RESULTS OF THE MULTISTATE CFL MODELING EFFORT

Final

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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 the Connecticut Energy Efficiency Board (CEEB), and Connecticut Light & Power (CL&P), and the United Illuminating Company (UI), which offer lighting programs sponsored by the Connecticut Energy Efficiency Fund (CEEF). As a group, these entities will be referred herein to as the "CT Sponsors". The other Sponsors of this study include the following: California Public Utilities Commission (CPUC), New York State Energy Research and Development Authority (NYSERDA), Wisconsin Public Service Commission (WPSC), Consumers Energy in Michigan (CE), the Cape Light Compact (Cape Light), NSTAR, National Grid, Unitil, Western Massachusetts Electric (WMECO), and Xcel Energy in Colorado (Xcel). This report draws on data from 16 different geographic areas in the United States, but was written specifically for the CT Sponsors. The analyses draw on random-digit dial (RDD) telephone surveys of over 9,300 households and onsite saturation surveys (including confirmation of when CFLs were purchased) for about 1,400 households. Note that the report uses the term "sponsors" 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 analyses of the models is that the estimated NTG for Connecticut for 2008 is approximately 0.81 with the 90% confidence interval ranging from 0.31 to 1.30. This executive summary provides an overview of the approach, methods, and findings that have led to this conclusion. It also describes the final steps to be taken in this multistate modeling effort that will likely improve our understanding of CFL program effects in the current and changing CFL market.

Study Background

Methods of estimating the net impacts of CFL programs have evolved over time to account for free ridership and spillover, adoption of upstream programs, and changes in the CFL market. Recently, Sponsors in various areas have turned to a "non-program comparison state" approach to estimate NTG, but rapid expansion of CFL programs and recent changes in the CFL market have hindered the ability of this approach to provide a reliable NTG estimate.

The principal goals of the statistical analyses presented in this report are to identify and examine factors associated with 2008 CFL purchases generally and the effect of CFL programs on those purchases specifically in this changing CFL market. The evaluation team uses the modeling results to estimate NTG for each study Sponsor. The team bases these estimates on the models that we believe best describe CFL purchases in 2008.

Areas Included in the Analyses

The multistate modeling effort relies on data drawn from RDD telephone and onsite surveys conducted in areas with longstanding CFL programs, those with newer or smaller programs, and those with no CFL programs through 2008. The Sponsors of this effort collectively account for the following areas:

- California (CA): areas served by Pacific Gas and Electric (PG&E), San Diego Gas and Electric (SDG&E), and Southern California Edison (SCE) or collectively the investor owned utilities (IOUs) service territory
- Colorado (CO): the area served by Xcel Energy
- Connecticut (CT): the entire state
- Massachusetts (MA): the entire state
- Michigan (MI): the area served by Consumers Energy (CE) only
- New York State (less New York City and Nassau and Suffolk Counties, NYS) and New York City (NYC): Surveyed separately due to the demographic and economic differences between the two regions; the Long Island Power Authority was not a study sponsor
- Wisconsin (WI): the entire state

The Sponsors and evaluation team selected comparison areas that, to the extent possible, shared demographic characteristics similar to their own. Furthermore, they sought comparison areas with no CFL programs or relatively small or newer ones. The Sponsors variously funded the fielding of data collection in the following states or areas:

- Georgia (GA), Kansas (KS), and Pennsylvania (PA): funded by the CPUC, who chose three combined states because no one non-program state was similar to the IOU service territory. Together with California, we refer to these as the "CPUC states."
- The District of Columbia (DC) and Houston: funded by NYSERDA, who chose two comparison areas because no one non-program city or county resembled NYC
- Ohio (OH): funded by NYSERDA as a comparison to NYS; the team excluded the 513/283 area code which overlaps heavily with the Duke Energy service territory because the utility had an active CFL program there in 2008
- Maryland (MD): funded by the Sponsors of the MA ENERGY STAR Lighting Program as a comparison to MA. The MD electric utilities launched CFL programs in late 2007 and expanded them in 2008; therefore, it represents a substantial but new program area in our model
- Indiana (IN): funded by the WPSC as a comparison area for Wisconsin

RDD and Onsite Surveys: Comparability across Areas

The Sponsors and the evaluation team collectively fielded seven RDD surveys and seven onsite surveys in sixteen areas, with some questions tailored to either program or non-program respondents. To achieve comparability on the key issues explored in the multistate modeling effort, each RDD survey instrument included a core set of questions about awareness, familiarity, satisfaction, use, and purchases, as well as a standard suite of demographic questions. Likewise, each onsite survey followed similar procedures to identify CFLs, perform socket counts, and ascertain when CFLs were obtained by the household.

While each Sponsor was interested in gathering information to develop a NTG, most also had additional issues they wanted to explore in the surveys. For this reason, both the RDD and onsite surveys differed in question number and order, topics addressed, response categories, and (to a small extent) wording of core questions. In order to preserve comparability among surveys, we limited these differences as much as possible. Some potential sources of differences involving timing, survey design, and onsite methodology still remain. For this reason, we have applied statistical controls, when possible, to account for these differences. Not all differences could be eliminated among the instruments, and this sometimes meant that data on a specific question was missing or not comparable for a specific state or area. As a result, some models do not include data for all areas.

In reviewing the data, the team came to the conclusion that the onsite survey provided more accurate estimates of CFL purchases and use than did the RDD survey. Systematically higher reporting, in the RDD survey, points to the likelihood that the onsite data were more accurate than the RDD data. Furthermore, social theory holds that the more salient an issue or object is to an individual, the more likely she is to provide accurate responses about it. Given that most RDD survey respondents are probably sitting in one location on the phone, trying to complete the survey as quickly as possible, most likely give a thoughtful but not always accurate response to the number of CFLs they purchased in 2008. In contrast, during the onsite survey, the respondents physically walk around their homes with a trained technician; they are looking at the CFL at the time the technicians ask when the bulbs were purchased, thereby raising the salience of the issue in their minds.

Development of Program Variables

The primary independent variable of interest summarized CFL program activity in each of the areas included in the current analysis. To develop this important variable, the team began 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 each program through 2008. We supplemented this document review with direct inquiries to energy efficiency and CFL program managers and through searches of the utility, public service agency, and energy service organization websites. Experts on CFL programs across the nation also collectively assessed the cumulative strength of each program through 2007 in an effort to capture the effect of prior activity on current levels of saturation and recent purchases.[1]

The team combined the information on programs within states or areas into three different program variables. The cumulative strength variable represented the average rating provided by the experts and required no transformations for inclusion in the model. The 2008 program activity variable represented a statistically transformed and combined measure that included data on the per-household CFL program budget and number of CFLs incented by programs in the state. Finally, the composite program variable combined the cumulative strength and 2008 program activity variables.

Modeling Procedures

Because this and other evaluations have found the data collected in onsite surveys to be more accurate than those in RDD surveys, the onsite surveys provided counts of CFL purchases, use, and storage as well as saturation. While we converted the counts of total sockets and CFLs installed into a percentage representing CFL saturation, the count data for purchases, storage, and use did not have the so-called normal curve assumed by the most common statistical modeling procedure, Ordinary Least Square Regression (OLS); instead they were right skewed, making OLS an inappropriate model for the count data of CFL use and purchases (see Section 4 for more detail). In response we turned to a statistical procedure appropriate for the data distribution: the negative binomial regression model (NBRM). The data on CFL saturation—measured as a percentage of all sockets in the home filled with CFLs—were not count data, so the team relied on the more familiar OLS methods for modeling saturation.

The team ran multiple models designed to explain CFL purchases in 2008 and the past three months as well as current use and current saturation. The results suggest that CFL programs had a statistically significant net positive effect on CFL purchases in 2008 as well as on current CFL use and saturation; however, the models did not find a net positive program effect on CFLs purchased in the past three months most likely due to the small number of respondents who had actually purchased CFLs in the past three months and the variation in the three month period in question across surveys.

Results: 2008 Purchases and NTG Estimates

Table 1 includes the best 2008 purchase model derived from onsite data ("best" as determined by the ability of the model to predict purchases accurately), while Table 2 displays an alternative model that includes saturation at the beginning of 2008. The team developed the alternative model because analyses presented in the full body of the report suggest that 2008 purchases were

[1] The experts were instructed to provide ratings on a zero to ten scale on the historic budget, marketing, CFLs incented, and overall impression of strength of programs in each state in order to account for how prior program activity may be affecting current program-induced sales of CFLs.

lower in states with relatively high saturation rates at the beginning of 2008. The models are derived from NBRM, to see the impact of any individual variable on purchase, on would multiply the variable by the impact score, not by the coefficient as in OLS regression.

Table 1: Best Fit 2008 Purchase Model – Onsite

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Composite Program	0.11	0.06	0.16	0.11
Years using CFL	0.10	0.06	0.14	0.10
Number of Sockets in Home	0.01	0.00	0.01	0.01
Number of Persons in Household	0.10	0.02	0.18	0.10
Self reported as White	0.42	0.09	0.74	0.52
Conducted During Fall Season	0.60	0.33	0.86	0.82
Constant	-0.79	-1.21	-0.38	n/a

* Sample size = 1,034 and pseudo R^2 = 1%. Excludes CPUC states as 2008 purchase data were not collected onsite.

Table 2: 2008 Purchase Model with Saturation– Onsite

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Composite Program	0.06	0.01	0.11	0.07
Years using CFL	0.13	0.08	0.18	0.14
CFL Saturation at beginning of 2008	-0.03	-0.04	-0.02	-0.03
Self reported as White	0.43	0.04	0.81	0.53
Number of Sockets in Home	0.01	0.00	0.01	0.01
2008 County Partisan Voting Index	-0.01	-0.01	0.00	-0.01
Constant	-0.17	-0.53	0.20	n/a

* Sample size = 950 and pseudo R^2 = 1%.

The purchase model presented in Table 1 is identical to the purchase model presented in the November 2009 draft of this report with the exception of the composite program variable. The evaluation team received data from one Sponsor after finalizing the models in the previous draft that made a recalibration of the program variable necessary. This recalibration led to some changes in the model coefficients and resulting impact scores, and, therefore to the NTG estimate. The current report finds an estimated NTG of 0.81 (81%), with a confidence interval ranging from 0.31 to 1.30 as calculated from the recommended best model (Table 3). The estimated NTG in CT fell toward the middle of the range for estimates calculated for all Sponsors. Although the team believes that the model presented in Table 1 is the best model based on its superior ability to predict the observed number of CFLs purchased in 2008, we also developed NTG estimates based on the alternative model (shown in Table 2). We stress that this second model does not provide as accurate a prediction of observed purchases as the first, but its inclusion of saturation at the beginning of 2008 may, in fact, better capture the factors that drive

CFL purchases. The NTG estimate based on this alternative model is 0.91 for CT, with a confidence interval ranging from 0.42 to 1.41.

Table 3: Range of NTG Estimates Calculated for All Areas Included in Study

	Without Saturation	With Saturation
CT NTG Estimate	0.81	0.91
90% Confidence Interval	0.31 to 1.30	0.42 to 1.41
Minimum NTG estimated for any area	0.19	0.54
Maximum NTG estimated for any area	5.47	9.12

Recommendations

The multistate CFL modeling effort represents a groundbreaking attempt by numerous program sponsors to pool their resources in an effort to explain what drives CFL purchases, use, and saturation in the rapidly changing CFL market. To that end, the results presented in this report have demonstrated that CFL programs are still having a positive effect on CFL purchases and leading to positive NTG ratios. In some areas those ratios are rather small, but in others they point to continued substantial program effects. It is important to note that the models presented here likely do not fully capture the complex web of relationships between variables that interact to affect CFL sales, although we have included analyses in the full body of the report that explore these relationships to some extent.

The estimated NTG for Connecticut for 2008 is approximately 0.81 and ranges from 0.31 to 1.30 at the 90% confidence interval. It is important to note that this NTG applies to the *2008 program* that preceded recent changes in the CT CFL program that have de-emphasized general service CFLs and increased support for specialty CFLs. The data we present here provide evidence that the CT Sponsors should continue their efforts to redesign the CFL programs. Strategies for doing so may include both (1) targeting efforts to promote spiral CFLs on the types of people who do not currently use CFLs at all or in large numbers and (2) focusing a greater portion of incentives on specialty bulbs. The program could attempt to increase the availability of both specialty and spiral CFLs in venues and retail channels where CFLs are sold in only limited quantities or at which non-users typically shop. Finally, the program could further educate consumers on the benefits of using general service (spiral) and specialty CFLs in the applications where CFLs are still not frequently used even in the homes of committed CFL users.

The final conclusion of the modeling effort may, in fact, be the most important: The methods used to date to estimate NTG for upstream CFL programs have all suffered from reliability and validity concerns. Respondent self-report error and bias related to who responds to RDD and onsite surveys leads to imprecise estimates of NTG, although these methods can have the advantage of controlling for household level drivers of CFL purchases when comparison state approaches are not possible. Methods that turn to CFL shipments find that the location to which the products are shipped does not translate neatly to where they are sold, affecting the accuracy of NTG estimates. Existing studies that rely on sales data often fail to capture the actual CFL market because they are sometimes unable to gather accurate or representative sales data; states that have successfully used this approach in the past now face the challenges of finding a comparison state or otherwise controlling for the demographic factors that affect CFL purchases. While this study has quantified those concerns as evidenced through varying estimates of NTG and wide confidence intervals, more often the impact of reliability and validity is unknown or difficult to quantify.

The evaluation team believes that having wider access to representative sales data will be a key component of determining the impact of CFL programs in the face of the changing CFL market. Paired with data that allow for the ability to control for the household and state-level demographic, economic, and social factors that also affect CFL purchases, sales data could allow for more accurate and precise NTG estimates if those data accurately represent the entire CFL market. The CFL program community, however, has largely been unsuccessful in gaining access to these data particularly from non-program retailers; some Sponsors even have trouble gather such information from participating retailers and manufacturers. Given this situation, the team presents the final recommendation: If CFL program sponsors remain committed to calculating NTG for CFLs (also LEDs and other small, relatively inexpensive products), they must work together with retailers and manufacturers to find acceptable ways of sharing sales data that do not threaten retailer and manufacturer competition but that still allow programs to assess in the most accurate way possible what their impact has been on the CFL market. Without such data, any estimate of the net impact of CFL programs will suffer from reliability and validity concerns to varying and sometimes unquantifiable degrees.

1 Introduction

This report summarizes the analyses conducted to date in support of the multistate CFL modeling effort, highlighting the results as they pertain to the net-to-gross ratio (NTG) for the Connecticut Energy Efficiency Board (CEEB), and Connecticut Light & Power (CL&P), and the United Illuminating Company (UI), which offer lighting programs sponsored by the Connecticut Energy Efficiency Fund (CEEF). As a group, these entities will be referred hereinto as the "CT Sponsors". The other Sponsors of this study include the following: California Public Utilities Commission (CPUC), New York State Energy Research and Development Authority (NYSERDA), Wisconsin Public Service Commission (WPSC), Consumers Energy in Michigan (CE), the Cape Light Compact (Cape Light), NSTAR, National Grid, Unitil, and Western Massachusetts Electric (WMECO), and Xcel Energy in Colorado (Xcel).[2] The evaluation team under contract with the CT Sponsors includes NMR Group and KEMA. Together with The Cadmus Group, PA Consulting, and APPRISE, Inc. they are the primary firms responsible for data collection and analysis that are collaborating as part of this groundbreaking multi-Sponsor and multistate effort. This report draws on data from 16 different geographic areas in the United States (US), but was written specifically for the CT Sponsors. The analyses draw on random digit dial (RDD) telephone surveys of over 9,300 households and onsite saturation surveys (including confirmation of when CFLs were purchased) for about 1,400 households.

1.1 Changing CFL Market and the Multistate Modeling Approach

The sponsors of CFL programs across the US have been conducting market effects analyses and calculating NTG since the first programs appeared in the late 1980s. Over time, the NTG methods have evolved to take into account free ridership and spillover, new program design, and changes in the CFL market. The multistate modeling approach represents the efforts of multiple Sponsors and evaluators to test a new method for estimating NTG in the face of increased CFL shipments and sales as well as rapid expansion of CFL programs throughout North America. This section briefly describes this evolution and the need for a new approach to estimating NTG.

Many early CFL programs relied heavily on coupon and catalog approaches to support the technology. Sponsors of such programs with this reliance generally calculated net energy savings using the following equation:

Net energy savings = Gross energy savings x (1 + spillover rate – free ridership rate)

The NTG portion of this equation involved free ridership and spillover rates, which some program sponsors estimated by surveying participants about the influence of the program on their in-program and out-of-program CFL purchases while in-program sales data came from

[2] Note that we refer to the Sponsors of this study because they comprise a mixture of state agencies, public service commissions, energy service organizations, and electric utilities. When capitalized, Sponsors refers to individual or multiple Sponsors of this study; when used in the lower-case form, we are referring more generally to sponsors of CFL lighting programs throughout North America.

tracking databases. This method relied heavily on having contact information for participants and a general idea of the number of program-supported products each participant had obtained.[3]

The shift to upstream markdown and buydown programs, which began gradually and has recently accelerated, led to a switch in the methods many program sponsors used to estimate NTG. One of the key characteristics of upstream approaches is that they are largely invisible to the consumer, who simply sees a discounted CFL on the store shelf.[4] The consumer does not have to fill out rebate coupons or catalog forms to get the incented CFL, and therefore sponsors generally are not able to collect participant contact information that facilitates surveying customers to help determine free ridership and spillover rates.[5] Furthermore, free ridership is built into the program design; a participant no longer has the option of purchasing the CFL at full price when a particular store carries the CFL only at the discounted price, and the participant is often not aware of the subsidy (which would be necessary for accurate self-reporting on free ridership and spillover).

In response, many CFL program sponsors adopted a NTG estimation method in which sales from their service territories where compared with sales from one or more non-program comparison areas, sometimes selected to be demographically similar to the program area. Such approaches relied on data from RDD or retail store surveys, CFL shipment data, or on retailer manufacturer sales data to estimate the NTG. [6] The NTG equaled the CFL sales in the program area minus CFL sales in the comparison area all divided by program-supported sales in the program area, sometimes doing so on a per-household basis, other times on a per-store basis, and still other times for all sales in the state. Additionally, some studies developed NTG estimates for separate sales channels (*e.g.* grocery stores, home improvement stores, *etc.*).

More recent changes in the CFL market, however, have hampered the comparison area approach to NTG. An increasing number of parties across the nation (and Canada) are now sponsoring upstream CFL programs, thereby severely limiting the number of potential non-program comparison areas, particularly those that are demographically similar to areas with longer

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[3] See, for example, Nexus Market Research and RLW Analytics, *Impact Evaluation of the Massachusetts, Rhode Island, and Vermont 2003 Residential Lighting Programs*, prepared for The Cape Light Compact
State of Vermont Public Service Department for Efficiency Vermont, National Grid, Northeast Utilities, NSTAR Electric and Unitil Energy Systems, Inc., October 1, 2004.

[4] Some programs may include point-of-sale materials explaining that the discounted price is the result of a CFL program, but this is not universally the case.

[5] For a method of identifying upstream participants, see Wilson-Wright, L. J. Zynda, R. Prahl, K. Oswald, and A. Li (2009) "They're Out There – Somewhere: Locating and Evaluating CFLs Distributed through Markdown and Buydown Programs." In the *Proceedings of the 2009 International Energy Program Evaluation Conference*. Portland, OR, August 12-14, 2009.

[6] See, for example, Nexus Market Research, *2005 Baseline and Net-to-Gross Sales*, prepared for Cape Light Compact, National Grid, NSTAR, Western Massachusetts Electric, Unitil, October 27, 2006, and Glacier Consulting, *FY04/05 Net-to-Gross Savings Adjustments for CFLs Rewarded through the ENERGY STAR Products Program*, Prepared for Wisconsin Department of Administration, January 11, 2006.

histories of supporting CFLs.[7] Similar demographics are vital to the comparison state approach to control for such intervening factors as income, education, concentration of big box stores, housing type, and homeownership patterns that prior studies have found relate to CFL awareness and use.

Further muddying the field is increasing—though debated—evidence that CFL sales in the remaining *non-program* areas rival those in program areas.[8] Some explanations on why sales in non-program states have increased revolve around broader changes in the CFL market. In particular, the spiral medium-based screw-in CFL has become one of the primary symbols of energy efficiency, the image of which many media outlets and advocacy groups turn to when wanting to represent the concept of energy efficiency as a whole.[9] Moreover, due in large part to the successful efforts of longstanding programs and ENERGY STAR® partner manufacturers and retailers, CFLs have become increasingly available throughout the US, with the successful Wal-Mart campaign to sell one hundred million CFLs in 2007 (they sold 137 million) exemplifying this trend.[10] It is important to note that analyses conducted by Hoefgen (2007) strongly suggest that Wal-Mart sold many of these CFLs in places that *lacked* longstanding CFL incentive programs.[11]

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[7] In fact, some non-program areas included in this analysis for 2008 are sponsoring upstream CFL programs in 2009 (*e.g.*, Consumers Energy in Michigan) while other programs are being planned (*e.g.*, in parts of Ohio and Pennsylvania). Maryland had new programs in 2008 that are reflected in the analysis.

[8] Most observers agree that CFL sales have increased in non-program areas. The debate, however, reflects whether sales in non-program areas rival those in program ones. The debate revolves around the accuracy of the methods to estimate sales, namely RDD survey and onsite self-reported purchases, CFL shipments, and retailer surveys and shelf counts, all of which have relative strengths and weaknesses. Such disputes could be laid to rest if accurate, comparable sales data that truly captured all the major CFL sales venues became available for each state in the nation. To date, sales data have been reported sporadically and have not been representative of where consumers shop for CFLs nationwide. For example, see Hoefgen, L. (2007) "What the CFL Data in 18seconds.org Really Mean." May 3, 2007.

[9] See, for example, nwalliance.org, the website for the Northwest Energy Efficiency Alliance.

[10] Wal-Mart Stores (2009) "Compact Fluorescent Light Fact Sheet" PDF file accessed August 19, 2009 at http://walmartstores.com/FactsNews/FactSheets/#Sustainability.

[11] Hoefgen, L. (2007) "What the CFL Data in 18seconds.org Really Mean." May 3, 2007.

Table 1–1 provides a view of how the CFL market changed in the mid to late 2000s. National CFL shipments increased dramatically in 2006, and again in 2007, before falling off in 2008. The implication is that households in the US bought three to four times more CFLs in 2007 and 2008 than they did in 2004; given the long average lifetime of CFLs,[12] the number of CFLs installed could have increased by an even greater proportion.

Table 1–1: CFL Shipments to the United States

Year	Number of Units	Adjusted for Non-Residential Applications*
2004	93,475,116	82,258,102
2005	101,772,949	89,560,195
2006	184,686,594	162,524,203
2007	397,128,692	349,473,250
2008	337,485,972	296,987,655

Source: US Department of Commerce
* Shipment data in the second column include CFLs installed in commercial applications; the estimates in this third column include only those estimated shipments that will be installed in residential applications.

Similarly, there was a change in the areas of the country where CFLs were being sold during the same time period. While CFL sales were historically higher in states or areas with CFL incentive programs,[13] research conducted in California suggests that recent CFL sales in non-program comparison areas have been as great as or greater than those in California (CA).[14,15] The CA researchers have developed a number of hypotheses to explain these findings (see Cadmus *et al* 2009 for details), but preliminary analyses point toward the following explanation (quoted verbatim):

> ***Erosion of Incremental Market Effects over Time (Spillover Hypothesis)***. California's programs may have caused market effects in both California and nationally in the past but, at this point, sales and awareness in the national market are very similar to conditions

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[12] About seven years for markdown CFLs, according to Nexus Market Research and RLW Analytics, *Residential Lighting Measure Life Study*, Prepared for New England Residential Lighting Program Sponsors, June 4, 2008.

[13] *Market Progress Evaluation Report (MPER) for the 2007 Massachusetts ENERGY STAR® Lighting Program*. Prepared by Nexus Market Research, RLW Analytics, and Dorothy Conant for Cape Light Compact, National Grid, NSTAR Electric, Unitil and, Western Massachusetts Electric Company, July 1, 2008. *Second Annual Comprehensive CFL Market Effects Study*. Prepared by Glacier Consulting for Wisconsin Focus on Energy, September 30, 2008.

14 Compact Fluorescent Lamps Market Effects Interim Report Draft, by Cadmus Group, KEMA, Itron, Nexus Market Research, and A. Goett Consulting. Report produced for California Public Utilities Commission, January 22, 2009.

[15] Although manufacturers who took part in the panel "The Future of CFL Programs - Should We Eliminate Financial Incentives to Encourage Customers to Purchase Standard Compact Fluorescent Lamps?" at the 2009 International Energy Program Evaluation Conference held August 12-14, 2009 in Portland, Oregon argued that the decrease in CFL sales in 2008 was smaller in program states than in non-program states. Their conclusions were based on sales data from retailers who carry their products, and these data are not available outside of their organizations for independent review or comparisons to other retailers.

observed in California. Therefore, the California programs are likely no longer generating incremental market effects beyond any positive net impacts they may be generating, and any differences between California and other states have largely eroded.

While the hypothesis directly references CA, one could make the argument that it applies equally to other longstanding CFL program states. For example, Winch and Talerico (2008) reported that WI saw a 132% increase in CFL sales from 2005 to 2007, but neighboring MI, which until recently did not sponsor CFL programs, experienced a 210% increase during the same time period.[16] CFL sales in WI still exceeded those in Michigan, but MI was closing the gap. In short, non-program states may be in the process of "catching up" to the level of sales and CFL use in program states. CFL sales in places with historic incentive programs may have leveled off as the market in those areas approached transformation, while CFL sales have increased in those states without programs or with recently implemented programs as more people become aware of and adopt the technology. However, more rigorous testing involving a diversity of states is needed to confirm this hypothesis.

A hypothetical example, depicted in Figure 1-1, illustrates why such a trend should not be unexpected.[17] Suppose a program in its first year is responsible for all sales of a given efficient technology in the program area, based on the fact that a non-program or baseline area has no sales; if the program did not exist, there would be no sales. From a sales perspective—that is, without considering actual vs. expected savings—the NTG is 1.0. Beginning in the second year, the program starts affecting the local market, even while the non-program market is developing to a lesser extent, and the NTG increases through year six, to a high of 3.1. After that, however, both the local and the non-program markets continue developing, with non-program sales eventually beginning to catch up to program ones as more households in those areas become aware of and adopt CFL and the markets in both program and non-program areas become transformed; thus the NTG falls below 1.0 by year ten, and to 0.0 by year 12.

Hence one function of an effective market transformation program is to accelerate the market adoption curve. This suggests that the pattern, not the timing or the numbers, applies more broadly. Based on the rapid development of the national CFL market, some observers suggested in 2008 (based on analysis of 2006 data) that the NTG in active program states had either started to decline or would do so soon, and that the decline would occur over a fairly short period.[18]

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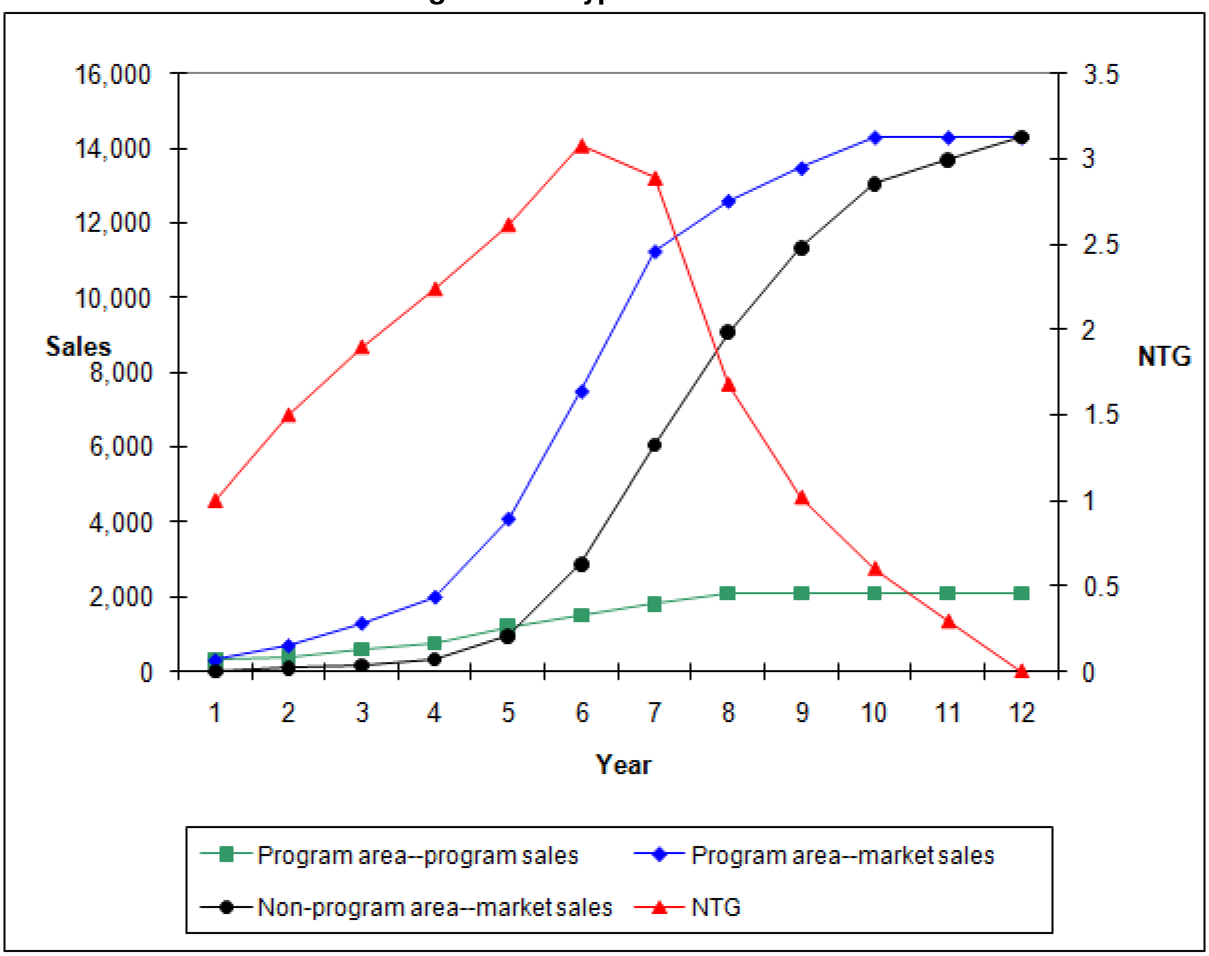
[16] Winch, R. and T. Talerico of Glacier Consulting, Group, LLC. 2008. *Second Annual Comprehensive CFL Market Effects Study – Final Report*. Delivered to the State of Wisconsin Public Service Commission, September 2008.
[17] This example is explained more fully in Hoefgen, L., A. Li, G. Azulay, Prahl R., and S. Oman, (2008) "Market Effects: Claim Them Now or Forever Hold Your Peace." In the *Proceedings of the 2008 Summer Study on Energy Efficiency in Buildings*, Asilomar, CA, August 17-22, 2008.
[18] Hoefgen, L., A. Li, G. Azulay, Prahl R., and S. Oman, (2008) "Market Effects: Claim Them Now or Forever Hold Your Peace." In the *Proceedings of the 2008 Summer Study on Energy Efficiency in Buildings*, Asilomar, CA, August 17-22, 2008

Of course, these expectations are subject to other factors—many of which are at play in the CFL market—such as the development and introduction of new technologies, which could start the cycle over again, or changes in codes and standards, which could accelerate it, or disruptions in the economy. There are also at least two additional caveats to these expectations. First, an assumption underlying the oversimplified pattern depicted in Figure 1-1 is that market penetration of efficient technologies in both the program area and the comparison area will follow the standard S-shape curve, and that in both areas it will reach a limit near 100% of its long-term potential. If manufacturers and retailers were to change their strategies abruptly and fundamentally, or if prices were to increase substantially, the expected S-shape curve might not develop. Even without such fundamental supply-side changes, the market penetration could level off at a lower level in the comparison area. It is also possible that the NTG could fall relatively slowly—particularly, again, if the curve in the comparison area should level off before that in the program area. Hence, given recent declines in the sales of CFLs nationwide, predictions about the future of the CFL market should be made cautiously.

Figure 1-1: Hypothetical NTG



The statistical analyses presented in this report seeks to provide tests of the hypothesis that non-program states may be in the process of "catching up" to the level of sales and CFL use in program states, and to examine the drivers of and barriers to CFL use and sales in this changing CFL market. One of the primary goals is to isolate the net impact of programs—including the cumulative effect of past program activity—on current CFL sales and saturation. Isolating the net impact allows the team to develop estimates of NTG for each of the study Sponsors, an estimate that takes into account the changing CFL market in many areas across the nation. This analysis draws on random digit dial (RDD) surveys of over 9,300 households and onsite saturation surveys (including confirmation of when CFLs were purchased) for about 1,400 households (Table 1–2; see Section 2.1 for discussion of the choice of comparison areas).[19] In this report, the team presents statistical models and NTG estimates that seem to best describe CFL purchases, use, and saturation in the time periods under examination.

[19] The evaluation team attempted to conduct about 1,500 saturation studies, but fewer homeowners than expected agreed to participate in the onsite portion of this study.

Table 1–2: Participating Areas, Sample Sizes, and Survey Dates

Area	Program Status		Telephone Survey	Onsite Survey	Survey Timing
	2008	Past 3 Months	Sample Size	Sample Size	
California IOU service territories	**Established program**	**Established program**	**699**	**77**	**Fall, Winter 2008**
Colorado - Xcel Energy	Moderate Program	Moderate Program	600	70	**Early fall 2009**
Connecticut	**Established program**	**Established program**	**500**	**95**	**Spring, Summer 2009**
District of Columbia	No program	No program	500	97	Winter 2009 Summer 2009
Georgia	Minor program	Minor program	579	62	Fall, Winter 2008
Houston, TX	No program	No program	503	99	Winter 2009 Summer 2009
Indiana	No program	No program	600	88	Spring, Summer 2009
Kansas	No program	No program	525	71	Fall, Winter 2008
Maryland	New program	New program	500	57	Spring, Summer 2009
Massachusetts	**Established program**	**Established program**	**503**	**100**	**Spring, Summer 2009**
Michigan – Consumer Energy service territory	**No program**	**New program**	**657**	**86**	**Summer 2009**
New York State, excluding New York City, Nassau and Suffolk Counties	**Moderate program***	**Moderate program***	**1,000**	**203**	**Winter 2009 Summer 2009**
New York City	**Moderate program***	**Moderate program***	**502**	**100**	**Winter 2009 Summer 2009**
Ohio, excluding Duke Energy service territory	No program	No program	501	98	Winter 2009 Summer 2009
Pennsylvania	No program	No program	653	59	Fall, Winter 2008
Wisconsin	**Established program**	**Established program**	**503**	**82**	**Spring, Summer 2009**
TOTAL SAMPLE AVAILABLE			**9,325**	**1,444**	

* Past NYSERDA CFL programs mainly supported CFLs through education, advertising, and marketing, including in cooperation with retailers and manufacturers, but markdown CFLs were a smaller component of the program. The current CFL expansion program expands the markdown component, among other activities, but had not been implemented at the time of the survey.

2 Survey Procedures

The data used in the modeling effort rely on two sources: an RDD telephone survey and an onsite saturation survey in which team members also verified when installed and stored CFLs were purchased. This section describes the choice of comparison areas, development of the surveys, sample designs and sampling error, and weighting schemes.

2.1 Choice of Comparison Areas

The multistate modeling effort relies on RDD and onsite data from areas with longstanding CFL programs, those with newer or smaller programs, and those with no CFL programs through 2008. As shown in Table 1–2, the seven Sponsors of this effort collectively account for the following areas:

- California (CA): areas served by Pacific Gas and Electric (PG&E), San Diego Gas and Electric (SDG&E), and Southern California Edison (SCE) or collectively the investor owned utilities (IOUs) service territory
- Colorado (CO): the area served by Xcel Energy
- Connecticut (CT): the entire state
- Massachusetts (MA): the entire state
- Michigan (MI): the area served by Consumers Energy (CE) only
- New York State (NYS) less New York City and Nassau and Suffolk Counties
- New York City (NYC): Surveyed separately due to the demographic and economic differences between the two regions; the Long Island Power Authority was not a study sponsor.
- Wisconsin (WI): the entire state

In order to select comparison areas, the Sponsors and the evaluation 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 or with only new 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 ones 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). As a result, the comparison areas chosen for this study include a mixture of areas that currently do not have CFL programs, those with newer programs, and some that first implemented programs in 2009 but after the fielding of the telephone and onsite surveys that provide the data for this study.

The Sponsors and evaluation team settled on the use of the following comparison areas:[20]

- Georgia (GA), Kansas (KS), and Pennsylvania (PA): funded by the CPUC, who chose three combined states because no one non-program state was similar to the IOU service territory. Together with California, we refer to these as the CPUC areas or states.
- The District of Columbia (DC) and Houston: funded by NYSERDA, who chose two comparison areas because no one non-program city or county resembled NYC
- Ohio (OH): funded by NYSERDA as a comparison to NYS; the team excluded the 513/283 area code which overlaps heavily with the Duke Energy service territory because the utility had an active CFL program there in 2008.
- Maryland (MD): funded by the Sponsors of the MA ENERGY STAR Lighting Program as a comparison to MA. The MD electric utilities launched CFL programs in late 2007 and expanded them in 2008; therefore, it represents a substantial but new program area in our model.
- Indiana (IN): funded by the WPSC as a comparison area for Wisconsin

If the current or additional Sponsors decide to repeat this effort in the future, it is possible that the models will include areas representing a greater diversity of program experience and location—including more states in the South and West and some Canadian provinces.

2.2 Random-Digit Dial Telephone Surveys

While every Sponsor of this study desired an estimate of NTG, their individual study objectives differed to an extent. Therefore, the Sponsors and evaluation team worked together to develop RDD survey questionnaires that balanced the need for comparability across study areas while still meeting the individual needs of each Sponsor.[21]

After finalizing the RDD survey questionnaires, survey implementation in most states proceeded according to standard practices for RDD surveying methods. The evaluation teams purchased blocks of random residential ten-digit telephone numbers for the areas to be included in the survey, randomly called households, and attempted to interview the person responsible for lighting purchases, until reaching the desired survey sample size. The method differed slightly in CA, CO, and MI where the evaluation team randomly called residential customers in the included service territories.[22] In no area did the evaluation teams stratify the sample design, and the only residential respondents excluded from the study across areas were those who refused to answer the survey and the people who could not respond in either English or Spanish (fielded only in the CPUC areas, NYC, and Houston).

[20] Note that all Sponsors of this effort are funding the data merging, analysis, and reporting efforts. We only mention who funded the survey because this relates to differences in the questionnaires and responses, as discussed in Section 2.4.
[21] The team thanks the Sponsors for their willingness to strike this balance in order to ensure comparability.
[22] Note that a few of the Xcel Energy customers were known program participants; we have kept their responses and information in the summary statistics presented in this report, but removed from them from the models.

Although the team relied on random selection, the demographic characteristics of willing respondents in all areas differed from the population as reported in the US Census on two factors often found to be related to CFL use: homeownership and education, specifically the underrepresentation of renters and those with less than a high school education.[23] The team developed a weighting scheme to correct for this underrepresentation using data on education by homeownership as reported by the US Census Bureau using the combined 2005 to 2007 *American Community Survey* (ACS) estimates for each area.[24] Appendix A discusses the development of the weighting scheme more fully and includes a table showing the scheme as well as sample design and sampling error for each area included in the current analysis.

Please note that the weighting schemes used in this study *differ* from those used in other reports delivered to individual Sponsors. The weighting schemes in other reports reflect concerns unique to those Sponsors. In contrast, this effort required a *consistent weighting scheme* across areas, and the ACS provided the source for this consistency. 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 Sponsors 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.

2.3 Onsite Visits

The Sponsors and the evaluation team decided to pair the RDD surveys with an onsite saturation study because of a general concern with the ability of respondents to provide accurate estimates of their CFL use, storage, and purchases during a RDD survey. Although respondents generally provide thoughtful estimates on the phone, most cannot give accurate on-the-spot estimates of the number of CFLs they have purchases or the number currently installed in their home. Some telephone surveys ask customers to walk through their home counting CFLs and sockets in each room in order to estimate saturation, but this can make the survey lengthy and tedious for the respondents, thereby reducing response rates. The onsite survey provides a more accurate approach of counting the number of CFLs and all other lighting products in use (otherwise known as a socket count) and in storage as well as determining CFL saturation rates (*i.e.* percentage of sockets filled with CFLs). It is also likely that respondents provide a more accurate estimate of when they purchases CFLs found in the home when actually looking at the product with a technician than when asked during a telephone survey while sitting or standing in one place. Such estimate of purchases still include some amount of self-report error, but, as the

[23] Such underrepresentation is common in RDD surveys. For example, see Galesic, M., R. Tourangeau, M.P. Couper (2006) "Complementing Random-Digit-Dial Telephone Surveys with Other Approaches to Collecting Sensitive Data." *American Journal of Preventive Medicine*. Volume 35, Number 5.

[24] United States Bureau of the Census (2009) *2005-2007 American Community Survey 3-Year Estimates*. http://factfinder.census.gov/servlet/DatasetMainPageServlet?_program=ACS&_submenuId=datasets_2&_lang=en.

analyses below show, the onsite based estimates are likely more reliable than those obtained during the RDD survey.

2.3.1 Recruiting Onsite Participants

The respective evaluation teams identified onsite participants through the RDD surveys. Twenty to 25% of RDD survey respondents voiced initial interest in the onsite survey. Sponsors offered $100 to $150 incentives to the homeowners, 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 Sponsor (in non-program states), and distrust of letting strangers into the home. Thus, while the team originally anticipated an onsite sample size of about 1,600, the final sample size was actually 1,444.

2.3.2 Conducting the Onsite Visit

The Sponsors and the evaluation team cooperatively developed onsite survey instruments. As with the RDD survey questionnaires, the onsite surveys differed somewhat, but struck a balance between meeting the needs of the individual Sponsor and comparability for the multistate modeling effort. Likewise, the actual details of the onsite methods varied slightly among data collection firms, but they all generally followed the pattern described here.

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 technician then asked the respondent a series of questions about household demographics, the characteristics of the home, and lighting usage. The respondent and the technician next 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. With the exception of the CPUC states, the technician also asked the respondent to estimate when he or she purchased that particular CFL. The technician and householder also examined bulbs in storage, again noting similar detailed information on stored CFLs. Visits averaged two hours in most areas, although some Sponsors also collected information on home electronics adding to the length of the visit.

In order to account for any potential bias toward CFL enthusiasts or homeowners, the evaluation team weighted the onsite sampled back to the telephone survey reported familiarity with CFLs and the percentage of households that own or rent in each area included in the study. The weighting scheme is presented in Appendix A

2.4 Comparability among Survey Instruments

The Sponsors and the evaluation team collectively fielded seven RDD surveys and seven onsite surveys in 16 areas, with some questions tailored to either program or non-program respondents. To achieve comparability on the key issues explored in the multistate modeling effort, each RDD survey included a core set of questions about awareness, familiarity, satisfaction, use, and purchases, as well as a standard suite of demographic questions. Likewise, each onsite survey followed similar procedures to identify CFLs, count sockets, and ascertain when CFLs were obtained by the household.

While each Sponsor was interested in gathering information to develop a NTG, most also had additional issues they wanted to explore in the surveys. For this reason, both the RDD and onsite surveys differed in question number and order, topics addressed, response categories, and (to a small extent) wording of core questions. In order to preserve comparability between surveys, we limited these differences as much as possible. Some potential sources of differences involving timing, survey design, and onsite methodology still remain. As the discussion below indicates, these differences nearly always involve the CPUC telephone and onsite surveys to some extent. This reflects the fact that the telephone and onsite surveys conducted for the CPUC were developed and fielded prior to the formation of the multistate modeling effort; the surveys for all other areas were designed after the multistate modeling effort had begun to coalesce, allowing the respective evaluation teams to create comparable instruments and methods across the other 12 areas in the study.

2.4.1 Differences in Timing

Survey timing is one of the differences that may have had an impact on comparability. This involves three different considerations.[25] The first is the time period under consideration in the CPUC study areas. Because of the three-year budget and evaluation period used by the CPUC, the RDD and onsite surveys conducted in CA, GA, KS, and PA asked about CFLs obtained and used from 2006 through the fall of 2008 as well as about those obtained in the past three months. The team created a dummy variable to control for differences that may be associated with the timing and, as discussed below, survey instruments and methodologies.

The second issue reflects the timing of the RDD surveys. The evaluation team conducted the RDD surveys funded by the CPUC and NYSERDA (NYS, NYC, DC, OH, and Houston) in late fall and early winter, respectively, which tend to be peak periods for lighting purchases and use. The team fielded the other RDD surveys in the summer, when lighting use and purchases are less frequent. Furthermore, CFL purchases made in “past three months” are embedded within those made in 2008. It is also the fact that the onsite surveys in the NYSERDA states took place seven to nine months after the fielding of the RDD survey, likely contributing to differences in onsite

[25] Luckily, the collapse of the financial markets is not one of them. All of the RDD and onsite surveys were conducted after September of 2008, the period many identify as a major turning point in the economy.

and RDD reports of purchases and use. It is also the case that the onsite efforts to explain what happened to all CFLs reported as purchased in the past three months means that there was at least some “truing up” of the 2008 purchases for the NYSERDA areas as the three months represented the last quarter of 2008. Because we found evidence of this effect on the purchase and use data (see Section 3.4), the team created a second dummy variable to control for the states in which the RDD surveys were conducted in the fall or early winter.

2.4.2 Differences in the Survey Instrument and Methodology

In addition to timing, differences in questioning techniques and wording may also have affected some responses. These apply largely to comparisons between the CPUC states of CA, GA, KS, and PA and the other areas and reflect the fact that the CPUC study was designed and fielded prior to the development of the multi-Sponsor, multi-state modeling effort. Moreover, the instruments used in the CPUC states differ from those used in the other areas due to the focus on evaluating the entire 2006 to 2008 program period for the CPUC but only 2008 and early 2009 for the other areas. The team has also noticed some systematic differences in the CO data that may be attributable to the RDD and onsite survey instruments and their implementation. We have identified a number of concerns related to the differences between the CPUC and CO surveys and those conducted in other states.

First, the CPUC telephone survey instrument used a different format to capture self-reported purchases, use, and storage. For purchases, the respondents provided estimates of their total purchases from 2006 to 2008 and then were asked to parcel out the number purchased in each year, starting with 2006 and working forward. This approach appears to have resulted in systematically lower RDD survey estimates of CFL purchases in 2008 in the CPUC states when compared to estimates from the other states. For use and storage, the respondents were asked to estimate how many CFLs they were using or storing at the time of the survey; then they were asked if that number was the same three months ago. Only those responding “no” to this prior question were subsequently asked how many CFLs they were using or storing three months ago. This approach led to systematically higher estimates of use and storage rates “three months ago” (see Appendix B).

Second, the CPUC telephone and onsite surveys both asked respondents how many CFLs they had purchased in the past three months. For the RDD survey (fielded in October and November of 2008), this period largely corresponded to July through October, depending on when the respondent answered the survey. The onsite visits were conducted almost exclusively in December of 2008; once again, respondents were asked to estimate the number of CFLs purchased in the past three months. However, the reference point was then September through December, again depending on the exact date of the onsite visit. The implication is that the RDD survey generally asked about late summer purchases—typically a time of relatively low lighting purchases—while the onsite survey asked about purchases in the fall—typically a time of high lighting purchases. Although the CPUC instrument asked a follow-up question about purchases between the telephone and onsite surveys, a discrepancy in the two estimates remains. In contrast, the other surveys did not ask the onsite participants to restate an estimate of purchases in the past three months. Instead, the technician specifically asked the respondents if they had purchased individual CFLs *in same three month time period corresponding to the RDD survey*. The implication is that the difference in estimates of three month purchases between the RDD and onsite surveys was greater for the CPUC states than for the other areas (Table 3–3).

Third, CPUC onsite saturation methods counted only medium screw-based sockets, whereas all other states included all lighting sockets. The evaluation team addressed this issue in slightly different ways in California versus the other three CPUC states. In California, the evaluation team received data on the number of small screw and pin-based sockets counted in onsite saturation surveys being conducted independently from those onsite visits summarized here. With these data, we estimated that about 31% of all sockets and eight percent of CFLs were not medium-screw based. In the other three CPUC states of GA, KS, and PA, the team examined the base type of sockets in all other areas in the study, estimating that, on average, homes had about three percent of CFLs and 25% of all bulbs in sockets other than medium-screw based ones. We then increased the onsite estimate of CFLs in California homes by eight percent and in Georgia, Kansas, and Pennsylvania homes by three percent. For all sockets, we added an additional 31% of sockets to each California home and an additional 25% of sockets to homes in the other three CPUC states.

Fourth, the CPUC instrument did not ask about CFL storage or use at the beginning of 2008; therefore, we cannot use these states in models explaining use at the beginning of 2008 or 2008 purchases when "use at the beginning of 2008" is a key variable.

The CO data demonstrate some idiosyncrasies, in particular high onsite estimates of purchases in 2008 (1.5 CFLs more than the next state, CT). A portion of the CO data was gathered directly from program participants listed in tracking databases instead of a random dialing of all residential electric customers in the their service territory. This accounts for some systematic differences from the other areas in the study, but concerns about high average use and purchase numbers remain even after removing these known participants. Another potential source of differences reflects the fact that only a small number of renters were surveyed (See Appendix A) and, given the weighting scheme that includes homeownership, has caused a few renting respondents to have a disproportionate impact on the data. Other oddities in the data may be attributable to the administration of the survey, but this is not something that can be confirmed at this time and requires further investigation. An attempt was made to include the CO data in modeling for this draft, but the model validation showed a significant decline in predictive power. After removing CO from the statistical analyses, the models behaved as expected, with model-based predicted values falling much closer to observed ones.. Note that the report summarizes data for the CO respondents but excludes them from the more advanced statistical analyses.

3 Variable Specification

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

3.1 Program variables[26]

The program variables were the key components of the statistical models guiding the calculation of the NTG. The team began development of this variable 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 2008 in each area. Specifically, we searched for data on the program budgets, the number of CFLs incented, when the current program and any of its predecessor programs had been launched, marketing and advertising support, and the method of support (*e.g.*, retail coupons, catalog, and/or upstream approaches). The team had relatively few problems gathering such information from the Sponsors of this study for 2008 program activity (although we did ask the Sponsors to confirm or clarify the information), but we found it necessary to turn to alternative sources for information on program activity in states with newer or smaller CFL programs and for program activity that occurred in earlier years. We relied heavily on web-based searches for gathering this information and, when programs existed and managers could be identified, contacting the program managers to gather the necessary information.

We were not able to locate consistent program data across areas on programs prior to 2008 but the team believed it was important to account for potential cumulative effects of earlier program activity on 2008 CFL purchases. For this reason, we decided to have individuals knowledgeable about CFL programs nationally rate the strength of prior program activity for each of the 16 states on four key variables: marketing and advertising, budget, and CFLs incented, as well as an overall rating of program strength. Although we asked six individuals not directly associated with this evaluation to provide ratings, three of the six could not provide ratings for various reasons.[27] One wanted to participate, but felt he did not have sufficient knowledge to do so. The

[26] 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.

[27] Two worked for organizations that would not allow them to rate members, and one did not have the time.

last two individuals provided ratings, and to supplement these, three evaluation team members also rated the programs on the same variables. We then averaged the scores of the five raters on each individual component of cumulative program strength (*e.g.,* budget, overall, etc.), weighting those of the two independent raters higher than those from the evaluation team. Finally, we summed the scores for each component into one "cumulative program strength" variable ranging from a possible low of zero to a high of 20 for each state.[28]

For the 2008 program activity variable, we computed state-level per-household estimates of CFL program budgets and products incented in that year for each study area. Because we had distributions that did not conform to the normal (*aka* bell-shaped) curve, we used the cubic root of these per-household estimates of budget and CFL incented. Furthermore, to adjust for different units of measurement (*i.e.*, dollars and CFLs), we standardized each estimate of per-household budget and of per-household CFLs. Finally, we summed the standardized scores to create the state-level 2008 program activity variable.

As a final step we also developed a "composite program variable" by summing the 2008 program activity variable and the standardized cubic root of the cumulative program strength rating. The composite program variable treated prior program activity as part of the current program, rather than searching for its unique effects as did the disaggregated cumulative effect variable. Table 3–1 lists the variables for each area used in the analysis.

Table 3–1: Program Variable by Area

	Prior Program Rating	2008 Program Activity	Composite Score
CA	19.000	3.451	4.913
CO	6.500	0.822	1.341
CT	14.722	2.893	4.088
DC	0.000	-1.937	-3.149
GA	3.056	-0.262	-0.169
IN	0.000	-1.937	-3.149
KS	0.000	-1.937	-3.149
MA	16.056	1.849	3.254
MD	1.278	2.076	1.717
MI	0.000	-1.937	-3.149
NYS	7.833	0.389	1.113
NYC	7.833	0.325	1.085
OH	0.333	-1.937	-2.478
PA	1.333	-1.937	-2.085
Houston	0.000	-1.937	-3.149
WI	13.611	2.014	2.965

[28] We subjected the ratings to tests of reliability using Cronbach's alpha, and, for each measure, reliability exceeded 80%, pointing to high levels of consistency between the raters.

3.2 Additional Non-survey Variables

The evaluation team believed that certain external factors may have affected CFL sales and use, including the local economic conditions and the concentration of box stores.[29] Turning first to economic conditions, the team considered multiple ways of capturing their potential impact on CFL sales, ultimately focusing on county-level foreclosure and unemployment rates. However, after thorough searching, we could not identify a reliable source of foreclosure rate data; the sources we found were either out of date (*i.e.*, preceded the mortgage crisis) or did not adequately cover the entire state or area (*e.g.*, data on rural areas was often missing). Therefore, we decided to turn solely to unemployment rates to capture economic conditions.

The question then became which unemployment rate to use. Some of the RDD surveys questioned respondents about their employment status, but the question was not included in all of them. The US Bureau of Labor Statistics (BLS) was utilized to gather consistent unemployment data from all study areas.[30] The analyses included two different measure of unemployment, both measured 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 December 2008. 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 four different variables to capture the concentration of big box stores, specifically Home Depot, Lowes, Menards, and Wal-Mart (including Sam's Club).[31] 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, on 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. The fourth variable used a state-level estimate of the concentration of Wal-

[29] 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 needed to develop the external variables were not always available at such smaller units of analysis such as the zip code.

[30] 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.

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

Mart stores per household to acknowledge the fact that people may shop outside of their county of residence.[32]

The evaluation team also tested whether the political climate of the respondent's county influenced their CFL use and purchase behavior using data compiled by the Many Eyes website.[33] This variable, the 2008 Partisan Voting Index (PVI) was found by subtracting the percentage of the republican votes received in a county from the percentage of democratic votes received in a county; this figure was then subtracted from the national democratic margin of victory to yield the county's PVI. The more negative the PVI, the more heavily the area leaned Democratic in the 2008 election.

Finally, the evaluation team created a dummy variable using the current US Census Bureau designations of 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., less than 50,000 people in any of the cities or towns in the county).

3.3 Variable Transformation[34]

Many of the survey-based variables required minor transformations to prepare them for statistical analysis. First, we recoded all respondents in the RDD survey who said they did not know the number of CFLs they had purchased, were in use, or were in storage as "zero" in order to include them in the analysis.[35] In contrast, for the onsite data, a trained technician was able to collect CFL use, purchase, and storage data from respondents, including those not aware of CFLs. A few respondents reported that they did not recall when they purchased some of the CFLs found in their homes and the team treated such data as "missing".

Second, the RDD surveys asked respondents to provide their annual household income in the broad categories used by the US Census Bureau. However, the cost of living (COL) differs greatly among the 16 areas included in the study requiring that we adjust the income categories to a consistent base. The team adjusted COL in all states and DC to an average US base using data compiled by the Missouri Department of Economic Development.[36] For Houston, we used a

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[32] The team continues to consider alternative ways of capturing the potential impact of major CFL retailers on the results. These variables *may* be adjusted in future models.

[33] Many Eyes at http://manyeyes.alphaworks.ibm.com/manyeyes/ is a research lab at IBM that maintains a number of public data sets including voting records.

[34] Note that the team also carefully adjusted the response codes to force them into agreement between the various versions of the surveys. To offer just one example, some surveys coded female as 1 and male as 2, while other flipped the order.

[35] Note that we recognize that some people who are not aware of CFLs may in fact have used or even purchased them, but in a RDD survey one cannot question someone about a product of which they have no knowledge. The onsite saturation study helps to correct for this possible scenario by looking for CFLs in all households, even those of people not aware of them.

[36] Missouri Department of Economic Development (2009) *Cost of Living Data Series, 1st Quarter 2009.* http://www.missourieconomy.org/indicators/cost_of_living/index.stm

2008 estimate provided by the Greater Houston Convention and Visitors Bureau.[37] NYS and NYC provided a greater challenge as the extremely high COL in Manhattan biases the results not only for NYC but also for the entire state and New York. The American Chamber of Commerce Researchers Association (ACCRA) provides the most commonly used information on COL data and drives nearly all COL calculators reported for the US.[38] ACCRA keeps data on cities, however, and not states. Furthermore, for NYC, it lists Manhattan, Brooklyn, and Queens separately because they have such different COL but does not track the Bronx or Staten Island. We used online calculators to locate areas with very similar COL to cities in upstate New York and found that Connecticut has a COL similar to most of them; we therefore applied the CT COL adjustment to New York State. The COL in Manhattan far exceeds that of any other city in the US but is balanced by the four other boroughs with Queens (and likely the similar Staten Island) having higher COL than Brooklyn and the Bronx falling far below the others. On balance, it seemed as if the COL in DC served as a useful adjustment for NYC, striking a balance between Manhattan and the other four boroughs and being relatively similar to the COL in Queens.

Third, categorical data require special treatment in the types of statistical procedures we used to model CFL sales and use. The procedures we used attempt to provide the net impact of a unit change in each variable on CFL purchases or use, for example, how much recent CFL purchases change for each percentage of sockets already containing a CFL. The analysis and interpretation is rather straightforward when the dependent (explained) and independent (explanatory) variables are quantitative and continuous (assuming all other statistical assumptions are valid), but they become less clear when the independent variables are categorical, meaning that a number stands in place for a characteristic, concept, or idea (*e.g.*, yes, no, do not know; homeowner, renter; etc.). Although some statistical procedures allow for the inclusion of categorical independent variables with no transformations (*e.g.*, analysis of covariance or ANCOVA), the nature of our dependent variables (*i.e.*, CFL purchase and use) forced us to use procedures that are less adept at handling untransformed categorical data.

The accepted statistical procedure for dealing with categorical data in such cases is to make them dichotomous variables—that is, coded as one for having the characteristic and zero for not. When more than two responses are possible, the analyst creates a series of dichotomous variables, one for each of the characteristics under question. We followed this accepted procedure, but found that we needed to limit the number of dichotomous variables to a manageable size.[39] We reviewed the data for each categorical variable and then combined response categories into larger groups before creating the dichotomous choices. Table 3–2 summarizes the variables treated in this manner.

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[37] Greater Houston Convention and Visitors Bureau (2009) *Cost of Living*. http://www.visithoustontexas.com/media/statistics/Houston_Stats_Cost_of_Living

[38] See ACCRA Cost of Living Index at http://www.coli.org/

[39] For example, if we had categorized all response possibilities for just income and education alone, we would have had nearly 20 individual variables to capture just those two variables.

Table 3–2: Transformation of Categorical Variables

Variable	Transformation
Home size	Divided into three individual dichotomous variables 1. Less than 2,000 square feet or not 2. 2,000 to 3,999 square feet or not 3. 4,000 or more square feet or not Note that we also include home size as a single variable grouped into these three categories as they represent “steps” of 2,000 square feet each.
Education	Divided into a two separate dichotomous variable: 1. College degree or not 2. High school diploma or not
COL Adjusted Income	After adjusting for the COL, divided into three individual dichotomous variables: 1. Low income (approximate annual income less than $30,000, which is 60% of the federal median for a household of three, the average household size) or not 2. Moderate income (income between $30,000 and $99,999) or not 3. High income (income $100,000 or more) or not Note that about one-fourth of the sample refused to respond to our inquiry about their household income.
Self-reported Race	Divided into a single dichotomous variable: race self-reported as white or not.

Appendix B summarizes the key RDD survey reported demographic and CFL-related variables (e.g., purchase, storage, use) across all sixteen states.

3.4 Comparison of RDD and Onsite Purchases and Use

Table 3–3 and Table 3–4 compare the RDD and onsite survey reported CFL purchases and use for the onsite participants.[40] The comparisons in Table 3–3 suggest that onsite participants overstated their purchases for 2008 in the RDD survey, but their reporting differences for purchases in the past three months were mixed. Note that the CPUC states of CA, GA, KS, and PA consistently show much larger onsite verified purchases in the past three months than other states, perhaps reflecting the fact that the RDD captured three late summer months while the onsite survey captured three late fall and early winter months, as discussed above in Section 2.4.2.

Alternatively, the NYSERDA study areas (NYS, NYC, DC, Houston, and OH) generally show higher purchases during the RDD than the onsite survey; although the onsite technicians asked respondents if they had purchased the CFLs in the same three months asked in the RDD survey, the more than seven to nine month delay between the RDD and onsite likely contributed to the

[40] Individual reports delivered to each sponsor highlight the differences between RDD and onsite respondents more thoroughly. We do not report the comparison between RDD and onsite respondents here because we believe the RDD reports are more susceptible to respondent self-report error and may not accurately reflect their actual CFL use or purchases.

observed differences, namely that people may have forgotten which CFLs they had purchased in the relevant three month period. Overall the RDD and onsite survey reports of three-month purchases are typically closer because respondents in most areas (although not in the CPUC states or CO) were asked to account for differences in three month purchases between the two surveys. It is also the case that very few people reported purchasing CFLs in the past three months in either the RDD or onsite survey, further contributing to the closer estimates. Table 3–4, in contrast, suggests that respondents often understate their current use of CFLs during the RDD survey—only respondents in Houston overstated their current CFL use and they did so by 0.7 CFLs.

Table 3–3: Self-Reported Purchases for Onsite Participants by RDD and Onsite Responses

(Base = onsite participants, weighted on familiarity, education, and homeownership)

State	Sample Size	CFL Purchased Past Three Months*		CFL Purchased in Past Year	
		RDD	Onsite	RDD	Onsite
CA	77	0.4	2.9	1.3	n/a
CO	70	0.4	0.5	4.1	5.1
CT	95	0.5	0.5	3.9**	3.6
DC	97	0.7	0.5	2.6	2.0
GA	62	0.4**	3.5	1.2	n/a
IN	88	0.8	0.9	3.3	1.6
KS	71	1.9	3.3	0.9	n/a
MD	57	0.4	1.0	3.6	2.0
MA	100	0.3	0.8	3.3	1.6
MI	86	0.2	1.2	2.8	2.7
NYS	203	1.2	0.5	5.0	3.8
NYC	100	1.2	0.4	3.1	2.6
OH	98	1.4	0.6	4.0	2.6
PA	59	0.5	1.7	1.1	n/a
Houston	99	0.9	0.3	5.0	1.1
WI	82	0.6	0.6	4.2	3.1

* The "past three month" onsite purchase estimates from the CPUC data have been verified to be higher than RDD reports in separate analyses of the same data. The CPUC onsites asked respondents about their purchases "in the past three months" but those three months varied from the period referenced in the RDD survey. Although the CPUC onsite instrument attempted to correct for this by also determining how many of the CFLs purchased in the past three months had been obtained since the telephone survey, the discrepancy still remains. In contrast, the "three months" about which we inquired in the other states are the same three months (*e.g.*, April, May and June for MD and MA in both the onsite and RDD surveys). Respondents were explicitly asked to account for differences in three month purchases between the onsite and telephone surveys.

** One outlier removed from estimate.

Table 3–4: Self-Reported CFL Use for Onsite Participants by RDD and Onsite Responses*

(Base = onsite participants, weighted on familiarity, education, and homeownership)

State	Sample Size	CFL Currently in Use	
		RDD	Onsite
CA	77	8.0	12.3
CO	70	5.9	10.0
CT	95	9.1	10.4
DC	97	3.4	4.2
GA	62	7.2*	8.6
IN	88	6.2	7.7
KS	71	7.1	12.7
MD	57	5.8	7.3
MA	100	7.1	9.5
MI	86	7.8	9.0
NYS	203	6.3	11.0
NYC	100	3.5	5.8
OH	98	5.2	7.5
PA	59	6.8	7.3
Houston	99	5.9	5.2
WI	82	7.8	10.5

* One outlier removed from estimate.

The lack of awareness accounts for some of the observed differences between RDD and onsite survey estimates of use. RDD survey respondents not aware CFLs could not be asked questions about their use or purchases, and we assumed that they would not have installed or purchased any CFLs. In fact, some of them were CFLs users and had recently purchased the product. Likewise, although those not at all familiar with CFLs were asked some use and purchase questions, it is reasonable to assume their answers may suffer from bias associated with their lack of familiarity. Overall, however, awareness and familiarity account for only a small part of the error as the following graphs demonstrate.

Figure 3-1 through Figure 3-6 compare the number of CFLs that RDD survey respondents reported currently purchasing or using by the onsite verified purchase or current use. Specifically, Figure 3-1 plots RDD reported purchases in 2008 by onsite verified purchases for the same year, and Figure 3-3 shows similar data for purchases in the past three months. Each graph suggests that there was only a slight positive relationship between RDD reported and onsite verified purchases. Figure 3-2 and Figure 3-4 compare the RDD survey reported purchases in each time period by the self-reporting error as determined by the difference between the RDD estimate and onsite verified purchases; these two graphs suggest that those who originally reported purchasing a greater number of CFLs exhibited higher levels of reporting error than those with just a few self-reported purchases. The current CFL use data tell a contrasting story to the purchase data. Figure 3-5 displays the RDD survey reported estimates of current CFL use and the onsite verified current use, while Figure 3-6 plots RDD reported use against the difference between the RDD and onsite estimates. In these graphs we find that RDD survey respondents generally knew that they had zero, a few, or many CFLs installed, but they still exhibited a great deal of error in their actual point estimates of use. Furthermore, also unlike purchases, the error in the point estimates was not related to the number of CFLs reported as used in the RDD survey.

Figure 3-1: Telephone Survey Reported vs. Onsite Verified CFL Purchases in 2008

(n=1,012; excludes outliers and respondents not familiar with or aware of CFLs; intercept set equal to zero; not available for CPUC states)

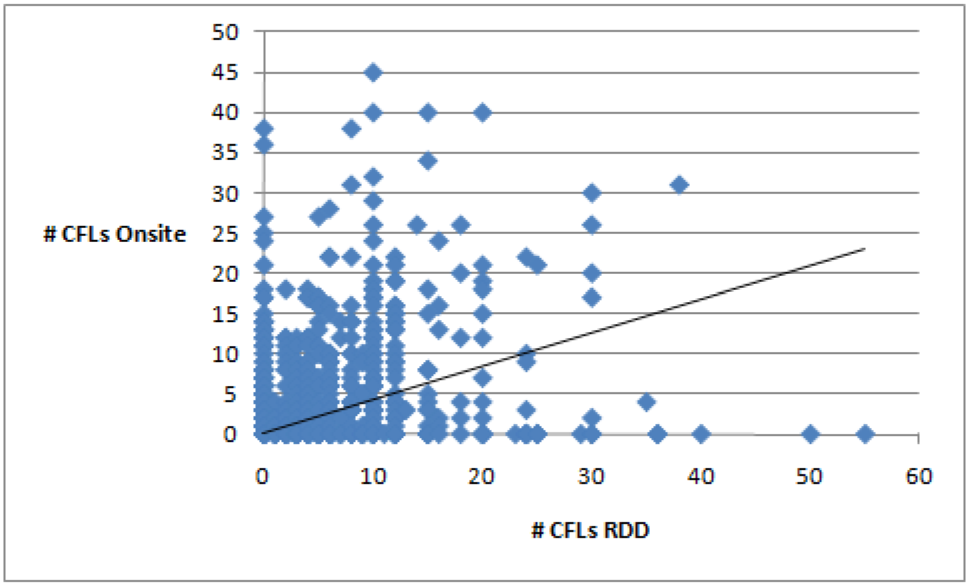


Figure 3-2: Difference between Telephone Survey Self-Reported and Onsite Verified CFL Purchases in 2008

(n=1,012; excludes outliers and respondents not familiar with or aware of CFLs; not available for CPUC states)

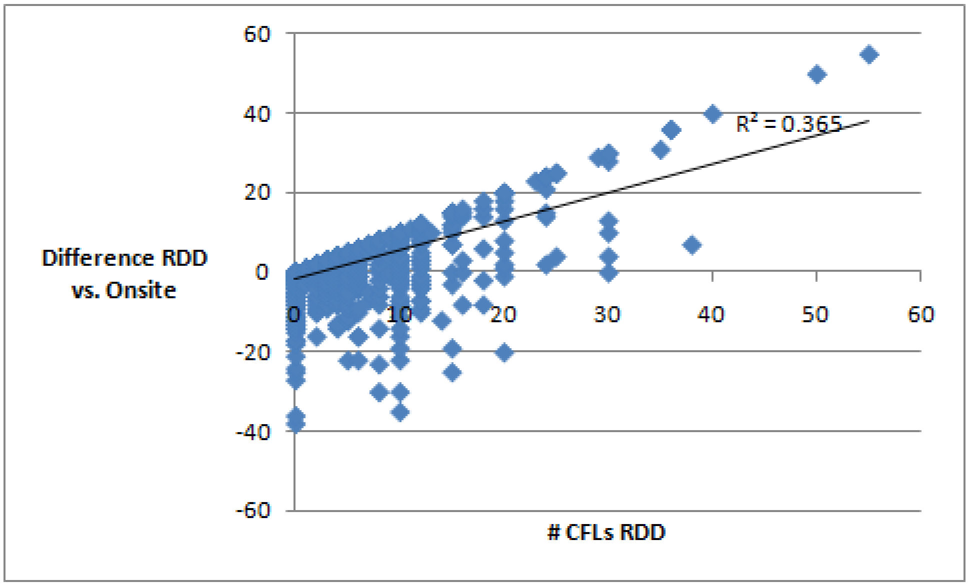


Figure 3-3: Telephone Survey Reported vs. Onsite Verified CFL Purchases in the Past Three Months

(n=1,255; excludes outliers and respondents not familiar with or aware of CFLs; intercept set equal to zero)

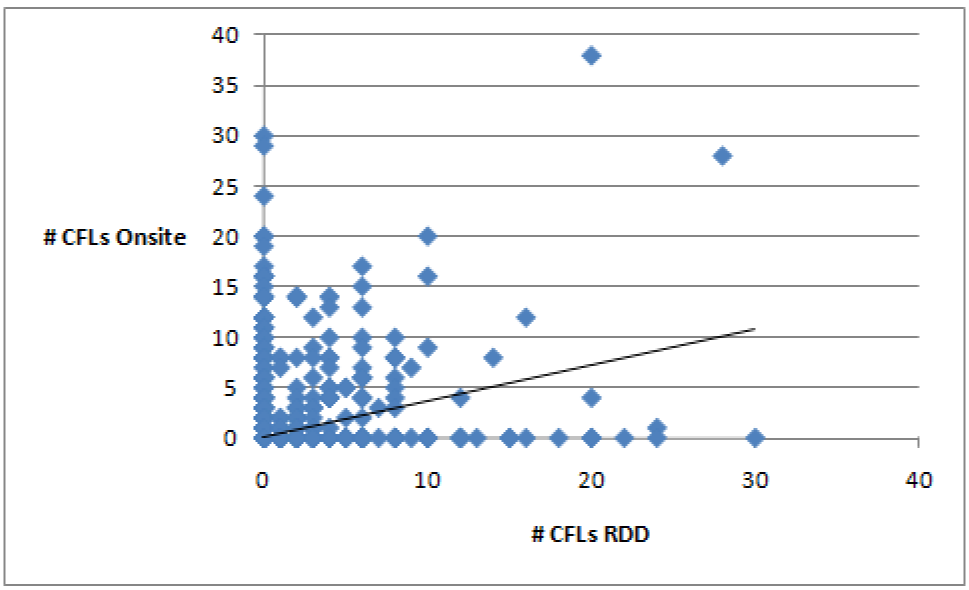


Figure 3-4: Difference between Telephone Survey Self-Reported and Onsite Verified CFL Purchases in the Past Three Months

(n=1,255; excludes outliers and respondents not familiar with or aware of CFLs)

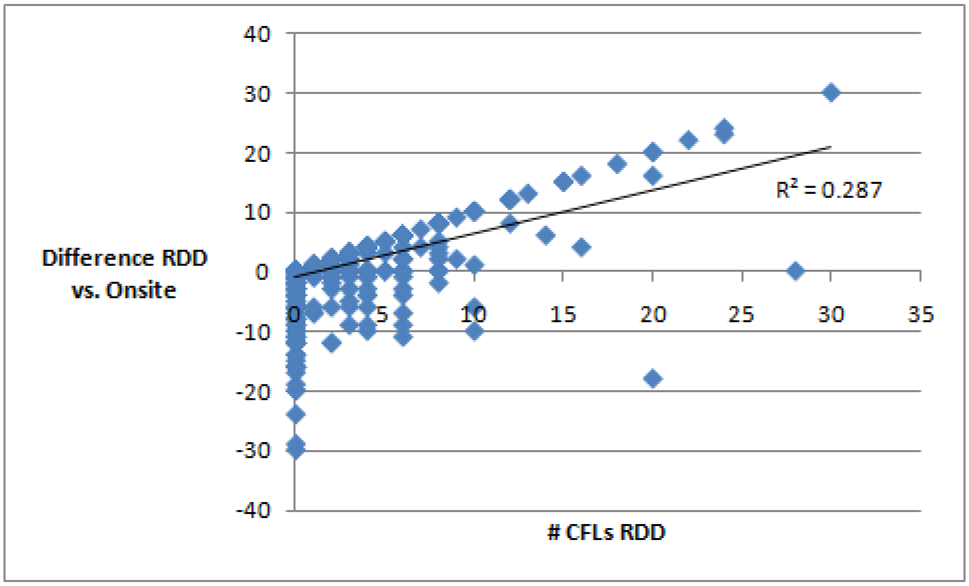


Figure 3-5: Telephone Survey Reported vs. Onsite Verified Current CFL Use

(n=1,261; excludes outliers and respondents not familiar with or aware of CFLs; intercept set equal to zero)

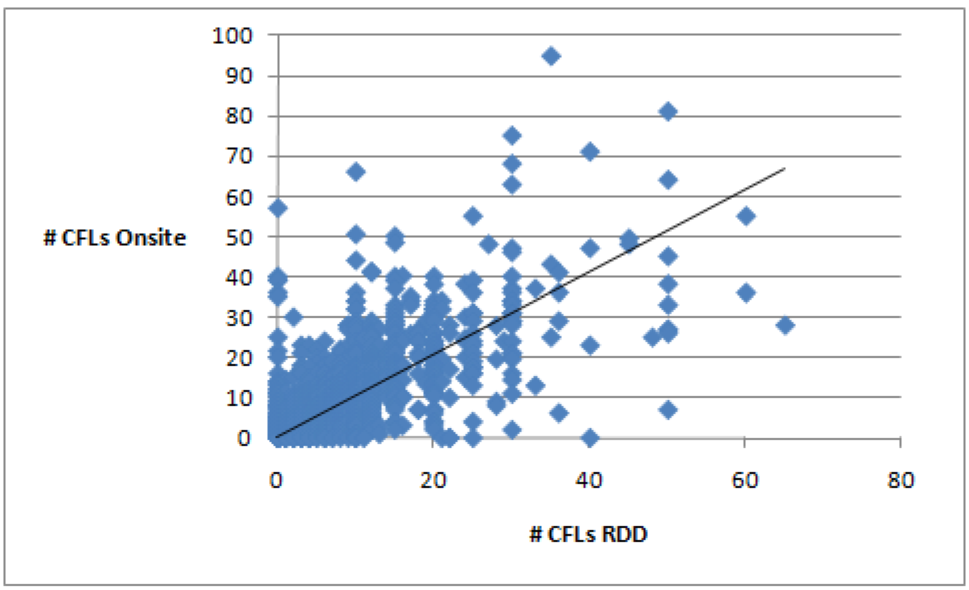
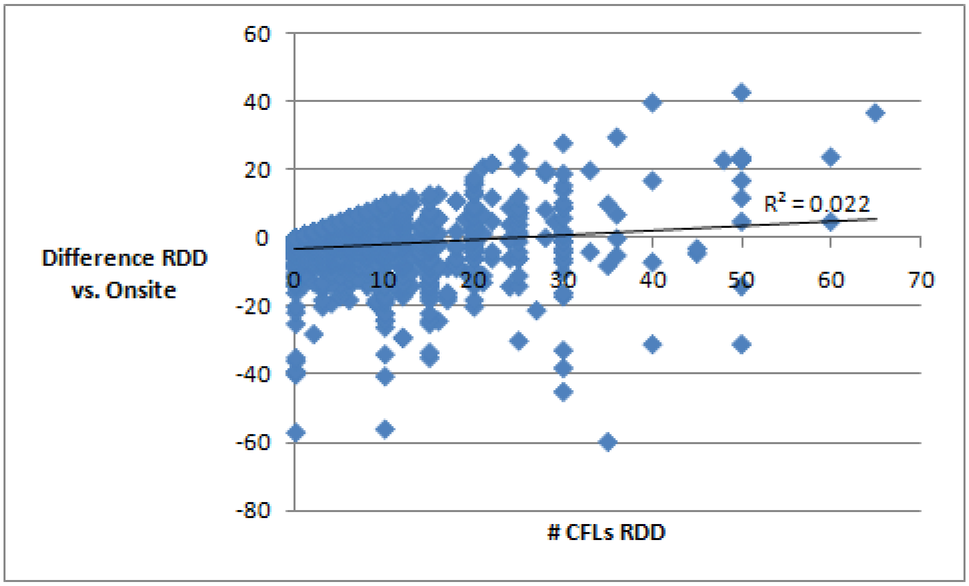


Figure 3-6: Difference between Telephone Survey Self-Reported and Onsite Verified Current CFL Use

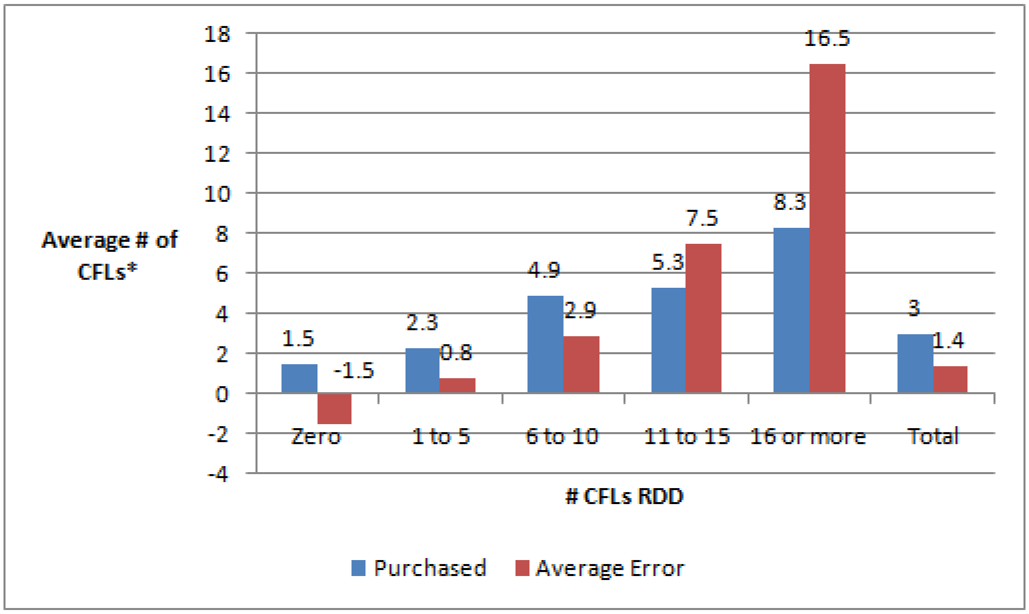
(n=1,261; excludes outliers and respondents not familiar with or aware of CFLs)



Given that Figure 3-1 through Figure 3-4 suggest at least some variation in accuracy by the number of CFLs RDD respondents reported as purchased, the evaluation team compared the mean number of onsite verified purchases and average error in reporting (negative scores indicate underestimates in the RDD while positive scores indicate overestimates) by how many CFLs the respondent originally reported buying during the specified time period while answering in the RDD. Those not aware of or familiar with CFLs and outliers have been removed from the analysis. Figure 3-7 displays these results for purchases in 2008. On average, those who said they purchased one to five CFLs showed the greatest accuracy in self-reports, actually purchasing an average of 2.3 CFLs and erring in their estimates by less than one CFL on average. Respondent who reported purchasing zero CFLs had actually purchased an average 1.5 CFLs. Those who reported purchasing more than five CFLs in the RDD showed the greatest levels of error, and the error increased with the number originally reported as purchased. Figure 3-8 demonstrates a similar pattern for purchases in the past three months, although the small number of people who purchased CFLs at all during this time period means that the results should be interpreted with caution.

Figure 3-7: Comparison of Telephone Survey Self-Reported and Onsite Verified CFL Purchases in 2008 by Number Self-Reported

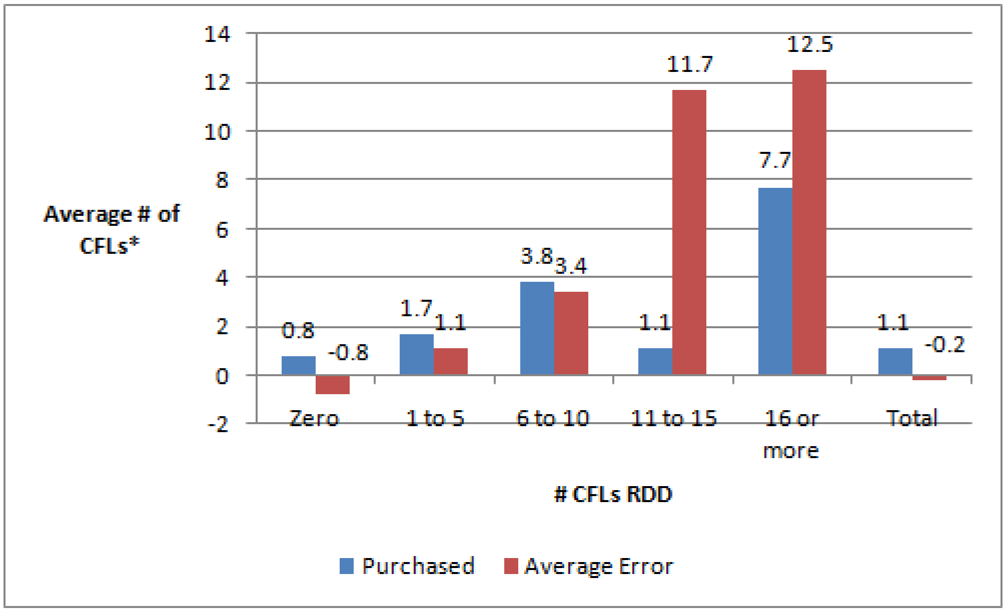
(n=1,011 but varies by number of CFLs purchased; excludes outliers and respondents not familiar with or aware of CFLs; not available for CPUC states)



* Blue bars indicate the average number of CFLs purchased as verified onsite; red bars indicate the average error in reporting between the RDD and onsite (*i.e.* RDD estimate minus onsite estimate).

Figure 3-8: Comparison of Telephone Survey Self-Reported and Onsite Verified CFL Purchases in Past Three Months by Number Self-Reported

(n=1,252 but varies by number of CFLs purchased; excludes outliers and respondents not familiar with or aware of CFLs; not available for CPUC states)



* Blue bars indicate the average number of CFLs purchased as verified onsite; red bars indicate the average error in reporting between the RDD and onsite (*i.e.* RDD estimate minus onsite estimate).

The analysis presented in this section point to three systematic differences between the RDD and onsite self-reports of CFL use and purchases: 1) RDD survey respondents have a tendency to underestimate their use of CFLs compared to verified use onsite, 2) respondents more frequently reported purchasing more CFLs in 2008 during the RDD survey than they reported during the onsite survey, and 3) respondents who gave greater estimates of CFL purchases for 2008 or the past three months during the RDD survey were more likely to demonstrate greater differences between the RDD and onsite reports of purchases than those who said they purchased fewer CFLs. These systematic differences point to the likelihood that the onsite data for 2008 purchases were more accurate than the RDD data. With the backing of the social theory of salience referenced above, the team drew the conclusion that the onsite data—while not without error—were more accurate than the RDD survey data and prioritized the use of onsite based data on CFL use and purchases in the models.

3.5 Onsite Saturation: Current and Beginning of 2008

As described in Section 2.3, one of the key purposes of the onsite visits was to conduct a socket count in order to estimate CFL saturation. Table 3–5 summarizes the area-wide saturation rate (i.e., all installed CFLs divided by all sockets in the state), the per household saturation rate (i.e., the average percentage of sockets for each household), and the per household median saturation rate (i.e., the mid-point in the percentage of sockets for each household). Although most programs compute saturation on an area-wide basis, recent work conducted by D&R International and the Department of Energy (DOE) has drawn attention to the fact that saturation rates may be strongly influenced by outliers—households with CFLs installed in a far higher percentage of sockets than normal.[41] This work compared the mean (the average) and median (the midpoint) saturation on a per-household basis, showing that the median is far lower than the mean nationally and in at least some program states as well. The discrepancy between the mean and median shows that a relatively few homes drive average saturation rates, while even more homes still have very few or no CFLs installed.

The results presented here add to this discussion. Similar to the D&R and DOE studies, we find that mean saturation area-wide and on a per-household basis are usually higher than the median (CO is the exception). However, we also find that program states have higher saturation rates by all measures—especially the median—and that the median saturation is closer to the mean in program states, suggesting less variation in saturation in program areas than in places without

[41] See presentation delivered by Stephen Bickel in the panel "The Future of CFL Programs - Should We Eliminate Financial Incentives to Encourage Customers to Purchase Standard Compact Fluorescent Lamps?" at the 2009 International Energy Program Evaluation Conference held August 12-14, 2009 in Portland, Oregon; also in the presentation "The CFL Market: Long Way to Go, Little Time to Get There" as part of the AESP brownbag seminar *The CFL Market: Past, Present and Future*, September 24, 2009. See also the DOE publication *Big Results, Bigger Potential: CFL Market Profile* March 2009. Available at http://www.energystar.gov/ia/products/downloads/CFL_Market_Profile.pdf

programs or with newer or moderate programs.[42] Program areas have succeeded in getting CFLs into a larger number of homes (penetration) and equalizing the percentage of sockets within those homes that contain CFLs (saturation) relative to non-program areas.

Table 3–5: Current CFL Saturation by State

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

State	Sample Size	Area-wide	Per Household		
		Mean	Mean	Median	Difference
CA*	77	25.8	29.7	26.1	3.6
CO	70	18.6	23.6	20.7	2.9
CT	95	21.9	26.3	20.2	6.1
DC	97	13.4	14.1	3.5	10.6
GA*	62	16.2	16.0	5.6	10.4
IN	88	17.1	20.7	10.9	9.8
KS*	71	20.7	22.6	7.0	15.6
MD	57	15.5	18.6	12.4	6.2
MA	100	23.4	26.9	20.2	6.7
MI	86	18.5	19.8	12.5	7.3
NYS	203	18.2	21.0	14.8	6.2
NYC	100	22.4	24.0	21.1	2.9
OH	98	13.5	17.1	9.5	7.6
PA*	59	16.0	17.6	9.7	7.9
Houston	99	12.3	12.5	0.0	12.5
WI	82	20.9	23.7	17.6	6.1

* Adjusted to account for small screw and pin based sockets as described in Section 2.4.2.

Table 3–6 compares current saturation with the best approximation the data allow for saturation at the beginning of 2008. We developed this estimate by using the number of *currently installed* CFLs purchased *prior to 2008* as the numerator and the current number of total sockets as a denominator.[43] The approximation of saturation at the beginning of 2008 suggests a large increase in saturation in nearly all areas in the study, including some with longstanding CFL programs. The increase was smallest in IN (5.1%) and largest in CO (14.6%). MA had the highest saturation of all the areas at the beginning of 2008 (17%), but subsequently—and perhaps consequently—saw the second smallest increase in saturation (6.2%) over the course of

[42] The high saturation rates in NYC are driven by the small size of homes there; NYC has fewer sockets per home than the other areas in the study, so just a few CFLs make a large difference in CFL saturation

[43] This approach has three problems. First, it suffers from respondent self-report error regarding the time of purchase. Second, the approach assumes that none of the currently installed CFLs purchased after 2008 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 2008. Therefore, the evaluation team stresses that the approximation of saturation of 2008 is most accurately portrayed as *the percentage of sockets currently filled with CFLs purchased prior to 2008*, but for ease of discussion we will refer to it as saturation at the beginning of 2008. It should also be noted that these data are not available for the four CPUC states.

2008. Furthermore, three longstanding programs (*i.e*. CT, NYC, and WI) saw their saturation rates increase substantially since the beginning of 2008 an now exhibit saturation rates nearly as high as MA.

Table 3–6: Comparison of Current Saturation and Approximate Saturation at the Beginning of 2008*

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

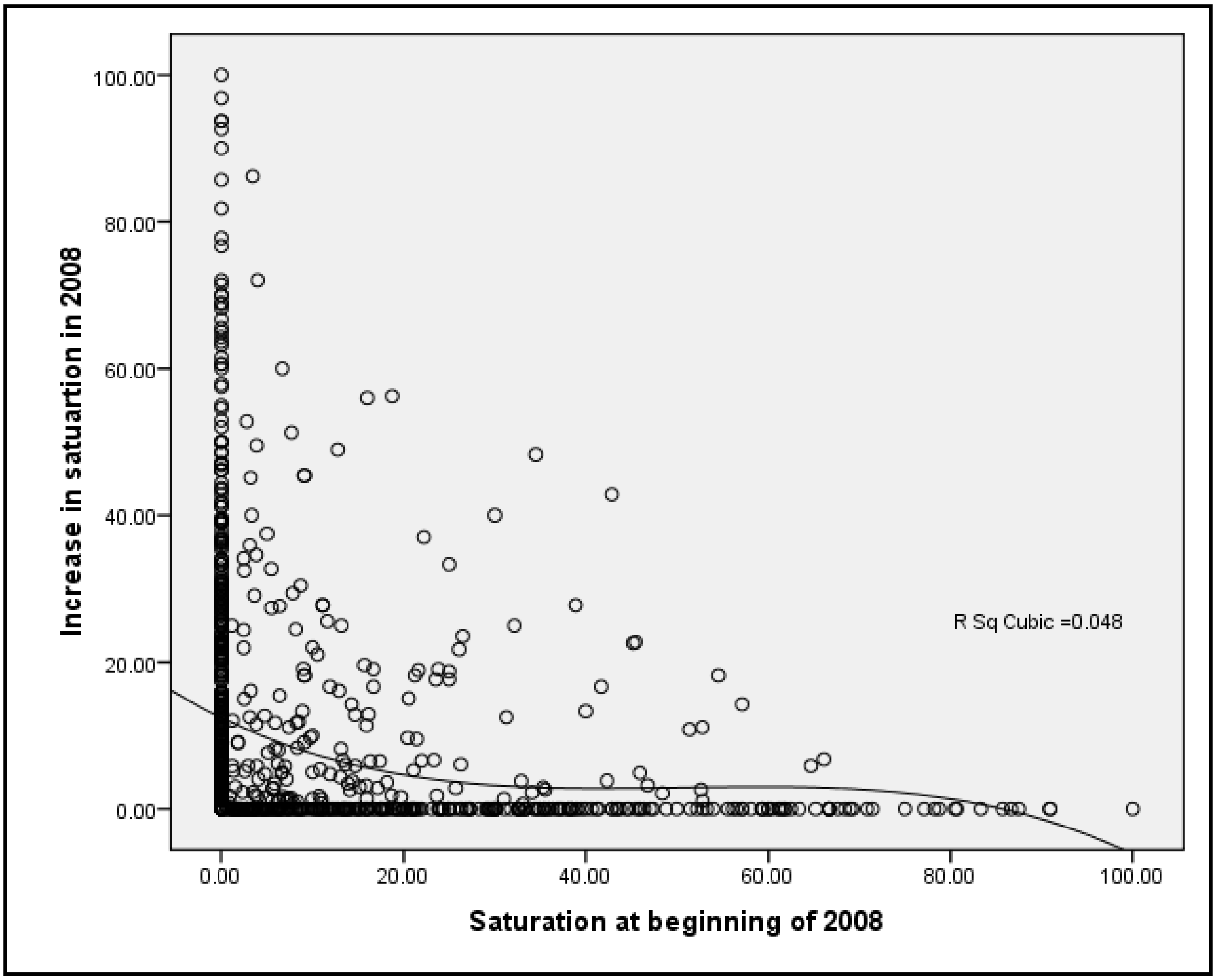
State	Sample Size	Area-wide		
		Current	Beginning of 2008	Increase since Jan. 08
CO	66	18.6	4.0	14.6
CT	95	21.9	11.4	10.5
DC	91	13.4	5.3	8.1
IN	88	17.1	12.0	5.1
MD	57	15.5	7.3	8.2
MA	100	23.4	17.2	6.2
MI	59	18.5	7.0	11.5
NYS	169	18.2	8.8	9.4
NYC	92	22.4	8.5	13.9
OH	78	13.5	3.9	9.6
Houston	90	12.3	3.2	9.1
WI	82	20.9	9.8	11.1

* Not available for the CPUC states.

The scatterplot in Figure 3-9 compares the proxy variable for saturation at the beginning of 2008 with the change in household saturation in 2008. The graph suggests that increases in saturation followed a non-linear function. Increases in saturation were highest in the households that had saturation of zero percent at the beginning of 2008. The increase leveled off for households that had saturation between about 30% and 70% at the beginning of 2008. Not surprisingly, increases in saturation were very rare for households that had 70% or more of their sockets filled with CFLs at the beginning of 2008.

Figure 3-9: Comparison of Saturation at the beginning of 2008 and the Increase in Saturation in 2008 – Onsite*

(n = 1,067, excludes the CPUC states and CO as well as outliers)



* Curvilinear line and explained variance based on a cubic function, not a linear one

3.6 Demographic Variation in Current CFL Use and 2008 Purchase Behavior – Onsite Verified Data

Table 3–7 to Table 3–12 summarize demographic, housing, and other characteristics of respondents by the number of CFLs currently in use or purchased in 2008 as verified in the onsite surveys. These tables contain a great deal of information, so we highlight a few key findings here.[44] In many ways, CFL use and purchases vary in predictable ways. Respondents living in apartments, who rent, and who do not directly pay their electricity bill were less likely to use CFLs when compared to homeowners living in single family homes who paid their electricity bill directly. Similarly, lower-income households, those in which the respondent did not self-identify as white, and in which the primary language spoken was not English were less likely to use CFLs. Finally, households that currently use more CFLs or purchased a greater number in 2008 were also more likely to have used CFLs for a longer period of time.

A few of the findings, however, are less expected. Perhaps the most striking is the small percentage of respondents in *all* categories who reported purchasing CFLs in 2008; in no single demographic group did a majority of respondents purchase CFLs in 2008. In short, participating households are using CFLs, but few actually bought them in 2008. Another unexpected finding is the fact that households in which a female answered *the RDD survey* had fewer CFLs in use and purchased in 2008 *as verified in the onsite survey* than in households in which men answered the survey. We explored potential reasons for this and find women who responded to the RDD survey were more likely than men to be low income or renters or to identify their race as non-white—all correlates of lower CFL awareness, use, and purchases as stated above—suggesting that these factors and not gender drives the result. This same group was slightly more likely to agree to the onsite, perhaps because of the substantial incentives.[45]

Another finding that requires more explanation is that households were less likely to use or buy CFLs in counties that leaned more heavily Democratic in the 2008 election according to the partisan voting index for 2008 (PVI08). This, likely, points to lower CFL use in city centers, which tend to lean strongly Democratic but also to have larger concentrations of the types of households that are least likely to use CFLs. The fact that households in nonmetropolitan counties were more likely to use CFLs and to use them in large numbers provides some evidence to support the latter hypothesis.

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[44] See Appendix C for a similar set of tables for onsite reported CFL use and purchases.
[45] While this may create a slight bias in the onsite sample, such households still made up a small minority of all that took part in the household and actually ensured that we had ample representation of this hard-to-reach population.

Table 3–7: Current CFL Use by Key Housing Characteristics – Onsite Survey

Variable	Sample Size	Number of CFLs				
		Zero	1 to 5	6 to 10	11 to 15	16+
Type of Home						
Single Family Detached	978	18%	26	17	13	26
Single Family Attached	148	21%	26	26	14	13
Apartment 2-4 units	86	34%	32	15	15	4
Apartment 5+ units	179	38%	36	18	4	4
Mobile/Other	48	15%	26	9	30	19
Homeownership						
Own	1080	17%	26	17	14	27
Rent	360	34%	34	18	10	5
Home Size						
Less than 2,000 sqft	759	27%	31	19	11	12
2,000 to 3,999 sqft	582	17%	26	17	13	27
4,000 sqft or more	87	14%	24	14	19	28
Who Pays Electric Bill						
Pays Bill Directly	1082	21%	29	18	12	20
Included in Rent/Fee	71	41%	36	16	7	1

Table 3–8: 2008 CFL Purchases by Key Housing Characteristics – Onsite Survey

		Number of CFLs				
Variable	**Sample Size**	**Zero**	**1 to 5**	**6 to 10**	**11 to 15**	**16+**
Type of Home						
Single Family Detached	780	67%	14	8	6	6
Single Family Attached	127	57%	15	13	7	8
Apartment 2-4 units	77	77%	14	6	2	2
Apartment 5+ units	153	76%	14	8	1	1
Mobile/Other	33	67%	15	3	9	6
Homeownership						
Own	878	65%	15	8	5	7
Rent	293	74%	13	7	4	1
Home Size						
Less than 2,000 sqft	685	71%	14	8	4	3
2,000 to 3,999 sqft	437	63%	15	8	7	7
4,000 sqft or more	45	68%	18	3	5	8
Who Pays Electric Bill						
Pays Bill Directly	1082	67%5	15	8	5	5
Included in Rent/Fee	71	84%	10	3	2	1

Table 3–9: Current CFL Use by Key Demographic Characteristics – Onsite Survey

Variable	Sample Size	Number of CFLs				
		Zero	1 to 5	6 to 10	11 to 15	16+
Primary Language						
English	1,396	23%	29	18	12	19
Another language	44	28%	28	12	22	12
Self-Identified Race						
White	1,064	20%	28	18	13	22
Another race(s)	373	36%	31	15	10	8
Education						
Beyond high school	1,021	19%	27	18	13	22
High school or less	403	30%	31	16	10	13
*Income COL Adjusted**						
Less than $30,000	399	31%	31	18	10	9
$30,000 or higher	828	17%	28	18	13	25
Gender						
Male	657	18%	27	19	12	23
Female	787	27%	29	17	12	16
County Metropolitan Status						
Metropolitan	1,233	24%	29	17	12	18
Non-metropolitan	203	17%	22	18	16	27

* Adjusted for the cost of living

Table 3–10: 2008 CFL Purchases by Key Demographic Characteristics – Onsite Survey

Variable	Sample Size	Number of CFLs				
		Zero	1 to 5	6 to 10	11 to 15	16+
Primary Language						
English	1,150	68%	14	8	5	5
Another language	21	74%	11	7	4	4
Self-Identified Race						
White	860	68%	14	8	5	6
Another race(s)	216	78%	12	7	2	1
Education						
Beyond high school	816	66%	16	7	6	6
High school or less	340	74%	11	9	3	3
*Income COL Adjusted**						
Less than $30,000	346	75%	12	7	4	2
$30,000 or higher	652	65%	16	9	5	6
Gender						
Male	531	66%	16	8	4	6
Female	644	70%	13	7	5	4
County Metropolitan Status						
Metropolitan	165	68%	15	8	5	5
Non-metropolitan	1,010	70%	9	9	5	7

* Adjusted for the cost of living

Table 3–11: Average Values for Key Variables by Number of CFLs Currently in Use – Onsite Survey

	Number of CFS									
	Zero		1 to 5		6 to 10		11 to 15		16+	
Variable	**n**	**Mean**	**n**	**Mean**	**n**	**Mean**	**n**	**Mean**	**n**	**Mean**
Household size	262	2.7	376	2.5	256	2.8	175	3.0	315	3.0
County unemployment rate	278	8.1	390	8.6	259	8.5	186	8.4	323	8.5
Years Using CFLs	278	0.5	393	1.6	262	2.3	187	2.8	324	3.3
Density of Wal-Marts	278	4.0	390	4.3	259	4.5	186	4.0	323	4.9
Density of Other Box Stores	278	2.6	390	2.7	259	2.6	186	2.8	323	3.1
Density of All Box Stores	278	6.6	390	7.0	259	7.1	186	6.7	323	8.0
Partisan Voting Index*	278	-17.7	390	-16.3	259	-14.4	186	-7.5	323	-6.7

* The more negative the score, the more heavily democratic leaning the area

Table 3–12: Average Values for Key Variables by Number of CFLs Purchased in 2008 – Onsite Survey

	Number of CFS									
	Zero		1 to 5		6 to 10		11 to 15		16+	
Variable	**n**	**Mean**	**n**	**Mean**	**n**	**Mean**	**n**	**Mean**	**n**	**Mean**
Household size	760	2.6	174	2.4	98	2.8	58	3.0	68	2.9
County unemployment rate	771	8.9	176	8.7	100	9.2	58	8.6	70	9.0
Years Using CFLs	771	1.6	176	2.5	100	2.5	58	2.6	70	2.8
Density of Wal-Marts	771	3.9	176	3.8	100	4.2	58	3.4	70	4.2
Density of Other Box Stores	771	2.7	176	2.8	100	2.6	58	2.4	70	2.9
Density of All Box Stores	771	6.6	176	6.6	100	6.8	58	5.8	70	7.1
Partisan Voting Index*	771	-16.7	176	-17.7	100	-16.1	58	-14.3	70	-9.7

* The more negative the score, the more heavily democratic leaning the area

4 Model Choice, Development, and Analysis

The evaluation team analyzed the telephone and onsite survey data using a variety of statistical modeling techniques. This section briefly describes the choice of the various procedures and summarizes the development of the models presented in Section 5.

4.1 Exploring Correlates of Being a CFL User or Purchaser

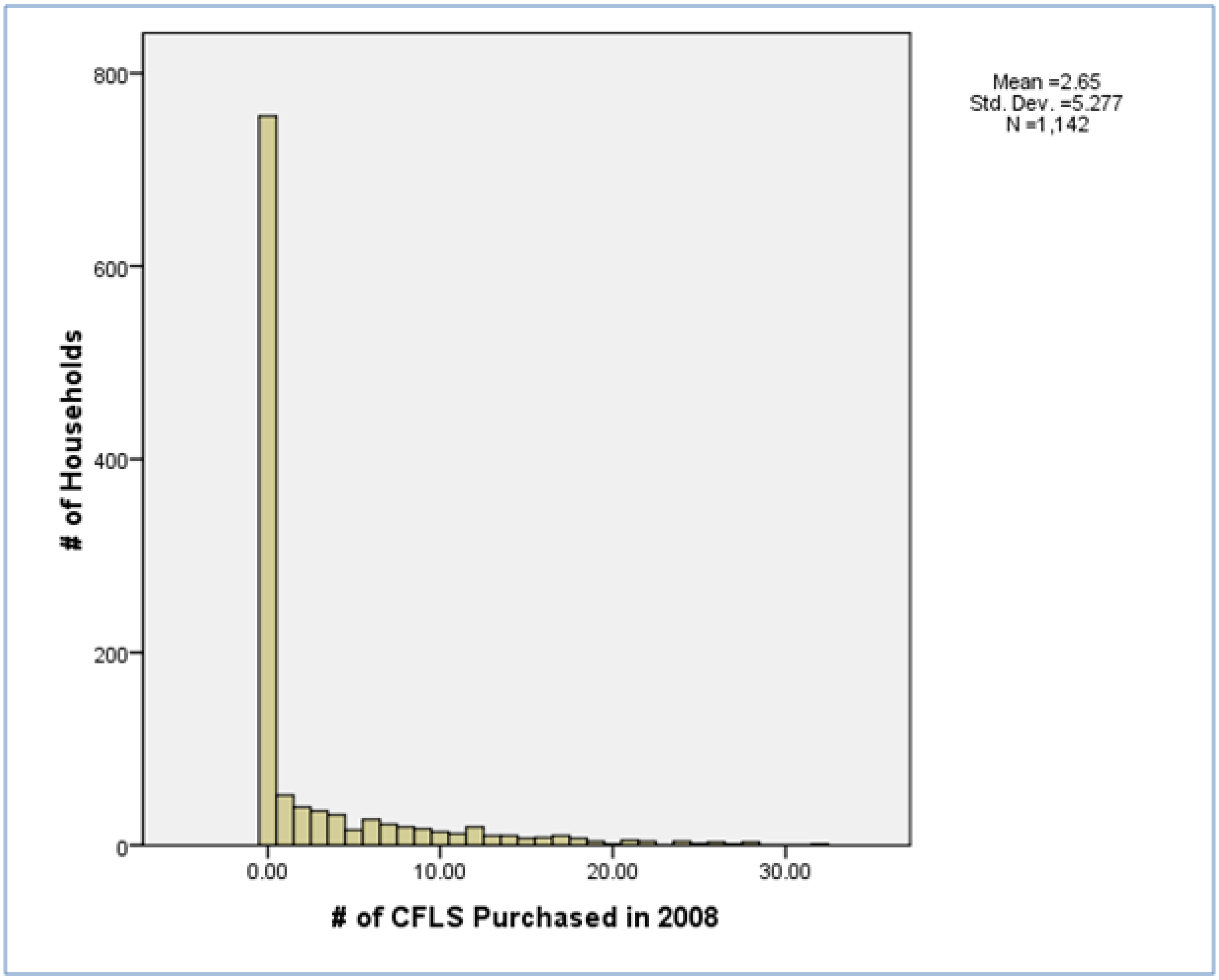
Although the main purpose of the multistate modeling effort was to explain *how many* CFLs households purchase or use as well as their saturation rates, the evaluation team believed it was important to explore the factors that contribute to whether or not a household uses or purchases *any* CFLs. In order to examine these factors, the 2008 purchase and use data were transformed from counts of the number of bulbs into two dichotomous variables—one for buyers and one for users in which the non-buyers and non-users were coded as zero and buyers and users as one. Dichotomous variables were entered into the logistic regression models—which were used to examine dichotomous outcomes—as the dependent variables. While these models cannot be used to estimate NTG, cost effectiveness, or electricity savings, they provide additional insight into what drives CFL use and purchases.

4.2 Modeling CFL Purchases, Use, and Saturation

The team considered using a number of different statistical techniques to identify the net effect of CFL programs and other variables on CFL purchases, use, and saturation. The fact that we have a mixture of categorical and continuous independent variables suggests the use of ANCOVA or a regression model (after transforming the categorical data into dichotomous ones as described above). We rejected ANCOVA and ordinary least squares (OLS) regression as analysis procedures to model counts of CFL purchases and use primarily because of "right skew" in our dependent variables, as shown below for onsite self-reported 2008 CFL purchases (Figure 4-1). In particular, many households tend to have zero or few CFLs installed or have made zero or few recent CFL purchases; rarely do they have numerous CFLs installed. In contrast, ANCOVA and OLS assume a normal or bell-shaped curve in the dependent variable (*i.e.*, CFLs installed or recently purchased or socket saturation), and a common way in OLS to deal with such right skewed data is to take their square or cubic root. Many of our data points, however, are at zero; their square roots and cubic roots are still zero, and therefore, the procedure does not resolve the right skew. The implication is that we cannot use ANCOVA or OLS to model CFL use and purchases. A statistical distribution and related analysis technique that more accurately match the data is the negative binomial regression model (NBRM). The NBRM 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.[46] Note that the NBRM is a non-linear procedure and its interpretation differs from that of OLS models, addressed below in Section 5.

Figure 4-1: Histogram of Onsite Reported CFLs Purchased in 2008



Similar to use and purchase, the data for CFL saturation also suffer from right skew. However, because they represent continuous proportion data, CFL saturation cannot be analyzed using NBRM which applies only to 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 OLS.[47]

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[46] 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.

[47] 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 most appropriate to model market share despite that fact that the variable is a rate and has a heavy right skew. Market

4.3 Model Development and Analysis

The team initially ran models by entering the composite program effect as the sole independent variable to explain CFL use, saturation, and purchases in order to understand the simple statistical relationship between them, and then repeated this effort with the separated cumulative effect and 2008 program variables. The purpose of the modeling effort, however, is to identify the program effect after controlling for other factors that may also influence CFL use and purchases. Therefore, the team proceeded by adding other variables into the equations—including ones that captured respondent demographics, the economic conditions in the state, the concentration of box stores, length of time the respondent has used CFLs, CFL storage, and CFL use prior to the purchase period under consideration. In all models, we drew the demographic data from respondent self-reports in the telephone survey; however, when exploring the relationship between CFL use, saturation, and purchases, we pulled the CFL data from either the telephone or the onsite survey data. The team excluded variables found to be excessively collinear with other variables in the model or that had little statistical effect on CFL use, saturation, and purchases.[48] The models presented in Section 5 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 predictive capability of the model. In short, they represent the best models yielded by the analyses.

The team excluded from all analyses the Colorado respondents identified through retail coupon tracking databases and outliers from the 2008 onsite purchase model, as it was the model used to predict NTG. We removed these outliers because they represent CFL enthusiasts, having far more CFLs in their state than the usual household in the state. Potential outliers were identified using the boxplot approach, but the team only removed those that differed substantially from the respondent with the next lowest reported 2008 purchases in the state.

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 no 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.

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

5 Results and Implications for NTG

The evaluation team ran multiple models using different analysis techniques in an attempt to understand the effects of CFL programs on 2008 CFL purchases, use, and saturation. The results of these models and their implication for the total net impact estimate are explored below. Given what the evaluation team believes to be their greater level of reliability, findings from models drawing on purchase, use, and saturation data collected during the onsite visits were prioritized, although models developed using RDD survey estimates of use and purchases are presented in Appendix D.

Because the models are not typically linear in nature, 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 the log likelihood of the independent variable affecting a change in the dependent variable increase. To convert the coefficient—commonly denoted as 'b'—into a form that is more user-friendly requires two steps. The first is to exponentiate the 'b' by raising the natural log to the 'b' power (commonly seen as $e^{\wedge b}$ or e^b), giving a value known as the factor change for the dependent variable. The factor change still is not directly applicable to predicting the dependent variable, so one takes the second step in making the coefficient easier to interpret by subtracting one from the factor; this yields what has been termed the 'impact score'. The impact score can be interpreted multiplicatively—each increase (or decrease) in the independent variable program brings about an increase (or decrease) in the dependent variable by the amount of the impact score.

5.1 Logistic Models Exploring CFL Use and Purchase vs. Non-Use and Non-Purchase

To explore the differences between who did and who did not purchase CFLs in 2008, a dummy variable was created, with 2008 CFL purchasers scored with a one, and non-purchasers scored with a zero. Three different logistic regression models were run to explain the likelihood of being a CFL purchase in 2008: one for all respondents (full set)[49], the second for respondents that used at least one CFL at the beginning of 2008 (users), and the last for respondents who did not use CFLs prior to 2008 (non-users) (Table 5–1). The composite program variable was *not* a significant predictor of use when looking at all respondents. It was a significant predictor of use in both the users and non users' models, but the direction of the relationship differed between the models. Among prior users, the composite program score was *negatively* related to the likelihood of a person purchasing CFLs, while among non-users

[49] The respondents in the Full Set models were further restricted by their responses to the questions dealing with the predictor variables. If the respondent refused to answer a question or said that the question was not applicable to their situation they were given no score for their response and therefore can not be measured and were not included in the model.

the presence of a program *increased* the likelihood of a respondent being a purchaser. In short, program activity had little impact on the purchase behavior of prior users, *but programs were still getting non-users to try CFLs*. Likewise, saturation at the beginning of 2008 was negatively related to the likelihood of purchasing CFLs in 2008, likely because households with higher levels of saturation had fewer sockets left to fill with CFLs in 2008. The only factors positively related to CFL purchases in the prior users model were the concentration of Wal-Mart stores at the state level and having a college degree or higher level of education.

Table 5–1: Likelihood of Being a 2008 CFL Purchaser by Prior CFL Use

	Full Set		**Users**		**Non-users**	
	Coef.	Impact	Coef.	Impact	Coef.	Impact
Composite Program	n/a	n/a	-0.222	-0.199	0.257	0.293
2008 County Partisan Voting Index	-0.007	-0.006	-0.022	-0.022	0.010	0.010
Concentration of Wal-Mart, state	0.102	0.108	0.184	0.202	n/a	n/a
County Unemployment Rate	n/a	n/a	-0.117	-0.110	0.078	0.081
Self reported as White	0.448	0.565	n/a	n/a	0.643	0.902
Years using CFLs	0.091	0.095	n/a	n/a	n/a	n/a
Utility Bill Paid Directly	0.684	0.983	n/a	n/a	n/a	n/a
College Degree or Higher	n/a	n/a	0.666	0.946	n/a	n/a
2008 CFL Saturation	n/a	n/a	-0.026	-0.025	n/a	n/a
Female Respondent	n/a	n/a	n/a	n/a	-0.459	-0.368
Constant	-2.385	n/a	-0.320	n/a	-1.601	n/a
Sample size	1,078		472		513	
R^2	3%		14%		11%	

The evaluation team next explored what drives CFL saturation by creating a dichotomous variable for 2008 saturation and one for current saturation. In both, respondents having saturation greater than zero were coded as one, and those with saturation of zero were coded as zero. Three models of the likelihood of having some CFL saturation using logistic regression were developed—the first for 2008 saturation (which is not available for the CPUC states), the second for current saturation excluding the CPUC states for comparability to the 2008 saturation model, and the third for current saturation including the CPUC states (Table 5-2). Three variables—the composite program variable, length of CFL use, and the county unemployment rate—consistently predicted the likelihood that a respondent had CFL saturation above zero. However, the direction of the unemployment rate varied across models suggesting that living in an area with high unemployment was associated with lower levels of saturation, but, currently, households in areas with high unemployment rates had higher saturation. The only other variable to show up in more than one model was homeownership, which had a positive effect on the likelihood of having saturation above zero in the models that excluded the CPUC states but not in the model that included the CPUC states.

Table 5–2:Likelihood of having Saturation Greater than Zero: 2008 and Current

	2008 Saturation		Current Saturation, no CPUC states		Current Saturation, includes CPUC States	
	Coef.	Impact	Coef.	Impact	Coef.	Impact
Composite Program	0.09	0.10	0.18	0.20	0.17	0.19
Years using CFLs	0.18	0.20	0.60	0.83	0.62	0.86
Homeownership	0.54	0.72	0.48	0.61	n/a	n/a
Self reported as White	0.32	0.38	n/a	n/a	n/a	n/a
County Unemployment Rate	-0.12	-0.11	0.13	0.14	0.13	0.14
Metropolitan County	-0.52	-0.41	n/a	n/a	n/a	n/a
Female Respondent	n/a	n/a	n/a	n/a	-0.27	-0.24
Concentration of Box Stores	n/a	n/a	n/a	n/a	0.03	0.03
Total Sockets in Home	n/a	n/a	n/a	n/a	0.01	0.01
Home Size	n/a	n/a	0.40	0.49	n/a	n/a
Constant	0.91	n/a	-1.34	n/a	-1.09	n/a
Sample size	1,314		1,151		1,411	
Pseudo R^2	9%		17%		18%	

There are two major conclusions to be drawn from the logistic models. First, different factors drove new CFL users and prior CFL users to purchase CFLs in 2008. Second, the factors that explain CFL saturation changed from the beginning of 2008 through the "current" time period associated with data collection in each area. Both of these findings support the hypothesis that the CFL market is changing. A wider variety of households in a greater diversity of places are using CFLs. Programs that support CFLs are bringing in new users and still boost CFL saturation, but other factors also go far in explaining why people purchase and use CFLs. The next two sections explore in more detail what drives the number of CFLs people purchase and use and the level of their CFL saturation.

5.2 Bivariate Model Results

Table 5–3 summarizes the *bivariate* models in which we explored the relationship between the composite program variable and current saturation, current use,, CFL purchases in 2008 and the past three months . We also examined these same relationships with the disaggregated program components, but the results were very similar to those for the composite variable so we only show its effects here. The data in Table 5–3 show a positive relationship between current onsite saturation and the composite program using OLS. The relationship suggests that current saturation increases 1.30% for every increase in the program score for a state. The remaining models rely on NBRM. These models find a small but significant relationship between current CFL use and the composite program variable. Furthermore, there is no significant bivariate program effect on onsite verified purchases in the past three months.

Table 5–3: Bivariate Composite Program Effect Models

Dependent Variable	Sample Size	Data Source	Coef.	90% Confidence Interval		Impact Score
				Low	High	
Current Saturation	1,374	Onsite	1.30	0.75	1.85	*
Purchase 2008	1,073	Onsite	0.08	0.04	0.13	0.09
Purchase Past 3 Mos.	1,336	Onsite	Program effect was not statistically significant			
Current Use	1,374	Onsite	0.05	0.03	0.07	0.05

*Ordinary least squares regression was used to model program effect, so the impact on purchases is captured by the regression coefficient.

5.3 Advanced Model Results for Program Impact on Number of CFLs in Use and Purchased and on CFL Saturation

The team also ran more advanced models that incorporated other independent variables (Table 5–4 through Table 5–8**Error! Reference source not found.**).[50] [51] After controlling for these other variables, the composite program variable had significant and positive effects on 2008 purchases (derived from either onsite or RDD data), current saturation, and current use. The approaches failed to find a statistically significant program effect on purchases in the past three months, most likely reflecting the fact that the "three months" under question differed across states and very few people in any state actually reporting purchasing CFLs during the time period.

[50] As with the bivariate models, we also tested the models below with the disaggregated program components (*i.e.,* rating of prior program strength and 2008 program activity), and the results were very similar. Therefore, we only present the results for the composite program in this section.
[51] The team also ran advanced models on RDD data and have included those models in Appendix D.

More specifically, Table 5–4 and Table 5–5 present the 2008 purchase model from which the team derives the NTG estimate presented in Section 5.4. The model in Table 5–4 demonstrates that the program activity has a positive impact on 2008 CFL purchases, as does the number of years the respondent reported using CFLs and number of sockets in the home. In addition to these CFL related variables, a household's purchases of CFLs increases with each additional person living in the home and when the respondent identified as white. The dummy variable created to capture responding in the fall also had a positive effect on CFL purchases in 2008 indicating that those answering the survey at the very end of 2008 or beginning of 2009 provided higher estimates of 2008 purchases than those responding in the late Spring and early Summer of 2009.[52]

The purchase model presented in Table 5–4 is identical to the purchase model that was presented in the November 2009 draft of this report with the exception of the composite program variable. The evaluation team received updated data about one Sponsor's lighting program after the models in the November draft had been finalized. The team had to recalibrate the program variable accordingly. This recalibration changed the model coefficients and resulting impact scores, but not the variables in the model

Table 5–4: Best Fit 2008 Purchase Model – Onsite*

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Composite Program	0.11	0.06	0.16	0.11
Years using CFL	0.10	0.06	0.14	0.10
Number of Sockets in Home	0.01	0.00	0.01	0.01
Number of Persons in Household	0.10	0.02	0.18	0.10
Self reported as White	0.42	0.09	0.74	0.52
Conducted During Fall Season	0.60	0.33	0.86	0.82
Constant	-0.79	-1.21	-0.38	n/a

* Sample size = 1,034 and pseudo R^2 = 1%.

The model presented in Table 5–4 was the closest predictor of observed 2008 purchases among the various models the team considered. However, give the data presented in Section 3.5 that pointed to a likely connection between 2008 purchases and prior saturation, an alternative 2008 purchase model that includes saturation was developed in order to demonstrate the importance of saturation on 2008 CFL purchases (Table 5–5). The composite program score, years using CFLs, race of the respondent and number of sockets in the home were common predictors for the 2008 purchase models presented in Table 5–4 and Table 5–5. As the data in Section 3.5 suggested, saturation had a significant *negative* effect on 2008 CFL purchases, indicating that he higher a household's CFL saturation rate at the beginning of 2008 the less likely it was to purchase CFLs during 2008.

[52] The "fall" indicator variable in this model applied to the five areas surveyed by NYSERDA.

Table 5–5: 2008 Purchase Model with Saturation* – Onsite

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Composite Program	0.06	0.01	0.11	0.07
Years using CFL	0.13	0.08	0.18	0.14
CFL Saturation at beginning of 2008	-0.03	-0.04	-0.02	-0.03
Self reported as White	0.43	0.04	0.81	0.53
Number of Sockets in Home	0.01	0.00	0.01	0.01
2008 County Partisan Voting Index	-0.01	-0.01	0.00	-0.01
Constant	-0.17	-0.53	0.20	n/a

* Sample size = 950 and pseudo R^2 = 1%.

The three-month purchase model failed to find a statistically significant relationship with program activity, most likely due to the differences in survey timing and the very small number of people who purchased CFLs in the three months under question (Table 5–6). Significant positive predictors of three month purchases instead included years using CFLs (removing this variable does not make the program activity variable become significant), whether the respondent was a homeowner and the unemployment rate in the county of residence. From a methodological standpoint, the evaluation team believes that people were more likely to provide accurate self-reports of their three month purchases than when asked about a full year; but this study also suggests that too few households actually purchased in the time period to draw meaningful evaluation conclusions about purchases in the past three months.

Table 5–6: Best Fit Three Month Purchase Model – Onsite*

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Years using CFL	0.12	0.05	0.18	0.13
Homeowner	0.63	0.15	1.10	0.87
Unemployment	-0.08	-0.14	-0.03	-0.08
Constant	-0.06	-0.74	0.61	n/a

* Sample size=1,394 and Pseudo R^2 = 1%.

As in the 2008 purchase models (Table 5–4 and Table 5–5), there was a positive relationship between CFL program as well as length of CFL use on saturation (Table 5–7). Moreover, two additional variables entered the saturation model: the change in the county unemployment rate in 2008 and whether the household paid its electricity bill directly. The change in the county unemployment rate was positively associated with saturation, indicating that persons living in counties whose unemployment rates increased the most also had higher rates of CFL saturation. Likewise, households that paid their electricity bills had higher rates of saturation.

Table 5–7: Best Fit Current Saturation Model – Onsite*

Variables	Coefficient**	90% Confidence Interval	
		Low	High
Composite Program	1.80	1.28	2.31
Years Using CFL	1.22	0.80	1.63
Pay Electricity Bill Directly	10.04	7.43	12.65
Change in County Unemployment Rate	5.15	3.68	6.63

* Sample size = 1,094. Because the intercept was set to zero, it is not appropriate to use the explained variance (R^2).

** 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%, we set the intercept equal to zero. CPUC respondents were not asked who pays their electricity bill, so they are excluded from the model.

The best fit onsite current use model is shown below in Table 5–8. Composite program score, years using CFLs, and the *current* saturation rate (*i.e.* at the time of the onsite survey) had a positive significant effect on the number of CFLs being used in the home. A number of other demographic and contextual variables are also present in the model, namely positive relationships between CFL use being a homeowner, self-identification as white, speaking English as the primary language, and the square feet of Wal-Mart stores in the state. The model found a negative relationship between CFL use and having no more than a high school diploma suggesting that those with more than a high school diploma used CFLs in greater numbers.

Table 5–8: Best Fit Current Use Model – Onsite*

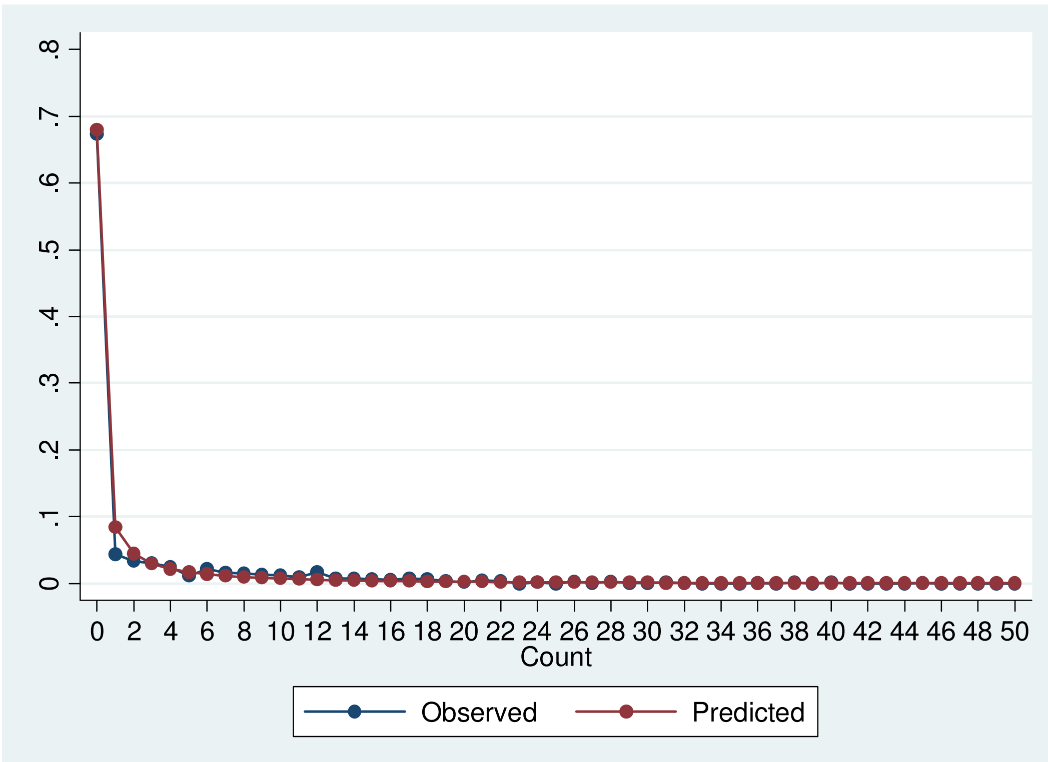
Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Composite Program	0.02	0.01	0.04	0.02
Years Using CFLs	0.04	0.03	0.06	0.04
CFL Saturation in the Homer	0.04	0.04	0.05	0.04
Homeowner	0.76	0.64	0.88	1.14
Home Size	0.32	0.25	0.39	0.38
Self reported as White	0.29	0.18	0.41	0.34
English is Primary Language	0.38	0.17	0.59	0.47
Sqft Wal-Mart per Household (state)	0.07	0.04	0.10	0.07
High School Degree or Less	-0.19	-0.29	-0.10	-0.18
Constant	-1.01	-1.28	-0.74	n/a

* Sample size = 1,315; Pseudo R^2 = 16%.

One statistical note of importance: the estimates of fit for all the models are low. The explained variance (R^2) is typically used to determine how well an OLS model fits the data, while the likelihood ratio index (Pseudo or McFadden's R^2) addresses the likelihood of a NBRM. The explained variance and likelihood ratios for our models are small. Although it is usual for likelihood ratios to be smaller than explained variances, the ratios reported here are small enough to suggest that other factors not captured in our models also drive CFL purchases and use. We suspect that CFL price and availability may be among the missing variables based on preliminary evaluation findings from in-store surveys being conducted for the CPUC that are not yet publicly available. Apart from the CPUC, the Sponsors in all areas decided against store surveys because their budgets and schedules did not allow for this activity; therefore, CFL price data are not available for all areas in the study. Given that the CPUC findings suggest that CFL prices vary a great deal, we do not believe it would be accurate to apply price data from the four CPUC states to all areas in the analysis. There is no guarantee that the inclusion of variables for CFL price or availability (should we be able to arrive at a consistent and defensible measure of them) would increase the explained variances or likelihood ratios a great deal. Other unknown and currently not identified variables may be driving CFL sales, and without them, the models would still not be close fits to the data.

Despite the low likelihood ratios, the Figure 5-1 displays the observed vs. predicted probabilities for the 2008 purchase model, and demonstrates that the predicted probabilities are very close to the observed ones. Therefore, the models may not have high actual or pseudo R^2 but they appear to be good predictors of actual purchases.

Figure 5-1: Observed vs. Predicted Probabilities for Composite Program Variable 2008 Purchase Model – Onsite



Furthermore, the team recognizes that prior program activity may, in fact, have boosted the number of households that have used CFLs for a longer period of time, however, it is also the case that some households in non-program areas have also used CFLs for a long time, requiring tests for the *independent effect* of this variable apart from program activity, to the extent that appropriate statistical techniques allow. The 2008 purchase models—and all other models in this report—pass appropriate tests for multi-collinearity as determined through the tolerance statistic and variance inflation factor. For those still concerned about the potential that the length of CFL use, storage, or saturation take explanatory power away from the program variable sensitivity analyses (i.e. running models with and without the variables to show the impact on the results) were conducted and are presented in Appendix D.

5.4 Calculation of NTG for Connecticut

The evaluation team presents a total of four possible NTG figures for CT—two based on observed 2008 purchase data from the models first presented in Table 5–4 and Table 5–5, and two based on the predicted 2008 purchase values estimated from those models. We developed multiple NTG estimates for two reasons. First, the team created NTG estimates using both 2008 purchase models presented in Section 5.3. As will be seen, the model in Table 5–4 displays closer agreement between predicted and observed values of purchases in 2008, but the data in Section 3.5 and Table 5–5 also show the importance of household CFL saturation on CFL purchases.[53] Second, the evaluation team members also decided to develop NTG estimates based solely on data predicted by the model for reasons of statistical consistency. As we will see, each of the four methods has strengths and weaknesses that we discuss more fully after presenting the NTG estimates.

To calculate NTG, the team multiplied the impact score estimate for each *non-program* independent variable across the onsite respondents in the sample. For the *program variable,* we multiplied the impact on purchases by the actual score for the composite program variable for CT (4.09); we next repeated this step setting the composite program score equal to that for non-program areas (-3.15), creating a hypothetical CT in the absence of a program. This latter calculation was used to develop an estimate of NTG. Table 5–9 provides an example of these calculations for one respondent in CT. For this individual, the predicted number of CFL purchases was 2.59, but would have been 1.79 in the absence of the program. The team could not predict purchases for the few people who responded “don’t know” to or refused to answer questions included as variables in the model, which we take into account when calculating NTG.

[53] The team ran many different models with multiple specifications in an attempt to produce a model that includes saturation and also that more accurately predicted observed purchases, and the model presented represents the best one of all of those considered.

Table 5–9: Predicted Purchases for One Connecticut Respondent Based on the 2008 Purchase Composite Program Variable Model – Onsite

Characteristic	Impact Score	Respondent Data	Contribution to Predicted Purchases	
			Program Scenario	No Program Scenario
Composite Program	0.11	4.09 with program -3.15 w/o program	0.45	-0.35
Years using CFL	0.10	10	1.00	1.00
Number of Sockets in Home	0.01	42	0.42	0.42
Number of Persons in Household	0.10	2	0.20	0.20
Self reported as White	0.52	1	0.52	0.52
Conducted During Fall Season	0.82	0	0.00	0.00
Total Purchase			2.59	1.79

To develop the actual NTG estimates, we counted the number of CFLs purchased in 2008 as reported by CT households in the onsite for each of the two 2008 purchase models (Row A, Table 5–10) and calculated the average number purchased across households (Row E). We next summed the predicted purchases under both the with program (Row B) and without program (Row C) scenarios across all onsite participants, again calculating the average predicted purchase per household for each scenario (Row F and Row G). These calculations *predict* that each CT household purchased an average 1.79 in the program scenario for the model without saturation and 1.22 for the model with saturation. The observed value, in contrast, was 2.68 CFLs purchased in 2008. The predicted non-program scenario in the model without saturation suggests that 0.97 CFLs would have been purchased in the absence of the program, while the with saturation model puts that number at just 0.75. Subtracting the without-program estimates from the observed purchase data yields estimate of net observed program purchases listed in Row I, while doing the same with the predicted program scenario yields an alternative estimate of net predicted program purchases (Row K). Dividing the net program purchase estimates by the incented CFLs per household (Row H), yields NTG estimates in Row J based on observed data and Row L based on predicted data. The estimates range from a low of 0.22 (based on predicted data from the with saturation model) to 0.91 (based on observed data applied to the with saturation model). Although the team cannot develop confidence intervals around the NTG estimates based solely on predicted values, the intervals around the NTG estimates are somewhat large. The width of the confidence intervals reflects, first and foremost, the variation in reported 2008 purchases across households. Unlike many other approaches in which the error related to reliability and validity is often unknown and difficult to quantify, our approach shows wide variation because the error is quantifiable and embedded within our confidence interval. Furthermore, the confidence interval approach assumes a normal distribution, and the purchase data are right-skewed. This inflates the variance in the data, and leads to a wide confidence interval. The team tried alternative approaches to calculating a confidence interval for the NTG, but each of them yielded similarly wide intervals.

While the evaluation team is not yet at liberty to share the NTG estimates developed specifically for the other Sponsors of this study, it is worth noting that CT fell in the middle of the NTG estimates developed using observed data and towards the low end of the group for estimates developed using predicted data. Table 5–11 compares the CT NTG estimates to the range developed for all areas included in the study.

Table 5–10. Calculation of NTG

Input	Estimate 2008 Purchase Model without Saturation	90% Confidence Level		Estimate 2008 Purchase Model with Saturation	90% Confidence Level	
		Low Estimate	High Estimate		Low Estimate	High Estimate
A. Observed purchases	247			247		
B. Predicted purchases with program	165			112		
C. Predicted purchases without program	89			69		
D. Onsite sample size	92			92		
E. Per-household purchases with program observed	2.68			2.68		
F. Per-household purchases with program predicted	1.79			1.22		
G. Per-household purchases without program	0.97			0.75		
H. Incented CFLs per household	2.12	2.12	2.12	2.12	2.12	2.12
I. Net program purchases per household observed*	1.71	0.66	2.76	1.93	0.88	2.98
J. Total NTG observed**	0.81	0.31	1.30	0.91	0.42	1.41
K. Net program purchases per household predicted	0.82	n/a	n/a	0.47	n/a	n/a
L. Total NTG predicted***	0.39	n/a	n/a	0.22	n/a	n/a

* Calculated according to procedure for confidence intervals of the difference between two means

** The wide interval reflects the fact that confidence interval development is based on assumptions of normality, but the data are strongly right skewed, and, therefore, display high levels of variability.

*** Development of a confidence interval is not possible for this approach because the difference between the with and without program scenarios is constant, so the NTG does not vary.

Table 5–11: Range of NTG Estimates Calculated for All Areas Included in Study

	Without Saturation		With Saturation	
	Observed	Predicted`	Observed	Predicted
Connecticut NTG estimate	0.81	0.39	0.91	0.22
Minimum NTG estimated for any area	0.19	0.25	0.54	0.22
Maximum NTG estimated for any area	5.47	1.68	9.12	0.98

The presentation of the four different NTG estimates raises the question—which should be used to estimate the impact of the program in 2008 and to plan for future programs? The evaluation team believes that all the estimation techniques have strengths and weaknesses. The strength of the 2008 purchase model without saturation is that the predicted values fall closer to observed values across all areas in the study than do those developed using the model with saturation (Table 5–12). The strength of the 2008 purchase model with saturation is that it may provide the better description of what actually drives CFL sales, as the data in Section 3.5 suggest a connection between CFL saturation and purchases that the model without saturation fails to capture. The NTG estimates based solely on predicted values have the advantage of keeping the calculations within the same statistical basket—the model—but, the predicted values in both models nearly always fell short of the observed values gathered by trained technicians meaning that net program purchases could be underestimated using predicted values. The strength of the observed values is that they were the data collected directly from respondents, and these numbers serve as the basis for the models and, therefore, inform the predicted values. Their weakness is self-report error, and the possibility that the estimates given for 2008 purchases are not indicative of actual behavior.

Table 5–12: Difference between Observed and Predicted Estimates of 2008 CFL Purchases

	Without Saturation	With Saturation
Difference observed – predicted for Connecticut	0.89	1.46
Minimum difference observed – predicted	-0.01	0.20
Maximum difference observed – predicted	1.21	2.41
Average difference observed - predicted	0.50	1.15

Given their strengths and weaknesses, these four estimates could be seen as the range of potential NTG resulting from the 2008 program. It is the opinion of the evaluation team that the NTG estimate developed from observed data using the 2008 purchase model without saturation is the best estimate—this value is 0.81. We base this opinion on the fact that the model demonstrates the closest correspondence between predicted and observed values for all of the areas included in the analysis. We believe there are also arguments to be made for instead using the model with saturation or predicted values, but, in our opinion, the strength of the observed data and the predictive capability of the model outweigh the strengths of the other approaches.

6 Conclusions and Recommendations

The multistate CFL modeling effort represents a groundbreaking attempt by numerous program sponsors to pool their resources in an effort to explain what drives CFL purchases, use, and saturation in the rapidly changing CFL market. To the end, the results presented in this report have demonstrated the following:

- CFL programs are still having a positive effect on CFL purchases and leading to positive NTG ratios. In some areas those ratios are rather small, but in others they point to continued substantial program effects.
- As the logistic regression results make clear, the factors that drive existing CFL users to purchase new CFLs differ from those that drive CFL purchases among those who never used a CFL before. Importantly, CFL program activity remains an important driver of CFL purchases among new users, but appears to be less important than demographic and contextual factors in boosting purchases among existing CFL users.
- Another key finding from the logistic regression models is that the profile of households with higher CFL saturation switched from the beginning of 2008 to the time of the onsite studies. This points to a shift in the households and counties that added large numbers of CFLs to their homes in 2008.

One of the most consistent predictors of CFL use, purchases, and saturation throughout the models is the length of CFL use. Households that have used CFLs for a long time continue to buy and use them and to install them in a greater percentage of sockets. Yet new households start to use CFLs, and the findings suggest that most will continue using them. This points to the importance of converting non-users to users, which appears to be a key accomplishment of the CFL programs taking part in this study.

The estimated NTG for Connecticut for 2008 is approximately 0.81 and ranges from 0.31 to 1.30 at the 90% confidence interval. It is important to note that this NTG applies to the *2008 program* that preceded recent changes in the CT CFL program that have de-emphasized general service CFLs and increased support for specialty CFLs..

The data we present here provide evidence that the CT Sponsors should continue their efforts to redesign the CFL programs. Strategies for doing so may include both (1) targeting efforts to promote spiral CFLs on the types of people who do not currently use CFLs at all or in large numbers and (2) focusing a greater portion of incentives on specialty bulbs. The program could attempt to increase the availability of both specialty and spiral CFLs in venues and retail channels where CFLs are sold in only limited quantities or at which non-users typically shop. The data we present here provide evidence that the CT Sponsors should continue their efforts to redesign the CFL programs. Finally, the program could further educate consumers on the benefits of using general service (spiral) and specialty CFLs in the applications where CFLs are still not frequently used even in the homes of committed CFL users.

The final conclusion of the modeling effort may, in fact, be the most important: The methods used to date to estimate NTG for upstream CFL programs have all suffered from reliability and validity concerns. Respondent self-report error and bias related to who responds to RDD and onsite surveys leads to imprecise estimates of NTG, although these methods can have the advantage of controlling for household level drivers of CFL purchases when comparison state approaches are not possible. Methods that turn to CFL shipments find that the location to which the products are shipped does not translate neatly to where they are sold, affecting the accuracy of NTG estimates. Existing studies that rely on sales data often fail to capture the actual CFL market because they are sometimes unable to gather accurate or representative sales data; states that have successfully used this approach in the past now face the challenges of finding a comparison state or otherwise controlling for the demographic factors that affect CFL purchases. While this study has quantified those concerns as evidenced through four quite different estimates of NTG and wide confidence intervals around those relying observed onsite data, more often the impact of reliability and validity is unknown or difficult to quantify.

The evaluation team believes that having wider access to representative sales data will be a key component of determining the impact of CFL programs in the face of the changing CFL market. Paired with data that allow for the ability to control for the household and state-level demographic, economic, and social factors that also affect CFL purchases, sales data could allow for more accurate and precise NTG estimates if those data accurately represent the entire CFL market. The CFL program community, however, has largely been unsuccessful in gaining access to these data particularly from non-program retailers; some Sponsors even have trouble gather such information from participating retailers and manufacturers. Given this situation, the team presents the final recommendation: If CFL program sponsors remain committed to calculating NTG for CFLs (also LEDs and other small, relatively inexpensive products), they must work together with retailers and manufacturers to find acceptable ways of sharing sales data that do not threaten retailer and manufacturer competition but that still allow programs to assess in the most accurate way possible what their impact has been on the CFL market. Without such data, any estimate of the net impact of CFL programs will suffer from reliability and validity concerns to varying and sometimes unquantifiable degrees.

Appendix A: Sample Design, Sampling Error, and Weighting Schemes

In most cases, the development of the weighting scheme to correct for underrepresentation of renters and those with less than a high school diploma was straightforward: the team downloaded data from the 2005 to 2007 *American Community Survey* on homeownership by educational attainment for the households in each state, county, or city included in the study. When developing estimates for areas not already summarized in the Census, the team had alter the approach slightly. We discuss our method for each below.

California: To limit the weighting scheme to the areas served by the IOUs, the team compared a map of the IOU service territories to that of the counties of CA. We then downloaded the Census data for the entire state and subtracted out the following areas because most or all of the area appeared to be outside of the IOU service territory: Del Norte, Imperial, Lassen, Riverside, Sacramento, Stanislaus, and the City of Los Angeles. Note that some smaller counties served by other utilities remain in the state total because they were too small to have their own ACS estimates of households by homeownership and education at the time we collected the data.

Colorado: The surveys were fielded only in the Xcel Energy service territory. To isolate a weighting scheme for this area, we extracted ACS data for the entire state and then subtracted out the counties in which active residential electric accounts for Xcel Energy comprised fewer than 10% of the households listed for the county. Note that some smaller counties served by other utilities remain in the state total because they were too small to have their own ACS estimates of households by homeownership and education at the time we collected the data. We balanced this tendency by keeping in those counties with as few as 10% of their households served by Xcel. . The estimate of 1.2 million households is very close to the 1.1 million customers served by Xcel in Colorado in early January 2009.

Michigan: The surveys were fielded only in the CE service territory but the CE service territory overlaps heavily with those of other electric utilities and cooperatives. Furthermore, even within the CE service territory, some customers can chose to purchase electricity from a different utility. This made it difficult to isolate the CE service territory using common US Census Bureau geographies such as zip codes and counties. In the end, to keep consistency with other states the team used the county. Specifically, ACS data was extracted for the entire state and then subtracted out the counties in which active residential electric accounts for CE comprised fewer than 25% of the households listed for the county. Most excluded counties were located in the Upper Peninsula, the southern part of the state, and the area around Detroit.

New York State: To estimate NYS, we extracted data on the entire state and subtracted out similar information for NYC and Nassau and Suffolk Counties. Note that Westchester County—often included with NYC because of the shared Con Edison service territory—is included with the remainder of NYS for this analysis. The implication is that the weighting scheme is based on counties that collectively have over 2.2 million households, although CE only serves 1.3 million households. Yet, the area covered by the weighting scheme and served by CE should be similar given the proximity of service area boundaries.

Ohio: In order to exclude the Duke Energy service territory in Ohio (which had a CFL program) we excluded the four counties largely located in the 513/283 area code: Butler, Clermont, Hamilton, and Warren.

Table A–1 on the next three pages displays the sample design, sampling error (based on absolute precision with 50/50 break in responses), and weighting scheme for each state. However, we stress that the sample design was applied *after* conducting the surveys to account for underrepresentation in of renters and those with less than a high school diploma.

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

Area	Owner/Renter	High Level Education	Population	Sample Size	Sampling Error	Weight
CA	Owner	LT High School	664,485	35	14%	1.3
	Owner	High School	1,040,714	76	9%	1.0
	Owner	Some College	1,760,827	110	8%	1.1
	Owner	College or higher	2,222,234	280	5%	0.6
	Renter	LT High School	786,110	21	18%	2.7
	Renter	High School	869,115	32	15%	1.9
	Renter	Some College	1,183,320	49	12%	1.7
	Renter	College or higher	977,377	72	10%	1.0
	Area Total		9,504,182	675	**11%**	
CO	Owner	LT High School	65,569	11	26%	2.9
	Owner	High School	164,741	119	8%	0.7
	Owner	Some College	222,286	127	7%	0.9
	Owner	College or higher	321,354	284	5%	0.6
	Renter	LT High School	64,678	2	82%	16.0
	Renter	High School	103,726	16	21%	3.2
	Renter	Some College	123,223	7	34%	8.7
	Renter	College or higher	100,336	10	27%	5.0
	Area Total		1,165,913	576	**26%**	
CT	Owner	LT High School	70,385	13	24%	1.9
	Owner	High School	232,152	75	10%	1.1
	Owner	Some College	233,643	71	10%	1.2
	Owner	College or higher	386,777	247	5%	0.6
	Renter	LT High School	79,051	9	29%	3.1
	Renter	High School	132,256	17	21%	2.8
	Renter	Some College	97,005	22	18%	1.6
	Renter	College or higher	92,162	18	20%	1.8
	Area Total		1,323,431	472	**15%**	
DC	Owner	LT High School	8,693	9	29%	1.9
	Owner	High School	13,606	35	14%	0.7

Area	Owner/Renter	High Level Education	Population	Sample Size	Sampling Error	Weight
	Owner	Some College	18,401	55	11%	0.6
	Owner	College or higher	69,534	188	6%	0.7
	Renter	LT High School	25728	26	16%	1.9
	Renter	High School	33393	47	12%	1.4
	Renter	Some College	26067	52	12%	1.0
	Renter	College or higher	54383	68	10%	1.5
	Area Total		249,805		**12%**	
GA	Owner	LT High School	299,850	27	16%	1.8
	Owner	High School	612,508	108	8%	0.9
	Owner	Some College	608,806	112	8%	0.9
	Owner	College or higher	764,720	224	6%	0.6
	Renter	LT High School	240,407	13	24%	3.0
	Renter	High School	335,087	22	18%	2.5
	Renter	Some College	306,650	24	17%	2.1
	Renter	College or higher	196,721	24	17%	1.3
	Area Total		3,364,749		**13%**	
Houston	Owner	LT High School	127,526	20	19%	2.3
	Owner	High School	158,057	52	12%	1.1
	Owner	Some College	206,918	91	9%	0.8
	Owner	College or higher	285,704	208	6%	0.5
	Renter	LT High School	144,922	12	25%	4.4
	Renter	High School	144,564	31	15%	1.7
	Renter	Some College	146,669	39	13%	1.4
	Renter	College or higher	108,831	33	15%	1.2
	Area Total		1,323,191	486	**14%**	
IN	Owner	LT High School	204,034	16	21%	3.0
	Owner	High School	627,957	161	7%	0.9
	Owner	Some College	485,284	121	8%	0.9
	Owner	College or higher	447,405	206	6%	0.5
	Renter	LT High School	131,880	6	37%	5.2
	Renter	High School	243,255	37	14%	1.6
	Renter	Some College	204,589	21	18%	2.3
	Renter	College or higher	103,483	11	26%	2.2
	Area Total		2,447,887	579	**15%**	

Area	Owner/Renter	High Level Education	Population	Sample Size	Sampling Error	Weight
KS	Owner	LT High School	65,548	18	20%	1.7
	Owner	High School	213,936	104	8%	0.9
	Owner	Some College	231,881	113	8%	0.9
	Owner	College or higher	247,853	194	6%	0.6
	Renter	LT High School	47,338	6	37%	3.6
	Renter	High School	100,310	17	21%	2.7
	Renter	Some College	112,300	23	18%	2.2
	Renter	College or higher	64,702	20	19%	1.5
	Area Total		1,083,868	495	**14%**	
MD	Owner	LT High School	128,732	8	31%	3.8
	Owner	High School	331,337	86	9%	0.9
	Owner	Some College	372,569	81	9%	1.1
	Owner	College or higher	612,788	227	5%	0.6
	Renter	LT High School	106,104	4	47%	6.2
	Renter	High School	181,390	24	17%	1.8
	Renter	Some College	180,608	29	16%	1.5
	Renter	College or higher	169,045	31	15%	1.3
	Area Total		2,082,573	490	**17%**	
MA	Owner	LT High School	117,237	4	47%	5.8
	Owner	High School	375,594	59	11%	1.3
	Owner	Some College	390,311	77	9%	1.0
	Owner	College or higher	707,515	262	5%	0.5
	Renter	LT High School	155,673	8	31%	3.8
	Renter	High School	256,204	23	18%	2.2
	Renter	Some College	200,304	23	18%	1.7
	Renter	College or higher	245,770	28	16%	1.7
	Area Total		2,448,608	484	**17%**	
MI	Owner	LT High School	161,484	22	18%	2.1
	Owner	High School	497,755	150	7%	0.9
	Owner	Some College	545,681	184	6%	0.8
	Owner	College or higher	508,844	221	6%	0.7
	Renter	LT High School	81,506	6	37%	3.9
	Renter	High School	169,007	28	16%	1.7
	Renter	Some College	180,415	20	19%	2.6
	Renter	College or higher	100,591	11	26%	2.6
	Area Total		2,245,283	642	**13%**	

Area	Owner/Renter	High Level Education	Population	Sample Size	Sampling Error	Weight
NYS	Owner	LT High School	192,252	15	22%	3.9
	Owner	High School	630,006	197	6%	1.0
	Owner	Some College	604,150	208	6%	0.9
	Owner	College or higher	741,480	387	4%	0.6
	Renter	LT High School	173698	16	21%	3.3
	Renter	High School	325303	51	12%	1.9
	Renter	Some College	285186	49	12%	1.8
	Renter	College or higher	205718	37	14%	1.7
	Area Total		3,157,793	960	**11%**	
NYC	Owner	LT High School	124,446	4	47%	4.9
	Owner	High School	250,452	52	12%	0.8
	Owner	Some College	215,427	59	11%	0.6
	Owner	College or higher	433,111	126	7%	0.5
	Renter	LT High School	456,265	27	16%	2.7
	Renter	High School	507,218	69	10%	1.2
	Renter	Some College	401,363	52	12%	1.2
	Renter	College or higher	633,869	87	9%	1.1
	Area Total		3,022,151	476	**14%**	
OH	Owner	LT High School	288,088	20	19%	1.8
	Owner	High School	967,505	127	7%	0.9
	Owner	Some College	751,623	101	8%	0.9
	Owner	College or higher	732,982	152	7%	0.6
	Renter	LT High School	210887	7	34%	3.8
	Renter	High School	420482	38	14%	1.4
	Renter	Some College	343033	31	15%	1.4
	Renter	College or higher	183121	10	27%	2.3
	Area Total		3,897,721	486	**14%**	
PA	Owner	LT High School	376,781	20	19%	2.4
	Owner	High School	1,273,333	174	6%	0.9
	Owner	Some College	802,021	130	7%	0.8
	Owner	College or higher	1,031,937	207	6%	0.6
	Renter	LT High School	243,469	8	31%	3.9
	Renter	High School	514,171	36	14%	1.8
	Renter	Some College	340,709	27	16%	1.6
	Renter	College or higher	276,088	24	17%	1.5
	Area Total		4,858,509	626	**13%**	
WI	Owner	LT High School	137,004	14	23%	2.2
	Owner	High School	512,057	93	9%	1.2
	Owner	Some College	468,286	123	7%	0.8
	Owner	College or higher	454,210	182	6%	0.5
	Renter	LT High School	104,231	7	34%	3.3

Area	Owner/Renter	High Level Education	Population	Sample Size	Sampling Error	Weight
	Renter	High School	230,239	37	14%	1.4
	Renter	Some College	210,758	15	22%	3.1
	Renter	College or higher	118,461	21	18%	1.2
	Area Total		2,235,246	492	**14%**	

Table A–2 presents the weighting scheme for the onsite survey.

Table A–2: Sample Design, Error, and Weighting Schemes for Onsite Data

Area	Owner/Renter	Familiarity with CFLs	Population	Sample Size	Sampling Error	Weight
CA	Owner	Familiar	4,461,380	40	12%	0.9
	Owner	Not Familiar	1,226,880	11	25%	1.1
	Renter	Familiar	3,228,857	22	17%	1.1
	Renter	Not Familiar	587,065	4	46%	1.7
	Area Total		9,504,182	77	**21%**	
CO	Owner	Familiar	583,379	11	25%	1.1
	Owner	Not Familiar	190,571	5	40%	2.7
	Renter	Familiar	161,634	49	11%	0.7
	Renter	Not Familiar	230,329	5	40%	1.9
	Area Total		1,165,913	70	**26%**	
CT	Owner	Familiar	779,120	65	9%	0.8
	Owner	Not Familiar	143,837	12	23%	1.4
	Renter	Familiar	200,237	9	27%	1.7
	Renter	Not Familiar	200,237	9	27%	1.6
	Area Total		1,323,431	95	**19%**	
DC	Owner	Familiar	85,093	44	10%	0.6
	Owner	Not Familiar	25,141	13	22%	1.1
	Renter	Familiar	59,318	17	19%	1.3
	Renter	Not Familiar	80,253	23	16%	1.4
	Area Total		249,805	97	**16%**	
GA	Owner	Familiar	1,446,172	31	14%	1.0
	Owner	Not Familiar	839,712	18	18%	.7
	Renter	Familiar	497,938	6	36%	1.6
	Renter	Not Familiar	580,927	7	32%	1.4
	Area Total		3,364,749	62	**23%**	
Houston	Owner	Familiar	611,447	55	9%	.7
	Owner	Not Familiar	166,758	15	20%	1.5
	Renter	Familiar	300,682	16	19%	1.0
	Renter	Not Familiar	244,304	13	22%	1.9
	Area Total		1,323,191	99	**18%**	

Area	Owner/Renter	Familiarity with CFLs	Population	Sample Size	Sampling Error	Weight
IN	Owner	Familiar	1,384,595	51	11%	.9
	Owner	Not Familiar	380,085	14	21%	1.2
	Renter	Familiar	534,684	18	18%	.9
	Renter	Not Familiar	148,523	5	39%	1.8
	Area Total		2,447,887	88	**19%**	
KS	Owner	Familiar	556,760	44	11%	.8
	Owner	Not Familiar	202,458	16	20%	1.0
	Renter	Familiar	59,027	2	81%	5.5
	Renter	Not Familiar	265,623	9	27%	1.1
	Area Total		1,083,868	71	**36%**	
MD	Owner	Familiar	1,092,100	34	13%	.8
	Owner	Not Familiar	353,326	11	25%	1.1
	Renter	Familiar	231,690	4	46%	2.7
	Renter	Not Familiar	405,457	7	31%	.9
	Area Total		2,082,573	56	**27%**	
MA	Owner	Familiar	1,332,175	67	9%	.7
	Owner	Not Familiar	258,482	13	22%	1.1
	Renter	Familiar	600,566	14	21%	1.5
	Renter	Not Familiar	257,385	6	35%	2.4
	Area Total		2,448,608	100	**19%**	
MI	Owner	Familiar	1,483,557	58	10%	.9
	Owner	Not Familiar	230,207	9	28%	1.7
	Renter	Familiar	413,404	14	10%	.9
	Renter	Not Familiar	118,115	4	46%	1.8
	Area Total		2,245,283	85	**21%**	
NYS	Owner	Familiar	1,736,922	133	6%	.8
	Owner	Not Familiar	430,966	33	13%	1.2
	Renter	Familiar	668,855	25	16%	1.5
	Renter	Not Familiar	321,050	12	24%	2.1
	Area Total		3,157,793	203	**13%**	
NYC	Owner	Familiar	827,459	38	11%	.6
	Owner	Not Familiar	195,977	9	15%	1.4
	Renter	Familiar	960,921	25	16%	1.4
	Renter	Not Familiar	1,037,794	27	27%	1.1
	Area Total		3,022,151	99	**16%**	
OH	Owner	Familiar	2,064,045	58	9%	.8
	Owner	Not Familiar	676,153	19	18%	1.6
	Renter	Familiar	636,638	11	24%	1.3
	Renter	Not Familiar	520,885	9	27%	1.2
	Area Total		3,897,721	97	**18%**	
PA	Owner	Familiar	2,737,485	33	14%	.9

Area	Owner/Renter	Familiarity with CFLs	Population	Sample Size	Sampling Error	Weight
	Owner	Not Familiar	746,587	9	28%	1.4
	Renter	Familiar	970,191	12	23%	.8
	Renter	Not Familiar	404,246	5	40%	1.5
	Area Total		4,858,509	59	**23%**	
WI	Owner	Familiar	1,360,452	58	10%	.8
	Owner	Not Familiar	211,105	9	27%	1.4
	Renter	Familiar	486,705	11	25%	1.5
	Renter	Not Familiar	176,984	4	45%	1.8
	Area Total		2,235,246	82	**22%**	

Appendix B: Summary of Key Variables: RDD Survey

This appendix summarizes the key RDD survey variables used in the analysis across participating areas. We present the results to provide an overall picture of the data; the footnotes highlight and explain unexpected findings and discuss our responses to them. We also refer the reader to Section **Error! Reference source not found.** for a detailed discussion about comparability among the surveys.

Table B–1: Comparison of Key Variables Across Participating Areas – Means, RDD Surveys*

	Number of CFLS Currently Installed in Home**		Number of CFLs Installed One Year Ago		Number of CFLS Purchased Last Year / in 2008***		Number of CFLS Purchased in the Last Three Months****	
	Sample Size	Mean	Sample Size	Mean	Sample Size	Mean	Sample Size	Mean
CA	699	7.2			699	1.4	698	0.9
CO	600	4.8	600	2.6	600	3.0	600	0.3
CT	500	6.4	499	3.5	499	2.7	500	0.3
DC	500	3.2	500	2.1	499	3.0	500	0.7
GA	578	6.2			579	1.4	578	1.0
IN	600	5.3	600	2.4	600	2.9	600	0.4
KS	525	6.1			525	1.1	525	1.1
MD	500	5.5	500	3.1	500	3.0	500	0.4
MA	503	5.8	503	3.4	503	2.8	503	0.3
MI	657	6.2	657	3.4	657	2.8	657	0.4
NY State	1,000	5.5	999	3.5	1000	4.2	1000	1.1
NY City	502	3.5	502	2.4	502	3.5	502	1.1
OH	501	4.3	501	2.9	501	3.5	501	1.0
PA	653	5.4			653	1.2	653	0.9
Houston	503	4.9	502	3.0	503	4.1	503	0.8
WI	503	6.5	503	3.7	503	2.5	503	0.4
OVERALL	**9,324**	**5.5**	**6,865**	**3.0**	**9,323**	**2.7**	**9,323**	**0.7**

	Percent of Bulb Purchased in 2008 that were CFLs*****		Percent of Bulb Purchased in Last Three Months that were CFLs*****		Number of CFLs in Storage		Years Using CFLS	
	Sample Size	Mean	Sample Size	Mean	Sample Size	Mean	Sample Size	Mean
CA			259	30%	699	2.9	688	1.9
CO	455	36%	144	28%	600	2.2	600	1.4
CT	379	31%	113	28%	500	2.5	500	1.8
DC	411	27%	240	26%	500	1.3	500	1.4
GA			573	10%	579	1.7	579	1.8
IN	455	32%	123	34%	600	1.8	600	1.5
KS			519	12%	525	1.9	525	2.0
MD	403	29%	114	33%	500	2.1	500	1.6
MA	416	30%	95	33%	503	2.5	503	2.4
MI	467	35%	135	34%	657	2.2	657	1.7
NY State	886	39%	462	38%	1000	1.8	1000	1.8
NY City	426	33%	232	34%	502	1.5	502	1.7
OH	426	32%	233	32%	501	1.5	501	1.3
PA			648	10%	653	1.7	653	1.9
Houston	424	31%	215	26%	503	1.3	503	1.2
WI	386	31%	105	38%	503	2.5	503	2.2
OVERALL	**5,534**	**33%**	**4,210**	**23%**	**9,325**	**2.0**	**9,314**	**1.7**

	Unemployment Rate		Household Size		Square Footage of Box Stores per Household in County			
	Sample Size	Mean	Sample Size	Mean	Sample Size	Wal-Mart Stores - Mean	Other Box Stores - Mean	All Box Stores - Mean
CA	699	7.9	563	3.4	699	2.0	2.6	4.6
CO	600	7.5	596	2.3	600	6.3	3.6	9.9
CT	500	8.1	472	2.5	500	1.2	1.4	2.6
DC	500	9.6	478	2.3	500	0.0	0.4	0.4
GA	578	7.0	453	2.9	578	7.8	4.4	12.3
IN	600	10.7	578	2.4	600	8.3	2.7	11.0
KS	485	4.4	391	2.9	460	9.7	2.6	12.3
MD	500	7.9	486	2.6	500	4.0	3.4	7.4
MA	503	8.8	488	2.5	503	2.6	3.0	5.5
MI	657	14.6	642	2.4	655	2.2	2.3	4.5
NY State	1000	8.5	959	2.5	1000	5.2	3.7	8.9
NY City	502	7.4	475	2.7	502	0.0	0.6	0.6
OH	501	10.4	491	2.6	501	6.9	3.6	10.5
PA	613	5.6	487	3.0	578	5.1	2.7	7.8
Houston	503	6.4	488	3.0	503	5.5	3.4	8.9
WI	503	9.4	497	2.4	503	7.5	3.7	11.1
OVERALL	**9,242**	**8.5**	**8,544**	**2.6**	**9,242**	**4.7**	**2.8**	**7.5**

Table footnotes on next page.

* The sample sizes change for different variable because not all respondents answered all questions. Furthermore, the team is still matching some CPUC state cases to individual counties, a task that will be completed in October. Finally, we also remove outliers for household size and the use and purchase data.
** The CPUC survey first asked respondents the number of CFL currently in use and storage. Then, the survey asked if the respondent was using or storing the same number of CFLs three months ago and one year ago. If the respondent said "yes" the three month and one year ago use and storage numbers were assumed to be the same as the current number. The other surveys simply asked the number of CFLs stored currently, three months ago, and one year ago (or the beginning of 2008, depending on the survey). The differences in methodology likely underlie the slight but apparent differences between the CPUC states and other areas in the study on these variables. However, the estimates are relatively close, so we have included these variables for the CPUC states in the analyses.
*** The CPUC survey asked respondents to name the number of CFLs purchased since January 1, 2006 and then to isolate from that number purchased in 2006, 2007, and 2008. Furthermore, the survey was fielded in the fall of 2008 before the year's end. Therefore, the results are not comparable to those developed for other areas and will be excluded from the analysis. We report the summary statistics here to show the impact of these differences on the estimates.
**** These results demonstrate the effect of survey timing, with estimates from the surveys fielded in the fall and winter showing higher rates of purchases in the past three months than those fielded in the summer.
***** Limited to only those who purchased any light bulbs in the time period. Most surveys forced respondents to limit their estimated "past three month" purchases to less than or equal to the number purchased to date in the preceding year (e.g., all of 2009 for surveys conducted in the summer of 2009, all of 2008 for surveys conducted in January 2009). However, the CPUC instrument asked only about the past three months, and this may explain the divergent market share estimates for the four CPUC states.

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

	Aware of CFLS		Somewhat to Very Familiar with CFLs		Satisfied with CFLS		Pay Electric Bill Directly to Electric Company	
	Sample Size	Percentage	Sample Size	Percentage	Sample Size	Percentage	Sample Size	Percentage
CA	699	96%	699	76%	564	86%		
CO	600	90%	600	64%	416	76%	600	94%
CT	500	86%	500	67%	362	88%	500	92%
DC	500	72%	500	51%	250	90%	500	75%
GA	579	88%	579	63%	389	89%		
IN	600	91%	600	71%	431	86%	600	89%
KS	525	93%	525	64%	381	82%		
MD	500	87%	500	66%	331	82%	500	89%
MA	503	87%	503	71%	367	86%	503	90%
MI	657	94%	657	74%	500	82%	657	95%
NY State	1,000	90%	1,000	69%	722	89%	1,000	87%
NY City	502	78%	502	57%	281	93%	502	77%
OH	501	86%	501	62%	301	87%	501	88%
PA	653	91%	653	65%	458	85%		
Houston	503	74%	503	52%	295	87%	503	90%
WI	503	93%	503	57%	397	83%	503	96%
OVERALL	**9,325**	**88%**	**9,325**	**66%**	**6,419**	**86%**	**6,869**	**89%**

Table B–3: 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	
	Sample Size	Percentage	Sample Size	Percentage	Sample Size	Percentage	Sample Size	Percentage	Sample Size	Percentage
CA	699	65%	699	8%	699	8%	699	15%	699	3%
CO	600	73%	600	14%	600	9%	600	4%	600	0%
CT	500	66%	500	12%	500	6%	500	12%	500	1%
DC	500	26%	500	23%	500	12%	500	36%	500	1%
GA	579	76%	579	4%	579	4%	579	9%	579	5%
IN	600	74%	600	7%	600	7%	600	7%	600	4%
KS	525	76%	525	6%	525	4%	525	9%	525	4%
MD	500	59%	500	20%	500	4%	500	13%	500	4%
MA	503	55%	503	17%	503	11%	503	16%	503	2%
MI	657	75%	657	6%	657	3%	657	10%	657	7%
NY State	1,000	65%	1,000	10%	1,000	9%	1,000	9%	1,000	6%
NY City	502	20%	502	18%	502	15%	502	38%	502	7%
OH	501	70%	501	11%	501	2%	501	10%	501	5%
PA	653	70%	653	10%	653	5%	653	9%	653	5%
Houston	503	61%	503	9%	503	5%	503	20%	503	5%
WI	503	67%	503	9%	503	6%	503	12%	503	7%
OVERALL	**9,325**	**63%**	**9,325**	**11%**	**9,325**	**7%**	**9,325**	**14%**	**9,325**	**4%**

Table B–4: Comparison of Key Variables across Areas – Homeownership and Home Size

	Own Home		Home Size (Sq. Ft.)					
	Sample Size	Percentage	Sample Size	Percentage Less than 2,000 sqft	Sample Size	Percentage, between 2,000 and 3,999 sqft	Sample Size	Percentage 4,000 or more sqft
CA	699	60%	690	34%	690	55%	690	12%
CO	600	66%	552	63%	552	34%	552	3%
CT	500	87%	500	64%	500	28%	500	8%
DC	500	43%	485	76%	485	20%	485	4%
GA	579	67%	567	28%	567	55%	567	17%
IN	600	72%	591	62%	591	38%	591	0%
KS	525	70%	508	36%	508	54%	508	11%
MD	500	69%	493	56 %	493	36%	493	7%
MA	503	64%	496	64%	496	30%	496	6%
MI	657	76 %	657	60%	657	28%	657	3%
NY State	1,000	68%	981	67%	981	31%	981	2%
NY City	502	34%	488	82%	488	16%	488	2%
OH	501	70%	494	64%	494	32%	494	4%
PA	653	70%	617	36%	617	54%	617	10%
Houston	503	59%	493	66%	493	31%	493	3%
WI	503	71%	500	69%	500	37%	500	0%
OVERALL	**9,325**	**65%**	**9,113**	**58%**	**9,111**	**37%**	**9,111**	**6%**

Table B–5: Comparison of Key Variables across Areas – Demographic Factors

	English Primary Lang. Spoken at Home		More than High School Education		White		Female		Income Under $30,000**	
	Sample Size	Percentage	Sample Size	Percentage	Sample Size	Percentage	Sample Size	Percentage	Sample Size	Percentage
CA	699	77%	699	62%	666	69%	699	60%	699	33%
CO	600	95%	600	63%			600	68%	600	31%
CT	500	92%	500	59%	500	75%	500	56%	500	26%
DC	500	97%	500	65%	500	32%	500	59%	500	32%
GA	579	90%	579	54%	571	63%	579	63%	579	18%
IN	600	96%	600	49%	600	85%	600	64%	600	28%
KS	525	94%	525	57%	520	86%	525	56%	525	15%
MD	500	95%	500	63%	500	68%	500	64%	500	29%
MA	503	97%	503	60%	503	86%	503	59%	503	28%
MI	657	98%	657	58%	657	87%	657	64%	657	32%
NY State	1,000	97%	1,000	56%	1,000	86%	1,000	58%	1,000	37%
NY City	502	81%	502	54%	502	53%	502	58%	502	31%
OH	501	98%	501	50%	501	83%	501	55%	501	33%
PA	653	95%	653	49%	649	84%	653	60%	653	14%
Houston	503	86%	503	56%	503	51%	503	60%	503	34%
WI	503	99%	503	55%	503	91%	503	56%	503	27%
OVERALL	**9,325**	**93%**	**9,325**	**57%**	**8,675**	**74%**	**9,325**	**60%**	**9,325**	**28%**

* Sample sizes vary based on the number of respondents asked the question. For example, only respondents currently using CFLs were asked how satisfied they were with the products.
* The CPUC instrument used different income categories, with the second category grouping individuals in the $20,000 to $49,999 category. After adjusting for cost of living, only those individuals who made less than $20,000 (non-adjusted) were able to be categorized as "low income" in our scheme.

Appendix C: Demographic Variation in Current CFL Use and 2008 Purchase Behavior – RDD Self-Reported Data

The data presented in Table C–1 through Table C–6 summarize RDD self-reported current CFL use and 2008 purchases by key housing, demographic, and other variables much the same way that Section 0 does for onsite verified use and reported 2008 purchases. The evaluation team reminds the reader that this and other evaluations have shown that the RDD self-reported data on use and purchases are not reliable, and the CFL counts must be interpreted with this in mind. However, the data are useful in showing the patterns that relate to self-reported CFL use and purchases as well as lack of awareness and familiarity.

Table C–1: Current CFL Use by Key Housing Characteristics – RDD Survey

Variable	Sample Size	Number of CFLs					Not aware / familiar
		Zero	**1 to 5**	**6 to 10**	**11 to 15**	**16+**	
Type of Home							
Single Family Detached	6,759	18%	23	21	11	11	15
Single Family Attached	922	23%	24	18	7	7	21
Apartment 2-4 units	408	27%	25	18	4	2	24
Apartment 5+ units	849	29%	25	12	4	1	30%
Mobile/Other	292	23%	23	13	9	7	25
Homeownership							
Own	7,457	18%	23	21	11	12	15
Rent	1,748	27%	24	14	5	2	27
Home Size							
Less than 2,000 sqft	4,549	22%	25	18	7	5	24
2,000 to 3,999 sqft	3,911	19%	24	21	11	12	13
4,000 sqft or more	652	20%	18	19	12	18	12
Who Pays Electric Bill							
Pays Bill Directly	6,296	21%	23	19	9	8	20
Included in Rent/Fee	295	30%	21	12	2	<1	35

Table C–2: 2008 CFL Purchases by Key Housing Characteristics – RDD Survey

Variable	Sample Size	Number of CFLs					Not aware / familiar
		Zero	1 to 5	6 to 10	11 to 15	16+	
Type of Home							
Single Family Detached	6,759	48%	17	13	4	4	15
Single Family Attached	922	45%	16	11	4	4	21
Apartment 2-4 units	408	49%	13	10	2	1	24
Apartment 5+ units	849	49%	13	7	1	1	29
Mobile/Other	292	52%	10	9	2	3	25
Homeownership							
Own	7,457	47%	17	13	4	4	15
Rent	1,748	49%	12	8	2	2	27
Home Size							
Less than 2,000 sqft	4,549	45%	16	10	3	2	24
2,000 to 3,999 sqft	3,911	51%	15	13	4	4	13
4,000 sqft or more	652	54%	12	12	6	5	12
Who Pays Electric Bill							
Pays Bill Directly	6,296	39%	18	14	4	4	20
Included in Rent/Fee	295	43%	13	7	1	1	35

Table C–3: Current CFL Use by Key Demographic Characteristics – RDD Survey

Variable	Sample Size	Number of CFLs					Not aware / familiar
		Zero	**1 to 5**	**6 to 10**	**11 to 15**	**16+**	
Primary Language							
English	8,833	21%	24	19	9	9	18
Another language	330	20%	23	15	7	5	31
Self-Identified Race							
White	6,729	20%	25	21	10	10	15
Another race(s)	1,492	24%	20	14	5	5	32
Education							
Beyond high school	6,372	20%	25	22	10	10	13
High school or less	2,640	23%	22	15	7	5	28
*Income COL Adjusted**							
Less than $30,000	1,902	24%	24	15	6	5	27
$30,000 or higher	4,889	20%	24	22	11	12	12
Gender							
Male	3,837	19%	23	21	10	11	17
Female	5,484	23%	24	18	8	7	21
County Metropolitan Status							
Metropolitan	7,738	21%	23	19	8	8	20
Non-metropolitan	1,507	20%	25	19	11	10	16

* Adjusted for the cost of living

Table C–4: 2008 CFL Purchases by Key Demographic Characteristics – RDD Survey

Variable	Sample Size	Number of CFLs					Not aware / familiar
		Zero	**1 to 5**	**6 to 10**	**11 to 15**	**16+**	
Primary Language							
English	8,833	48%	16	12	4	3	18
Another language	330	50%	6	8	3	2	31
Self-Identified Race							
White	6,729	49%	17	12	4	3	15
Another race(s)	1,492	45%	10	8	2	3	32
Education							
Beyond high school	6,372	47%	18	14	4	4	13
High school or less	2,640	48%	12	8	2	2	28
*Income COL Adjusted**							
Less than $30,000	1,902	47%	14	8	2	2	27
$30,000 or higher	4,889	49%	17	14	5	4	12
Gender							
Male	3,837	45%	17	13	4	4	17
Female	5,484	49%	14	10	3	3	21
County Metropolitan Status							
Metropolitan	7,738	47%	15	11	4	3	20
Non-metropolitan	1,507	51%	16	11	3	3	16

* Adjusted for the cost of living

Table C–5: Average Values for Key Variables by Number of CFLs Currently in Use – RDD Survey

	Number of CFS										Not aware / familiar	
	Zero		1 to 5		6 to 10		11 to 15		16+			
Variable	n	Mean	n	Mean	n	Mean	n	Mean	n	Mean	n	Mean
Household size	1,644	2.6	2,014	2.5	1,793	2.7	890	2.9	916	3.0	1,287	2.5
County unemployment rate	1,792	8.6	2,162	8.4	1,912	8.5	954	8.6	961	8.4	1,434	8.4
Years Using CFLs	1,801	0.7	2,210	2.2	1,926	2.7	961	3.1	969	3.6	1,448	0.0
Density of Wal-Marts	1,792	4.6	2,192	5.0	1,910	4.5	954	4.5	961	5.1	1,434	4.3
Density of Other Box Stores	1,792	2.8	2,192	2.9	1,910	2.8	954	2.9	961	2.9	1,434	2.6
Density of All Box Stores	1,792	7.4	2,192	7.9	1,910	7.3	954	7.5	961	8.0	1,434	6.9
Partisan Voting Index*	1,792	-8.7	2,192	-7.6	1,910	-7.3	954	-6.1	961	-2.4	1,434	-14.1

* The more negative the score, the more heavily democratic leaning the area

Table C–6: Average Values for Key Variables by Number of CFLs Currently in Use – RDD Survey

	Number of CFS										Not aware / familiar	
	Zero		1 to 5		6 to 10		11 to 15		16+			
Variable	n	Mean	n	Mean	n	Mean	n	Mean	n	Mean	n	Mean
Household size	3,893	2.6	1,499	2.5	1,154	2.8	375	3.0	336	3.1	1,287	2.5
County unemployment rate	4,318	8.3	1,563	8.7	1,192	8.8	386	8.6	352	8.7	1,434	8.4
Years Using CFLs	4,362	1.9	1,572	2.6	1,195	2.6	387	2.5	351	2.4	1,448	0.0
Density of Wal-Marts	4,317	4.9	1,563	4.6	1,191	4.5	386	4.4	352	4.4	1,434	4.3
Density of Other Box Stores	4,317	2.9	1,563	2.8	1,191	2.8	386	2.9	352	2.9	1,434	2.6
Density of All Box Stores	4,317	7.8	1,563	7.4	1,191	7.3	386	7.3	352	7.2	1,434	6.9
Partisan Voting Index*	4,317	-5.4	1,563	-9.9	1,192	-9.8	386	-8.4	352	-8.2	1,434	-14.1

* The more negative the score, the more heavily democratic leaning the area

Appendix D: Additional Regression Models, including Sensitivity Analyses

The evaluation team presents additional regression models in this section. These models help to clarify the relationship between the program variable and the other independent variables, others serve as potential alternatives to the recommended models described in the main body of the text, and the remainder provides "sensitivity analyses" to ascertain whether or not such variables as historic CFL use, saturation, and storage rob explanatory power from the program variable.. We explain the purpose of each model prior to its presentation, but we do not include detailed descriptions of the model.

Relationship between Program and Other Independent Variables

The evaluation team developed an OLS regression model that treated the composite program variable as the *dependent variable* in order to determine which independent variables most closely tied to the existence and strength of programs.[54] We did so using only variables gathered through the RDD survey and excluded key dependent variables (*i.e.,* use, purchases, or saturation). This model, presented in Table D–1, should not be seen as a *causal* model, but instead one that shows which independent variables are most closely tied to program activity. The coefficients ("b" in most statistical package outputs) are the primary results of interest and show how much the composite program variable changes with a one unit increase in each independent variable. We also present the standardized coefficients ("Beta" in most statistical package outputs), which adjust for the different scales of the original coefficients and allow for easier comparisons of the impact of the independent variables on the composite program variable.[55]

The results indicate that areas with more non-metropolitan counties, counties that have lower unemployment rates, and those with higher percentages of respondents who self-identify as white are the most likely to have strong program variables. Likewise, it is also the case that areas marked by respondents who have used CFLs for a long time, store more CFLs, and who are likely to pay their own electricity bills are also more likely to have strong programs.

[54] The team could use OLS in this model because we had standardized the program variable, therefore forcing it into a normal distribution.

[55] We present the standardized coefficients here for the sake of comparison, but the evaluation team recognizes that doing so creates interpretative issues for dichotomous variables (*i.e.* the income, language, bill pay, and self-identified race variables).

Table D–1: Predictors of Composite Program Variable – Best Model

Dependent Variable = Composite Program Variable **Independent Variables**	**Coefficient**	**Standardized Coefficient**	**t**
County metropolitan status	-0.67	-0.09	-6.12
County Unemployment Rate	-0.44	-0.43	-29.61
Years using CFL	0.07	0.07	4.86
Current CFLs in storage	0.03	0.04	2.56
Pays Electricity Bill Directly	0.41	0.04	3.02
Adjusted income <$30,000**	0.22	0.04	2.76
Sq Ft. of Other Box Stores Per person at the County Level***	0.06	0.06	3.86
Sq Ft. of Wal-Mart Per person at the State Level****	-0.22	-0.12	-8.11
English is Primary Language*****	1.11	0.07	4.89
Self-Identify as White	1.23	0.19	13.04
Constant	2.17	n/a	6.79

* Sample Size = 4,427, Adjusted R^2 = 20%

** Adjusted for the cost of living

*** Other indicates Home Depot, Lowe's, and Menards (where it exists)

**** Wal-Mart shown at the state level to avoid collinearity with the county level variable

***** The survey was fielded in languages other than English in only a few places, so this variable includes some selection bias.

The model presented in Table D–1 does not incorporate data from the CPUC states—because respondents were not asked who paid the electricity bill. Therefore, we also present the model in Table D–2 which includes data for all states except CO for reasons discussed in Section 2.4.2. The explained variance (R^2) is much lower than found for the model presented in Table D–1. This second model excludes the variables about paying electricity bills. Doing so causes the metropolitan status variable to become positively related to program and the percentage of respondents self-identifying as white to drop out of the model.[56]

[56] The sample size is smaller than 9,326 because we excluded people who refused to answer specific questions, with 2,500 of them being accounted for by the refusal to provide an estimate of income.

Table D–2: Predictors of the Composite Program Variable – All States Model

Dependent Variable = Composite Program Variable Independent Variables	Coefficient	Standardized Coefficient	t
County Metropolitan Status	0.23	0.03	2.41
County Unemployment Rate	-0.15	-0.15	-12.16
Years using CFL	0.06	0.06	4.43
Current CFLs in storage	0.06	0.08	6.15
Adjusted income <$30,000**	0.39	0.07	5.32
Sq Ft. of Other Box Stores Per person at the County Level***	0.12	0.10	8.30
Sq Ft. of Wal-Mart Per person at the State Level****	-0.50	-0.25	-19.05
English is Primary Language*****	-0.62	-0.05	-3.95
Constant	2.04	n/a	9.19

* Sample Size =6,320; Adjusted R2 = 9%
** Adjusted for the cost of living
*** Other indicates Home Depot, Lowe's, and Menards (where it exists)
**** Wal-Mart shown at the state level to avoid collinearity with the county level variable
***** The survey was fielded in languages other than English in only a few places, so this variable includes some selection bias.

Sensitivity Analyses

The model in Table D–3 serves as a sensitivity analyses for the model presented in Table 5–4, allowing us to see the impact of removing "years using CFLs" and "saturation at the beginning of 2008" on 2008 purchases given that these two variables are positively correlated with CFL program activity. The program variable retains its effect on 2008 purchases in the absence of the years using CFL variable, the saturation at the beginning of 2008. Excluding these variables *lowers* the impact of the composite program variable impact slightly from 0.09 to 0.08. In short, controlling for length of time using CFLs and saturation *improved* the program store in the recommended model (Table 5–4).

Table D–3: Best 2008 Purchase Model Absent Saturation and Length of CFL Use –Onsite

		90% Confidence Interval		
Variables	**Coefficient**	Low	High	**Impact Score**
Composite Program	0.10	0.05	0.15	0.10
Number of Sockets in Home	0.01	0.00	0.01	0.01
Number of Persons in Household	0.10	0.02	0.17	0.10
Self reported as White	0.49	0.17	0.80	0.63
Conducted During Fall Season	0.52	0.27	0.78	0.68
Constant	-0.61	-1.00	-0.21	n/a

* Sample size = 1,047; Pseudo R^2 = 1%.

There is a significant positive composite program effect on current saturation with the exclusion of length of CFL use (Table D–4). The composite program coefficient increases slightly (from 1.67 to 1.98) in the absence of the length of CFL use variable while the explained variance is reduced by a single percent. There other explanatory variables also change slightly but all remain significant predictors of current saturation. Thus, length of CFL use removed slight explanatory power from the model, but it also slightly strengthened the composite program variable.

Table D–4: Best Current Saturation Model Absent Length of CFL Use – Onsite*

Variables	Coefficient	90% Confidence Interval	
		Low	High
Composite Program	1.98	1.50	2.50
Pay Utility Bill Directly	11.78	9.22	14.34
County Unemployment Rate	5.59	4.10	7.09

* Sample size = 1,094

Table D–5 depicts the best current use models without current saturation or length of CFL use in the models. The onsite composite program impact is very similar in the absence of length of CFL use (changing by three hundredths of a point). Again, removing these variables from the model does have an impact on the program score, but it remains a minor predictor of CFL use and the explanatory power of the model suffers, also slightly.

Table D–5: Best Current Use Model Absent Saturation Length of CFL Use –Onsite

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Composite Program	0.06	0.04	0.08	0.06
Homeowner	0.68	0.54	0.83	0.98
Home Size	0.23	0.14	0.33	0.26
Self reported as White	0.29	0.12	0.46	0.34
English is Primary Language	-0.18	-0.51	0.14	-0.17
Sqft Wal-Mart per Household (state)	0.06	0.02	0.10	0.06
High School Degree or Less	-0.21	-0.34	-0.08	-0.19
Constant	1.13	0.78	1.48	n/a

* Sample size = 1,315 and pseudo R^2 = 2%.

Advanced RDD Survey Model Results

The team also presents three sets of RDD survey based models, one focused on 2008 purchases, one on purchases in the past three months, and one on current use (**Error! Reference source not found.** and **Error! Reference source not found.**). Because we believe the RDD data are less reliable, we focus here only on the fact that 2008 purchases of CFLs were self-reported to be *lower* in areas with stronger programs than in those with no programs or newer or moderate ones. Similarly, the model for purchases in the past three months finds no program effect at all. A positive program effect, however, was found on self-reported estimates of current use. Again, we stress that the RDD data have been shown to be less reliable, and we urge the reader to focus on the more reliable results from the onsite surveys.

Table D–6: Best Fit 2008 Purchase Model – RDD*

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Composite Program	-0.03	-0.04	-0.01	-0.03
Years Using CFLs	0.04	0.02	0.06	0.04
CFLs Currently in Storage	0.16	0.14	0.17	0.17
Homeowner	0.36	0.23	0.49	0.43
Sqft Wal-Mart per Household (state)	0.14	0.10	0.18	0.15
Female Respondent	-0.19	-0.29	-0.09	-0.17
High School Diploma or less	-0.32	-0.44	-0.21	-0.28
County unemployment rate	0.04	0.02	0.06	0.04
Partisan Voting Index 2008**	-0.01	-0.01	0.00	-0.01
Constant	-0.29	-0.51	-0.06	n/s

* sample size = 8,880; Pseudo R^2 = 2%

** Positive relationship indicates higher use in areas with greater Republican leaning

Table D–7: Best Fit Three Month Purchase Model – RDD*

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Years Using CFLs	0.10	0.06	0.14	0.11
Number of Incandescents Bought**	0.02	0.01	0.03	0.02
Homeowner	0.56	0.29	0.83	0.75
Home Size	0.20	0.04	0.36	0.22
English is Primary Language	-0.01	-0.02	-0.01	-0.01
Conducted in the Fall	1.18	0.98	1.39	2.26
Female Respondent	-0.24	-0.45	-0.02	-0.21
High School Diploma or less	-0.47	-0.69	-0.25	-0.37
County Unemployment Rate	0.05	0.01	0.09	0.05
Constant	-2.30	-2.81	-1.79	n/a

* Sample size = 6,555; pseudo R^2 = 2%

** In the past three months

Table D–8: Best Fit Current Use Model – RDD*

Variables	Coefficient	90% Confidence Interval		Impact Score
		Low	High	
Composite Program	0.03	0.02	0.04	0.03
Years Using CFLs	0.19	0.17	0.21	0.21
CFLs Currently Stored in the Home	0.14	0.12	0.15	0.15
Homeowner	0.37	0.29	0.44	0.44
Home Size	0.20	0.15	0.26	0.23
Self reported as White	0.24	0.15	0.32	0.27
Female Respondent	-0.09	-0.15	-0.03	-0.09
High School Diploma or Less	-0.23	-0.30	-0.17	-0.21
County Level Unemployment	0.02	0.00	0.03	0.02
Partisan Voting Index 2008**	<0.01	<0.01	<0.01	<0.01
Constant	-0.09	-0.04	0.28	n/a

* Sample size = 7,898; pseudo R^2 = 5%

** Positive relationship indicates higher use in areas with greater Republican leaning