Club).[23] First, the team used the "store locator" search engine on each retailer's website to count the number of their stores in each county in the study area. We then converted the store counts to estimated total square feet by county. For Wal-Mart, we used estimates gathered from its corporate website about the average square footage of each of its various store types (*i.e.*, Supercenter, Discount, Marketside, Neighborhood, and Sam's Club). We also located a national estimate of average square footage for Home Depot and applied that not only to Home Depot but also Lowes and Menards, because we were unable to locate a similar number for Lowes and Menards. We then summed the results into three different county-level estimates of total square footage for Wal-Mart stores and non-Wal-Mart stores, and then combined Wal-Mart and all other box stores. To adjust for the size of the county, the square footage of each box store per county was divided by the number of households in the county to yield variables capturing the concentration of box stores per household.

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[20] We chose the county level because it allowed for greater variation than state-level statistics, which would have been collinear with the program variable. The data required for developing the external variables were not always available at such smaller units of analysis such as the zip code.

[21] The team also included a question in the telephone surveys about the respondent's satisfaction with their standard of living.

[22] The BLS defines unemployment as jobless workers actually seeking employment; the measure excludes so-called "discouraged" jobless, those who have given up their job search.

[23] While Menards stores exist only in the parts of the Midwest, the chain is responsible for large numbers of CFL sales in these areas.

Finally, the evaluation team created a dummy variable using the current US Census Bureau designations of metropolitan, micropolitan, and non-metropolitan counties to control for effects that may be associated with central cities and their immediate suburbs as opposed to areas with smaller cities and towns (i.e., fewer than 50,000 people in any of the cities or towns in the county).

4 Comparisons across Participating Areas

Many of the PAs sponsoring this effort expressed an interest in the levels of CFL purchases, use, and saturation in their areas compared to the levels in the other areas taking part in this study. This section presents these comparisons. We find it extremely important, however, to caution against comparisons without understanding the context of the programs, the characteristics of each area, and the nature of CFLs. While the programs included in this study predominantly rely on an upstream approach, the details of their agreements with manufacturers and retailers differ: some support small packages of CFLs, others incent only large multipacks; most predominantly support spiral CFLs, but a few areas target specialty products. Moreover, the program history and the demographic, economic, and social characteristics of the areas differ, which in turn influences the lighting-related behavior of individual household. To offer one simple example, New York City households have the smallest number of sockets and the smallest number of CFLs installed, but they also displayed high levels of saturation. This is because homes in NYC tend to be small, multifamily units with very few sockets; the use of a few CFLs resulted in high saturation rates. Furthermore, purchase and use patterns must take into account one of the major selling points of CFLs: they last a long time. If a household purchased many CFLs in 2009, they may not do so again in 2010 because they do not have any more sockets they want to fill with CFLs.[24] Therefore, a declining purchase rate in the periods under examination does not necessarily point to a decline in program effectiveness. The rate could very well jump again in the next year. Finally, the purchase estimates for each time period are based on *respondent self-reports*, and these self-reports are subject to a high degree of measurement error, as purchasers often forget exactly when (and where) they purchased CFLs, as they are small in size and relatively inexpensive compared to such larger purchases as an appliance or a car. This problem becomes exacerbated as CFL adoption increases; CFLs become just another regular household purchase and do not stand out in the memories of individuals.

With these cautions and caveats in mind, we present information in this chapter on CFL socket saturation, awareness, familiarity, satisfaction, purchase, storage, and use for those households taking part in the onsite surveys. Appendix C contains similar comparisons for other key variables such as demographic, economic, and social characteristics.

CFL Socket Saturation

One of the primary purposes of the onsite visits was to conduct a socket count in order to estimate CFL saturation. Table 4–1 summarizes the area-wide saturation rate (i.e., all installed CFLs in the state divided by all sockets in the state) and the per-household saturation rate (i.e.,

[24] Having sockets they *want* to fill with CFLs is distinct from having sockets they *can* fill with CFLs.

the average percentage of sockets for each household) at the time of the onsite study.[25] It also lists the per-household saturation rate at the beginning of 2009, calculated backward by taking current saturation and subtracting any CFLs reported as purchased in 2009 or 2010.[26] The two per-household estimates of saturation are those used in the multistate model precisely because the model operates at a household level. The area-wide rate is the one most commonly reported by PAs nationwide because they are most concerned with describing the entire program area, not individual households. The data show that area-wide *current* saturation rates vary from 14% in the Consumers service territory to 28% in New York City; overall, the saturation rate is 21%. The per-household estimates of current saturation range from 15% in Indiana to 28% in Massachusetts. Importantly, we find no systematic differences in current saturation rates in program areas vs. non-program areas. Although saturation rates are relatively low in three of the non-program areas (Indiana, Kansas, and Houston), these rates are similar to or higher than those in many program areas. Pennington County, a non-program area, has one of the higher saturation rates in the sample, exceeded only by New York City and Massachusetts.

Looking at our proxy variable for saturation at the beginning of 2009, the data suggest that long-standing program areas tended to have the highest saturation rates—with the newer program area Ameren Illinois and the non-program area of Pennington County serving as exceptions. Saturation rates at the beginning of 2009 ranged from a low of three percent in Indiana to 20% in Massachusetts. Increases in saturation varied from six percent in the Consumers service territory to 14% in New York City and Houston. Three of the four non-program areas reported increased saturation of between 12% and 14%—exceeding the increase for the entire sample.

These wide-ranging saturation rates point to one of the critical needs for this study: factors other than programs influence whether households use or do not use CFLs. This effort seeks to untangle the effects of programs from those other factors.

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[25] To illustrate the difference, consider these three hypothetical households. The first has just one CFL installed in its 20 sockets, the second has 40 CFLs installed in its 60 sockets, and the third house has five CFLs installed in its 10 sockets. The sum of the CFLs is 46, and the sum of the sockets is 90. This yields an area-wide saturation rate of 51%. However, the saturation rate for the households are 5%, 67%, and 50%, respectively. Averaging these saturations yields a saturation rate of 41%.

[26] This approach has three problems. First, it suffers from respondent self-reporting error regarding the time of purchase. Second, the approach assumes that none of the currently installed CFLs purchased after 2009 had replaced CFLs in the same socket. Finally, the method does not account for changes in the number of sockets in the home that may have occurred after the beginning of 2009. Therefore, it almost certainly *underestimates* saturation at the beginning of 2009, exaggerating the increase in saturation over time. Evidence from previously reported saturation rates in states such as Massachusetts (*e.g.* NMR 2007 *MPER*; NMR 2010 *Market for CFLs*) suggest saturation of 21% in 2007 and 26% in 2009 support this claim.

Table 4–1: Current CFL Saturation by State

(Collected during onsite visits; saturation = percentage of sockets)

Area	Sample Size	Area-wide	Per Household		
		Summer 2010	Summer 2010	Beginning 2009	Change
Program Areas					
Ameren IL	92	23%	25%	15%	10%
Ameren MO	87	17%	16%	7%	9%
ComED	98	20%	24%	12%	12%
Consumers	61	14%	17%	11%	6%
DP&L	72	15%	19%	10%	9%
EmPower	79	19%	20%	9%	11%
Massachusetts	150	25%	28%	20%	8%
New York City	100	28%	25%	11%	14%
New York State	200	21%	24%	12%	12%
Rhode Island	100	20%	23%	13%	10%
SRP	101	23%	24%	12%	12%
Non-program Areas					
Houston	100	18%	19%	5%	14%
Indiana	67	17%	15%	3%	12%
Kansas	95	19%	21%	9%	12%
Pennington Cnty, SD	93	24%	25%	15%	10%
OVERALL	**1,495**	**21%**	**23%**	**12%**	**11%**

As part of our data exploration prior to running CFL purchase and use models, the team also created scatterplots that graphed the relationship between purchases across the entire eighteen month period (2009 and early 2010) with saturation at the beginning of 2009, as well as the relationship between current household-level CFL use, determined by the number of CFLs in use, and household-level current CFL saturation, calculated as the percentage of all sockets containing CFLs. The relationship between saturation and purchases illustrates a challenge for successful CFL programs: those households with high saturation rates buy fewer CFLs (Figure 4-1). They have CFLs in many sockets—though usually not a majority of them—and for some reason either stop converting other sockets to CFLs or do so at a slower rate. Also, participants with the highest rates of saturation (100%) have some of the lowest number of bulbs installed (Figure 4-2). This reflects the fact that small homes have fewer sockets and, therefore, reach high levels of saturation through the use of fewer CFLs than larger homes with many sockets. Saturation may be high even if purchase numbers are small, depending on the size of the home. Both of these issues have important implications for programs—and for the modeling process—and the relationships have an impact on how the models behave.

Figure 4-1: Saturation at the Beginning of 2009 by Total Purchases

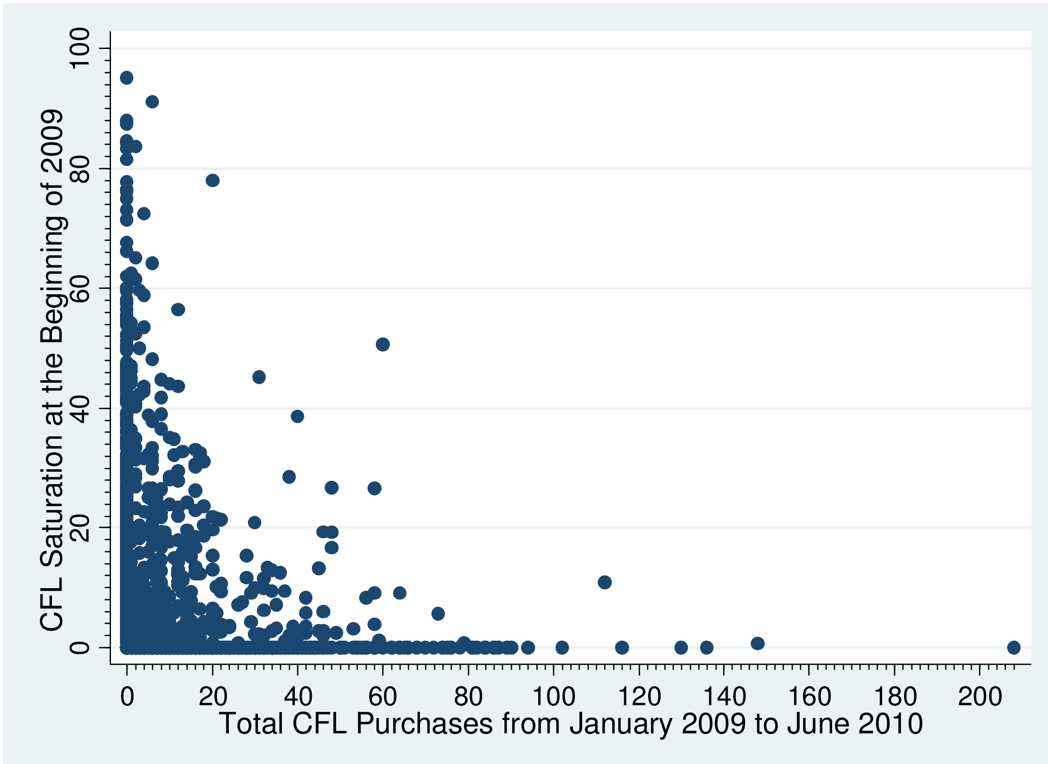
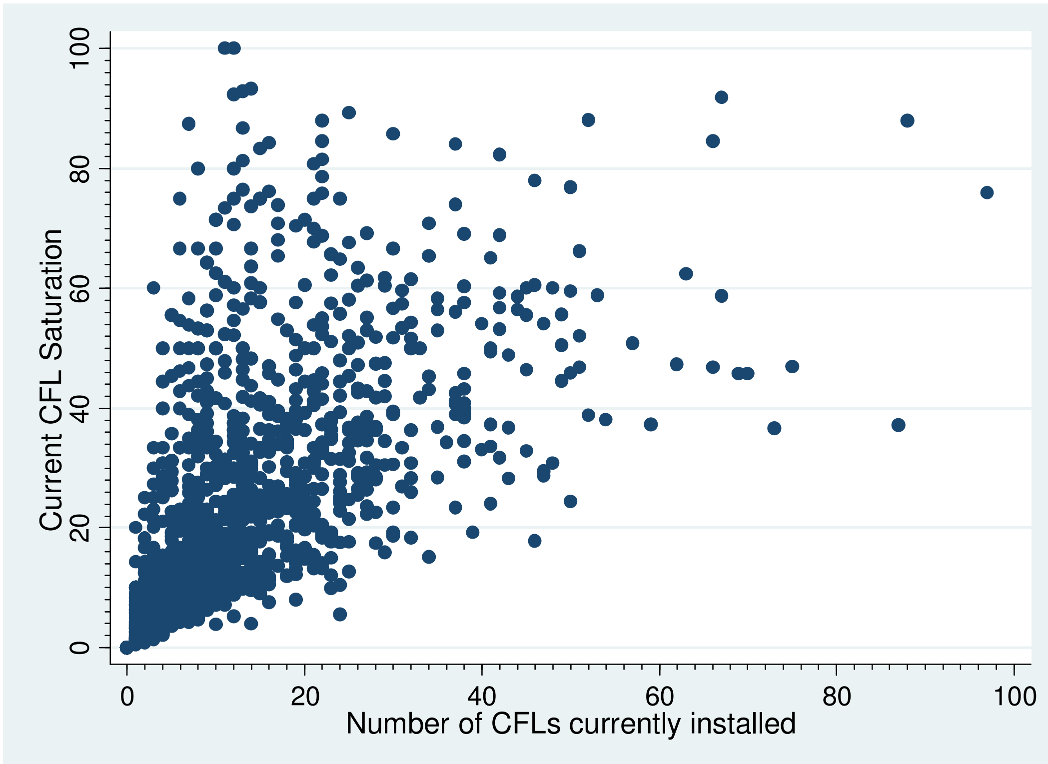


Figure 4-2: Current CFL Saturation by CFLs in Use



Comparison of Key Variables across Areas

We have identified some notable findings and patterns in the CFL purchase, use, and saturation data as shown in Table 4–2 and Table 4–3 (the shaded cells indicate areas with values greater than found for the entire sample). The data collected across numerous geographic areas and service territories for the multistate modeling effort show widespread awareness, familiarity and satisfaction with CFLs (Table 4–2). In all areas included in the analysis, the majority of respondents is aware, familiar and satisfied with CFLs. The area with the lowest level of CFL awareness and familiarity (New York City at 81% and 64%, respectively) also boasted a 93% satisfaction rate with CFLs among self-identified CFL users. The Salt River Project service territory exhibited the highest level of CFL awareness (98%) and households in the Ameren Illinois service territory voiced the highest level of familiarity with CFLs (86%).

Only one program area, New York State, reported increasing CFL sales, albeit small ones, across all three time periods included in the study (the first half of 2009, the second half of 2009, and the first half of 2010) (Table 4–3). Two program areas also displayed decreasing CFL sales across all three time periods; both areas—the Consumers service territory of Michigan and the Ameren IU service territory of Illinois—have fairly new programs. Among non-program areas, Kansas reported declining CFL purchases over time, while Houston and Pennington County exhibited increasing CFL purchases over time, with substantial increases in 2010.[27]

[27] A handful of Pennington County onsite participants who had purchased or were using or storing CFLs explicitly told the technician that they bought them "on sale" at a retailer. This suggests that some areas lacking CFL programs are exposed to CFL promotions sponsored by parties other than utilities, public service commissions, or energy-efficiency organizations.

Table 4–2: Comparison of Key Variables across Areas – CFL Related Factors

Area	Aware of CFLS		Somewhat or Very Familiar with CFLs		Satisfied with CFLS	
	n	%	n	%	n	%
Program Areas						
Ameren IL	92	95%	92	86%	78	82%
Ameren MO	87	91%	85	83%	73	93%
ComED	98	94%	90	84%	73	91%
Consumers	61	93%	61	77%	45	76%
DP&L	72	93%	68	79%	53	90%
EmPower	79	86%*	79	86%*	68	87%
Massachusetts	150	95%	150	85%	130	89%
New York City	100	81%	100	64%	56	93%
New York State	200	93%	200	77%	164	91%
Rhode Island	100	92%	100	75%	84	89%
SRP	101	98%	97	85%	87	85%
Non-program Areas						
Houston	100	94%	100	67%	67	92%
Indiana	67	84%	67	72%	44	93%
Kansas	95	96%	91	86%	79	89%
Pennington Cnty, SD	93	90%	93	76%	72	84%
OVERALL	**1,495**	**91%**	**1,495**	**79%**	**1,173**	**88%**

* These data reflect adjustments made to account for the fact that only CFL users were surveyed in Maryland. Similar adjustments were made for a subset of the Ameren Missouri sample.

Table 4–3: Comparison of Purchases and Current Use of CFLs*

	Number of CFLs Purchased Jan – June 2009		Number of CFLs Purchased July – Dec 2009		Number of CFLs purchased in 2010		Number of CFLs Currently Stored		Number of Bulbs Installed**		Number of CFLs Currently Installed	
	n	Mean	n	Mean	n	Mean	n	Mean	n	Mean	n	Mean
Program Areas												
Ameren IL	92	3.3	92	2.5	92	2.2	92	2.7	92	55.8	92	12.9
Ameren MO	87	1.5	87	2.4	87	2.9	87	2.7	87	67.3	87	11.4
ComED	98	2.8	98	3.1	98	3.0	98	3.0	98	62.8	98	12.5
Consumers	61	3.0	61	1.3	61	0.9	61	2.0	61	52.6	61	7.6
DP&L	72	2.0	72	1.4	72	3.4	72	2.9	72	61.7	72	9.2
EmPower	79	2.2	79	1.7	79	2.9	79	2.4	79	55.0	79	10.2
MA	150	0.8	150	2.9	150	2.2	150	2.4	150	48.1	150	12.1
NYC	100	2.7	100	1.8	100	2.2	100	1.6	100	29.2	100	8.2
NYS	200	2.3	200	2.4	200	3.0	200	2.0	200	58.5	200	12.6
RI	100	0.6	100	1.9	100	1.3	100	1.8	100	44.1	100	8.8
SRP	101	4.4	101	1.8	101	2.6	101	2.8	101	52.4	101	11.8
Non-program Areas												
Houston	100	0.7	100	1.5	100	5.1	100	0.5	100	52.3	100	9.3
Indiana	67	2.4	67	3.2	67	2.8	67	1.8	67	50.6	67	8.7
Kansas	95	4.0	95	2.2	95	1.5	95	1.8	95	58.1	95	11.2
Pennington	93	0.1	93	1.4	93	5.6	92	2.4	93	48.0	93	11.6
OVER-ALL	**1,495**	**2.1**	**1,495**	**2.1**	**1,495**	**2.7**	**1,495**	**2.2**	**1,495**	**52.5**	**1,495**	**10.8**

* Does not account for households that did not know when they purchased their CFLs. Protocols in some areas allowed "don't know" responses more frequently than in other areas.

** Includes all lighting technologies, not just CFLs.

5 Model Choice, Development, and Analysis

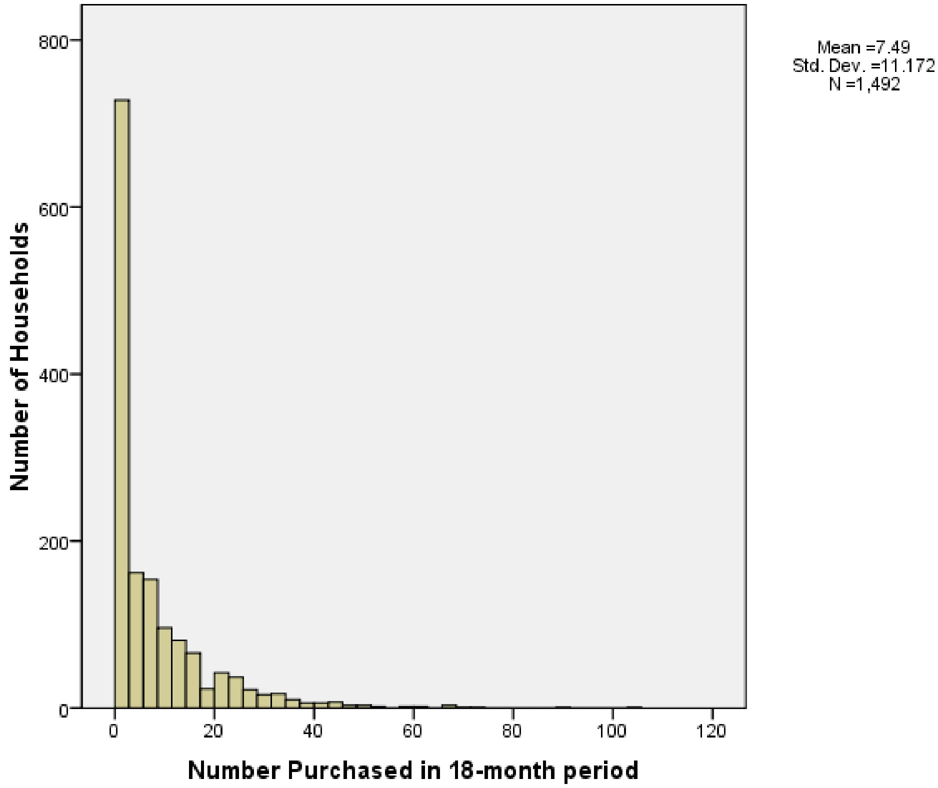
The nature of the data led the team to turn to non-linear models to estimate CFL purchases and use. Moreover, we also attempted models using a wide range of variables due to the complexity of CFL purchase and use behavior and the social and economic context in which this behavior occurs. This section explains model choice, development, and analysis.

Model Choice

The team used a zero-inflated negative binomial (ZINB) model to predict CFL purchases. Similar to the related model, the negative binomial regression model (NBRM), the ZINB is one of the more common methods of analyzing count data (*e.g.* the number of CFLs) with many cases falling at zero and with a fair degree of variability in the data (Figure 5-1).[28] In contrast to the NBRM, ZINB has the additional benefit of not treating all zeros the same. The team had used NBRM in the 2009 multistate effort and in earlier models considered for 2010 because we originally concluded that a "zero was a zero," which would make the NBRM the better choice. However, upon further discussion, we considered it likely that purchasing zero CFLs meant different things to households in the sample. Some households purchased zero CFLs simply because they did not need any CFLs during the time period under question. Other households, however, did not use CFLs and failed to buy them because they did not want CFLs or were not aware of them. We tested the ZINB to see if it supported this theory of underlying differences among, concluding it did.

[28] Long, J.S and J. Freese (2006) *Regression Models for Categorical Dependent Variables Using STATA*. STATA Press: College Station, TX. Elhai, J.D., P.S. Calhoun, and J.D. Ford "Statistical Procedures for Analyzing Mental Health Services Data." *Psychiatry Research* 160(2):129-236.

Figure 5-1: Histogram of CFLs Reported Purchased for the Eighteen-month Period



The ZINB model runs two simultaneous models, a logistic model and a negative binomial model. The logistic model distinguishes between the zeros, identifying the households that had a higher probability of never buying CFLs (*i.e.,* the always zero group) and those households who had a higher probability of simply not purchasing during the observation period (*i.e.,* the not-always zero group). The negative binomial portion of the procedure runs models that predict the number of purchases using those households in the not-always zero group from the logistic portion as well as households that actually reported purchasing CFLs in the observation period.

The team also developed statistical models to explain CFL use (number of CFLs installed) and saturation (percentage of sockets filled with CFLs), but we used different model types to do so for the following reasons. Because the CFL use data are count data with a strong right skew, we tested models using both NBRM and ZINB. We found that the two models performed almost identically, with model coefficients, probabilities, and maximum likelihood R^2 being the same.[29] Therefore, we concluded that there were no systematic differences driving "zero use" of CFLs as there was for purchases. Additionally, the ZINB was not an appropriate choice to model

[29] The maximum likelihood R^2 is one of various statistics reported for non-linear regression that attempts to mimic the explained variance R^2 of OLS models. However, most statistical sources warn that its interpretation is not the same as OLS because non-linear models behave differently than linear ones. For this reason, the maximum likelihood R^2 can be understood as a method to assess a model's goodness of fit but should not be considered to be equivalent to the OLS R^2.

saturation because saturation is measured as the proportion of sockets in the home filled with CFLs, not as a count. Since both ZINB and NBRM are suitable only for count data, the team explored other procedures and data transformations to confront the right skew in the saturation data, but we found none that fit the conditions. Therefore, the saturation models presented in this report rely on an ordinary least squares (OLS), the most common linear regression technique.[30] We did, however, suppress the constant, meaning that we forced the line described by the model to cross the X and Y axes at zero. This reflects the fact that saturation cannot fall below zero. The implication is that the explained variance of the model (R^2) is not applicable, even though, as we will see, it is rather high.

Model Development and Analysis

To develop the models, the team created models using the different program variables and other explanatory variables, including the following:

- Demographic, economic, and social characteristics
- Concentration and travel time to Big Box stores
- Duration of household CFL use
- CFL storage, CFL use, and CFL saturation prior to the purchase period under consideration
- Various measures of environmental opinions and early adoption behavior

The team excluded explanatory variables found to be excessively collinear with other explanatory variables in the model or that had little statistical effect on CFL use, saturation, and purchases, that were tautological, or that made little theoretical sense.[31]

For example, regarding tautology, the only ZINB model we successfully ran for CFL *use* that improved upon an NBRM included CFL saturation at the beginning of 2010 in the logistic portion of the model. This model found that households with high saturation in early 2010 were more likely to have at least some CFLs installed in June of 2010. While it is interesting to know that households with high saturation did not get rid of their CFLs, we concluded that this relationship was nearly tautological and rejected the model. We present the model in Appendix D for interested readers.

[30] In considering the best method to model market share we were limited in that Logit, Poisson, NBRM and Tobit models either required dichotomous or count data or "normalcy" in the dependent variable for the model to estimate reliably. Our data met none of these conditions, so we decided that OLS regression would be the most appropriate method to model market share despite that fact that the variable is a rate and has a heavy right skew. Market share was transformed by taking the arcsine root; the transformed variable was then modeled using OLS. We compared the model using the transformed variable to the non-transformed one, and they behaved very similarly to one another. Given that the transformed and original market share variable behaved similarly it was decided, for the sake of interpretation, to use the original form of market share in the models.

[31] Collinearity was determined by the tolerance statistic and the variance inflation factor.

The role of electricity price provides an example of a variable that made little theoretical sense. Reviewers of the 2009 multistate effort and earlier attempts at the 2010 effort often criticized the models for not including electricity price. For this reason, the team successfully ran ZINB models for 2010 purchases, but the coefficients indicated that *higher* electricity price was associated with *reduced CFL purchases*. Closer examination revealed that the electricity price variable was really capturing the fact that the East Coast areas in the model have higher electricity prices—and longer running programs—than the other areas in the model, a theory we tested by replacing electricity price with a dummy variable for East Coast and the prior program support variable. These models performed similarly or better than the electricity price variable. For this reason, we rejected the use of electricity price in the models and instead chose to use the prior program support variable which makes the most theoretical sense from a program standpoint and performed better than either the electricity price or East Coast variables. We present the electricity price model in Appendix D for interested readers.

One final note on the choice of program variables: although the team tested the various program variables in the model, we ultimately chose to use only the number of CFLs supported per household. This variable out-performed other program variables in the purchase models. In the use and saturation models, however, it behaved almost identically to the variable 'CFL budget spent per household'. As discussed in more detail in Appendix B, we opted for consistency in the program variable across models, even though both variables *entered individually* produced equivalent models.

The models presented in Section 6 are parsimonious in that every variable in them has a statistically significant net effect on CFL use or purchases (at the 0.10 level of significance); removing any of the variables reduces the strength of the model as determined by diagnostics such as the maximum likelihood R^2, the predictive capability of the model, or the statistical significance of other explanatory variables in the model. In short, they represent the best models yielded by the analyses.

6 Results and Implications for NTG

As described above, the evaluation team ran multiple models using different analysis techniques to understand the effects of CFL programs on CFL purchases, use, and saturation. In fact, multiple models worked for each time period under observation. In choosing between models, the team focused on the issues discussed in Section 5 as well as the probability associated with each variable in the model, the maximum likelihood R^2 statistic (related to, but different than, the explained variance for OLS regression models), and for purchases, the ratio of predicted to self-report purchases. We present the diagnostics for the selected models and alternative specifications in Appendix D.

Because the ZINB and NBRM utilized to predict CFL purchases and use are not linear modeling techniques, their interpretation is not immediately intuitive. As with OLS regression, the logistic and NBRM techniques produce "coefficients" for each independent variable. In OLS, the coefficient is the amount by which the dependent variable will change given a one-unit change in the independent variable. In nonlinear models, the direct interpretation of the coefficient is that it is the log likelihood of the independent variable bringing about a change in the dependent variable increase. Therefore, unlike in OLS model in which one can simply multiply the coefficient by the value of the explanatory variable to yield an estimate of the impact on the explained variable, the coefficients still point in the direction of the relationship. A positive coefficient suggests that the explanatory variable brings about an increase in purchases or use; a negative coefficient points to a decrease in purchases or use. In the 2009 effort and earlier drafts of the 2010 report, the team calculated the impact of each variable—and ultimately the NTG ratio—using an Excel spreadsheet. However, many readers found our explanations of the process confusing; moreover, this manual process increased the probability of data entry error. In response, the team ultimately turned to the statistical package STATA to model and predict purchases and to calculate NTG ratios. In order to verify the reliability of the STATA estimates, team members also reran the models and calculations in SAS, verifying the results.

CFL Purchase Models

The evaluation team presents two different recommended purchase models. The first model, shown in Table 6–2 on page 27, covers the entire eighteen-month period of January 1, 2009 to June 30, 2010. A number of reviewers suggested the development of this model for two reasons:

1. Using an eighteen-month model would reduce the self-report error in when households obtained CFLs. This reason is based on the assumption that allocating CFLs to 2009 or the first half of 2010—or even between the first and second half of 2009 as presented in earlier models—was difficult for respondents.
2. Some PAs preferred a description of the entire period, not portions of it.

Table 6–3 on page 29, in contrast, predicts purchases for the first-half of 2010 only. We developed this model for three different reasons:

1. Households may have superior recall of 2010 purchases because these purchases are more recent.
2. PAs with programs launched in late 2009 or the beginning of 2010 and those that had already filed NTG estimates for 2009 preferred the result for 2010 only.
3. National CFL shipment data pointed to improved purchases of CFLs, likely affected by the slowly improving economy, in 2010 compared to 2009. This suggests that the CFL purchase behavior in 2010 also differed from 2009, which may point to differing impacts on NTG ratios.

Regarding the third point, Table 6–1 displays national CFL shipment data from 2007 to 2010 by quarter. The data show increasing CFL shipments throughout 2007—the year of Wal-Mart's campaign to sell a hundred million CFLs—and the first quarter of 2008. Then shipments plunged in the latter half of 2008 and first three quarters of 2009. Shipments of CFLs did not begin to rebound until late 2009, and shipments remained strong in 2010. Given this change in shipments, which coincide to some extent with the slow improvement in the economy, the team and its advisors believe that models showing the entire period and 2010 alone were appropriate.

Table 6–1: 2007-2010 National CFL Shipments

	2007	2008	2009	2010
1st Quarter	76,939,726	98,776,098	63,135,546	89,653,617
2nd Quarter	82,341,541	79,972,622	64,826,208	91,602,221
3rd Quarter	112,582,206	72,356,258	62,453,600	82,335,303
4th Quarter	125,265,219	86,380,994	81,266,237	107,875,959*
Total	397,128,692	337,485,972	271,681,591	371,469,110*

Source: U.S. Imports of Selected Merchandise, U.S. Department of Commerce

*Note that the 4th Quarter 2010 imports (and therefore the 2010 total) are a projection, based on October 2010 imports.

For each of the purchase models presented below, the logistic portion indicates which households will likely never purchase CFLs versus those more likely to be purchasers. It only looks at households not purchasing CFLs in the time period. A negative coefficient means the chance of purchasing zero CFLs was lower in homes with higher values of that independent variable (*i.e.,* conversely, the chance of purchasing more than zero CFLs was higher). A positive coefficient means the chance of purchasing zero CFLs was greater in homes having a higher value of that variable (*i.e.,* conversely, the chance of purchase for more than zero CFLs was smaller).

The model's negative binomial portion is limited to those buying CFLs and zero purchasers more likely to buy. It estimates how many CFLs these households purchased in the time period and shows the explanatory variables and their coefficients.

6.1.1 Purchase Model for Eighteen Month Period

The logistic portion of the model predicts that:

- Households that own their homes were more likely to purchase some CFLs.
- Households with a greater CFL saturation at the beginning of 2009 were less likely to buy any CFLs, so they were considered to be in the always zero group. This is presumably because they already purchased CFLs and did not need them when asked (e.g., until their current CFLs burn out or they exhaust their stock of stored CFLs).
- Households that strongly agree that it is expensive to reduce energy use were less likely to buy any CFLs, presumably because they have already taken such low-cost options as buying CFLs.

The model's negative binomial portion predicts that the number of bulbs the program incented per household had a significant and positive effect on CFL purchases. Other factors influencing the number of CFL purchased included:

- Households with a higher saturation of CFLs at the beginning of 2009 also were likely to buy fewer CFLs than those with a lower CFL saturation. Similar to the model's logistic portion, this implies that those households with high levels of saturation simply did not need to buy CFLs because they already had enough.
- Households living in counties with high unemployment purchased fewer CFLs; considered with the logistic portion, this implies that households living in such areas bought CFLs, but not very many of them.
- The larger the participant's home the more CFLs they purchased.
- Households satisfied with their standard of living were more likely to buy CFLs, perhaps reflecting their greater comfort level with paying the higher price for CFLs.
- Households in which the respondent self-identified as white bought more CFLs.
- Finally, households that bought CFLs at various types of Big Box stores purchased more CFLs, presumably due to the larger package size typically sold at these stores versus grocery or lighting specialty stores. Note that, in the 2010 model presented below, a combined Big Box store variable performed better than these individual variables, but the individual variables performed better in the eighteen-month model.

Table 6–2: Best Fit Eighteen-Month Purchase Model*

Variables	Coefficient	Probability of z
Logistic Model		
Intercept	-1.169	0.000
County unemployment rate at the beginning of 2009	-0.656	<0.001
Homeownership (owner coded as 1)	0.023	<0.001
CFL Saturation at Beginning of 2009	0.179	0.055
Not expensive to reduce energy use (1 to 4, strongly agree coded as 1)	-1.169	0.000
Negative Binomial		
Intercept	1.457	<0.001
Bulbs supported/household	0.062	0.012
CFL Saturation at the beginning of 2009	-0.012	<0.001
County unemployment rate at the beginning of 2009	-0.050	0.006
Size of home (by 2K sqft, ascending scale)	0.302	<0.001
Satisfaction with standard of living (1 to 5, strongly agree coded as 5)	0.054	0.066
Self-identify as white	0.328	<0.001
Purchase CFLs at Warehouse Store**	0.858	<0.001
Purchase CFLs at Home Improvement Store**	0.405	<0.001
Purchase CFLs at Mass Merchandise Store**	0.279	0.002

* Sample size = 1,239 and Maximum Likelihood R^2 = 18%. Reduction in sample size from full 1,495 cases reflects exclusion of households who knew purchase date for fewer than 75% of CFLs in home (105 cases), no response for the energy question (73 cases; question was mistakenly excluded from one telephone survey; efforts to collect onsite yielded responses for only some households), and refusal to answer demographic (51 cases) and standard of living (23 cases). Note that some households were excluded for more than one of these reasons.
** In the 2010 model below, combining these variables into one "shop at Big Box store" dummy variable performed as well as treating them separately. In this eighteen-month model, doing so reduced model fit.

6.1.2 Purchase Model for 2010

The logistic portion of the model predicts that:

- Households with higher education levels had a greater probability of purchasing any CFLs, that is, of not being in the always zero group.
- Households visited in both 2009 and 2010 were more likely to purchase CFLs.
- Households with a greater CFL saturation at the beginning of 2010 were less likely to buy any CFLs, so they were considered to be in the always zero group. This is presumably because they already purchased CFLs and did not need them when asked (e.g., until their current CFLs burn out or they exhaust their stock of stored CFLs).
- Households that like to have new technology were more likely to buy CFLs than those who do not like to have new technology. Conversely, households that did like to have new technology (indicated by responses of three or four) were more likely to have zero purchases, indicating a lower likelihood of buying CFLs.

The model's negative binomial portion predicts that the number of bulbs the program incented per household had a significant and positive effect on CFL purchases. Other factors influencing the number of CFL purchased included:

- Homeowners were more likely to purchase a greater number of CFLs in 2010.
- The larger the participant's home the more CFLs they purchased in 2010.
- Even though they were more likely to buy CFLs than their counterparts who were skeptical of new technology, participants who responded that they like to have the latest technology purchased fewer CFLs than those technology skeptics that did buy CFLs, presumably because the early adopters already had a greater number of CFLs in their homes than the skeptics.
- Households with a higher saturation of CFLs at the beginning of 2010 also were likely to buy fewer CFLs than those with a lower CFL saturation. Similar to the model's logistic portion, this implies that those households with high levels of saturation simply did not need to buy CFLs because they already had enough.
- Those in areas with longer running programs were less likely to buy more CFLs. This variable indicates the cumulative impact of older programs, specifically that households in those areas have more CFLs because of the long program history. Therefore, they did not need to buy as many in 2010 compared to areas with newer programs.
- Households who purchased CFLs at Big Box stores were more likely to buy a greater number of CFLs, presumably due to the larger package size typically sold at these stores versus grocery or lighting specialty stores.
- Finally, two dummy variables associated with data collection were evident in the model. Those revisit households surveyed in both 2009 and 2010 purchased fewer CFLs in 2010 than households visited only in 2010. Also, those areas where onsite technicians did not require residents to guess their purchase period when they responded "don't know" to when the CFLs was purchased were likely to have lower CFL purchases. This could be because those asked to "guess" when bulbs were purchased, tended to guess more recently (a common memory bias).

Table 6–3: Best Fit Early 2010 Purchase Model*

Variables	Coefficient	Probability of z
Logistic Model		
Intercept	-0.453	0.185
Some college or higher education	-0.491	0.003
Revisit (yes coded 1; to account for potential impact of our first visit as evidenced in some MA, NY, Houston data	-0.517	0.007
CFL Saturation at Beginning of 2010	0.015	<0.001
Like to have new technology (1 to 4, strongly agree coded as 1)	0.318	0.001
Negative Binomial		
Intercept	1.000	<0.001
2010 Bulbs supported/household	0.385	<0.001
CFL Saturation at the beginning of 2010	-0.015	<0.001
Purchase CFLs at Big Box Store	0.441	0.008
Years supporting CFLs**	-0.038	<0.001
Data Collection Protocol treatment of Don't Know	-0.801	<0.001
Homeowner	0.441	<0.001
Size of home (by 2K sqft, ascending scale)	0.353	<0.001
Likes to have new technology (1 to 4, strongly agree coded as 1)	0.157	0.008
Revisit household	-0.403	0.009

* Sample size = 1,349 and Maximum Likelihood R^2 = 12%. Reduction in sample size from full 1,495 cases reflects exclusion of households who knew purchase date for fewer than 75% of CFLs in home (105 cases) and refusal to answer demographic or early adopter questions (41 cases).
** Years administering a CFL-specific program plus years administering an upstream program

Current CFL Use and Saturation Models

The CFL use model, developed using the NBRM, describes the number of CFLs installed in the home at the time of the onsite visit in the summer or early fall of 200 (Table 6–4). Controlling for other factors, the model predicts the following:

- The number of CFLs incented by the program per household in 2010 increased the number of CFLs found installed in homes.
- The number of CFLs installed in homes was smaller in areas that have supported CFLs for a greater number of years. This counterintuitive finding is driven by the smaller size of homes in the majority of the long-standing program areas compared to most of the newer program areas.
- Households with higher saturation at the beginning of 2010 also had more CFLs installed by the time of the onsite visit. While this variable may seem self-evident, the relationship between CFL saturation and use is often mitigated by the size of the home. Smaller homes may have relatively few CFLs installed but also have higher saturation because they have fewer sockets to fill. See the saturation model below for additional discussion on this topic.

- The greater the length of time it takes the respondent to travel to a home improvement, discount, or warehouse store, the fewer CFLs we found installed in the home. Note that this variable is a proxy for strongly rural conditions but also strongly urban ones such as those found in New York City. In New York City, the high price of real estate and lack of building spaces means there are relatively few Big Box stores and traveling to those that do exist is often a lengthy process.
- The data collection protocol associated with the treatment of "don't know" responses was associated with finding fewer CFLs installed in homes.
- Owner-occupied homes used CFLs in greater numbers than renter-occupied ones.
- Larger homes had a greater number of CFLs installed than smaller ones.
- Larger households (i.e., with more family members) used more CFLs than smaller ones.
- Households in which the respondent had at least attended some college had a greater number of CFLs installed.
- Households that bought CFLs at Big Box stores (where pack sizes are larger) or at hardware stores (which in long-standing program areas have historically been key program partners) used more CFLs.

Table 6–4: Best-Fit Current Use Model

Variables	Coefficient	Probability of z
Intercept	0.461	0.003
2010 Bulbs supported/household	0.188	<0.001
Years supporting CFLs**	-0.023	<0.001
CFL Saturation at the beginning of 2010	0.025	<0.001
Distance to a Big Box Store	-0.076	0.055
Data Collection Protocol treatment of Don't Know	-0.372	<0.001
Homeowner	0.444	<0.001
Size of home (by 2,000 sqft, ascending scale)	0.305	<0.001
Number of members in household	0.058	0.006
Some college or higher education	0.240	<0.001
Purchase Bulbs at Big Box Store	0.727	<0.001
Purchase Bulbs at Hardware Store	0.531	<0.001

* Sample size = 1,347; Maximum Likelihood R^2 = 46%. Reduction of sample size from 1,495 due entirely to refusal to answer demographic questions and to estimate distance to a Big Box Store.

** Years administering a CFL-specific program plus years administering an upstream program

The CFL saturation model suggests some results that readers may find counterintuitive. On closer examination, the results can generally be explained by smaller homes, which often have high saturation due to smaller number of sockets.[32,33] Specifically, the model predicts that:

- The number of CFLs incented by the program per household in 2010 increased CFL saturation at the time of the onsite visit.
- The number of years the area has supported CFLs was associated with higher levels of CFL saturation.
- CFL storage was also higher in households with high levels of saturation. The inclusion of this variable is somewhat controversial, as storage could be seen as being caused by having high levels of saturation—if households have sockets filled with CFLs, then they store the remainder of a multipack, for example. While this relationship certainly exists, it is also true that *very few households—even those with high levels of saturation—store CFLs*. Instead, we believe that the inclusion of storage in the model points to the existence of CFL enthusiasts among a *subset* of respondents with high levels of saturation. They use and store numerous CFLs because they like CFLs, not only because they have all of their sockets filled.[34]
- CFL saturation is higher in homes in which it takes more time travel to a home improvement, discount, or warehouse store (i.e., Big Box stores). This relationship stands in contrast to that reported above for use, in which households who lived farther from Big Box stores used fewer CFLs. The team believes that the size of the home is the chief factor bringing about this somewhat counterintuitive result. For example, two high saturation areas—New York City and Pennington County, South Dakota—are marked by smaller home size and lengthy travel times to Big Box stores.
- As stated above, smaller homes tend to have higher levels of CFL saturation. This is despite their using smaller numbers of CFLs. This finding is driven by the fact that smaller homes have fewer sockets, so even relatively modest use of CFLs will yield high CFL saturation.
- In another counterintuitive finding, saturation was lower in households in which the respondent had at least some college. Again, we believe that home size is likely an intervening factor, as households with lower levels of education are often more likely to live in smaller homes than those with higher levels of education.
- Households that primarily speak English have higher saturation rates than households that do not primarily speak English.

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[32] For example, one home in New York City had just 14 sockets, but 10 of them were filled with CFLs, yielding saturation of 71%. In a home in a state with a more typical 50 sockets per household, saturation would have been 20%.

[33] The team was limited in its ability to use interaction variables by the large number of dummy variables in our models, which would keep all households originally scored as zero in the dummy variable as zero in the interaction effect, thereby decreasing the amount of information the model has to estimate net impacts.

[34] Exclusion of the storage model has minimal impact on the overall model, with coefficients for other variables changing slightly but the overall specification being very similar.

- Three different variables to designate whether respondents shop for CFLs at various types of stores also point to higher CFL use. While these variables partly capture whether or not people use CFLs at all (and hence do or do not shop for them), they also capture relative CFL saturation among those who do use and shop for CFLs. As described above for CFL use, the inclusion of the flag for Big Box stores and hardware stores is likely related to the sale of multipacks and participation in CFL programs. Drugstores, however, often sell CFLs in smaller packs and have only recently begun to take part in CFL programs across the nation in large numbers. We believe that this variable may be capturing the fact that some households with high levels of saturation buy CFLs where ever they can, leading them to buy in such venues as drugstores, which are not usually thought of as a common source of CFLs.

Table 6–5: Best-Fit Current Saturation Model

Variables	Coefficient**	Probability of z
2010 Bulbs supported/household	1.733	0.087
Years supporting CFLs*	0.302	0.001
CFL Stored at the time of the onsite visit	0.422	0.001
Distance to a Big Box Store	2.206	0.007
Size of home (by 2,000 sqft, ascending scale)	-3.090	0.004
Some college or higher education	-2.812	0.031
Primarily speaks English at home	9.081	<0.001
Purchase Bulbs at Big Box Store	12.854	<0.001
Purchase Bulbs at Hardware Store	12.311	<0.001
Purchase Bulbs at Drugstore	10.092	0.006

* Sample size = 1,344. We do not report the R^2 because the constant was suppressed. Loss of sample is largely due to the refusal to answer the question about distance to a Big Box store and or demographic questions, particularly educational attainment or primary language spoken at home.
** Data derived from OLS regression so the coefficient captures the impact on CFL saturation. Because the models are OLS and saturation cannot drop below 0%, the intercept was set equal to zero. We do not report the explained variance (R^2) because the intercept was set to zero, rendering the R^2 an inappropriate description of the model.

Calculation of NTG

To develop the actual NTG estimates, we used STATA (and verified the results with SAS) to calculate the predicted purchases in the presence of the program (Row A, Table 6–6) and the absence of the program for both the eighteen-month and 2010 models (Row B). The non-program scenario removes *only* the impact associated with the number of CFLs incented per household (see below for an alternative specification). These calculations *predict* that each Rhode Island household purchased an average 5.64 CFLs across the entire eighteen-month period and 2.20 in the first half of 2010. The predicted non-program scenario suggests that 5.35 CFLs would have been purchased in the absence of the program across the entire period, and 2.03 in the absence of the program in early 2010. Subtracting the without-program estimates from the predicted program scenario yields an estimate of net predicted program purchases (Row

C). Dividing the net program purchase estimates by the incented CFLs per household (Row D) yields NTG estimates in Row E. The estimate for the entire eighteen-month period is 0.34 and for the first half of 2010 is 0.81. The confidence intervals were developed using a bootstrap method of 250 iterations; the width of the intervals reflect the non-linear nature of the models and the remaining uncertainty in the models.

Table 6–6: Rhode Island NTG Ratio Calculations

Input	Full 18 Months	First half of 2010
A. Per-household purchases with program	5.64	2.20
B. Per-household purchases without program	5.35	2.03
C. Net program purchases per household	0.36	0.17
D. Incented CFLs per household	0.85	0.21
E. Total NTG	0.34	0.81
F. Confidence Interval	0.08 to 0.80	0.45 to 1.41

Reviewers of this effort have argued that we should calculate NTG for 2010 by also treating prior program support as a program variable. Table 6–7 shows the calculations which follow the same procedures described above, except that, when computing the non-program scenario, we also assume that all programs had no prior activity. The implication for Rhode Island is a precipitous drop in NTG so that it falls well below zero. This strongly suggests that the Rhode Island and other long-standing programs *successfully* shifted CFLs sales that may not have occurred until 2010 to earlier time periods. Such activities mean that Rhode island has secured greater energy savings because its households adopted CFLs at an earlier time period than counterparts in non-program or newer program areas. Compared with the NTG for 2010 in Table 6–6, it also strongly suggests that *current program activity* continues to have a positive impact on CFL purchases that is above and beyond the spillover impacts from prior years of the program. We did not calculate confidence intervals for this method because we do not recommend use of this alternative NTG ratio except to illustrate the importance of prior program activity for influencing current CFL purchase behavior.

Table 6–7: Alternative 2010 NTG Ratio Calculations

Input	First half of 2010
A. Per-household purchases with program	2.20
B. Per-household purchases without program	4.15
C. Net program purchases per household	-1.95
D. Incented CFLs per household	0.21
E. Total NTG	-9.09

Finally, the evaluation team presents the range of NTG ratios for the eighteen-month period and for 2010 across all the participating areas (Table 6–8). However, we present only the range of results to protect the confidentiality of these other areas. The table reveals that the NTG ratio for Rhode Island was among the lowest NTG ratios in the eighteen-month and in the middle for the NTG resulting from the 2010 model. Only long-standing program areas experienced NTG ratios below zero in the alternative calculation of the 2010 model. Two other areas with NTG ratios similar to Rhode Island in the eighteen-month and 2010 models are also similar to Rhode Island in two additional ways: 1) they have relatively small programs compared to others in the model, and 2) they have also experienced substantial economic difficulties due to the recession. This may explain their lower ratios when compared to other areas in the model.

Table 6–8: Comparative NTG Ratios

Area	Eighteen Months	First Half 2010	2010 w/o Prior Support
Minimum	0.34	0.70	-9.09
Rhode Island	0.34	0.81	-9.09
Maximum	0.59	1.30	1.23

7 Conclusions and Recommendations

The eighteen-month CFL purchase model yields a NTG ratio of 0.34 for the period of January 2009 to June 2010, while the model limited to the first half of 2010 yields a NTG of 0.81 when years of prior program support is included, and -9.09 (negative 9.09) when years of program support is set to zero. The difference in the estimates reflects economic, statistical, and programmatic factors, as described below.

First, the slowly improving economy may have boosted the NTG in 2010—at least the NTG with years of prior program support included. National CFL shipment data point to a dramatic improvement in CFL sales in 2010 compared to 2009. Given that all areas included in the model enjoyed a higher NTG ratio in 2010 than in 2009, the model likely captured the improved CFL sales that accompanied the slowly improving national economy.

Second, from a statistical standpoint, in the 2010 model the team successfully isolated the impact of prior program activity on 2010 purchases, but the variable capturing prior activity was not significant in the 2009 model. The successful isolation of this variable is the principal *statistical* factor boosting NTG in one 2010 estimate, and dramatically reducing it in the other estimate.

This statistical factor relates to the third factor likely contributing to the different NTG ratios: program activity within and outside of Rhode Island. Within Rhode Island, the PAs revised the 2010 program to focus more on so-called "hard-to-reach" customers and specialty products, and the model likely captured the positive impacts of these efforts. Moreover, many of the other program areas in the model started supporting CFLs only in late 2009 or early 2010. Their new activity appears to have boosted CFL purchases beyond those observed in Rhode Island and other long-standing program areas, explaining the negative relationship between purchases and "prior program activity" in the 2010 model. Yet, controlling for prior program activity demonstrated that the Rhode Island ENERGY STAR Lighting program still had a positive, significant impact on purchases in 2010. The program, in other words, is still increasing adoption of CFLs, and the 2010 model suggests that the program should be continued.

The negative relationship between prior program activity and CFLs purchases in the 2010 model also verifies the success of previous Rhode Island CFL program activity. National Grid in Rhode Island has offered sustained CFL promotions since 1998. In doing so, they shifted CFL sales that may have occurred in 2010 to earlier years and claimed the resulting electricity and demand savings earlier and longer as well.

The NTG ratio of 0.88 resulting from the 2010 model confirms that current program activity continues to boost CFL purchases, after controlling for prior program activity. Based on this conclusion, we recommend that National Grid in Rhode Island continue some level of support for CFLs, at least until Energy Independence and Security Act of 2007 is fully implemented. However, for purposes of estimating NTG, the 2009 model is superior to the 2010 model, as evidenced by the larger maximum likelihood R^2 of 0.18 for the former compared to 0.12 for the latter. This may be at least partially because respondents could not accurately differentiate CFL purchases in 2009 from purchases in the first six months of 2010, whereas they could give more accurate estimates for the entire 18-month period. The use of the 2010 model is further complicated by the strong negative NTG ratio (-9.09) observed when the variable for prior program activity is set to zero. There is no clear solution for how to derive a NTG based on these two estimates of program impact resulting from the same model—one positive, and one very negative. Given the greater strength of the eighteen-month model and its more straightforward interpretation, we recommend using the NTG ratio of 0.34 for application to the 2009 and 2010 program years.

Appendix A: Sample Design and Weighting Scheme

The weighting scheme developed for this effort adjusts for home ownership rates for the service territory or geographic area in question and familiarity with CFLs. The data on home ownership rates and the number of households come from the *American Community Survey*. The data on familiarity come from the telephone surveys from which we drew the onsite samples, with two exceptions discussed below. We determined familiarity using two questions. First, we ascertained the telephone survey respondents' awareness with CFLs. Anyone familiar with CFLs was asked to state their level of familiarity, using a four-point scale in which one is "very familiar" and four is "not at all familiar". We considered anyone responding one or two to the scale as "familiar" with CFLs, and anyone responding three or four to the scale as "not familiar" with CFLs. Also, respondents not aware of CFLs were coded as not familiar with CFLs. We then ascertained the number of owners and renters who were familiar or not familiar with CFLs and developed the weighting scheme based on these counts as shown in Table A–1.

As noted above, two areas served as exceptions within this weighting scheme. Each area—Maryland and 22 Ameren Missouri cases—performed the lighting inventory as part of a metering study. They only metered homes of self-identified CFL users, and these users were all aware of and familiar with CFLs. Luckily, we could develop a weighting scheme for each area based on data from other sources. For Ameren Missouri, we simply weighted the households back to the proportions of owner/renter and familiar/not familiar in the remainder of the sample from the same service territory. For Maryland, we weighted back to data from the 2009 multistate effort, in which Maryland was surveyed as a comparison areas.

Table A–1 shows the resulting weights for each area.

Table A–1: Sample Design, Error, and Weighting Schemes for Onsite Data

Area	Owner/Renter	Familiarity with CFLs	Population	Sample Size	Weight
Ameren IL	Owner	Familiar	477,632	55	1.0
	Owner	Not Familiar	63,543	7	1.2
	Renter	Familiar	61,844	21	1.0
	Renter	Not Familiar	11,408	7	0.5
	Area Total		930,287	92	
Ameren MO	Owner	Familiar	955,271	41	1.4
	Owner	Not Familiar	135,475	26	0.3
	Renter	Familiar	107,543	12	1.3
	Renter	Not Familiar	46,090	7	1.0
	Area Total		2,065,037	86	

Area	Owner/Renter	Familiarity with CFLs	Population	Sample Size	Weight
ComEd	Owner	Familiar	1,461,252	62	1.0
	Owner	Not Familiar	236,960	12	0.8
	Renter	Familiar	242,480	15	1.4
	Renter	Not Familiar	74,020	8	0.8
	Area Total		3,482,588	97	
Consumers	Owner	Familiar	724,806	57	1.2
	Owner	Not Familiar	165,307	12	1.0
	Renter	Familiar	79,778	18	0.8
	Renter	Not Familiar	16,795	7	0.6
	Area Total		1,573,072	94	
Dayton Power & Light	Owner	Familiar	231,481	51	0.8
	Owner	Not Familiar	48,733	7	1.3
	Renter	Familiar	34,808	8	1.8
	Renter	Not Familiar	13,712	6	1.0
	Area Total		562,119	72	
EmPower	Owner	Familiar	853,698	46	1.0
	Owner	Not Familiar	138,974	9	0.8
	Renter	Familiar	174,665	20	1.1
	Renter	Not Familiar	26,200	4	0.8
	Area Total		2,086,828	79	
Massachusetts	Owner	Familiar	941,385	105	0.8
	Owner	Not Familiar	118,630	15	0.8
	Renter	Familiar	215,582	24	1.5
	Renter	Not Familiar	74,478	7	1.8
	Area Total		2,448,364	141	
New York City	Owner	Familiar	287,367	37	0.7
	Owner	Not Familiar	60,957	8	0.7
	Renter	Familiar	726,120	23	1.6
	Renter	Not Familiar	599,471	31	1.0
	Area Total		3,032,961	99	
New York State	Owner	Familiar	1,208,292	145	0.8
	Owner	Not Familiar	276,708	23	1.1
	Renter	Familiar	209,910	22	1.9
	Renter	Not Familiar	103,895	9	2.3
	Area Total		3,164,089	199	

Area	Owner/Renter	Familiarity with CFLs	Population	Sample Size	Weight
Rhode Island	Owner	Familiar	131,771	67	0.8
	Owner	Not Familiar	28,668	8	1.4
	Renter	Familiar	34,827	17	1.4
	Renter	Not Familiar	19,944	8	1.7
	Area Total		402,707	100	
Salt River Project	Owner	Familiar	626,954	59	1.1
	Owner	Not Familiar	49,311	9	0.6
	Renter	Familiar	100,126	28	0.8
	Renter	Not Familiar	45,218	5	2.0
	Area Total		1,448,679	101	
Houston, Texas	Owner	Familiar	325,076	60	0.7
	Owner	Not Familiar	141,195	15	1.2
	Renter	Familiar	145,803	15	1.7
	Renter	Not Familiar	87,945	10	1.6
	Area Total		1,360,297	100	
Indiana	Owner	Familiar	206,102	37	0.9
	Owner	Not Familiar	73,608	9	1.3
	Renter	Familiar	38,812	12	1.2
	Renter	Not Familiar	20,348	9	0.8
	Area Total		596,148	67	
Kansas	Owner	Familiar	374,301	65	0.9
	Owner	Not Familiar	61,666	13	0.7
	Renter	Familiar	67,824	15	1.5
	Renter	Not Familiar	9,974	2	1.7
	Area Total		883,697	95	
Pennington County, SD	Owner	Familiar	14,184	57	0.9
	Owner	Not Familiar	3,158	10	1.1
	Renter	Familiar	2,669	20	1.0
	Renter	Not Familiar	1,435	6	1.8
	Area Total		38,321	93	

Appendix B: Treatment of Program Variables in Modeling

When testing the impact of program variables on CFL purchases, use, and saturation, only the number of incented CFLs per household served as a significant predictor of CFL purchases. In the use and saturation models, the budget spent per household performed similarly to CFLs incented per household, but, in the interest of consistency, the team selected the CFLs incented per household for all models presented in the report. Various reviewers and advisors to this effort have expressed interest in understanding the process of building composite variables and of testing the numerous program variables in the models. This appendix describes these processes.

The multistate modeling team followed procedures for creating program variables as described by NMR and Shel Feldman for modeling the market share of ENERGY STAR appliances.[35] NMR and Feldman tested model specifications using individual program components and so-called "composite" program components in order to determine the following:

- Which individual program activities, if any, had the greatest impact on appliance market share, and
- Whether the entire suite of program activities (*i.e.*, amount of incentive, point-of-purchase displays, length of promotion, *etc*.,) combined into a "composite" had a collective impact that was greater than the sum of the parts

NMR and Feldman found that the individual program components did not explain appliance market share, but, when combined into a composite program variable, the results showed that program activity had a net positive impact on appliance market share.

The multistate modeling team mirrored the approach of NMR and Feldman by testing individual measures of program activity and composite program variables. Section 3.1 describes the development of the individual measures, while this appendix describes the development of the composite variables.

The process for combining the program variables began with testing their coherence as an index, using the Cronbach's alpha test. This test determines whether individual items correlate in a manner that allows them to be treated as components of a broader index variable. This effort found that only three of our potential program variables cohered into a broader index. The variables included:

- Number of CFLs per household
- Dollars spent per household
- Percent of budget allocated to incentives

While it would seem most straightforward to add these three variables together, this violates mathematical rules about combining different units of analysis. To overcome this barrier, we

[35] See NMR and Feldman (2005) *Statistical Analyses of Market Penetration of Energy Star-compliant Appliances*. Final delivered July 2005.

followed the accepted statistical procedure for combing measures with different units of analysis—we standardized them. In other words, based on the overall means and standard deviations for each variable, we assigned each area a z-score on that variable. We then summed these z-scores to form the composite program variable for each of the four time periods under consideration. However, despite their coherence in a scale, the composite program scores did not perform as well as the individual program components in any of our models.

This leads to the final issue concerning the program variables—how they were treated in the models. The entire modeling process was designed to determine if program activity boosted CFL purchases, use, and saturation. For this reason, our modeling specifications began with the inclusion of one program variable to which we added additional demographic, economic, social characteristics in the model. In the process, we included or excluded program and other contextual variables based on their statistical significance as well as diagnostics to make sure that the individual variables were not excessively collinear. In most cases, collinearity negated the use of two program variables in one model. In such cases, we chose the program variable with the strongest impact on purchases, use, and saturation.

In the end, all models performed best with the inclusion of a program variable. Moreover, CFLs incented per household was the only program variable found to perform well in every purchase, use, and saturation model presented in the full report. Although the budget spent per household performed equally well in the use and saturation models, the team preferred consistency across models and, therefore, used the CFLs incented per household in all models.

Appendix C: Comparison of Key Variables across Areas

Table C–1: Comparison of Key Variables across Areas – Homeownership and Home Size

	Own Home		Home Size (Sq. Ft.)					
	n	%	n	% Less than 2,000 sqft	n	%, between 2,000 and 3,999 sqft	n	% 4,000 or more sqft
Program Areas								
Ameren IL	91	74%	92	70%	92	25%	92	5%
Ameren MO	86	74%	86	69%	86	25%	86	6%
ComED	97	71%	98	60%	98	27%	98	13%
Consumers	58	74%	58	71%	58	28%	58	2%
DP&L	72	71%	72	75%	72	22%	72	3%
EmPower	79	68%	79	60%	79	39%	79	1%
Massachusetts	150	68%	150	68%	150	31%	150	3%
New York City	99	33%	100	87%	100	12%	100	1%
New York State	199	68%	200	68%	200	31%	200	2%
Rhode Island	100	63%	100	76%	100	23%	100	1%
SRP	101	69%	101	75%	101	25%	101	1%
Non-program Areas								
Houston	100	58%	100	61%	100	35%	100	4%
Indiana	67	69%	67	69%	67	28%	67	3%
Kansas	95	73%	95	65%	95	31%	95	4%
Pennington Cnty, SD	93	68%	93	70%	93	30%	93	0%
OVERALL	**1,487**	**66%**	**1,491**	**69%**	**1,491**	**28%**	**1,491**	**3%**

Table C–2: Comparison of Key Variables across Areas – Type of Home

	Single-Family Detached Home		Single-Family Attached Home		Apt. Building W/ 2-4 Units		Apt. Building w/ 5 or More Units		Mobile Home/Other	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Program Areas										
Ameren IL	91	74%	91	3%	91	4%	91	9%	91	9%
Ameren MO	86	69%	86	11%	86	7%	86	9%	86	4%
ComED	97	55%	97	13%	97	10%	97	16%	97	6%
Consumers	58	71%	58	5%	58	7%	58	5%	58	12%
DP&L	72	84%	72	6%	72	1%	72	7%	72	3%
EmPower	79	55%	79	30%	79	1%	79	11%	79	3%
Massachusetts	150	58%	150	12%	150	14%	150	14%	150	1%
New York City	99	18%	99	16%	99	17%	99	46%	99	2%
New York State	199	67%	199	9%	199	11%	199	9%	199	5%
Rhode Island	100	56%	100	12%	100	15%	100	15%	100	2%
SRP	101	67%	101	6%	101	2%	101	19%	101	6%
Non-Program Areas										
Houston	100	69%	100	8%	100	7%	100	13%	100	3%
Indiana	67	73%	67	12%	67	5%	67	9%	67	2%
Kansas	94	70%	94	10%	94	5%	94	13%	94	2%
Pennington Cnty, SD	93	61%	93	10%	93	6%	93	11%	93	13%
OVERALL	**1,486**	**62%**	**1,486**	**11%**	**1,486**	**8%**	**1,486**	**14%**	**1,486**	**5%**

Table C–3: Comparison of Key Variables across Areas – Language, Race, and Gender

	English Primary Lang. Spoken at Home		White		Female	
	n	%	N	%	n	%
Program Areas						
Ameren IL	92	98%	92	80%	92	45%
Ameren MO	86	100%	85	85%	87	59%
ComED	98	96%	98	70%	98	35%
Consumers	55	100%	56	84%	58	47%
DP&L	71	100%	69	74%	72	58%
EmPower	77	95%	72	63%	78	55%
Massachusetts	150	95%	143	85%	150	51%
New York City	99	97%	95	62%	100	57%
New York State	200	97%	198	86%	200	50%
Rhode Island	100	94%	98	89%	100	76%
SRP	100	100%	96	85%	101	51%
Non-program Areas						
Houston	100	96%	97	66%	100	62%
Indiana	67	94%	66	62%	67	55%
Kansas	95	100%	95	86%	95	56%
Pennington Cnty, SD	93	99%	93	88%	93	55%
OVERALL	**1,483**	**97%**	**1,453**	**81%**	**1,491**	**54%**

Table C–4: Comparison of Key Variables across Areas – Age of Home

		% ≤1930's	% 1940's – 1950's	% 1960's – 1970's	% 1980's – 1990's	% 2000
Program Areas						
Ameren IL	65	17%	26%	29%	11%	18%
Ameren MO	67	19%	13%	27%	25%	17%
ComED	85	11%	19%	28%	31%	11%
Consumers	44	17%	27%	15%	26%	17%
DP&L	63	18%	26%	26%	17%	13%
EmPower	66	18%	27%	26%	17%	12%
Massachusetts	115	33%	22%	24%	17%	5%
New York City	34	46%	18%	14%	7%	14%
New York State	159	21%	23%	32%	18%	6%
Rhode Island	70	20%	25%	21%	26%	8%
SRP	70	0%	14%	28%	42%	16%
Non-program Areas						
Houston	82	4%	13%	38%	19%	26%
Indiana	55	13%	24%	20%	20%	22%
Kansas	78	18%	11%	20%	29%	22%
Pennington Cnty, SD	63	10%	19%	29%	24%	19%
OVERALL	**1,116**	**17%**	**20%**	**26%**	**22%**	**14%**

Table C–5: Comparison of Key Variables across Areas – Distance to Large Discount Store and Square Footage of Box Stores per Household in County

	Distance to Large Discount Store				Square Footage of Box Stores per Household in County			
	n	% < 15 miles	% 15-29 miles	% ≥ 30 miles	n	Wal-Mart Stores - Mean	n	Other Box Stores - Mean
Program Areas								
Ameren IL	92	57%	34%	10%	84	9.7	84	3.8
Ameren MO	86	62%	33%	5%	86	7.1	86	4.1
ComED	75	81%	17%	3%	98	3.9	98	4.0
Consumers	59	71%	19%	8%	52	6.1	52	5.1
DP&L	53	71%	22%	8%	71	7.6	71	3.7
EmPower	77	56%	30%	14%	78	4.2	78	2.7
Massachusetts	150	59%	34%	7%	150	2.1	150	2.9
New York City	97	31%	27%	42%	100	0.0	100	0.9
New York State	200	50%	35%	15%	199	4.4	199	3.9
Rhode Island	100	65%	28%	7%	100	2.9	100	3.6
SRP	100	81%	16%	3%	101	6.9	101	4.4
Non-program Areas								
Houston	100	81%	13%	6%	100	5.0	100	3.4
Indiana	67	58%	36%	6%	67	6.3	67	5.1
Kansas	95	57%	32%	12%	87	8.5	94	2.9
Pennington Cnty, SD	93	43%	45%	12%	93	8.2	93	5.5
OVERALL	**1,444**	**60%**	**29%**	**11%**	**1,466**	**5.2**	**1,473**	**3.7**

Table C–6: Comparison of Key Variables across Areas – Standard of Living and Income

	Standard of Living				Income				
	n	% Satisfied	% Neither Satisfied nor Dissatisfied	% Dissatisfied	n	% ≤ $19,999	% $20,000 to $49,999	% $50,000 to $99,999	% ≥ $100,000
Program Areas									
Ameren IL	91	78%	4%	17%	86	35%	42%	19%	4%
Ameren MO	86	78%	7%	15%	75	28%	42%	22%	8%
ComED	97	88%	4%	8%	95	37%	33%	17%	14%
Consumers	57	82%	7%	11%	47	43%	38%	17%	2%
DP&L	68	78%	6%	16%	64	49%	34%	15%	2%
EmPower	79	67%	14%	19%	70	33%	27%	31%	19%
Massachusetts	142	76%	10%	14%	124	22%	32%	31%	15%
New York City	100	74%	6%	20%	87	42%	36%	18%	5%
New York State	200	75%	8%	18%	184	36%	38%	20%	6%
Rhode Island	100	69%	11%	20%	81	31%	44%	20%	5%
SRP	100	68%	4%	28%	90	45%	36%	24%	6%
Non-program Areas									
Houston	99	82%	6%	12%	83	40%	35%	21%	5%
Indiana	67	81%	4%	15%	63	37%	36%	24%	3%
Kansas	94	67%	23%	10%	92	35%	45%	17%	3%
Pennington Cnty, SD	90	74%	10%	16%	87	30%	50%	17%	3%
OVER-ALL	**1,470**	**76%**	**8%**	**16%**	**1,328**	**35%**	**39%**	**20%**	**6%**

Appendix D: Comparison of Selected and Alternative Models

We have compiled this appendix in the interest of readers who desire more information on the choice of models. Specifically, this section compares the following:

- Selected eighteen-month purchase model with an alternative specification based on the selected 2010 purchase model.
- Selected 2010 purchase model with an alternative specification that includes energy price.
- Selected current use model with an alternative ZINB specification that includes CFL saturation at the beginning of 2010 in the logistic portion of the model.

In all cases we present the applicable diagnostics, including the maximum likelihood R^2, the probability associated with each coefficient, and, for the purchase models only, the ratio of predicted to observed purchases. We do not discuss the models at length, but do present them for those who are interested in the details of the model selection.

Eighteen-Month Purchase Model Comparison

The models in Table D–1 compare the selected eighteen-month purchase model and an alternative specification based on the 2010 purchase model. Immediately following the models, we present the diagnostics used to select between the two models—namely the maximum likelihood R^2 and the ratio of the predicted to self-reported actual purchases for both program and non-program areas, suppressing the names of the areas (Table D–2).

Table D–1: Eighteen-Month Purchase Model Comparison

Variables	Selected Model		Alternative Model	
	Coefficient	**Prob z**	**Coefficient**	**Prob z**
Logistic Model				
Intercept	-1.169	0.000	-1.574	<0.001
Homeownership (owner coded as 1)	0.179	0.055		
CFL Saturation at Beginning of 2009	-1.169	0.000	0.023	<0.001
Not expensive to reduce energy use (1 to 4, strongly agree coded as 1)	-1.169	0.000		
Revisit Household			-0.915	0.001
Likes to have new technology (1 to 4, strongly agree coded as 1)			0.286	0.006
Some college education or higher			-0.439	0.016
Negative Binomial				
Intercept	1.457	<0.001	1.333	<0.001
2010 Bulbs supported/household	0.062	0.012	0.043	0.163
CFL Saturation at the beginning of 2009	-0.012	<0.001	-0.007	0.003
County unemployment rate at the beginning of 2009	-0.050	0.006		
Size of home (by 2K sqft, ascending scale)	0.302	<0.001	0.278	<0.001
Satisfaction with standard of living (1 to 5, strongly agree coded as 5)	0.054	0.066		
Self-identify as white	0.328	<0.001		
Purchase CFLs at Warehouse Store**	0.858	<0.001		
Purchase CFLs at Home Improvement Store**	0.405	<0.001		
Purchase CFLs at Mass Merchandise Store**	0.279	0.002		
Years supporting CFLs			-0.024	0.008
Data Collection Protocol Treatment of Don't Know			-0.256	0.060
Homeowner			0.461	<0.001
Likes to have new technology (1 to 4, strongly agree coded as 1)			0.063	0.226
Revisit household			-0.341	0.009
Purchase CFLs at Big Box Store			0.542	<0.001

Table D–2: Eighteen-Month Purchase Model Diagnostics and Actual Purchases

Area	Ratio Predicted to Actual	
	Selected Model	Alternative Model
1	1.03	0.93
2	0.78	0.74
3	0.77	0.81
4	0.91	0.93
5	1.86	1.66
6	1.13	0.93
7	1.06	1.19
8	0.78	0.78
9	0.83	0.85
10	0.88	1.17
Rhode Island	1.28	1.39
12	0.84	0.91
13	0.98	1.11
14	0.85	0.85
15	0.82	0.70
Average Ratio	0.99	1.00
R^2	18%	14%

2010 Purchase Model Comparison

The next table compares the selected 2010 model with an alternative specification that includes electricity price (Table D–3). The team strongly considered using the alternative model, but found some of the relationships perplexing, namely the behavior of electricity price and of CFL saturation. After ascertaining that electricity price was serving as a proxy variable for the East Coast—and long-standing program—areas, we returned to our modeling effort, settling on the selected model. The table immediately following the model comparison presents the model diagnostics (Table D–4).

Table D–3: 2010 Purchase Model Comparison

Variables	Selected Model		Alternative Model	
	Coefficient	Prob z	Coefficient	Prob z
Logistic Model				
Intercept	-0.453	0.185	-0.547	0.050
Some college or higher education	-0.491	0.003	-0.456	0.001
Revisit (yes coded 1; to account for potential impact of our first visit as evidenced in some MA, NY, Houston data	-0.517	0.007	-0.476	0.008
CFL Saturation at Beginning of 2010	0.015	<0.001	0.018	<0.001
Like to have new technology (1 to 4, strongly agree coded as 1)	0.318	0.001	0.306	<0.001
Negative Binomial				
Intercept	1.000	<0.001	2.318	<0.001
2010 Bulbs supported/household	0.385	<0.001	0.264	0.014
CFL Saturation at the beginning of 2010	-0.015	<0.001		
Purchase CFLs at Big Box Store	0.441	0.008		
Years supporting CFLs**	-0.038	<0.001		
Data Collection Protocol treatment of Don't Know	-0.801	<0.001	-0.390	0.015
Homeowner	0.441	<0.001	0.316	0.008
Size of home (by 2K sqft, ascending scale)	0.353	<0.001	0.308	<0.001
Likes to have new technology (1 to 4, strongly agree coded as 1)	0.157	0.008	0.168	0.005
Revisit household	-0.403	0.009	-0.282	0.045
County unemployment rate at the beginning of 2009			-0.110	<0.001
2010 Area Electricity Rate			-0.048	0.019
Purchase CFLs at Warehouse Store			0.739	<0.001

Table D–4: 2010 Purchase Model Diagnostics and Actual Purchases

Area	Ratio Predicted to Actual	
	Selected Model	Alternative Model
1	0.98	1.40
2	0.76	0.86
3	0.66	0.82
4	1.20	1.61
5	0.87	1.05
6	0.95	1.19
7	1.94	1.24
8	0.92	1.23
9	0.84	0.75
10	1.16	0.78
Rhode Island	1.53	1.28
12	0.64	0.86
13	0.87	0.64
14	0.93	1.03
15	0.84	0.87
Average Ratio	1.01	1.04
R^2	12%	11%

Current Use Model Comparison

The most important decision the team made regarding the current use model was whether to use a ZINB model with saturation in the logistic portion. For the most part, the model made logical sense and had a strong maximum likelihood R^2 even for non-linear models applied to social phenomena (Table D–5. Yet, we could not help but think that the strength of the model reflected the tautology of the inclusion of saturation in the logistic portion of the model. Without saturation in the logistic portion, all other ZINB models we developed to explain current use performed nearly identically to similarly specified NBRM models. We discuss the choice of NBRM over ZINB in the full report, but compare the two models here.

Table D–5: Best-Fit Current Use Model

Variables	Selected Model		Alternative Model	
	Coefficient	Prob z	Coefficient	Prob z
Logistic				
Intercept			-0.776	0.048
CFL Saturation at the beginning of 2010			-0.619	0.002
Some college or higher			-0.682	0.011
Plan to take steps soon to reduce energy use soon			0.343	0.026
Negative Binomial				
Intercept	0.461	0.003	1.027	<0.001
2010 Bulbs supported/household	0.188	<0.001	0.155	0.001
Years supporting CFLs**	-0.023	<0.001	-0.023	<0.001
CFL Saturation at the beginning of 2010	0.025	<0.001	0.020	<0.001
Distance to a Big Box Store	-0.076	0.055	-0.083	0.018
Data Collection Protocol treatment of Don't Know	-0.372	<0.001	-0.320	<0.001
Homeowner	0.444	<0.001	0.418	<0.001
Size of home (by 2,000 sqft, ascending scale)	0.305	<0.001	0.309	<0.001
Number of members in household	0.054	0.006	0.056	<0.001
Some college or higher education	0.240	<0.001	0.204	<0.001
Purchase Bulbs at Big Box Store	0.727	<0.001	0.337	<0.001
Purchase Bulbs at Hardware Store	0.531	<0.001	0.224	0.002
R^2	46%		54%	