Analysis of Selected Regulatory Interventions to Improve Energy Efficiency

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ABSTRACT

This dissertation includes three studies of public policy designed to improve energy efficiency in the United States. In an *ex ante* study of two residential lighting demand-side efficiency programs, I find that despite considerable uncertainty in the achieved energy savings it is unlikely that these programs are not cost-effective. Several recommendations are made to improve the reporting of these programs that would enable more learning from past activities and thus more cost-effective efficiency investments in the future. In an *ex post* study of a separate demand-side efficiency program I find that participation in the program is associated with a subsequent increase in household energy consumption. The likely reason for this counterintuitive finding is that consumers are using the rebate as an equipment subsidy to consume additional energy services rather than as an equipment replacement program to consume a constant level of energy services. The contradiction of the findings of these two studies highlights the need for *ex post* analyses of demand-side efficiency programs as a critical component of program design in order to ensure that anticipated benefits are being realized in practice. Finally, I create a model of fuel consumption by light-duty vehicles in the United States in order to generate a projection of fuel demand in the context of demographic changes and increasing fuel economy standards. I find that long-term trends in population growth are more than offset by increasing fuel efficiency, assuming that these standards are met.

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CHAPTER 1: MOTIVATION AND INTRODUCTION

This work is a study of public policies that are implemented with the intent to improve energy efficiency. But for policy-makers energy efficiency is not an end in itself, instead it is one of several strategies available to achieve more fundamental policy objectives. These objectives can include protecting the environment by reducing greenhouse gas emissions due to the carbon-intensive nature of the fossil-fuel based energy system, improving human health outcomes by avoiding emissions of harmful pollutants that affect population centers, mitigating trade dependence on unreliable supply sources by reducing demand for scarce energy resources, or improving society's economic-efficiency by redirecting economic activity towards other more socially-productive endeavors. As a consequence, recommendations which follow from the analysis of policy which affects energy efficiency should be formulated and considered in the context of these ultimate objectives. By studying energy efficiency policies, the analyses which follow are really indirectly studies in generating these policy outcomes.

This dissertation is organized into six chapters. Chapter 2 presents a case-study analysis characterizing the uncertainty associated with two demand-side management (DSM) programs to improve household electrical energy efficiency in lighting. Estimating uncertainty associated with efficiency programs is a useful exercise because while these programs almost exclusively calculate and report energy savings outcomes as point estimates there is considerable uncertainty in the parameters which underlie those calculations. Because the ultimate quantity of energy that is saved through these programs is uncertain, the associated cost-effectiveness of these programs is also uncertain. If the range of possible values of energy reduction is wide enough the cost-effectiveness of DSM program investment could be questionable. Three methods are employed to estimate the range of possible energy reduction outcomes for both a long-running lighting efficiency program in Vermont and a relatively newer program in Pennsylvania. While both programs were created through regulatory action in their respective states, they differ in administration and scope. Because aggregate state-level DSM program spending is expected to continue to increase rapidly (Foster et al., 2012; Goldman et al., 2012) this analysis is performed from the perspective of developing recommendations for best-practices.

While Chapter 2's analysis adopts an *ex ante* approach to estimating household energy consumption outcomes from DSM programs, Chapter 3 presents the results of an *ex post* analysis of another residential DSM program. This work relies on the data from a sample of approximately 30,000 smart-meters from the PG&E service territory in northern California. These data are combined with information about household participation in a utility-operated energy efficiency rebate program in order to estimate the change in household electricity consumption following participation in this program. Because household participation is not universal in the sample, these data lend themselves to econometric modeling in which non-participating households serve as a control group for comparison against those households that do. Performing an *ex post* analysis in this way adds to our knowledge of the energy consumption outcome of these DSM programs in a way that implicitly incorporates uncertain or unknowable factors that confound *ex ante* estimates. In addition to estimating the energy effect of household participation in the DSM program, the smart-meter data also allow us to estimate the temporal distribution of changes in electricity demand in the affected households. The timing of changes in electricity demand is important for at least two reasons. First, the capacity of the electrical system is finite, and electricity delivery is the ultimate just-in-time service; supply and demand must be equal at all times across generation, transmission, and distribution. In regions with histories of capacity constraints (like California, see Sweeney, 2002) influencing the timing of energy consumption can be critical for maintaining system reliability. Second, emissions associated with the electric power sector that are harmful to the environment or human health are not constant over time, but vary as a function of total system demand and the nature of the installed generation infrastructure (Siler-Evans, Azevedo, & Morgan, 2012). Energy savings from any given residential efficiency intervention happens on the margin, and the resulting emissions avoided associated with reduced electricity use at any time are the emissions from the marginal generation facility.

Chapter 4 presents a model for projecting fuel use in the transportation sector in light-duty vehicles (LDVs). The relevant regulatory intervention in this arena is the Corporate Average Fuel Economy (CAFE) standard, issued nationally by the National Highway Safety Administration (NHTSA). CAFE standards are the minimum sales weighted average fuel economy levels that all major auto manufacturers are required to meet in a given year. The model pairs the CAFE standards that have been announced through 2022 with a detailed projection of US population from the Census and historical vehicle sales fuel economy levels to estimate future demand for new vehicles, and ultimately the total fuel demand from all on-road LDVs. Since LDVs are durable goods, once they are sold they often stay in service for many years. However, they are only subject to CAFE requirements in the year that they are sold. Thus, the various “vintages” of LDVs that remain on the road introduce significant lag between the introduction of a new CAFE standard and achieved aggregate on-road fuel economy. As a result, much of the demand for fuel is locked-in in the short-term. Understanding the dynamics of that demand is useful in the context of policies that affect fuel supply.

Chapter 5 presents some summary conclusions and policy recommendations which follow from the analyses in the preceding three chapters. Chapter 6 lists the works cited.

CHAPTER 2: RESIDENTIAL DEMAND-SIDE MANAGEMENT LIGHTING PROGRAMS IN PENNSYLVANIA AND VERMONT.[1]

CHAPTER ABSTRACT

Demand-Side Management (DSM) programs for improving end-use electrical efficiency are increasingly being seen as an important tool by regulators and utilities in meeting future system demand requirements and as a cost-effective mechanism to reduce negative environmental and health externalities. While the ultimate energy savings impacts of many of these interventions are almost exclusively reported as point estimates, the uncertainty associated with these values is usually poorly understood. This research characterizes the uncertainty associated with residential lighting DSM programs in Vermont and Pennsylvania. We find that the range of uncertainty associated with these programs can be as high as a factor of two using standard estimation and reporting techniques, and we provide recommendations to improve the quality of these estimates without imposing burdensome requirements on DSM administrators.

SECTION 1: INTRODUCTION

Large investments in end-use energy efficiency are likely to be a necessary part of a portfolio of strategies pursued by U.S. states to meet energy efficiency resource standards (EERSs), curb emissions of greenhouse gases (GHGs), and manage criteria air pollutants (Friedrich et al., 2009, Hopper et al, 2006 and Pacala and Socolow, 2004). In many regions of the U.S., as a result of state legislative initiatives and public utilities commissions' (PUCs) rule-making, public benefit charges (PBC) have been collected in ratepayers' electric bills in order to develop demand-side management (DSM) energy efficiency programs. In 2011 the estimated total budgets for DSM

[1] A version of this chapter is being prepared for external publication as a stand-alone research paper: co-authored with H. Scott Matthews and Inês M. Lima de Azevedo

efficiency programs (which overlap with, but are distinct from, load management programs) was about $6 billion; representing more than a five-fold increase from the late 1990's (Foster et al, 2012). Goldman et al. (2012) project that spending will increase to $10.8 billion by 2025 if current policies continue. There is a strong case in support of energy efficiency programs on several fronts. First, there is a rich literature that shows that consumers do not independently invest in energy efficiency at an economically optimal level (Brown, 2001). Second, efficiency can be a cost-effective option in the context of integrated resource planning when compared with the costs associated with new generation, transmission, and distribution infrastructure (Azevedo, 2009 and Azevedo et al., 2012) – and often enjoys a greater degree of political support than locally-sited capacity additions (Whitfield et al., 2009 and Wüstenhagen et al., 2007). Finally, efficiency measures can be an effective way to reduce GHG and criteria air pollutant emissions associated with energy consumption (Siler-Evans et al., 2012). But there is considerable uncertainty associated with both the quantities that form the basis of policy outcomes and how these impacts should be valued (Heffner, 2009).

It is the uncertainty associated with energy savings estimates that motivates this work. While energy savings values from DSM interventions are generally reported exclusively as point-values, the parameters that underlie those estimates are inherently uncertain. DSM reporting by program administrators to the state-level regulatory body typically involves calculated energy savings values, expressed in units of power consumption (e.g., kWh) over the course of the reporting period (usually annually), along with programmatic expenditures. Energy savings values are calculated using prescribed algorithms for each approved technology type as defined in a "Technical Resource Manual" (TRM) which is published by the regulatory body responsible for oversight of the DSM administrator(s), (i.e., Public Utility Commissions or similar). While the parameters that are used in defining the calculation procedure that is to be used for a particular technology are usually inherently uncertain, TRM algorithms are overwhelmingly done using parameter point-estimates in order to generate a point energy savings value. This paper makes the case that the values associated with these energy savings calculations are sufficiently uncertain to warrant that the range of the realized energy impact for a given intervention be characterized by DSM administrators. The benefit of doing so from a policy-making perspective is in developing a better understanding of the range of possible realized impacts of specific DSM interventions. If, for example, a significant risk exists that a portion of a DSM program is not providing cost-effective returns or, conversely, if some DSM program has a significant up-side possibility, this could inform investment decisions in a way that simple mid-point estimates cannot. Indeed, one of the purposes of DSM reporting is (or should be) to identify those strategies that are most cost-effectively producing the intended policy outcomes. Particularly in the case in which one of the policy-objectives of a DSM program is to avoid a need for new generation or transmission infrastructure does having a more clear view of the possible energy effects of an efficiency intervention becomes especially valuable.

The type of DSM intervention considered here are case study examples of residential compact-fluorescent (CFL) lighting incentive programs in Vermont and Pennsylvania. This selection is made because lighting represents a large fraction of US energy demand (17% of residential and commercial electrical demand – EIA, 2013) and, since individual investments needed to implement more efficient lighting are generally smaller than investments in other energy end use consumer durables, lighting interventions are a large portion of the DSM program portfolio for many DSM-administrators (Nowak et al., 2011). Vermont is chosen as a case study because its energy efficiency efforts are generally considered to be among the most well-run and well-documented DSM programs in the country (Sedano, 2011). Pennsylvania is chosen because the state has less experience with this type of efficiency programs; and hopefully the findings of this analysis will provide useful guidance to Pennsylvania policy-makers, as well as those of other states. Since this analysis limits itself to a narrow-class of DSM interventions it does not characterize the uncertainty associated with all DSM programs. However the limited scope still allows for conclusions regarding the nature of DSM reporting generally and serves to illustrate the mechanisms that can be used to incorporate uncertainty characterization in DSM program reporting.

The history, intensity, and structure of DSM programs differ widely across the country as a result of state policy-making diversity (Schiller et al., 2011). A result of heterogeneity at the state policy-level is inconsistency in the methodologies employed for estimating the energy savings effects resulting from these DSM interventions, and has made comparisons between programs problematic and claims of counterfactual demand projections uncertain. Some variation in the way DSM investments are made, managed, measured, and reported in part reflects differing sets of desired policy goals.

LIGHTING DSM POLICIES IN VERMONT

In Vermont state DSM programs are operated through an Energy Efficiency Utility (EEU) called Efficiency Vermont which is managed by a third-party contractor who bids competitively in an open RFP process managed by the state Public Service Board (VT PSB, 2013). This third-party contractor (Vermont Energy Investment Corporation, or VEIC) is a non-profit entity, which has been the state's contractor since the inception of the program in its current form. VEIC undertakes efficiency programs throughout state. The state's fiscal agent is funded through a public benefit charge tariff included in the ratepayer utility bills for each of the utilities operating in Vermont. The contract has, in turn, been structured to reflect the policy objectives of the state. The policy objectives for Vermont include a focus on avoiding new generation and transmission requirements in the context of "least-cost integrated planning" as well as income-group equity, geographic targeting, and parity between residential and non-residential impacts (see Sec. 1. 30 V.S.A. §209 and §218c). As Efficiency Vermont makes investments consistent with the terms of its contract it submits invoices to the state's fiscal agent for reimbursement for those investments.

Data provided by Efficiency Vermont (2012a) on lighting projects done in 2011 indicates that nearly one million bulbs were included in 2011 prescriptive program activity, resulting in a gross energy savings[2] of about 44 GWh, split between residential and commercial/industrial applications[3]. Vermont's database includes 128 lighting product-applications[4], but four residential product-applications represent about 27 GWh of the savings; or just over 60% of all reported energy savings from lighting activity. Table 1 shows the residential lighting savings reported by VEIC from those four products in 2011.

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[2] Gross savings are the energy savings at the point of customer end-use. Net savings (which were about 51 GWh for the lighting measures discussed) account for line-losses, free-ridership and spillover factors and are calculated to represent generation capacity displaced. For simplicity, the analysis uses gross savings figures. Because each state's TRM will include differing assumptions about the factors that contribute to the difference between gross and net energy savings, gross savings are a less uncertain measure.

[3] The high majority of bulbs included in Efficiency Vermont prescriptive program activity are incentivized through coupons, rebates, or buy-down programs in which the customer is left with a non-zero remaining purchase cost. Prescriptive projects are those for which the off-the-shelf TRM calculation is appropriate, in contrast to custom energy projects that require site-specific calculations. The details of the Efficiency Vermont's estimated bulb cost and the value of the incentive provided for each bulb type is included in the TRM (17).

[4] A given product may be used by a residential or commercial end-user, and will have different TRM assumptions as a result.

Table 1: Top four products contributing to residential lighting energy savings in Vermont, 2011. Source: (Efficiency Vermont, 2012a)

Description	Savings per bulb (kWh)	Quantity Incentivized (# of bulbs)	Total (MWh)	% of lighting energy savings
Standard CFL Direct Installation	27	18,000	500	1%
Residential Standard CFL	22	301,000	6,600	15%
Specialty CFL, Small	42	205,000	8,500	19%
Specialty CFL, Large	66	170,000	11,300	26%
TOTAL			**27,000**	**61%**

Lighting DSM policies in Pennsylvania

In Pennsylvania the implementation of DSM programs in the current form has been established much more recently by Act 129, in 2008, and is managed directly by seven local electricity distribution utilities. Each of these utilities was mandated to reduce annual electricity demand within its service territory by 1% by May 2011 and by 3% by May 2013, respectively. While Act 129 is not the first policy-driven electricity efficiency program in Pennsylvania, it is the most prominent[5]. Each utility adds a public benefit charge to consumers' utility bills, with the approval of the state PUC. Also, each utility manages their DSM programs. The policy goals in PA include protecting human health, providing reliable and affordable electricity, and environmental sustainability[6]. Finally, the energy savings estimated using a TRM that is approved by the state PUC.

Of the seven distribution companies that are subject to Act 129 requirements, three have reported the number of bulbs associated with their residential lighting efficiency programs (Duquesne, 2011, PECO, 2011 and PPL, 2011). The others (all four are FirstEnergy Companies) bundle their

[5] Previous policy activity includes the Sustainable Energy Funds, which formed after restructuring in 1999 (see http://www.puc.pa.gov/utility_industry/electricity/sustainable_energy_fund.aspx) and had broadly defined goals which included improving energy efficiency as well as promoting renewable energy generation.
[6] See the text of Act 129, especially page 1 line 20 through page 2 line 15. http://www.puc.state.pa.us/electric/pdf/Act129/HB2200-Act129_Bill.pdf

residential lighting activity reporting with other types of DSM interventions (e.g., appliance rebates) and so the residential lighting portion of their reported energy savings cannot be isolated (MetEd, 2011, PENELC, 2011, PennPower, 2011 and WestPenn, 2011). For the three for which data are accessible, about 7 million bulbs were included in year 2011 program activity. PECO and PPL account for just over half of 2011 DSM spending.

The rest of this paper is organized as follows: section 2 presents the methods used to estimate the energy savings from lighting DSM in Vermont and in Pittsburgh. Section 3 provides the main results. In Section 4 we discuss the policy implications of the findings.

SECTION 2: METHODS

Three approaches are used to estimate the energy savings from lighting DSM interventions in Vermont and in Pennsylvania. Those estimates are compared with the energy savings reported by the implementing entity. The first method is an equipment stock-flow model for residential light bulbs (*"stock-flow"*). The second method involves a decomposition of the published energy impact estimate into the component data and assumptions of the TRM used by the DSM administrators in each region ("*decomposition*"). Finally, the third method is to analyze energy savings in the context of historical cost-effectiveness of the DSM programs ("*historical cost-effectiveness*"). The comparison of the estimates using these different methods is shown in Section 3.

STOCK-FLOW MODEL

The first method uses a stock flow model to estimate the turnover of the residential lighting bulbs stock over time, first assuming that there were no lighting DSM programs, and then by exogenously adding new CFL bulbs to the stock consistent with the activities of DSM programs.

To reflect the time periods over which DSM lighting programs have been active in each state we model Vermont from 2002 through 2011 and Pennsylvania for 2010 and 2011. To estimate the equipment stock in the starting period in each state we rely on two studies conducted by Navigant Consulting for the Department of Energy: Navigant (2002) provides an estimate the lighting stock of average household for the US which we assume is representative for Vermont households in 2002. Ashe et al (2012) provides a similar estimate of household lighting stock for the US in 2010, which we use as representative for Pennsylvania in 2010.

Table 2: Starting year assumptions for residential lighting equipment stock. Sources: Navigant 2002 and Ash et al. 2012.

	2002 (Vermont)			2010 (Pennsylvania)		
	All Bulbs	**Inc.**	**CFLs**	**All Bulbs**	**Inc.**	**CFLs**
Bulbs per Household	43	36	1	51	32	12
Watts per Bulb	63	63	15	46	56	16
Hours per Bulb per Day	2	1.9	2.2	1.8	1.8	1.8
Annual Energy Consumption (kWh)	1946	1573	12	1553	1170	123

Estimating a counterfactual in which no DSM lighting programs are present in these states we need to move these starting year stock estimates forward over time. We accomplish this by estimating the lifetime characteristics of these bulb types as well as the fraction of bulbs, by type, that would have been installed in the absence of a DSM program. Itron (2008) provides a report that provides some information on annual screw-based bulb sales for 2000 through 2007, which we use to estimate the relative market share of incandescent bulbs and CFLs in the absence of incentive programs for those years.

We calculate total bulb sales for each state and year in our model endogenously by estimating new bulb demand, which we calculate as the sum of the scrappage of the existing stock plus the growth in the number of sockets available in the state. Scrappage is determined according to a

Weibull distribution (Bebbington et al, 2008), with parameters specified separately for incandescents and CFLs (LEDs are not considered in this analysis). Socket population is estimated using the bulbs per household figures estimated by the two Navigant studies multiplied by US Census estimates of the number of households in each state (the 2000 Census, the 2011 American Community Survey, and a linear interpolation between those years).

Energy consumption is calculated as the number of bulbs of each type times their estimated average wattage and hours of use. For comparison to energy consumption with the DSM program, CFL sales are set equal to demand in the no DSM scenario plus the number of bulbs incentivized by the DSM program – with that incentivized quantity multiplied by a value to represent free-ridership and spillover rates. Table 3 shows key the input assumptions.

We perform multiple simulations: in a "market" simulation burnouts and new bulb demand are assigned by bulb type as described above. A "sticky socket" simulation modifies this methodology by assumption that once a consumer installs a CFL in a particular socket all future replacements in that socket remain CFL.

Table 3: Assumptions in the equipment stock-flow model

Parameter	Distribution Type	Min	Mode (Mid)	Max
Survival function '*B*': Incandescent	Triangle	1.5	2	2.5
Survival function '*B*': CFL	Triangle	6	7.5	9
Freerider Rate	Triangle	0.7	0.8	1
Spillover Rate	Triangle	1	1	1.2
CFL Baseline Sales Estimate	Uniform	85%	100%	115%

Figure 1 and Figure 2 show the results for Vermont and Pennsylvania, respectively, and for the *market* and *sticky-socket* scenarios. The lower charts in each figure show the results of a further modification in which the year-over-year difference in energy savings is calculated. This is done to create a measure that is more closely analogous to the TRM decomposition methodology, which considers the energy savings of a DSM intervention in the first full year of its operation only.

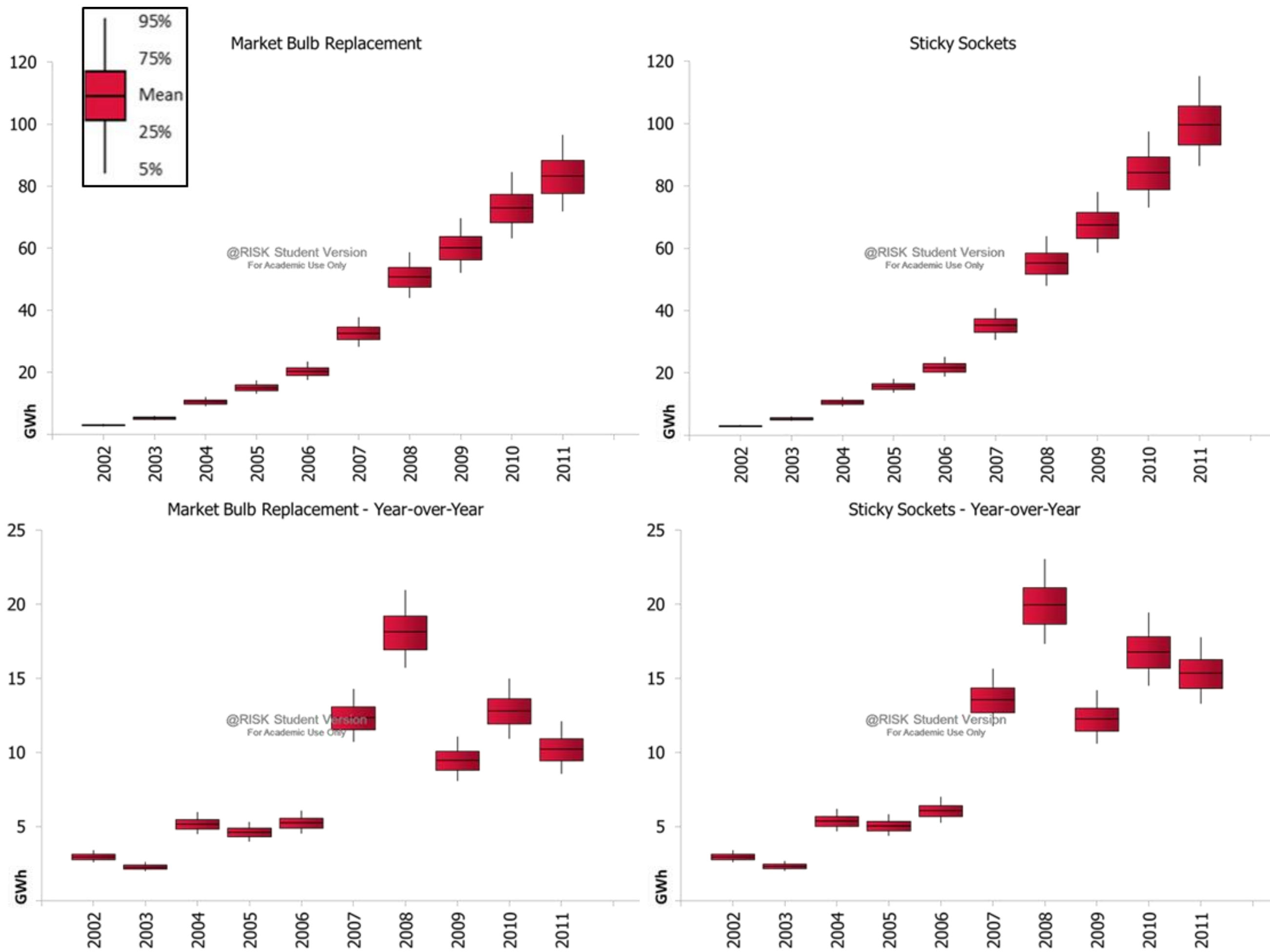

Figure 1: Equipment stock turnover model energy savings estimate with uncertainty range for Efficiency Vermont residential lighting program

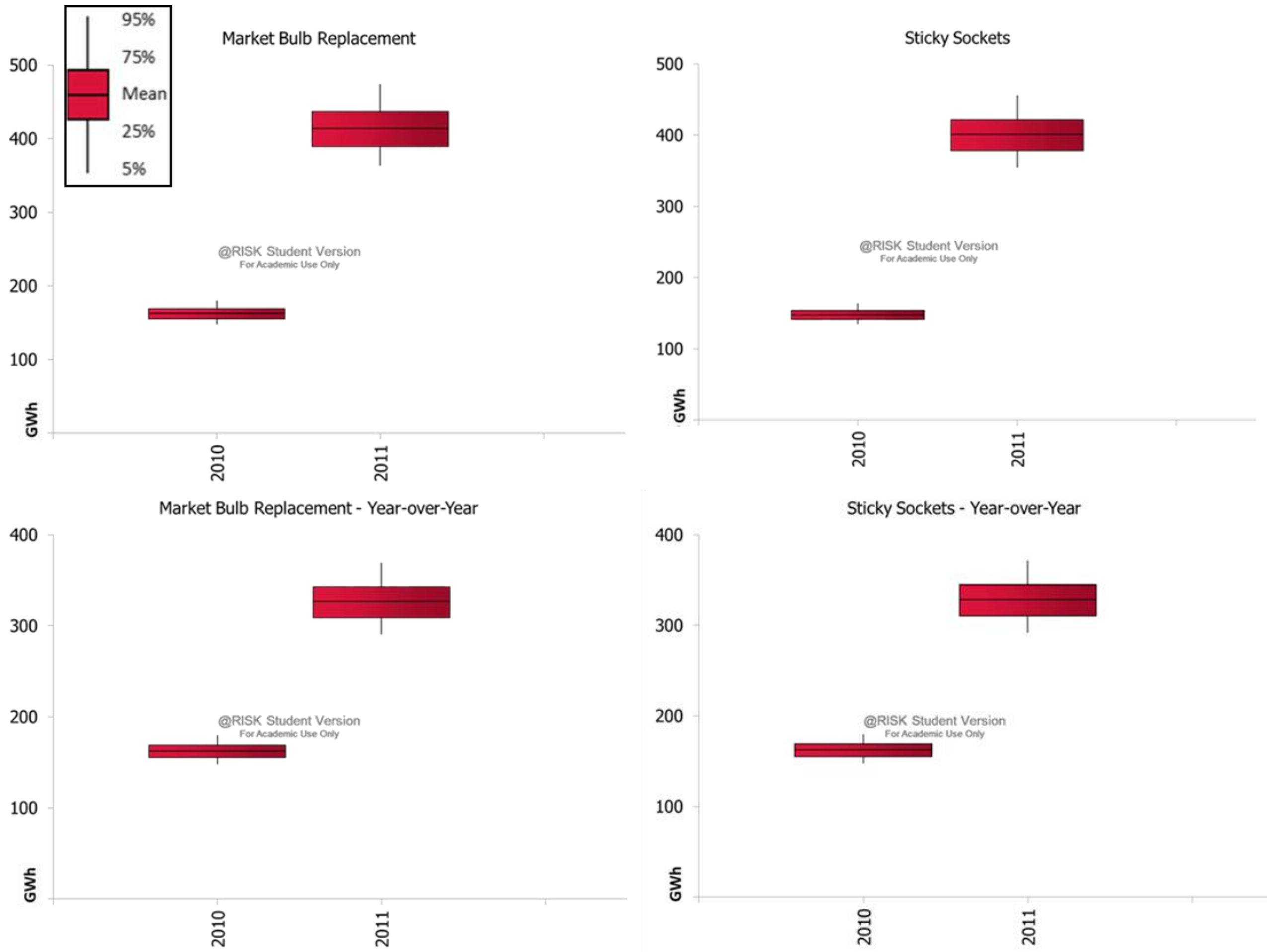

Figure 2: Equipment stock turnover model energy savings estimate with uncertainty range for Pennsylvania DSM residential lighting program

DECOMPOSITION METHOD

In the decomposition method, the energy savings are estimated using the methodology prescribed by the Technical Resource Manual, with the key difference that the parameters used in that calculation are assumed to be uncertain. Annual lighting savings per lightbulbs from DSM programs in Vermont (VT) and Pennsylvania (PA) are computed as follows (Efficiency Vermont, 2011a and PA PUC, 2012):

Method in VT's TRM: $kWh_{VT} = (\Delta Watts/1000) \times ISR \times Hours \times WHF$ **Equation 1**

Method in PA's TRM: $kWh_{PA} = ((Watts_{base} - Watts_{ee})/1000) \times ISR \times Hours$ **Equation 2**

In these equations *kWh* stands for the energy savings (in kWh) for each bulb over the first full year of use, *ISR* is the in-service rate for the bulbs, *Hours* is the number of hours per year that the bulb is used, and *WHF* is the waste-heat factor. The ISR is the proportion of bulbs that are distributed via the DSM program and that actually become installed. The WHF accounts for the cooling-load reduction that is achieved through a reduction in heat from the inefficient bulbs – for residential application however this term is set equal to one (indicating no additional energy savings gain or loss). Efficiency Vermont also includes a calculation of the loss from heating-load that is required to make up for that lost heat in winter months, but since the majority of heating in Vermont is met through non-electrical means (e.g., fuel oil) this loss is not included in the electricity savings calculations. In the Pennsylvania's equation the subscripts *base* and *ee* refer to the wattage ratings of the original bulb and the energy efficient replacement bulb, respectively[7]. This is necessary because the DSM administrator is directed by the TRM to input values for both the new bulb and the one it is replacing, whereas in the Vermont case the TRM makes an implicit assumption about the efficiency of the original bulb and can thus directly detail the wattage difference for each approved bulb type. In practice, however, it is clear from the data reported to the Pennsylvania PUC by the seven utility-operated DSM programs that common assumption has been made regarding the value of the difference of the wattage terms. Table 4 shows the TRM prescribed input assumptions for each of these parameters along with the calculated value of the wattage difference for Pennsylvania.

[7] An alternative method for calculating the change in wattage is to input the wattage of the efficiency bulb that is associated with the DSM program, and multiply by a typical efficiency factor differential to arrive at the equivalent wattage of the replaced bulb. This is the procedure used in New York (19), for example.

Table 4: TRM assumptions used in Vermont and in Pennsylvania.

Description	Per Unit Savings (kWh)	Δ Watts	ISR	Hours/year	WHF
VERMONT					
Standard CFL Direct Install	27	49.0	0.800	694	1
Residential Standard CFL	22	45.7	0.730	659	1
Specialty CFL, Small	42	43.7	0.766	1241	1
Specialty CFL, Large	66	69.9	0.766	1241	1
PENNSYLVANIA					
Residential CFL	48	52	0.84	1095	---

We perform a Monte Carlo analysis, and assume that these are values uncertain in order to recalculate the energy savings range that the Vermont and Pennsylvania residential lighting programs might have achieved in practice. Table 5 shows the range of values that we have assumed for each of these parameters along with the source from which each value was drawn. These values provide conservative, central and aggressive figures for different quantities of interest. The values are from different studies or guidelines produced in that same region.

Table 5: Values used in TRM decomposition calculations

	Conservative	Central	Aggressive
$Watts_{base}$	40 (assumed)	60 (assumed)	100 (assumed)
$Watts_{ee}$	13 (Energy Star, 2012)	17 (Energy Star, 2012)	25 (Energy Star, 2012)
Δ Watts	27 (calculated)	43 (calculated)	75 (calculated)
ISR	0.73 (Efficiency Vermont, 2011a)	0.87 (PA PUC, 2012)	1 (assumed)
Hours	657 (Ashe et al, 2012)	1004 (NEEP, 2012)	1460 (assumed)
WHF	1.00 (Efficiency Vermont, 2011a)	1.05 (assumed)	1.14 (VEIC, 2011)
Energy Savings (kWh)	13	40	125

Figure 3 shows the result of a Monte Carlo simulation using the number of bulbs that are included in Vermont's 2011 DSM program activity, and the values shown in Table 5, in which each of the uncertain parameters is defined using a triangular distribution. Figure 4 does the same using the number of bulbs included in Pennsylvania's 2011 DSM activity. Both figures also identify values of interest in each distribution.

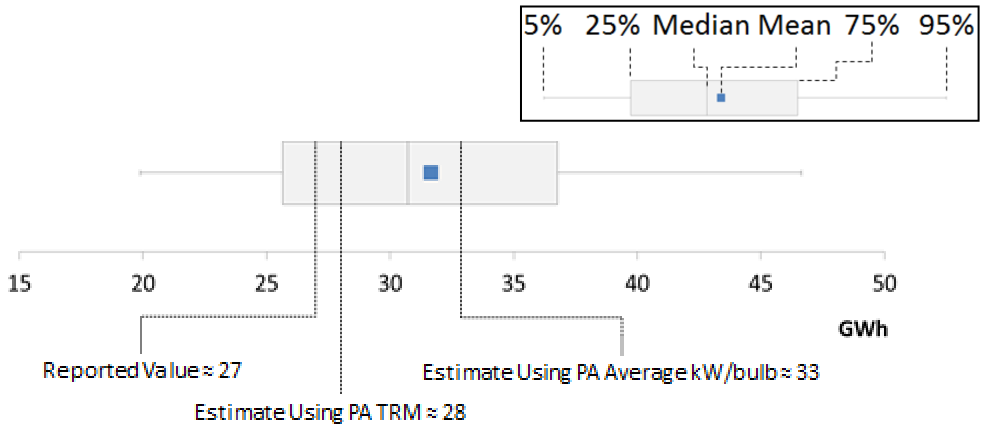

Figure 3: Monte Carlo distribution of Efficiency Vermont's residential lighting energy savings using uncertain TRM input values compared to calculated energy savings results

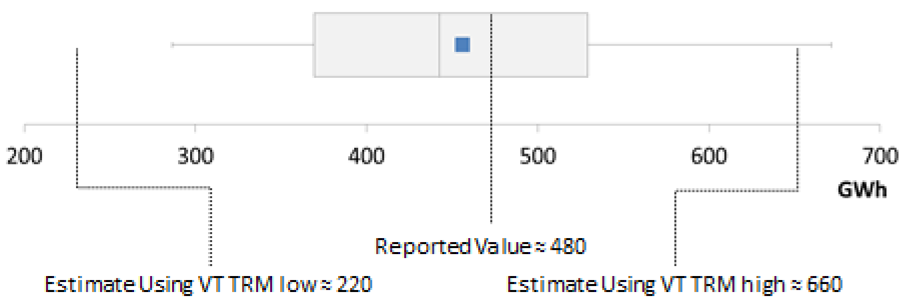

Figure 4: Monte Carlo distribution of Pennsylvania's residential lighting DSM energy savings using uncertain TRM input values compared to calculated energy savings results

As they originate from the same set of uncertain parameters, Figures 1 and 2 are identical distributions that vary only by a multiple that reflects the difference in the size of the two DSM programs. This distribution shows that the estimated energy impact can vary by a factor of two using the assumptions shown in Table 5 and a 90% confidence interval.

COST-EFFECTIVENESS METHOD

This method makes the coarse assumption that the cost-effectiveness of the Vermont and Pennsylvania residential lighting DSM programs, expressed strictly in terms of energy savings per dollar invested (that is, ignoring the value of other policy outcomes), can be compared to the cost-effectiveness achieved by other efficiency programs, as reported in the literature. Making this comparison allows us to estimate the energy savings of these DSM programs had they achieved the same level of cost-effectiveness. Cost-effectiveness is a useful guide to policy-makers in determining if a given program is providing benefits sufficient to justify the costs in the context of other policy options that are available. By comparing the cost-effectiveness of these DSM programs to that achieved by other efficiency programs (as well as to the price of power) we can both find if these programs are a worthwhile investment and, if they are, the tolerance for uncertainty in the benefits they provide that we should be willing to accept. That is, by comparing the reported energy savings to the energy savings achieved at different benchmark levels of cost-effectiveness we can find how much "slack" we have before we would be concerned (at some level of confidence) that the program may not be providing a worthwhile value.

Efficiency Vermont's *Annual Reports* (2004-2012) provide detail on the energy savings and expenditures of Vermont's DSM programs on an annual basis. We compare these values to the cost effectiveness estimated by Arimura et al (2011) and Friederich et al (2009) which found values of 5 cents/kWh and between 1.6 to 3.3 cents/kWh, respectively, expressed in 2007 dollars. Figure 5 compares the energy savings that would have been achieved in Vermont with these levels of cost-effectiveness with the reported energy savings and with a cost-effectiveness equivalent to the retail price of power in the state.

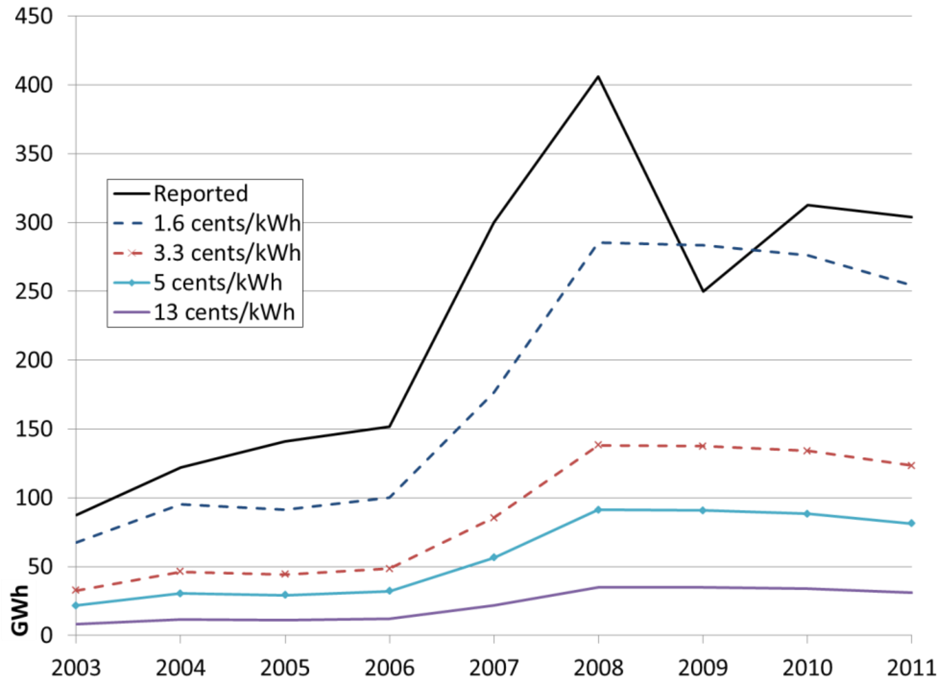

Figure 5: The reported lifetime energy savings of Efficiency Vermont's residential lighting program in comparison with benchmark cost-effectiveness values and the approximate retail price of power in 2010 in VT (13 cents/kWh), over time.

Figure 5 shows that Efficiency Vermont's residential lighting program, as reported, has consistently outperformed the reported typical cost-effectiveness values in the literature. As a point of comparison, Efficiency Vermont's average (kWh weighted) reported cost effectiveness for the period of 2003-2011 is about 2.4 cents per kWh – the residential lighting portion of their programmatic activities were substantially more cost-effective (in terms of energy savings only, neglecting other policy outcomes of interest) than the average cost-effectiveness of their other DSM activities. Because these values are calculated using the expected lifetime energy savings of the DSM interventions as the numerator, they are not directly comparable to the TRM-based calculations, which use the first full year of energy savings only. Figure 6 reports the one-year energy claims of Efficiency Vermont's residential lighting programs and compares those values to a subset of the values reported in Figure 5.

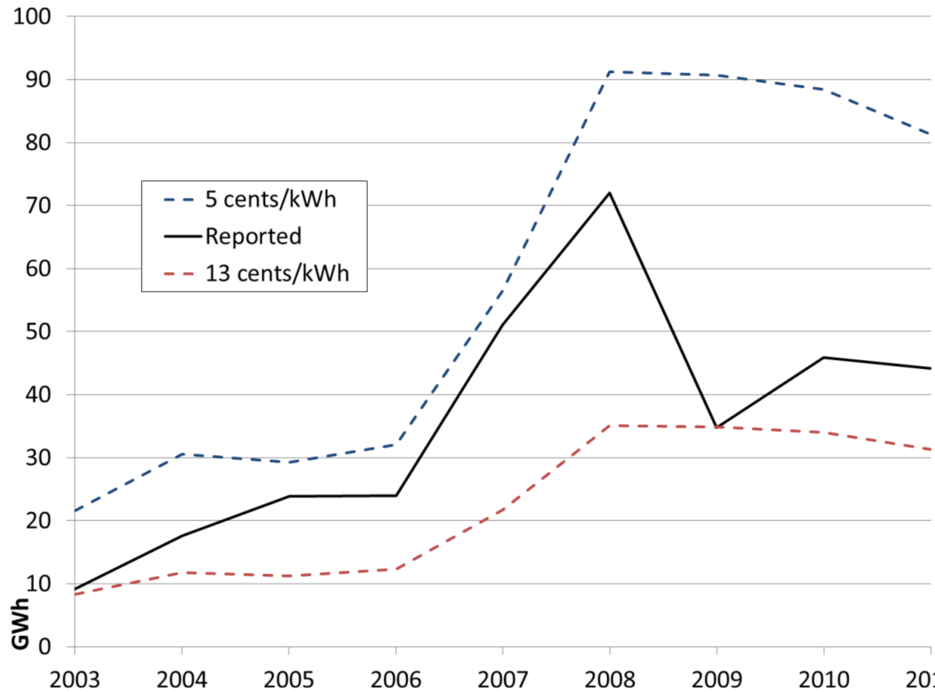

Figure 6: The reported first-year energy savings of Efficiency Vermont's residential lighting program in comparison with a benchmark cost-effectiveness value and the approximate retail price of power in 2010 in VT, over time.

Figure 5 and Figure 6 give some insight for policy-makers who need to understand if these DSM efforts are worthwhile. If we understand that reported energy savings claims are uncertain, we might wonder if we are running a risk of funding a DSM program that is actually not providing net positive social value. Figure 5 suggests that the energy savings reported from residential lighting programs would have to have been over-reported by a factor of six in 2011 to fail a resource-cost test based strictly on the price of power in the state.

In PA, lifetime energy savings estimates are not reported. As an estimate of the cost-effectiveness of the residential lighting programs, it is assumed that the utilities that report residential lighting energy savings separately are representative in first-year energy saving cost-effectiveness terms for the state. Using data from program year two reports, we calculate a one-year energy savings cost-effectiveness for these utilities of 5.2 cents per kWh (Duquesne, 2011 and PPL, 2011). For comparison, EIA (2012a) reports an average residential retail price of electricity of 12.7 cents per kWh in PA in 2010.

SECTION 3: CONTRASTING THE FINDINGS FROM EACH METHOD

Figure 7 and Figure 8 combine the reported values by Vermont and Pennsylvania in 2011 with estimated energy savings from lighting programs, and the findings from each of the three methods described above. The range shown for cost-effectiveness represents 2.4 and 5 cents per kWh for the high and low energy savings estimates, respectively. The bottom-up methodologies that allow for the cumulative effects of past investments show significantly higher energy savings values than the first-year only methodologies.

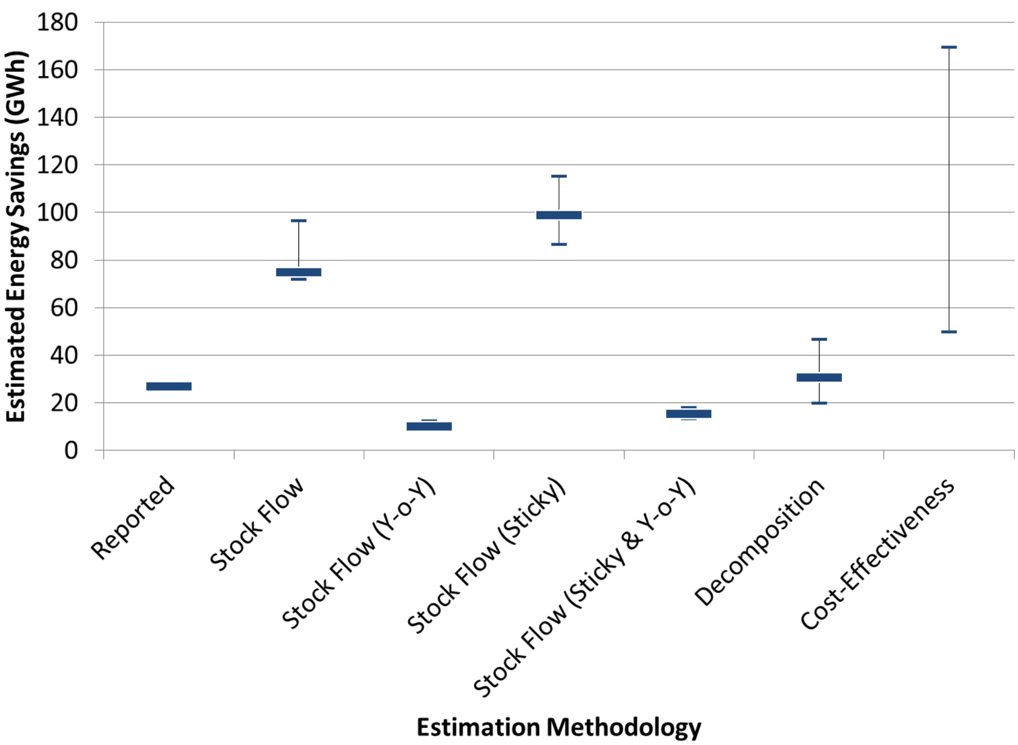

Figure 7: Range of estimated energy effects for selected residential lighting measures by Efficiency Vermont in 2011, by estimation methodology

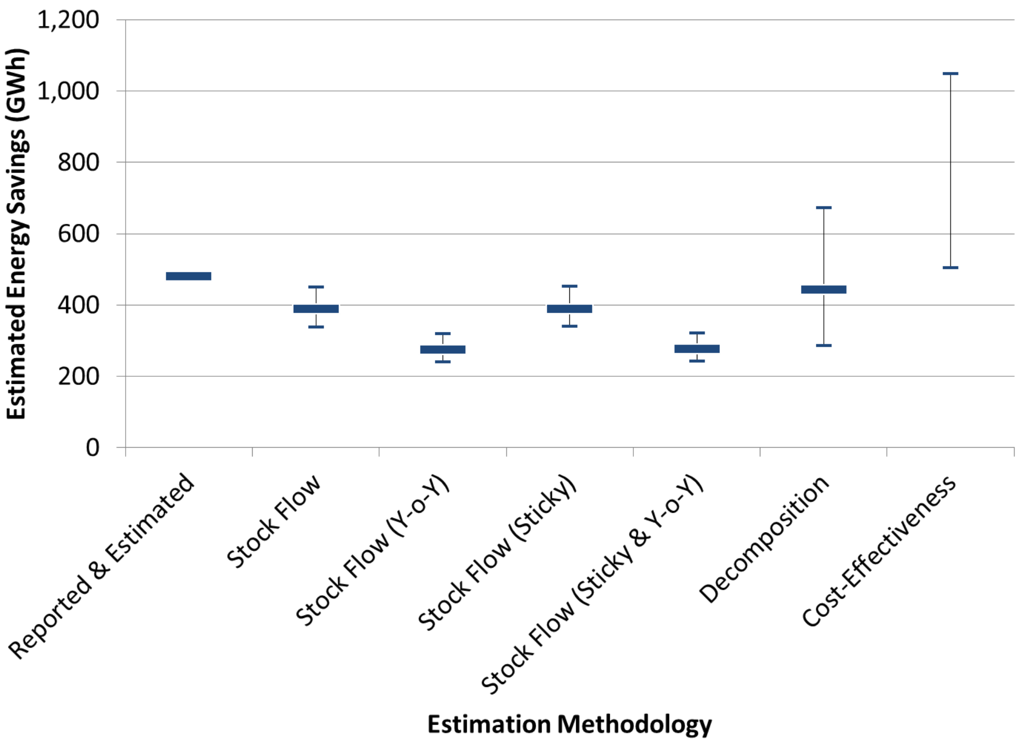

Figure 8: Range of estimated first-year energy effects for residential lighting measures by Pennsylvania utilities in 2011, by estimation methodology

A comparison of the stock flow models between the two states shows the effect of a prolonged programmatic effort – the annual energy savings estimated from previous years' investments contributes significantly to the annual energy savings that VT can expect. Pennsylvania's relatively new program is only beginning to build up a stock of efficiency investments that will continue to contribute to reduced demand over that stock's lifetime. The exercise of employing these different methodologies, and comparing their results, leads to some recommendations for ongoing reporting for DSM programs in general.

SECTION 4: DISCUSSION AND POLICY RECOMMENDATIONS

Energy efficiency has been one of the key strategies used by states to reduce the pace of demand growth in a cost-effective way. Much effort and resources has been devoted in designing and implementing energy efficiency programs, and a large proportion of those programs have focused on more efficient lighting technologies. However, less attention and effort has been provided to evaluation and monitoring of the effects of programmatic activity. In particular, there are uncertainties associated with the technologies that compose the stock of equipment, the new technologies selected by consumers, usage patterns and so forth. In this work, we implemented three methods that could help decisions makers and program managers characterize the uncertainty associated with lighting programs in a region. We provide two case studies as an application of those methods.

We show that assumption about how long the efficiency measure is in place has a key effect on the estimated savings in a given year. In many of the reporting mechanisms reviewed, the value of ongoing energy savings that accrue over time is not considered. Reporting energy savings values as a stream of expected (or achieved) energy savings would be useful both for understanding the cost-effectiveness achieved by a given efficiency investment as well as for better characterizing baseline conditions for future efficiency interventions.

To the extent possible, reporting DSM program information at the technology and end-use level would provide a clearer picture of the effects of energy efficiency programs and better guidance for how to deploy future scare public resources. This information is lacking in the public domain. For example, utilities do report to the Energy Information Administration their annual spending and savings on demand side programs (in form 861), but they do not include information by technology or measure type. Utilities do compile such estimates for their PUC, but those are generally only available in reports and documents as opposed to datasets that third parties could use for further evaluation and for research. Disaggregated reporting enables a better understanding of the types of programs that are achieving policy objectives most effectively. In the PA example it was not possible to get an accurate picture of residential lighting efforts in the state due to the lack of detail in the publicly available reports to the state PUC. As described above, one rationale for DSM reporting is the identification of the interventions that cost-effectively produce the intended policy-outcomes. While some program types may inherently mix technology-types in a way that disallows straight-forward disaggregation in this way, it does not seem likely that doing so in this case would be prohibitively burdensome.

TRM calculation procedures should incorporate the inherent uncertainty underlying the assumed input parameters. This can be done by incorporating, in the TRM, ranges for the parameters that DSM operators are to employ in making energy savings calculations and coupling that with a requirement to report high, low, and mid-points of the energy savings estimates. The additional burden on DSM operators would be minimal; it would simply require an extra column or two in the calculation spreadsheet to incorporate the specified range of the input parameters and the resulting range of energy savings estimates. In addition to helping policy-makers to better understand the range of possible realized impacts of the DSM programs, it also can help to identify those factors that most contribute to uncertainty in these outcomes (Messenger et al, 2010) and, in so doing, better direct future research efforts.

A useful complement to TRM estimation methodologies in the residential-sector would be in the form of cooperation from retailers and manufacturers in providing sales estimates by model of energy-intensive products. Trade concerns would have to be adequately addressed in data handling by state regulators. While the data would necessarily be an imperfect proxy for the installed equipment stock in the state such data would allow a better characterization of baseline conditions when considering new DSM program interventions. It would also provide an alternative mechanism for estimating energy-use changes in the state by enabling cross-border comparisons to test the efficacy of differing policy régimes.

Finally, state TRMs should reflect the full suite of policy outcomes of interest to the state. Energy savings and demand reduction are already included but other outcomes typically are not. If, for example, emissions avoided are an outcome of interest to the state the TRM should also specify a methodology for estimating those effects. Some policy outcomes might be difficult to quantify in this way but, uncertainty notwithstanding, expressing outcomes in energy terms exclusively can result in a cost-effectiveness calculation that incorrectly undervalues the public benefit of DSM programs.

The analysis above demonstrates the uncertainty associated with DSM energy savings claims using residential lighting interventions in Vermont and Pennsylvania as an illustrative example. This particular example was selected due to the relatively straightforward nature of the intervention; other, more complex, interventions can be expected to have uncertainty associated with the energy savings calculation that is more difficult to characterize. The uncertainty in the amount of energy demand avoided is important in its own right for regulators and utility operators in the context of resource planning. Large overall uncertainty in the amount of demand that can be avoided via DSM interventions can necessitate additional investment to ensure that supply is adequate – this is particularly critical once the timing of the efficiency intervention is considered and the effects of the load profile for the region are included.

Acknowledgments for Chapter 2

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Appendices to Chapter 2

Appendix A: Pennsylvania Bulb Count Estimation Methodology

The three utilities that show energy savings from residential lighting separately (Duquesne, PECO, and PPL) appear to report higher levels of energy savings from residential lighting as a fraction of total DSM activity than do the four utilities that do not separately report those values (the FirstEnergy Companies – MetEd, PENELC, PennPower, and WestPenn). For PPL, residential lighting energy savings represented about 32% of total energy savings claimed for program year two and for PECO the residential lighting share of reported energy savings is about 26% and for Duquesne the value is 31% (Duquesne, 2011, PECO, 2011 and PPL, 2011). The weighted average of the programs which contain residential lighting activities for the other four utilities is about 23% - since these other four utilities combine reporting of residential lighting with other residential efficiency activity, the residential lighting portion for these utilities is necessarily lower.

For the FirstEnergy Companies residential lighting is combined under a category labeled "Residential Energy Efficient Products Program" (EE Products) which also includes appliance and water heater rebates. To estimate the fraction of savings under this program that are attributable to residential lighting, an assumption is made that this fraction is roughly similar to the weighted average energy savings that residential lighting contributes to the sum of residential lighting reported energy savings plus that of appliances for the three utilities for which the disaggregated data are available.

Table 6: Residential lighting DSM reported energy savings as a fraction of residential lighting plus residential appliance rebate programs for three Pennsylvania utilities[8]

	Lighting	Appliances	Fraction Lighting of Sum
PPL	146,000	24,000	86%
PECO	189,000	26,000	88%
Duquesne	49,000	4,000	93%
		Weighted Average	**88%**

The three utilities that report residential lighting separately each use a value of energy savings per bulb of about 48 kWh/year. Due to the uniformity of the factor employed by these three utilities (and despite the fact that this does not seem to match the value prescribed by the state TRM) this factor is assumed to be used by the FirstEnergy Companies as well. This allows an estimate of the number of bulbs that the FirstEnergy Companies included in their DSM programs

[8] Table values do not sum due to rounding. Duquesne reports energy savings estimates at the generator level (net savings), including a line loss assumption of 7%. This is removed in the estimates made here for consistency with the reported values from the other utilities.

by first estimating the energy savings using the factor described above, and dividing by the assumed energy savings per bulb.

Table 7: Estimated bulb count for the FirstEnergy Companies for Pennsylvania Act 129 program year two and sum of total estimated CFL bulbs for all seven utilities in Pennsylvania for program year two

	EE Products (MWh)	Lighting (MWh)	Bulb Count (#)
MetEd	34,678	30,429	633,944
PENELC	35,279	30,957	644,931
PennPower	15,555	13,649	284,359
WestPenn	28,849	25,314	527,385
FirstEnergy Companies Subtotal		100,350	2,090,618
PPL		146,000	3,066,236
PECO		189,248	3,965,086
Duquesne		49,097	1,103,170
	Estimated Total		**10,000,000**

Because this is an estimation methodology, and does not represent values reported by the utilities, an order of magnitude value of 10 million will be used as the estimated number of bulbs in Pennsylvania under Act 129 for program year two. The same estimation procedure is used to estimate the number of bulbs in program year one. In this year, PECO, PPL and WestPenn reported residential lighting separately – and total DSM spending was much lower than in program year 2 as programs were still ramping up (Duquesne, 2010, MetEd, 2010, PECO, 2010, PENELC, 2010, PennPower, 2010, PPL, 2010 and WestPenn, 2010). The estimated CFL bulb count for program year one is 4 million.

APPENDIX B: DESCRIPTION OF FOURTH POTENTIAL METHODOLOGY AND WHY IT HAS BEEN EXCLUDED

A fourth potential methodology to estimate the energy savings associated with DSM programs would be to attempt to detect a change in aggregate state electricity demand consistent with the published estimate for energy savings by the DSM program. This approach would employ an econometric time-series multivariate regression analysis, incorporating predictors of electricity demand for the region. This approach would follow in style to that employed by (Parfomak and Lave, 1996 and Auffhammer et al, 2008), but would be severely restricted in this analysis due to data limitations. For Vermont, there is only one observation in each year. In Pennsylvania there are seven observations in each of two years. Expanding the scope of this analysis to include more observations (like in the work of those cited here) would allow this type of estimation to be included. In doing so, care will be needed in including adequate predictors of system demand in the model formulation. The predictor of interest in the model will be a term that consists of the annual energy efficiency estimates published by the DSM administrators. Finding a coefficient that is not statistically distinguishable from one will suggest that the true value of energy saved by the program corresponds to the published values (and uncertain according to the confidence interval associated with that coefficient). A slightly modified approach would be to exclude the vector of published efficiency savings estimates and test if the level of demand predicted by the model is equivalent to the observed demand plus the savings estimate.

CHAPTER 3: HOUSEHOLD ENERGY CONSUMPTION EFFECTS OF PG&E'S ELECTRICAL EFFICIENCY REBATE PROGRAM.[9]

CHAPTER ABSTRACT

Do rebate programs for residential energy efficiency lead to lower electricity consumption? To move towards sustainable, low-carbon, and affordable energy systems in the U.S., energy efficiency is likely needed to play a central role. That will require robust, large-scale programs that deliver the intended savings. With the roll-out of smart meter programs, utilities and policy makers have unprecedented data to evaluate the effects associated with energy efficiency programs, and continued careful of energy efficiency and demand-side programs continues to be needed. Using an unbalanced panel of smart-meter data from a sample of approximately 30,000 households in PG&E's service territory from 2008 to 2011, complemented with demand-side management and energy efficiency program participation, and weather information, we assessed the effect of rebates for household electrical efficiency improvements on household electricity consumption. We find that participation in the efficiency rebate program leads to an average increase in household electricity consumption of about 7%. We suspect that the reason is largely a result of the majority of rebate program eligibility not being contingent on equipment scrappage or recycling; and thus the program is likely behaving as an equipment subsidy program leading to additional household energy services for participants rather than maintaining the same level of household energy service with higher energy efficiency. These results strongly suggest that systematic effort must be made to pretest programs to examine whether households act as expected by program planners, and that continued evaluation of energy efficiency and demand-side management programs is needed.

[9] A version of this chapter is being prepared for external publication as a stand-alone research paper: co-authored with Inês M. Lima de Azevedo.

SECTION 1: INTRODUCTION

In the United States, the residential sector accounts for about 37% of total electricity consumption (EIA, 2013), and about 15% of greenhouse gas emissions (GHG) (WRI, 2008). Several energy efficiency strategies are available to provide the same or improved level of energy services while using less energy. Indeed, several bottom-up engineering-economic studies identify the large potential of energy efficiency in the residential sector (NRC, 2010; Rubin, et al., 1992; McKinsey, 2007; Brown et al., 1998; Crabtree, 2008; Nadel, Shipley, & Elliott, 2004; Meier, 1982; Blumstein & Stoft, 1995; Rosenfeld et al., 1991; Rosenfeld et al., 1993; Jackson, 1995; Rosenfeld, 1999; Koomey et al., 1991; Brown et al., 2008; IWG, 1997; IWG, 2000; NAS, 1992; OTA, 1991; Tellus, 1997; Koomey, 1991; Ürge-Vorsatz et al., 2009; Azevedo et al., 2013; Brown & Levine, 1997; Goldstein, 2008; Rufo & Coito, 2002; McKinsey, 2009), including many that identify large energy savings potential at zero or negative net cost to the end user.

Energy efficiency improvements can also be a cost-effective option in the context of integrated resource planning compared against the costs associated with new generation, transmission, and distribution infrastructure (Azevedo et al., 2013) and can be an effective way to reduce GHG and criteria air pollutant emissions associated with energy consumption (Siler-Evans, Azevedo, & Morgan, 2012). Indeed, nowadays some markets allow efficiency to bid directly against new generation in forward capacity markets (Jenkins, Neme, & Enterline, 2011) and the EPA Clean Power Plan under section 111d of the Clean Air Act includes demand-side efficiency as one of its four “building blocks” for setting state GHG targets (EPA, 2014).

Most traditional engineering-economic analyses of residential energy efficiency treat energy as a commodity using the assumptions of a standard microeconomics approach, even though it has long been recognized that behavioral factors influence energy use and efficiency efforts (Brown, 2001; Anderson & Claxton, 1982; Golove & Eto, 1996; Gillingham, Newell, & Palmer, 2009; Seligman, Darley, & Becker, 1977; Lutzenhiser, 1993). Academics have recently begun placing a greater emphasis on estimating the potential of these social and psychological contributions to reducing energy consumption and associated emissions (Lutzenhiser et al., 2009; Diets et al., 2009; Moezzi et al., 2009). While behavioral approaches can be used to achieve reductions in energy consumption, neglecting their consideration in program design can lead to mixed, or counterproductive, results (Wasi & Carson, 2011; Davis, Fuchs, & Gertler, 2012).

Section 2: Data Description

In this work we use an unbalanced panel of smart-meter data from a sample of approximately 30,000 households in PG&E's service territory from 2008 to 2011, complemented with demand-side management and energy efficiency program participation, and weather information to understand the effect of rebates for household electrical efficiency improvements on household electricity consumption.

Smart Meter Program and Sample Data

Households in the sample used for the analysis were selected by PG&E to include a random selection of account holders from each of the three climate zones covered by PG&E territory. Access to this sample data was facilitated by the Wharton Customer Analytics Initiative through a competitive proposal. The purpose of this process is to restrict access to the dataset to bona-fide academic researchers and to serve as an additional layer of security to protect the privacy of the customer data. As a consequence, the data are not made publicly available. PG&E began installing smart-meters in 2008 in a gradual roll-out across its service territory. The electricity consumption data is collected by the smart-meters on 15-minute interval energy readings, measured in kWh, which we aggregated to daily electricity consumption. Readings for a given household are only available once the smart-meter is installed, resulting in an unbalanced panel of observations. In Figure 9, we show the rollout of smart-meters by date of first reading for households in the sample in the data. The rollout of total smart meters over time by PG&E follows closely the rollout from the sample data provided by PG&E.

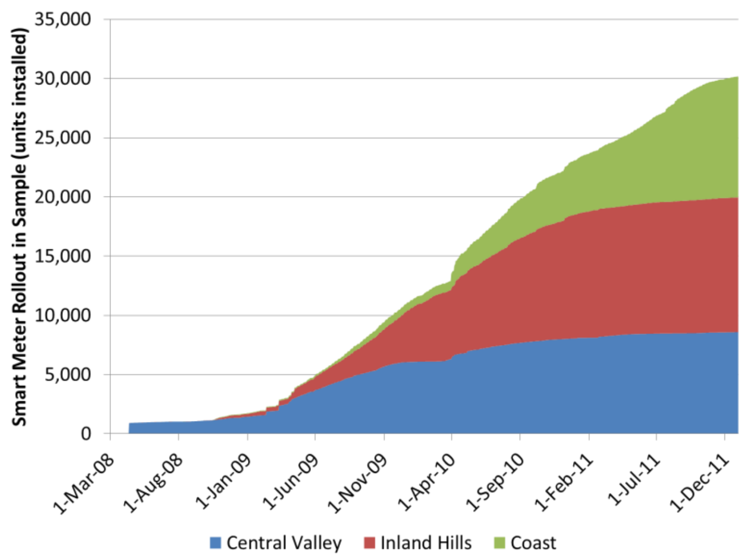

Figure 9: Smart meter rollout in PG&E, March 1, 2008 to December 31, 2011. The different colors correspond to number of smart meters in different regions (Central Valley, Inland Hills, and Coast).

In PG&E's program, smart-meters communicate high-time resolution (15 minute or 1 hour interval) energy consumption data back to the utility. That information is not displayed to the consumer. However, PG&E did develop a web portal through which customers could access detailed energy consumption data. The use of this portal has been limited, with 86% of households in the sample not logging in even once in 2011, and therefore we assume that the availability and use of the webportal had no influence in patterns of electricity consumption.

There was no option to allow customers to opt-out of having a smart meter installed over the period of the data set. There were no dropouts in the program other than for households in which the customer moved. Households are identified by a service point id (for the location) and an account id (for the customer). Selection for inclusion in this sample dataset was done by account id. If a customer moved from one service point id to another location served by PG&E with a smart meter installed, they remained in the sample dataset, but with a different service point id associated with the account from that date forward. If a customer moved out of the PG&E territory, that customer's data would stop at that point (and not be replaced by the new occupants at that service point id, if any).

The smart-meter energy data readings are associated with households via "service point id" numbers which are unique to each meter. Efficiency rebate program participation is associated with households via "service agreement id" numbers which are unique to service contract and additional program participation is associated with households via "account id" numbers which are unique to the individual within the household (e.g., the head of household). PG&E provided in the dataset a data table by which associations between the id numbers can be made. PG&E's selection for inclusion in the sample of approximately 30,000 households of this data set was determined by account id. By this selection design the data follows an account holder as they move from one household location to another. When an account holder moves out of a smart meter location, the data from that service point id ceases to be reported in the dataset. If the account holder moves to another location with a smart meter, that new service point id becomes active in the data set. In no cases was a service point id associated with one account id and then subsequently associated with another account id in the sample of the data set. All of the id numbers included in the data set as provided by PG&E were pseudo ids, masked for privacy such that they cannot be matched with actual customer account numbers or personally identifying information.

Table 8 provides the summary statistics for the neighborhoods of the households in the sample. While the smart meter data set did not include much demographic information, we complemented it with median Census Block information for each of the Census Blocks in the sample.

Table 8: Summary statistics for neighborhoods of households in the sample, overall and by region from March 1, 2008 to December 31, 2011.

	Central Valley	Inland Hills	Coast	Overall
Median Median Home Value*	281,500	586,400	597,200	479,100
Median Median Income*	51,759	78,542	63,373	65,625
Median % Renters	34	32	51	38
Median % Poor	12	6	9	8
Median % w/ Bachelors (or higher)	17	38	40	32
% of households applying for 1 or more rebates	7.7	11.3	8.3	9.2
Number of households	8,597	11,391	10,217	30,426

* These values are medians from our sample of Census Block neighborhood medians. These values are top-coded by the US Census at $1M and $250k, respectively.

Figure 10 shows the different climate zones in the PG&E territory. PG&E randomly selected approximately 10,000 households from each of the climate zone which are used in our analysis. Figure 11 shows seasonal trends in household electricity consumption by climate zone. The prevailing seasonal weather patterns for hot summers in the central valley can be seen in the sharp increase in demand in those months for that region, while the coastal region has comparably flat seasonal demand corresponding with its more temperate climate.

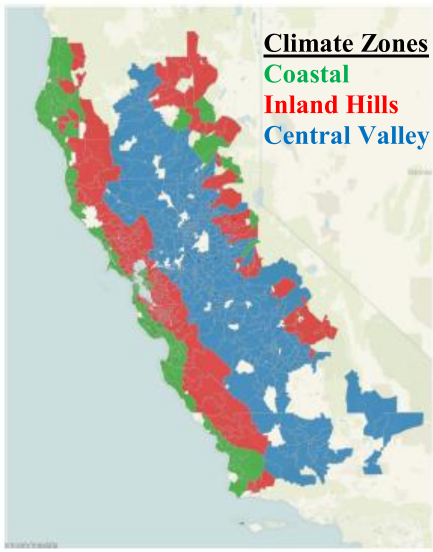

Figure 10: Climate zones in the PG&E service territory. PG&E randomly selected approximately 10,000 households from each of the climate zone to construct the sample. (Map provided by, and reproduced with the permission of, WCAI)

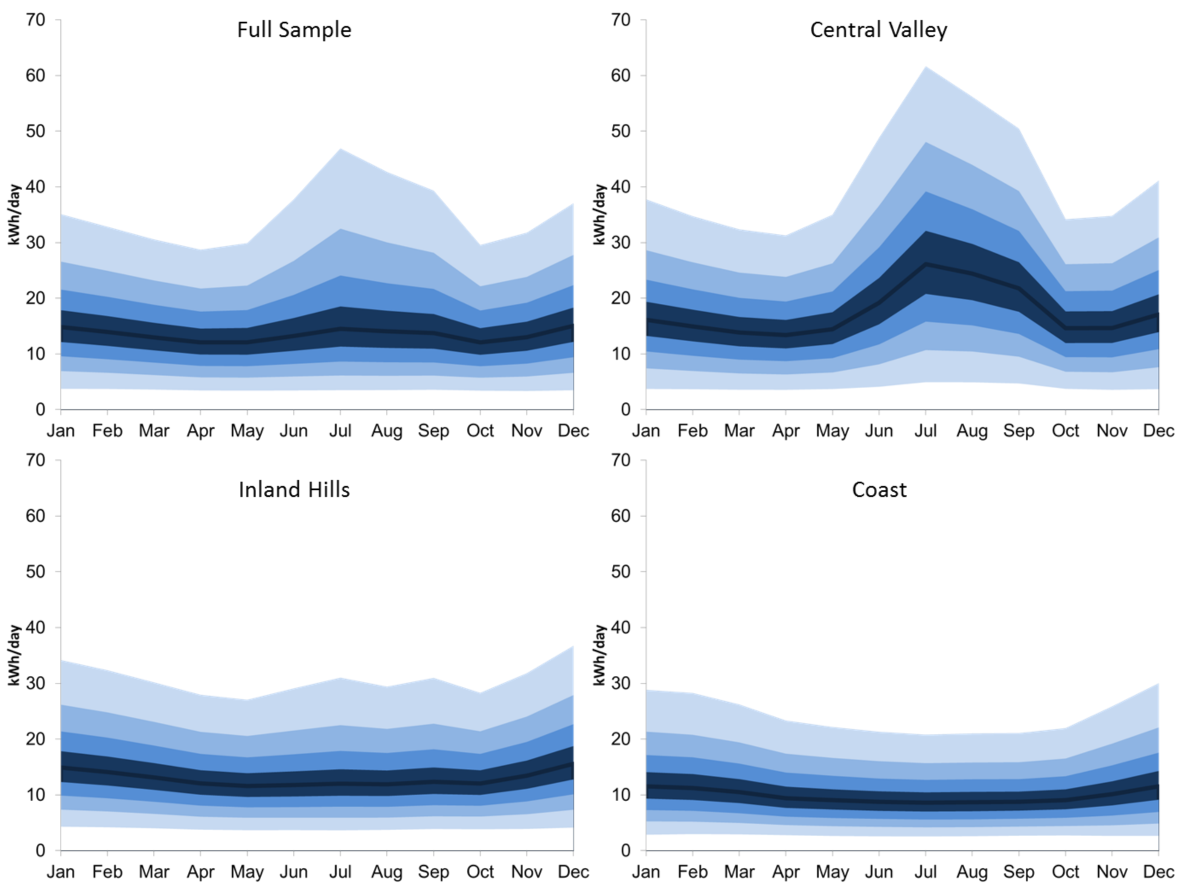

Figure 11: 10th to 90th percentiles of daily household electricity consumption shaded by decile, by Climate zone and month

ENERGY EFFICIENCY AND DEMAND SIDE MANAGEMENT PROGRAMS

One of the primary mechanisms for improving residential demand-side energy efficiency is for a local utility, an energy service company, or a similar entity (Sedano, 2011) to offer rebates to consumers following the purchase of approved energy-efficient household appliances. We analyze this type of demand-side efficiency program using a smart-meter dataset from Pacific Gas & Electric (PG&E), a large California utility. PG&E randomly sampled about 10,000 households from each of the three climate zones. We combine daily smart-meters readings for this unbalanced sample of approximately 30,000 customers with weather data and household participation in different efficiency and other PG&E programs to estimate the effect of the efficiency rebate program. From the sample of 30,349 households, 2,768 households applied for at least one rebate over the period of our observations.

During the period of this analysis, in addition to the rebate program, PG&E had several other demand side management (DSM) programs under way. Key programs that were under way during the period of observation include the Balanced Payment Plan (BPP), California Alternative Rates for Energy (CARE), Climate Smart, Direct Access, Smart AC, and Smart Rate. The BPP program provides a bill smoothing service, in which PG&E calculates the household's average monthly utility bill and the customer pays a flat amount for each monthly billing cycle. This value is an average annualized value, and this value is updated not more frequently than once every four months. The CARE program provides subsidies to household's monthly energy bills based on income and occupant criteria. Climate Smart is a program in which households can voluntarily opt-in to purchasing carbon-offsets through PG&E with their monthly utility bill. The Direct Access program allows customers to purchase their electricity from alternative (non-

PG&E) power providers, using PG&E as the distribution company. New customers have not been able to join the Direct Access program since the California energy crisis in 2001, though existing customers have been able to remain in the program. The Smart AC program allows customers to voluntarily opt-in to a central air-conditioning curtailment program that operates during peak-load events during the summer cooling season and customers are incentivized to join with a one-time $50 payment from PG&E. PG&E then installs a device on the cooling unit that allows PG&E to cycle the unit off for up to 15 of every 30 minutes during peak load events. The Smart Rate program offers customers a lower average electricity tariff (3 cents per kWh reduction) in exchange for accepting a significantly higher rate (60 cents per kWh) during peaking hours of "Smart Days" in the summer cooling months. These Smart Days are communicated to the consumer a day ahead via text, email, or by phone. Importantly, each of these programs, including the efficiency rebate program, was ongoing before and throughout the period of energy reading observation. We include participation in all these programs in our estimation model.

Efficiency rebates are awarded following the purchase of qualifying equipment and application by the customer to PG&E. PG&E makes applications available to its customers on its website as well as via a mail-in form. The rebates are funded via a "public goods charge", which is included in the electric rate base by the California Public Utilities Commission. Households are eligible to participate in the rebate program multiple times. In Figure 12, we show the applications for efficiency rebates in the sample, indicating those rebates associated with households from which multiple applications were observed. The number of active smart meters does not affect the number of rebate applications we observe. Indeed, about half of the applications in the dataset occur before a smart meter installation.

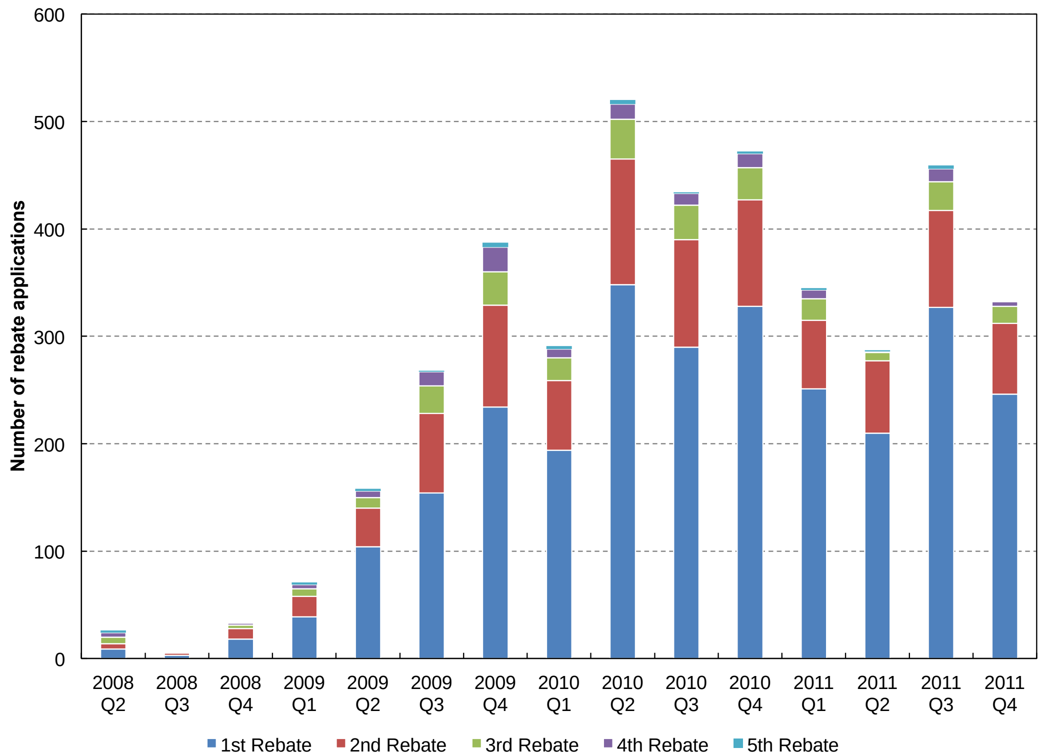

Figure 12: Energy efficiency rebate applications over time (by quarter).

Participation in either the efficiency rebate program or in the other PG&E programs is identified in a data table (separately for the rebate program from the other programs) with the corresponding id number and the date of participation. For the rebate program, three dates appear: the date on which the rebate application is received by PG&E, the date on which the rebate application is approved by PG&E, and the date on which the rebate check is mailed to the applicant. These date columns appear to include many missing values—for example, there are several instances in which a check mailing date appears without a corresponding preceding approval date. For this reason, all instances in which rebate date has a valid value are treated as participants in the efficiency rebate program. We believe this is justifiable since this would include all households that wished to participate in the rebate program (and thus the program could be influencing their household energy consumption) regardless of whether their application was approved or not. For comparison, we also report the results in which we define rebate participation as only households for which there is a valid approval or check issuance date.

For participation in the other PG&E programs, household participation can start, stop, and resume again several times over the course of the observation period. Dates for participation are identified by a start date for participation in the program as well as date for ceasing participation in the program. Subsequent participation periods for the same service agreement id are identified as separate records in the data as provided by PG&E. These records were transformed into binary indicator variables reflecting the dates of participation in each program after associating participation service agreement ids with service point ids via account ids.

Households that participate in the rebate program are, prior to participation, different from the remainder of the sample based on a comparison of household neighborhood characteristics in the 2010 Census. Geographic information about households is indicated in the dataset based on year 2000 Census blockgroup numbering. The geographic centroid of the 2000 Census blockgroups are taken and located within 2010 Census blockgroups in order to establish neighborhood characteristics for each household. Households that participated in the efficiency rebate program came from neighborhoods that had higher median home values (M = \$596,000, SE = \$4,806) than the remainder of households in the sample (M = \$505,000, SE = \$1,599, $t(30{,}116) = 18.1$, $p < 0.001$), higher median incomes (M = \$87,000, SE = \$757) than the remainder of households in the sample (M = \$71,000, SE = \$210, $t(30{,}116) = 21$, $p < 0.001$), a lower proportion of renters

($M = 30\%$, $SE = 0.43\%$) than the remainder of households in the sample ($M = 44\%$, $SE = 0.16\%$, $t(30{,}116) = 28.5$, $p < 0.001$), a lower proportion of households classified as "poor" (using the Census definition of "poor or struggling" which is household income less than twice the poverty level, $M = 8.8\%$, $SE = 0.18\%$) than the remainder of households in the sample ($M = 12.8\%$, $SE = 0.08\%$, $t(30{,}116) = 19.9$, $p < 0.001$), and a higher proportion of households with at least a bachelor's degree ($M = 40\%$, $SE = 0.42\%$) than the remainder of households in the sample ($M = 35\%$, $SE = 0.01\%$, $t(30{,}102) = 13.1$, $p < 0.001$).

Ongoing throughout the roll out of smart meters PG&E had several other programs that may influence overall electricity consumption. Figure 13 reports enrollment levels for these other programs in our entire sample and from March 1, 2008 to December 31, 2011. The highest enrollment program is the California Alternative Rates for Energy (CARE), which provides low-income customers a 20% rate reduction. The enrollment we find in our dataset is consistent with reported enrollment rates made by California Public Utility Commission research reports (which report a 32% household eligibility rate, and a 95% enrollment rate among eligible households) (Evergreen, 2013).

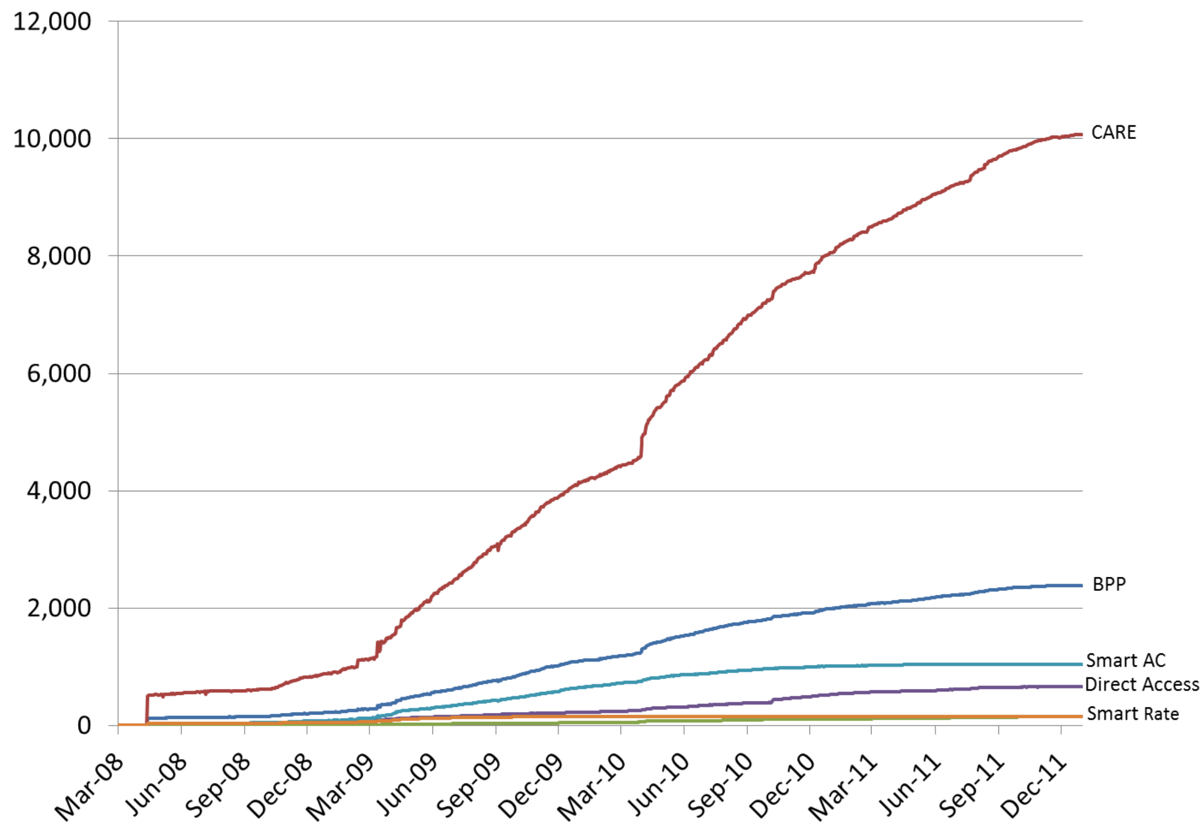

Figure 13: Enrollment in other PG&E programs among households in the dataset

<u>ADDITIONAL DATA SOURCES</u>

Demographic data: For privacy reasons the data do not include household addresses, but they do include blockgroups from the 2000 Census. Census blockgroups are collections of (on average, for this region) about 600 households. This geographical information enables linking to Census data files to capture neighborhood-level demographic characteristics of the households (using the 2010 Census) as well as the identification of the nearest weather stations, so detailed meteorological information can be associated with time-specific energy consumption patterns.

Weather data: To minimize the number of missing observations in the weather data, the three nearest stations to the centroid of the Census blockgroup are observed and average values are taken for the number of stations with valid data in each time period. Daily temperature data are from the NOAA National Climatic Data Center. To create a measure that reflects energy use associate with temperature changes, a degree-day-'like' measure is generated according to the following formulae:

$$High\,Temp = max\left[\frac{\sum_n T}{n} - 15°C, 0\right]$$

$$Low\,Temp = max\left[15°C - \frac{\sum_n T}{n}, 0\right]$$

Where *n* is the number of stations from which temperature observations are taken (between 1 and 3). These values, calculated for each block-group-day, are included in the models reported in both linear and quadratic forms.

Section 3: Methods

We use a fixed effects model to assess the effect of rebate programs on daily energy consumption, while controlling for several factors, as shown in Equation 1. We assume daily electricity consumption will be a function of weather, the programs the household applied for, and time. Using fixed effects, the time invariant, household specific aspects are controlled for.

$$\ln\left(kWh_{i,t}\right) = (\alpha + u_i) + \beta_j\left(Temp_{i,t}\right)_j + \gamma\left(RebateDummy_{i,t}\right) + \delta_k(TimeDummies_t)_k + \zeta(TimeTrend_t) + \varphi_q\left(Program_{i,t}\right)_q + \psi_q\left(RebateDummy_{i,t} * Program_{i,t}\right)_q + \varepsilon_{i,t} \tag{1}$$

In Equation (1) *kWh* is electricity consumption, in kWh, for household *i* on day *t*. The primary variable of interest is *RebateDummy,* which is an indicator variable for households in time periods following the household's first rebate application. *Temp* is a set of temperature controls related to daily high and low temperatures for each household (based on Census block-group location), *TimeDummies* is a set of *k* indicators for periodic time intervals (months of the year, and days of the week), *TimeTrend* is a linear time trend that is fitted to the model to capture secular trends in energy consumption over the period of observation unrelated to the variable of interest, *Program* represents the *q* additional PG&E programs described above, and ε is an unobserved error term. The model also includes a set of q interaction terms between the rebate program and the other PG&E program. The term $(\alpha + u_i)$ is the intercept plus the household specific fixed effect.

Equations 2 through 5 are alternative specifications from our primary equation. Each follows the same fixed effects functional form. Equation 2 excludes the other PG&E programs, including only the rebate program.

$$\ln\left(kWhs_{i,t}\right) = \alpha + \beta_j\left(Temp_{i,t}\right)_j + \gamma\left(Rebate_{i,t}\right) + \delta_k(TimeDummies_t)_k + \zeta(TimeTrend_t) + \varepsilon_{i,t} \qquad (2)$$

Equation 3 is similar to Equation 2 except that $m = 4$ rebate applications are allowed for each household to capture the energy effect of subsequent rebate applications originating from the same household.

$$\ln\left(kWhs_{i,t}\right) = \alpha + \beta_j\left(Temp_{i,t}\right)_j + \gamma_m\left(RebateNumber_{i,t}\right)_m + \delta_k(TimeDummies_t)_k + \zeta(TimeTrend_t) + \varepsilon_{i,t} \qquad (3)$$

Equation 4 modifies Equation 2 by introducing an interaction term, π, between household rebate participation and the synthetic time trend variable. This allows the energy effect of the rebate to decay or grow over time following the application date.

$$\ln(kWhs_{i,t}) = \alpha + \beta_j(Temp_{i,t})_j + \gamma(Rebate_{i,t}) + \delta_k(TimeDummies_t)_k + \zeta(TimeTrend_t) + \pi(Rebate_{i,t} * TimeTrend_t) + \varepsilon_{i,t} \quad (4)$$

Equation 5 disaggregates the rebate application indicator from Equation 2 by including *n* indicators for each of the reported rebate categories in the PG&E dataset.

$$\ln(kWhs_{i,t}) = \alpha + \beta_j(Temp_{i,t})_j + \gamma_n(RebateType_{i,t})_n + \delta_k(TimeDummies_t)_k + \zeta(TimeTrend_t) + \varepsilon_{i,t} \quad (5)$$

SECTION 4: RESULTS

Table 9 reports the full set of regression results from Equation 1. We find that participation in the rebate program has a positive and significant coefficient, which suggests that, on average, following participation in the efficiency rebate program household energy consumption increases by about 7%. December is the highest consumption month while the coefficients on the day of the week indicators suggest that Sunday is the highest consumption day. The linear time trend is statistically significant, but has a reasonably small magnitude (<1%/year). Temperature is found to have a relatively strong effect on HVAC efficiency. Sunday, excluded to avoid collinearity among the indicators, is the day associated with the highest average electricity consumption as can be inferred from the statistically significant and negative coefficients associated with each of the included day of the week dummies. This is as anticipated, more in-home activity is expected on non-weekdays—Saturday is the day with the next highest average daily electricity consumption. December, also excluded, is the month with the highest average daily electricity consumption—again inferred from the statistically significant and negative coefficients associated with each of the other months. The months with the lowest average daily energy consumption are the shoulder months of April and May (about 15% less average daily electricity consumption compared to December) and September and October (about 12% less average daily electricity consumption compared to December).

The temperature controls show the relationship of household HVAC system efficiency as a function of temperature. Both the daily high and low temperature display a similar relationship in which the linear term has a negative coefficient estimate and the quadratic term has positive coefficient estimate. The interpretation of this finding is that as the temperature deviates from the set-point temperature (15°C, as described above) household energy consumption increases at an increasing rate—reflecting the fact that electric heat pumps become thermodynamically less efficient as the temperature sink to which they reject (in the cooling season) or absorb (in the heating season) heat diverges from the desired indoor air temperature.

We suspect that the reason the rebate program leads to an increase in electricity consumption by the household may be twofold. First, the rebate likely represents the purchase of a new type of energy consuming device for the household, and is not simply replacing a device that is then retired. For example, the rebate may have enabled the household to buy a window air-conditioning unit that would not have been bought otherwise. Most of the rebates in the sample set do not require equipment recycling though that program did exist. Of the rebates issued, only approximately 8% were categorized as "Appliance Recycling" (and, as shown in Table 10, the coefficient estimate for these is not statistically significant). Second, incentive dollars provided by the rebate program may be freeing up household income that is used for additional consumption of the energy services provided by the item for which the rebate was earned (a direct rebound effect) or for other energy services in the house (indirect rebound effect).

Table 9: Effects of PG&E demand-side programs on average household electricity consumption, coefficient estimates

Independent Variable	Dependent Variable is ln(kWh/day) Equation 1
Rebate Participation	$7.0\text{x}10^{-2}$*** $(1.3\text{x}10^{-2})$
BPP	$6.9\text{x}10^{-2}$*** $(2.1\text{x}10^{-2})$
CARE	$1.2\text{x}10^{-1}$*** $(1.2\text{x}10^{-2})$
Climate Smart	$-2.2\text{x}10^{-1}$ $(1.9\text{x}10^{-1})$
Direct Access	$8.6\text{x}10^{-2}$*** $(3.2\text{x}10^{-2})$
Smart AC	$5.3\text{x}10^{-2}$* $(2.8\text{x}10^{-2})$
Smart Rate	$1.1\text{x}10^{-2}$ $(4.3\text{x}10^{-2})$
Rebate * BPP	$-6.8\text{x}10^{-2}$*** $(2.4\text{x}10^{-2})$
Rebate * CARE	$5.0\ \text{x}10^{-3}$ $(3.1\text{x}10^{-2})$
Rebate * Climate Smart	$1.3\text{x}10^{-3}$ $(8.5\text{x}10^{-2})$
Rebate * Direct Access	$-5.8\text{x}10^{-2}$* $(3.2\text{x}10^{-2})$
Rebate * Smart AC	$-4.6\text{x}10^{-2}$* $(2.6\text{x}10^{-2})$
Rebate * Smart Rate	$9.7\text{x}10^{-2}$*** $(2.7\text{x}10^{-2})$
Linear Time Trend	$-2.1\text{x}10^{-5}$** $(7.8\text{x}10^{-6})$
Daily High Temp	$-4.2\text{x}10^{-3}$*** $(4.6\text{x}10^{-5})$
Daily High Temp^2	$2.8\text{x}10^{-5}$*** $(2.0\text{x}10^{-7})$
Daily Low Temp	$-1.0\text{x}10^{-3}$*** $(9.6\text{x}10^{-5})$
Daily Low Temp^2	$4.4\text{x}10^{-6}$*** $(5.2\text{x}10^{-7})$
Mon	$-3.6\text{x}10^{-2}$*** $(8.6\text{x}10^{-4})$
Tue	$-5.2\text{x}10^{-2}$*** $(9.6\text{x}10^{-4})$
Wed	$-5.5\text{x}10^{-2}$*** $(9.6\text{x}10^{-4})$
Thu	$-5.3\text{x}10^{-2}$*** $(9.4\text{x}10^{-4})$
Fri	$-5.5\text{x}10^{-2}$*** $(9.0\text{x}10^{-4})$
Sat	$-1.8\text{x}10^{-2}$*** $(6.1\text{x}10^{-4})$
Jan	$-3.7\text{x}10^{-2}$***

	(2.5×10^{-3})
Feb	-7.3×10^{-2}***
	(2.9×10^{-3})
Mar	-1.2×10^{-1}***
	(3.1×10^{-3})
Apr	-1.5×10^{-1}***
	(3.1×10^{-3})
May	-1.5×10^{-1}***
	(3.3×10^{-3})
Jun	-1.1×10^{-1}***
	(3.5×10^{-3})
Jul	-8.0×10^{-2}***
	(3.8×10^{-3})
Aug	-8.9×10^{-2}***
	(3.6×10^{-3})
Sep	-1.2×10^{-1}***
	(3.5×10^{-3})
Oct	-1.2×10^{-1}***
	(2.7×10^{-3})
Nov	-8.5×10^{-2}***
	(1.8×10^{-3})
Intercept	2.7***
	(9.6×10^{-3})
Observations	18,306,105
# of groups, total	30,349
# of groups, rebate = 1	2,768
R^2 within	0.058
R^2 between	0.032
R^2 overall	0.046

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results of Equations 2-5 are reported in Table 10. The results for Equation 2, including the rebate program but excluding the other utility-sponsored programs, show a slight smaller estimate for the increase in energy consumption following participation in the program (5.9%) and no statistically significant effect of the synthetic linear time trend. The results from the model for Equation 3 show little average energy effect from subsequent participation events in the rebate program; each of the coefficients for second, third, and fourth rebate applications are not statistically significant. The results for Equation 4, which includes the interaction term of the time trend and the indicator for rebate participation, shows that this interaction is not statistically significant suggesting that there is not a non-cyclical time trend associated with magnitude of the energy effect on households following participation in the rebate program. In the results for

Equation 5, the appliance rebates have a strongly positive estimate; and since this is also the largest portion of the rebate program (about 45% of all applications) this seems to be the primary driver of the energy effect associated with the rebate application in Equations 1 and 2. The coefficients for building shell and unknown rebate categorizations are the other two with statistically significant values (at 95%, but not 99%).

Table 10: Effects of PG&E energy efficiency rebate program on household electricity consumption, coefficient estimates. Results for Equations 2-5

	Dependent Variable is ln(kWh/day)			
Independent Variable	**Equation 2**	**Equation 3**	**Equation 4**	**Equation 5**
Rebate	$5.9\text{x}10^{-2}$*** $(1.3\text{x}10^{-2})$	$5.6\text{x}10^{-2}$*** $(1.3\text{x}10^{-2})$	$3.7\text{x}10^{-2}$** $(1.9\text{x}10^{-2})$	
Linear Time Trend	$5.5\text{x}10^{-8}$ $(7.7\text{x}10^{-6})$	$-6.8\text{x}10^{-8}$ $(7.7\text{x}10^{-6})$	$-8.2\text{x}10^{-8}$ $(8.1\text{x}10^{-6})$	$-8.4\text{x}10^{-8}$ $(7.7\text{x}10^{-6})$
Rebate (second)		$1.0\text{x}10^{-2}$ $(2.6\text{x}10^{-2})$		
Rebate (third)		$6.8\text{x}10^{-2}$ $(5.1\text{x}10^{-2})$		
Rebate (fourth)		$-6.3\text{x}10^{-2}$ $(1.6\text{x}10^{-1})$		
Rebate * Linear Time Trend			$1.8\text{x}10^{-5}$ $(1.3\text{x}10^{-5})$	
Appliance Recycling				$-6.4\text{x}10^{-2}$ $(4.5\text{x}10^{-2})$
Appliance				$9.2\text{x}10^{-2}$*** $(1.8\text{x}10^{-2})$
Building Shell				$1.3\text{x}10^{-1}$** $(6.2\text{x}10^{-2})$
HVAC				$7.3\text{x}10^{-2}$ $(9.8\text{x}10^{-2})$
Lighting				$4.9\text{x}10^{-2}$ $(6.9\text{x}10^{-2})$
Pumps/Motors				$-1.9\text{x}10^{-2}$ $(7.6\text{x}10^{-2})$
Unknown				$3.6\text{x}10^{-2}$** $(1.7\text{x}10^{-2})$
Water Heating				$-2.0\text{x}10^{-2}$ $(9.0\text{x}10^{-2})$
Daily Temperature Controls	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included
Day of Week Dummies	Included	Included	Included	Included
Intercept	2.7*** $(9.3\text{x}10^{-3})$	2.7*** $(9.4\text{ x}10^{-3})$	2.7*** $(9.6\text{ x}10^{-3})$	2.7*** $(9.4\text{ x}10^{-3})$
Observations	18,306,105	18,306,105	18,306,105	18,306,105
# of groups, total	30,349	30,349	30,349	30,349
# of groups, rebate = 1	2,768	2,768	2,768	2,768
R^2 within	0.0566	0.0566	0.0566	0.0566
R^2 between	0.0388	0.0390	0.0387	0.0367
R^2 overall	0.0449	0.0450	0.0448	0.0446

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Tables 6, 7 and 8 show the results of robustness checks on the primary result found for Equation 1. Table 12 displays the same results as in Table 9 as well as results for restricted sample implementations of that model. The column labeled "Only Confirmed Rebates" restricts the policy indicator to being set equal to one only in cases in which either a valid rebate approval date or check issue date is found in the dataset. This is to correct for the potential issue described above in which there are several apparently missing values in these fields. Table 11 highlights this issue showing the disparity in the number of valid values that appear in the dataset for dates of participation in the rebate program, particularly the values for "check issues" which is inexplicably larger than the corresponding values for "approvals". The results of running the model with the restricted observation set show that there is not a substantive difference between the implementation of the data in which all identified rebate program participants are included in the program indicator (including some who may have attempted to participation but whose rebate application was not approved) and the implementation when that indicator is restricted to confirmed households. Similarly, excluding the households in the sample with mean average daily energy consumption values in the tails of the sample distribution, as is reported in the final column of Table 12 does not materially impact the estimate of the coefficient on the indicator of interest.

Table 11: Rebate program participation data description

Observations	18,580,095
# of groups (households)	30,426
Rebate Applications (# of rebates)	5,904
Rebate Approvals (# of rebates)	3,493
Rebate Check Issues (# of rebates)	5,253
Rebate Application Households (# of households)	3,476
Rebate Approval Households (# of households)	2,712
Rebate Check Households (# of households)	3,386
Rebate Application Households with Smartmeter Data (# of households)	2,804
Rebate Approval Households with Smartmeter Data (# of households)	1,984
Rebate Check Households with Smartmeter Data (# of households)	2,559

Table 12: Robustness checks on the effects of PG&E demand side programs on average household electricity consumption, coefficient estimates. Restricted sample results for Equation 1

	Dependent Variable is ln(kWh/day)		
Independent Variable	**Full-Sample As Reported**	**Only Confirmed Rebates**	**Excluding <5th and >95th consumption percentiles**
Rebate	7.0×10^{-2}***	7.0×10^{-2}***	7.3×10^{-2}***
	(1.3×10^{-2})	(1.4×10^{-2})	(1.4×10^{-2})
BPP	6.9×10^{-2}***	6.9×10^{-2}***	7.5×10^{-2}***
	(2.1×10^{-2})	(2.1×10^{-2})	(2.3×10^{-2})
CARE	1.2×10^{-1}***	1.3×10^{-1}***	1.2×10^{-1}***
	(1.2×10^{-2})	(1.2×10^{-2})	(1.3×10^{-2})
Climate Smart	-2.2×10^{-1}	-2.2×10^{-1}	-2.2×10^{-1}
	(1.9×10^{-1})	(1.9×10^{-1})	(1.9×10^{-1})
Direct Access	8.6×10^{-2}***	8.4×10^{-2}***	8.6×10^{-2}***
	(3.2×10^{-2})	(3.2×10^{-2})	(3.3×10^{-2})
Smart AC	5.3×10^{-2}*	5.4×10^{-2}*	5.7×10^{-2}*
	(2.8×10^{-2})	(2.8×10^{-2})	(3.0×10^{-2})
Smart Rate	1.1×10^{-2}	1.1×10^{-2}	-1.1×10^{-3}
	(4.3×10^{-2})	(4.3×10^{-2})	(4.5×10^{-2})
Rebate * BPP	-6.8×10^{-2}***	-6.5×10^{-2}**	-7.5×10^{-2}***
	(2.4×10^{-2})	(2.5×10^{-2})	(2.8×10^{-2})
Rebate * CARE	5.0×10^{-3}	-6.7×10^{-3}	8.5×10^{-3}
	(3.1×10^{-2})	(3.2×10^{-2})	(3.2×10^{-2})
Rebate * Climate Smart	1.3×10^{-3}	7.8×10^{-4}	6.8×10^{-3}
	(8.5×10^{-2})	(8.5×10^{-2})	(9.3×10^{-2})
Rebate * Direct Access	-5.8×10^{-2}*	-4.3×10^{-2}*	-6.0×10^{-2}*
	(3.2×10^{-2})	(3.3×10^{-2})	(3.3×10^{-2})
Rebate * Smart AC	-4.6×10^{-2}*	-5.4×10^{-2}**	-6.3×10^{-2}*
	(2.6×10^{-2})	(2.6×10^{-2})	(2.7×10^{-2})
Rebate * Smart Rate	9.7×10^{-2}***	1.0×10^{-1}***	1.1×10^{-1}***
	(2.7×10^{-2})	(2.8×10^{-2})	(2.9×10^{-2})
Linear Time Trend	-2.1×10^{-5}**	-2.1×10^{-5}**	-1.7×10^{-5}**
	(7.8×10^{-6})	(7.8×10^{-6})	(8.3×10^{-6})
Daily Temperature Controls	Included	Included	Included
Month Dummies	Included	Included	Included
Day of Week Dummies	Included	Included	Included
Intercept	2.7***	2.7***	2.7***
	(9.3×10^{-3})	(9.3×10^{-3})	(1.0×10^{-2})
Observations	18,306,105	18,306,105	16,560,777
# of groups, total	30,349	30,349	26,867
# of groups, rebate = 1	2,768	2,538	2,532
R^2 within	0.058	0.058	0.060
R^2 between	0.032	0.032	0.030
R^2 overall	0.046	0.046	0.049

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 13 shows results from Equation 1 along with results from that model with the data split by climate zone. The results show that there is not a statistically measurable effect of rebate program participation in the Central Valley, while the Coastal region has an energy effect approximately double the average effect found in the full sample. This would seem to be consistent with the price elasticity findings from (Ito, 2013) for the wealthier coastal region. Table 14 shows the results from Equation 4 with the data split by Census block median household income quintile. The results show that the largest energy effects from rebate program participation are in the 2nd and 4th neighborhood median income quintiles, and no identifiable effect in the lowest neighborhood median income quintile.

Table 13: Effects of PG&E demand-side programs on average household energy consumption coefficient estimates with split results by climate zone for Equation 1

	Dependent Variable is ln(kWh/day)			
Independent Variable	**Full-Sample As Reported**	**Central Valley**	**Inland Hills**	**Coastal**
Rebate	7.0x10^{-2}***	3.6x10^{-2}	7.6x10^{-2}***	1.2x10^{-1}***
	(1.3x10^{-2})	(2.5x10^{-2})	(1.8x10^{-2})	(3.1x10^{-2})
BPP	6.9x10^{-2}***	3.2x10^{-2}	1.7x10^{-1}***	1.5x10^{-1}***
	(2.1x10^{-2})	(2.6x10^{-2})	(4.1x10^{-2})	(5.2x10^{-2})
CARE	1.2x10^{-1}***	1.2x10^{-1}***	1.6x10^{-1}***	1.1x10^{-1}***
	(1.2x10^{-2})	(1.7x10^{-2})	(2.0x10^{-2})	(3.2x10^{-2})
Climate Smart	-2.2x10^{-1}	-1.8x10^{-1}	omitted	omitted
	(1.9x10^{-1})	(1.9x10^{-1})		
Direct Access	8.6x10^{-2}***	1.0x10^{-1}**	1.3x10^{-2}	1.2x10^{-1}
	(3.2x10^{-2})	(4.9x10^{-2})	(3.4x10^{-2})	(7.8x10^{-2})
Smart AC	5.3x10^{-2}*	5.8x10^{-2}	3.4x10^{-2}	3.4x10^{-1}
	(2.8x10^{-2})	(3.7x10^{-2})	(3.2x10^{-2})	(3.2x10^{-1})
Smart Rate	1.1x10^{-2}	3.3x10^{-2}	-3.7x10^{-1}	7.2x10^{-2}
	(4.3x10^{-2})	(6.3x10^{-2})	(4.2x10^{-2})	(8.8x10^{-2})
Rebate * BPP	-6.8x10^{-2}***	-7.3x10^{-2}**	-8.3x10^{-2}**	-1.2x10^{-1}**
	(2.4x10^{-2})	(3.4x10^{-2})	(4.2x10^{-2})	(5.9x10^{-2})
Rebate * CARE	5.0x10^{-3}	1.8x10^{-2}	9.1x10^{-3}	-3.8x10^{-2}
	(3.1x10^{-2})	(4.9x10^{-2})	(4.6x10^{-2})	(4.9x10^{-2})
Rebate * Climate Smart	1.3x10^{-3}	-6.9x10^{-2}	-9.1x10^{-2}	5.4x10^{-2}
	(8.5x10^{-2})	(4.9x10^{-2})	(7.1x10^{-2})	(1.4x10^{-1})
Rebate * Direct Access	-5.8x10^{-2}*	-1.9x10^{-2}	-5.7x10^{-2}	-9.5x10^{-2}
	(3.2x10^{-2})	(5.5x10^{-2})	(4.7x10^{-2})	(6.4x10^{-2})
Rebate * Smart AC	-4.6x10^{-2}*	2.2x10^{-2}	-4.5x10^{-2}	-3.4x10^{-1}
	(2.6x10^{-2})	(3.7x10^{-2})	(3.4x10^{-2})	(3.2x10^{-})
Rebate * Smart Rate	9.7x10^{-2}***	omitted	1.0x10^{-1}***	omitted
	(2.7x10^{-2})		(3.4x10^{-2})	
Linear Time Trend	-2.1x10^{-5}**	-2.3x10^{-6}	-2.7x10^{-5}**	-2.7x10^{-6}
	(7.8x10^{-6})	(1.2x10^{-5})	(1.1x10^{-5})	(2.3x10^{-5})
Daily Temperature Controls	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included
Day of Week Dummies	Included	Included	Included	Included
Intercept	2.7***	2.8***	2.6***	2.3***
	(9.3x10^{-3})	(1.3x10^{-2})	(1.3x10^{-2})	(2.7x10^{-2})
Observations	18,306,105	7,209,199	7,317,450	3,655,242
# of groups, total	30,349	8,572	11,368	10,190
# of groups, rebate = 1	2,768	648	1,282	838
R^2 within	0.058	0.104	0.027	0.026
R^2 between	0.032	0.002	0.005	0.021
R^2 overall	0.046	0.055	0.013	0.023

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Effects of PG&E demand-side programs on average household energy consumption coefficient estimates with split results by neighborhood median income quintile for Equation 1

	Dependent Variable is ln(kWh/day)					
Independent Variable	**Full-Sample As Reported**	**Lowest Quintile**	**2nd Quintile**	**Middle Quintile**	**4th Quintile**	**Highest Quintile**
Rebate	$7.0\text{x}10^{-2}$***	$3.6\text{x}10^{-2}$	$1.2\text{x}10^{-1}$***	$5.8\text{x}10^{-2}$*	$1.0\text{x}10^{-1}$***	$5.5\text{x}10^{-2}$***
	($1.3\text{x}10^{-2}$)	($4.0\text{x}10^{-2}$)	($4.5\text{x}10^{-2}$)	($3.5\text{x}10^{-2}$)	($2.9\text{x}10^{-2}$)	($1.8\text{x}10^{-2}$)
BPP	$6.9\text{x}10^{-2}$***	$1.2\text{x}10^{-1}$***	$3.0\text{x}10^{-2}$	$3.7\text{x}10^{-2}$	$1.2\text{x}10^{-1}$***	$3.0\text{x}10^{-2}$
	($2.1\text{x}10^{-2}$)	($3.5\text{x}10^{-2}$)	($6.3\text{x}10^{-2}$)	($3.4\text{x}10^{-2}$)	($4.5\text{x}10^{-2}$)	($5.2\text{x}10^{-2}$)
CARE	$1.2\text{x}10^{-1}$***	$1.1\text{x}10^{-1}$***	$1.3\text{x}10^{-1}$***	$1.4\text{x}10^{-1}$***	$1.3\text{x}10^{-1}$***	$1.3\text{x}10^{-1}$***
	($1.2\text{x}10^{-2}$)	($2.3\text{x}10^{-2}$)	($2.6\text{x}10^{-2}$)	($2.6\text{x}10^{-2}$)	($3.1\text{x}10^{-2}$)	($4.0\text{x}10^{-2}$)
Climate Smart	$-2.2\text{x}10^{-1}$	$-6.2\text{x}10^{-1}$***	omitted	omitted	$-3.3\text{x}10^{-1}$	$-2.3\text{x}10^{-1}$***
	($1.9\text{x}10^{-1}$)	($1.9\text{x}10^{-1}$)			($2.3\text{x}10^{-1}$)	($1.2\text{x}10^{-2}$)
Direct Access	$8.6\text{x}10^{-2}$***	$1.5\text{x}10^{-1}$**	$5.6\text{x}10^{-2}$	$-6.3\text{x}10^{-2}$	$1.4\text{x}10^{-1}$**	$1.0\text{x}10^{-2}$
	($3.2\text{x}10^{-2}$)	($6.1\text{x}10^{-2}$)	($6.4\text{x}10^{-2}$)	($7.3\text{x}10^{-2}$)	($5.6\text{x}10^{-2}$)	($9.2\text{x}10^{-2}$)
Smart AC	$5.3\text{x}10^{-2}$*	$1.0\text{x}10^{-1}$	$4.0\text{x}10^{-3}$	$1.0\text{x}10^{-1}$	$3.0\text{x}10^{-4}$	$6.9\text{x}10^{-2}$*
	($2.8\text{x}10^{-2}$)	($6.9\text{x}10^{-2}$)	($6.0\text{x}10^{-2}$)	($6.8\text{x}10^{-2}$)	($6.8\text{x}10^{-2}$)	($4.2\text{x}10^{-2}$)
Smart Rate	$1.1\text{x}10^{-2}$	$4.5\text{x}10^{-2}$	$1.1\text{x}10^{-1}$	$2.1\text{x}10^{-2}$	$-1.7\text{x}10^{-2}$	$-6.1\text{x}10^{-2}$
	($4.3\text{x}10^{-2}$)	($6.9\text{x}10^{-2}$)	($2.0\text{x}10^{-1}$)	($5.3\text{x}10^{-2}$)	($3.7\text{x}10^{-2}$)	($4.8\text{x}10^{-2}$)
Rebate * BPP	$-6.8\text{x}10^{-2}$***	$-1.5\text{x}10^{-1}$***	$-1.0\text{x}10^{-1}$*	$-1.4\text{x}10^{-2}$	$-7.1\text{x}10^{-2}$	$-3.1\text{x}10^{-2}$
	($2.4\text{x}10^{-2}$)	($5.3\text{x}10^{-2}$)	($6.0\text{x}10^{-2}$)	($4.7\text{x}10^{-2}$)	($4.5\text{x}10^{-2}$)	($6.1\text{x}10^{-2}$)
Rebate * CARE	$5.0\text{x}10^{-3}$	$1.1\text{x}10^{-1}$	$7.3\text{x}10^{-2}$	$-4.9\text{x}10^{-3}$	$1.4\text{x}10^{-2}$	$-5.0\text{x}10^{-2}$
	($3.1\text{x}10^{-2}$)	($7.2\text{x}10^{-2}$)	($6.9\text{x}10^{-2}$)	($4.1\text{x}10^{-2}$)	($6.5\text{x}10^{-2}$)	($8.9\text{x}10^{-2}$)
Rebate * Climate Smart	$1.3\text{x}10^{-3}$	omitted	omitted	$-1.1\text{x}10^{-1}$***	$-9.7\text{x}10^{-2}$**	$2.1\text{x}10^{-1}$
	($8.5\text{x}10^{-2}$)			($3.5\text{x}10^{-2}$)	($4.7\text{x}10^{-2}$)	($1.3\text{x}10^{-1}$)
Rebate * Direct Access	$-5.8\text{x}10^{-2}$*	$-2.1\text{x}10^{-2}$	$-2.4\text{x}10^{-1}$**	$8.2\text{x}10^{-3}$	$-9.8\text{x}10^{-2}$*	$-5.2\text{x}10^{-2}$
	($3.2\text{x}10^{-2}$)	($5.4\text{x}10^{-2}$)	($1.2\text{x}10^{-1}$)	($5.8\text{x}10^{-2}$)	($5.7\text{x}10^{-2}$)	($9.3\text{x}10^{-2}$)
Rebate * Smart AC	$-4.6\text{x}10^{-2}$*	$-6.7\text{x}10^{-2}$	$-1.9\text{x}10^{-2}$	$-1.3\text{x}10^{-1}$**	$2.7\text{x}10^{-2}$	$-6.6\text{x}10^{-2}$
	($2.6\text{x}10^{-2}$)	($6.7\text{x}10^{-2}$)	($6.2\text{x}10^{-2}$)	($6.1\text{x}10^{-2}$)	($6.1\text{x}10^{-2}$)	($4.4\text{x}10^{-2}$)
Rebate * Smart Rate	$9.7\text{x}10^{-2}$***	omitted	$-1.0\text{x}10^{-2}$	omitted	omitted	omitted
	($2.7\text{x}10^{-2}$)		($7.3\text{x}10^{-2}$)			
Linear Time Trend	$-2.1\text{x}10^{-5}$**	$-1.2\text{x}10^{-6}$	$-3.0\text{x}10^{-6}$	$8.9\text{x}10^{-6}$	$-4.2\text{x}10^{-5}$**	$-6.5\text{x}10^{-5}$***
	($7.8\text{x}10^{-6}$)	($1.8\text{x}10^{-5}$)	($1.9\text{x}10^{-5}$)	($1.7\text{x}10^{-5}$)	($1.7\text{x}10^{-5}$)	($1.6\text{x}10^{-5}$)
Daily Temperature Controls	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included
Day of Week Dummies	Included	Included	Included	Included	Included	Included
Intercept	2.7***	2.5***	2.5***	2.6***	2.8***	2.9***
	($9.3\text{x}10^{-3}$)	($2.1\text{x}10^{-2}$)	($2.2\text{x}10^{-2}$)	($2.2\text{x}10^{-2}$)	($2.0\text{x}10^{-2}$)	($1.9\text{x}10^{-2}$)
Observations	18,306,105	3,717,189	3,515,238	3,616,531	3,681,799	3,775,348
# of groups, total	30,349	5,998	6,008	6,013	6,016	6,314
# of groups, rebate = 1	2,768	298	397	499	664	910
R^2 within	0.058	0.075	0.055	0.056	0.055	0.045
R^2 between	0.032	0.075	0.053	0.054	0.069	0.015
R^2 overall	0.046	0.071	0.055	0.061	0.062	0.030

Robust standard errors in parentheses
*** p<0.01, **p<0.05, *p<0.1

SECTION 5: METHODS AND RESULTS II, HOURLY ANALYSES

Figure 14 shows the coefficient estimates for rebate participation from equation 1, run separately for each hour of the day. The figure shows two peaks in the effect size. These peaks correspond to daily peaks in residential electricity demand; one in the morning hours and one in the evening hours. This suggests that not only is participation in the rebate program leading to an increase in total electricity consumption, but that the increase is happening exactly when the residential transmission and distribution systems are most stressed. Weather data for this section come from Automated Surface Observing System (ASOS) database maintained by the Iowa Environmental Mesonet at the Iowa State University of Science and Technology.

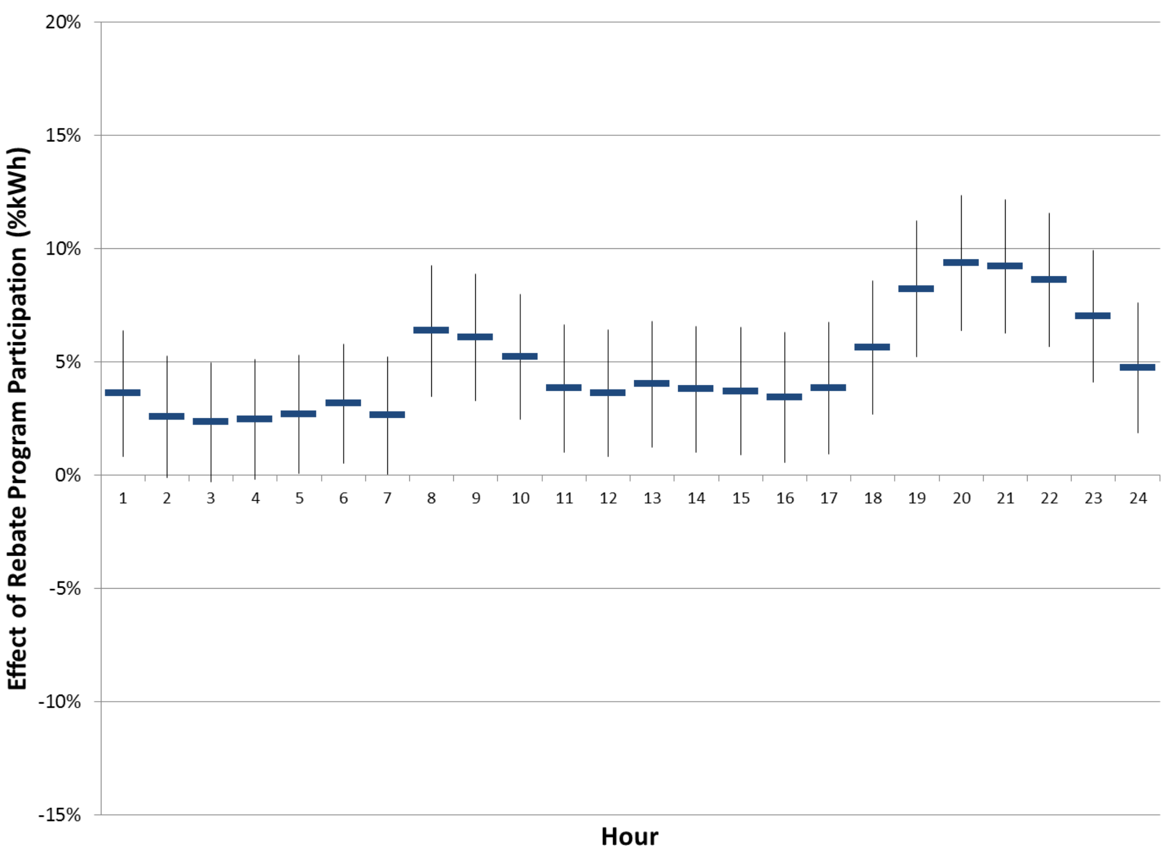

Figure 14: Hourly energy effect following household participation in the PG&E efficiency rebate program

Figure 15 shows results similar to those in Figure 14, but restricted only to days in which the local temperature for the household was greater than 30°C at some point in the day. The results do not show that afternoon peak demand for households participating in the rebate program is systematically higher on days with high ambient temperatures.

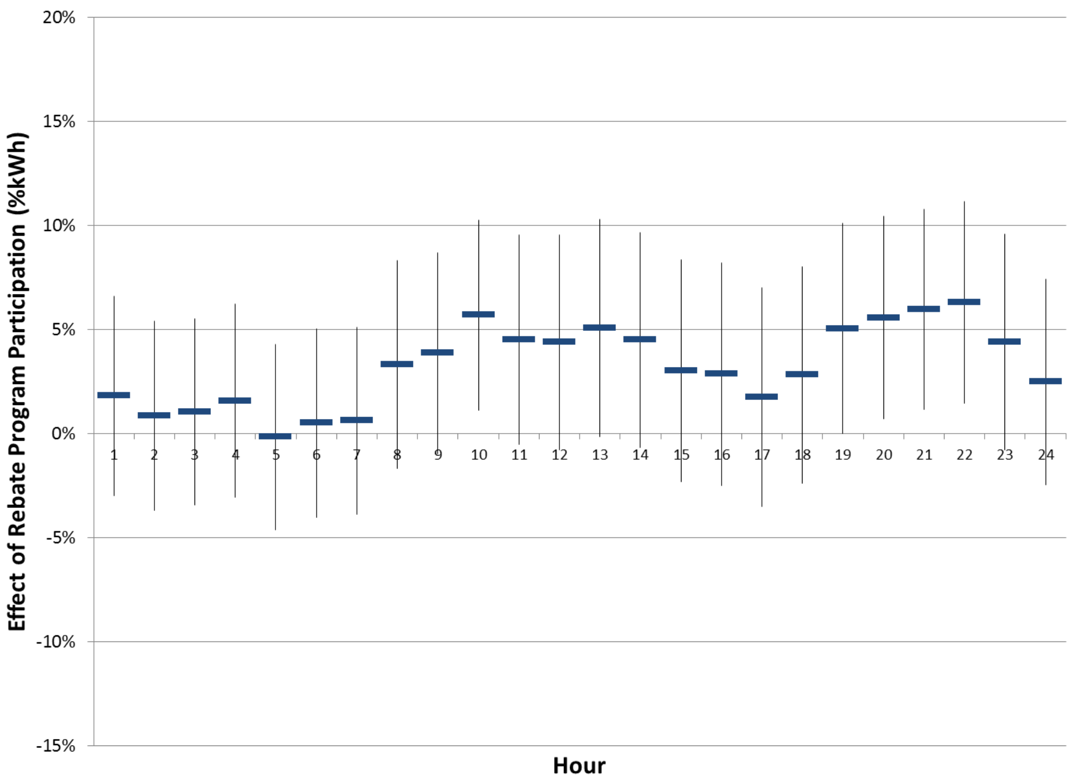

Figure 15: Hourly energy effect following household participation in the PG&E efficiency rebate program on days with a high temperature > 30°C

The following 12 figures show hourly results like those in Figure 14 separately for each month of the year. There does not appear to be a discernable statistically significant pattern in the hourly point estimates done separately by month. We can notice that the confidence interval reduces throughout the year as a result of the sample size of households being approximately one-third larger in December as it is in January as a result of the uneven household entry into the sample over the course of about three years.

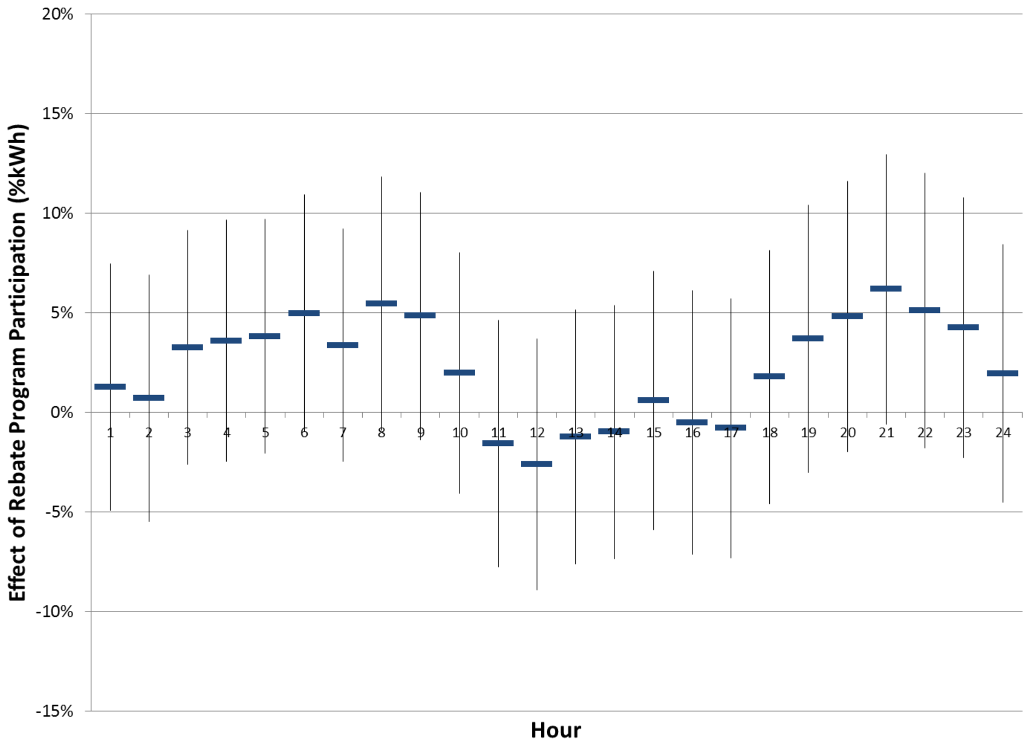

Figure 16: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in January from the unbalanced panel, 2008-2011

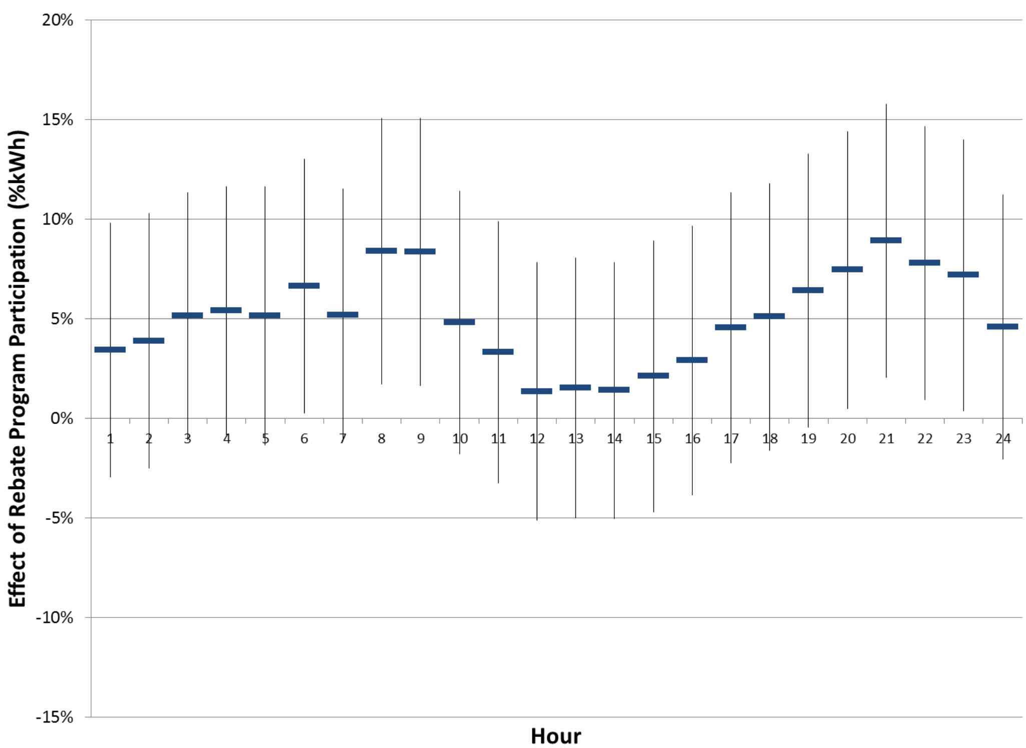

Figure 17: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in February from the unbalanced panel, 2008-2011

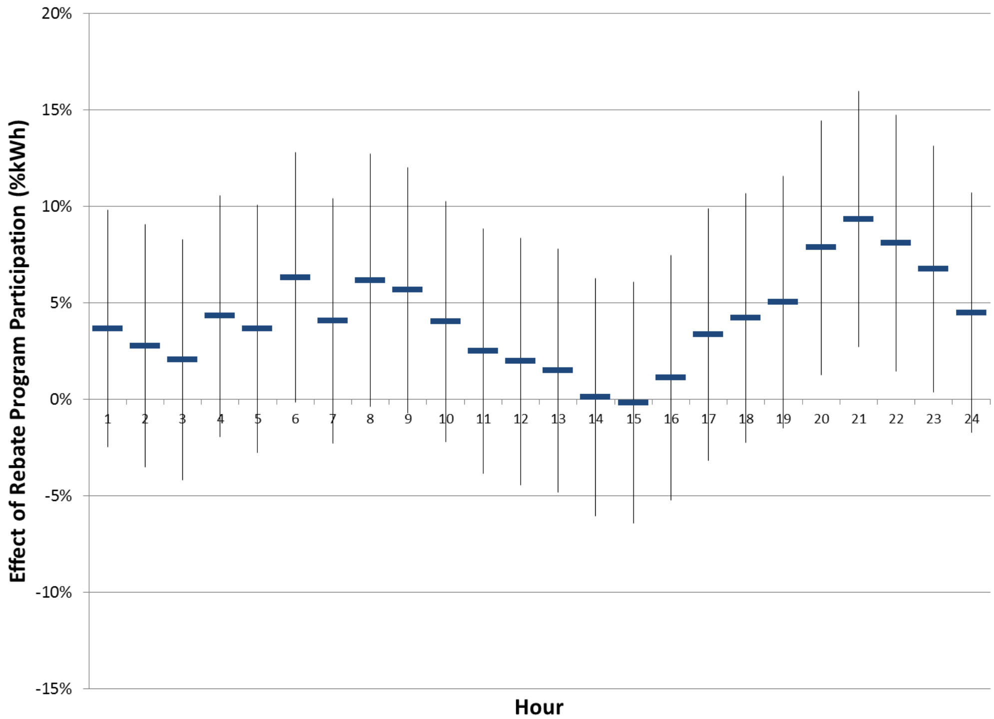

Figure 18: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in March from the unbalanced panel, 2008-2011

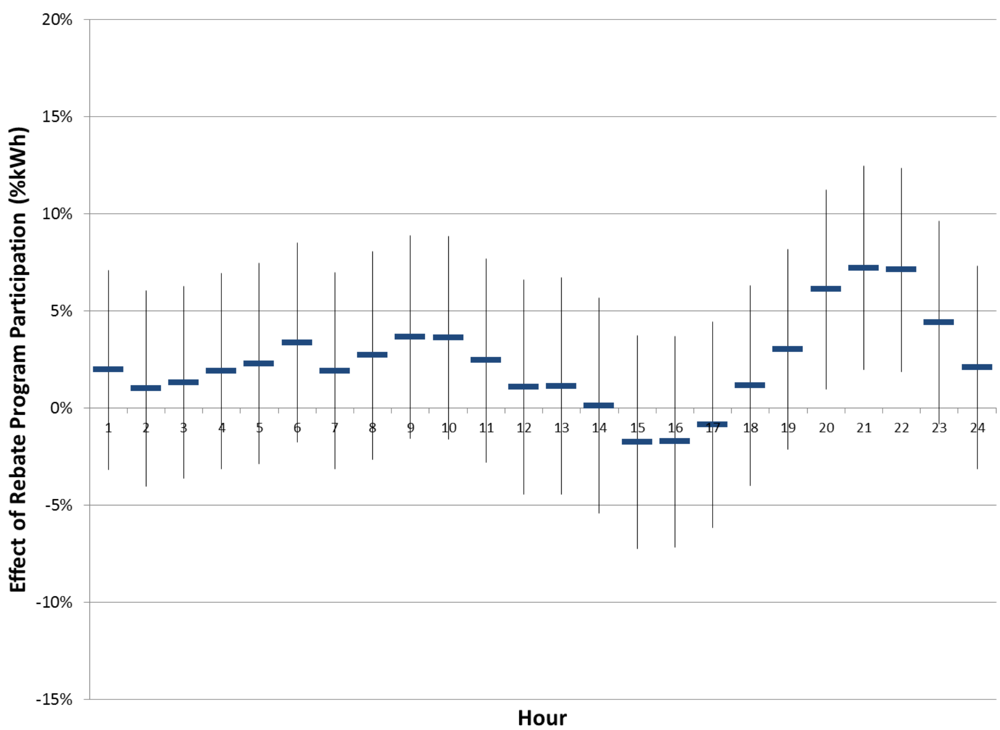

Figure 19: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in April from the unbalanced panel, 2008-2011

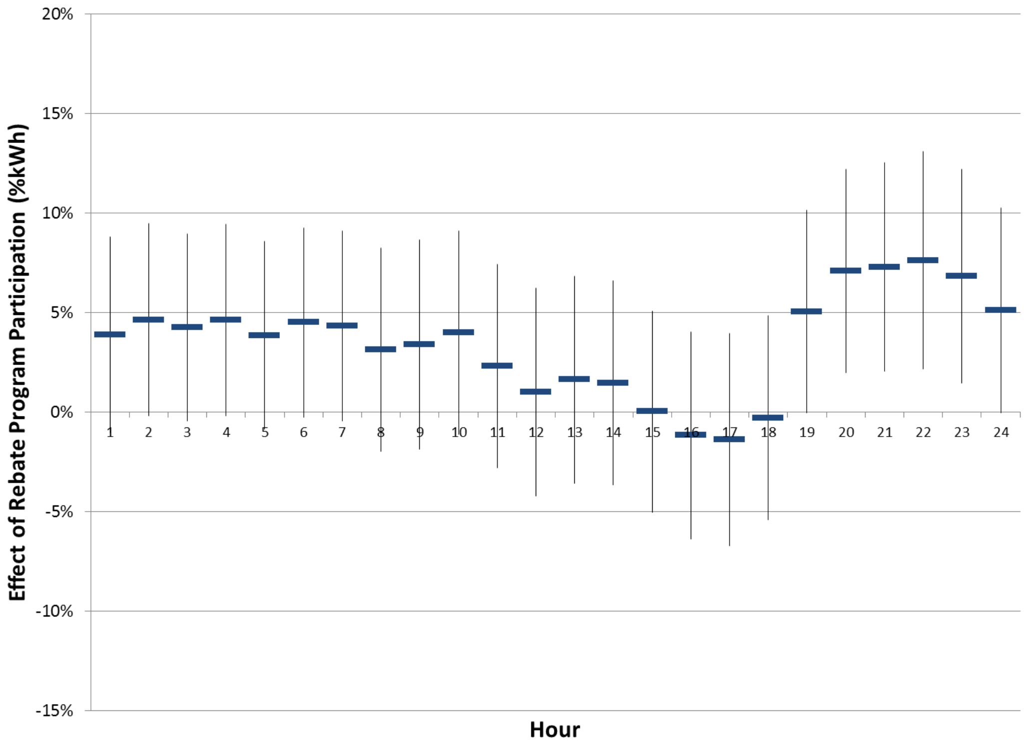

Figure 20: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in May from the unbalanced panel, 2008-2011

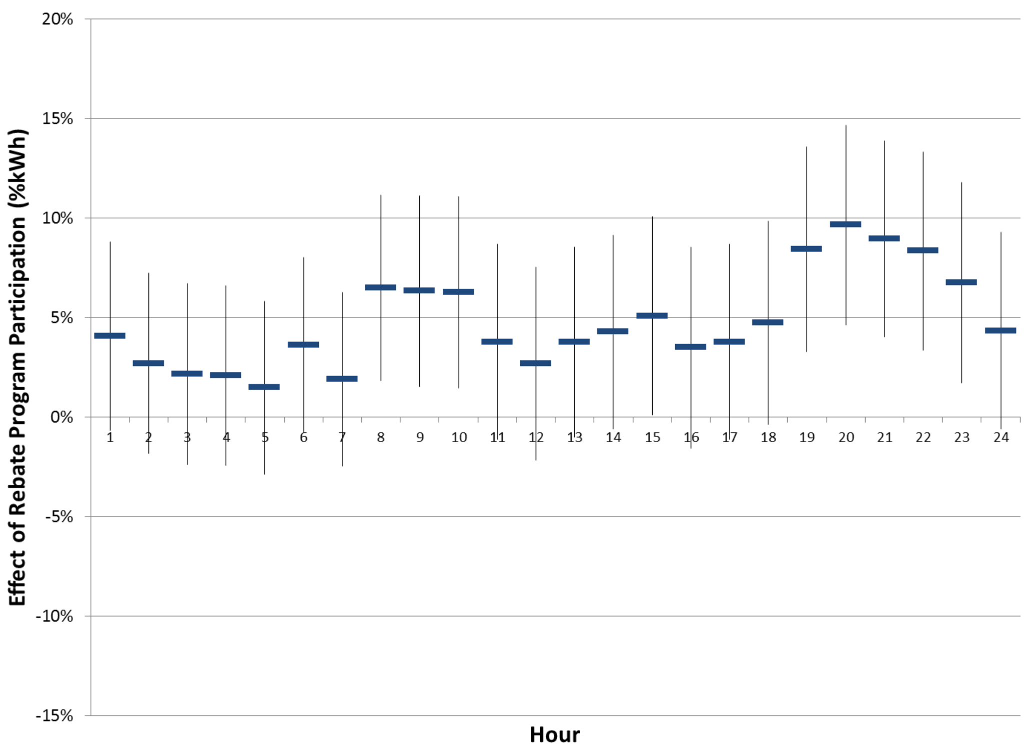

Figure 21: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in June from the unbalanced panel, 2008-2011

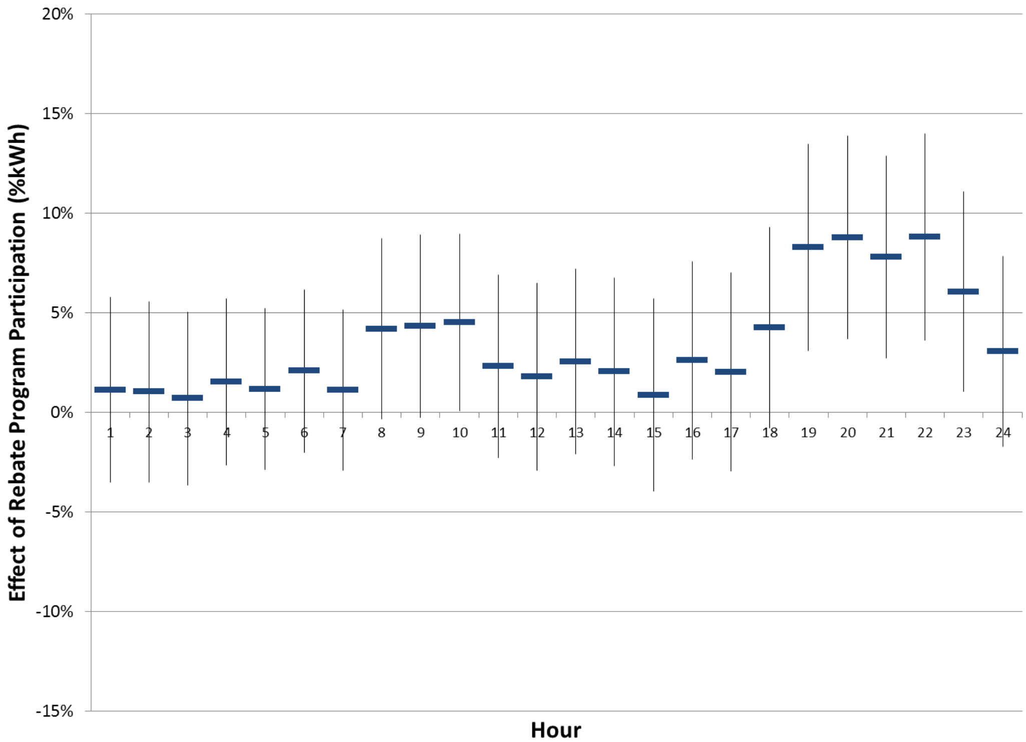

Figure 22: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in July from the unbalanced panel, 2008-2011

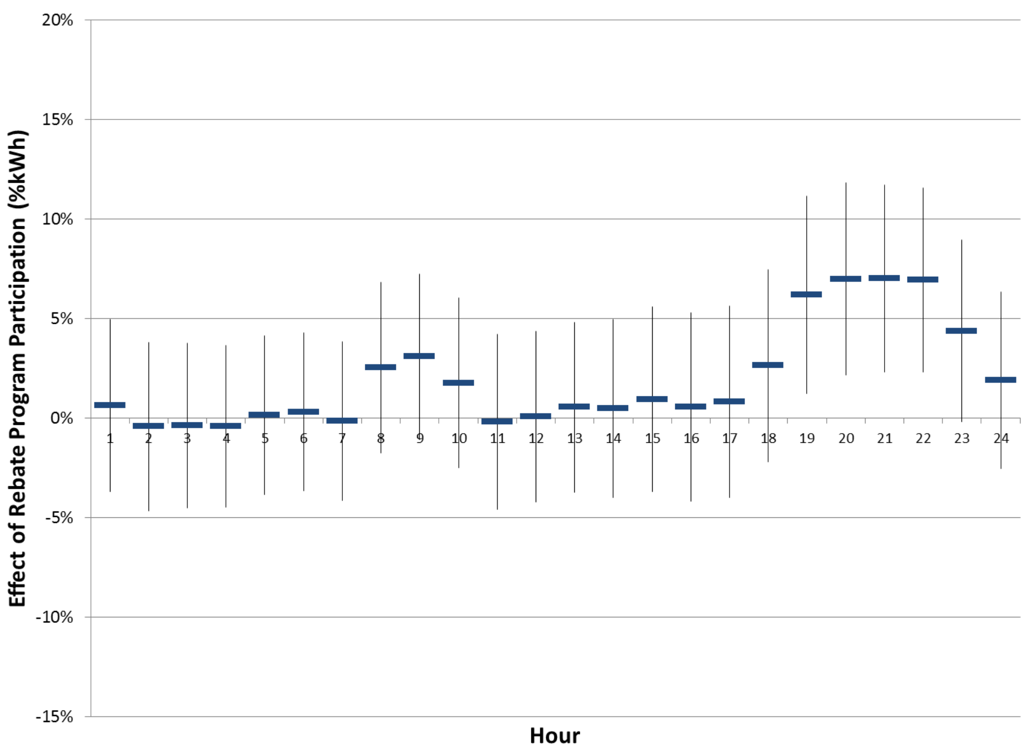

Figure 23: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in August from the unbalanced panel, 2008-2011

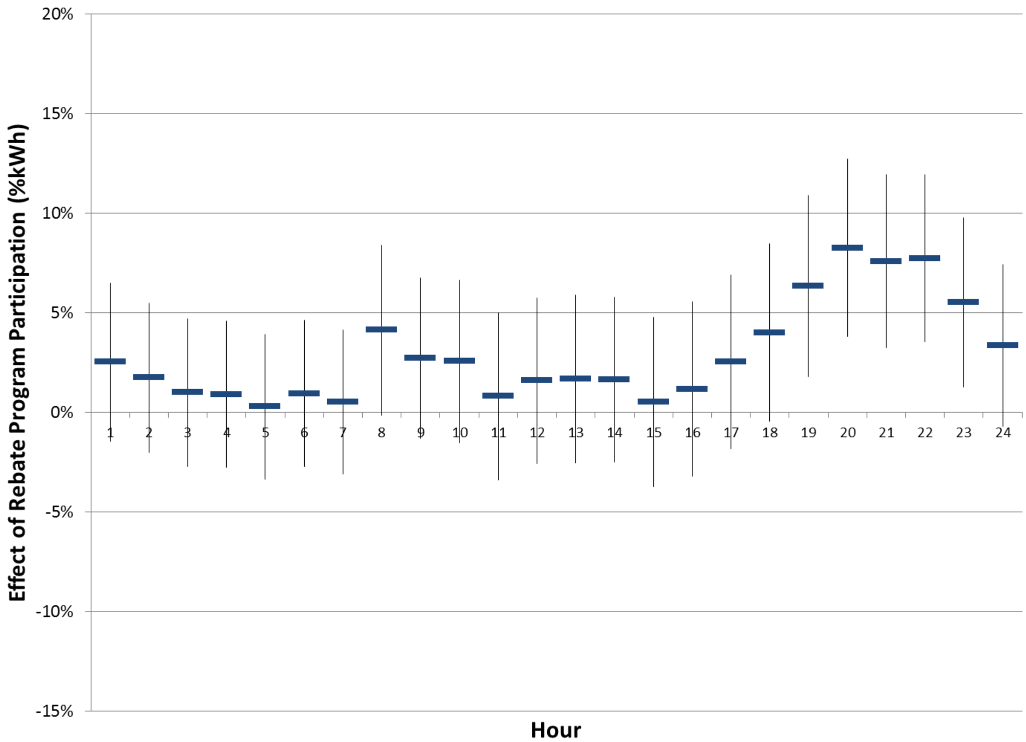

Figure 24: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in September from the unbalanced panel, 2008-2011

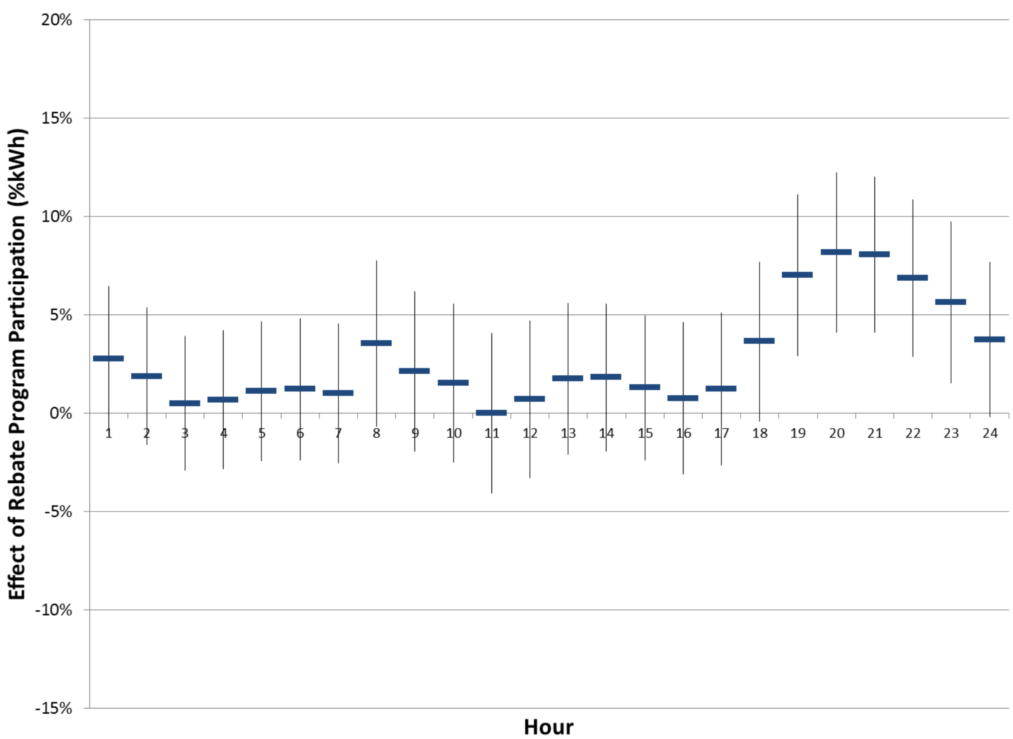

Figure 25: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in October from the unbalanced panel, 2008-2011

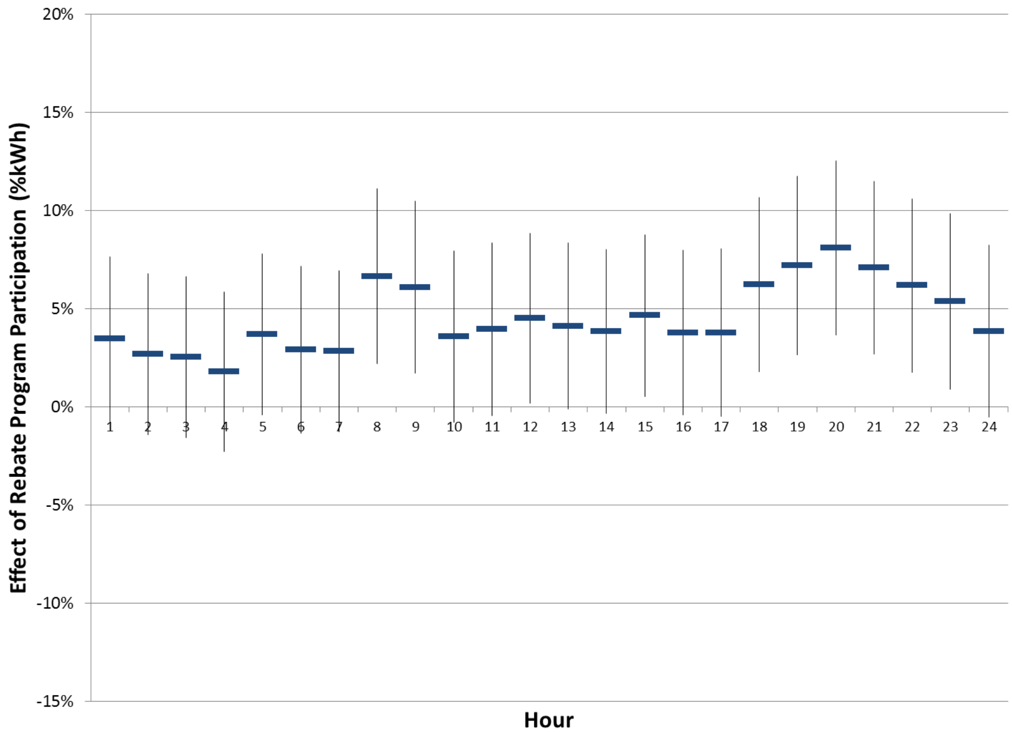

Figure 26: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in November from the unbalanced panel, 2008-2011

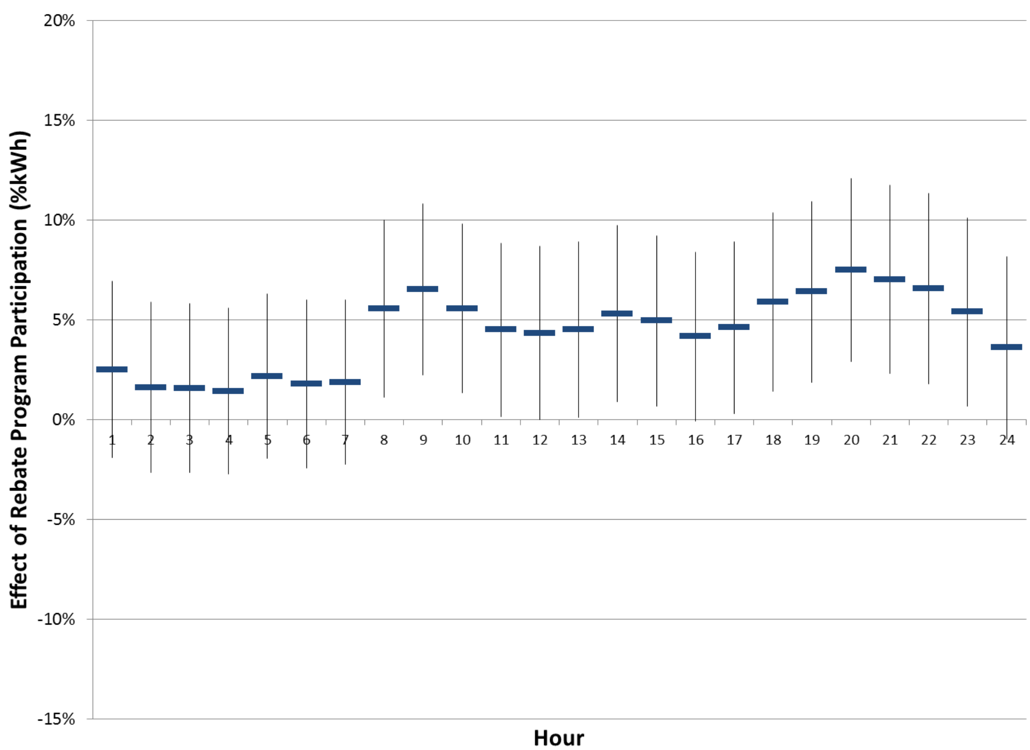

Figure 27: Hourly energy effect following household participation in the PG&E efficiency rebate program for days in December from the unbalanced panel, 2008-2011

Estimates of the hourly effects, done separately for weekday days and weekend days in order to compare the load shape effect of participating in the rebate program between the two, is shown in Figure 28 and Figure 29. Comparing the two charts, we can see that the point estimate evening peak effect of the rebate program is slightly more pronounced on weekdays and that the morning peak effect is slightly later on weekends (though these differences are not statistically significantly so).

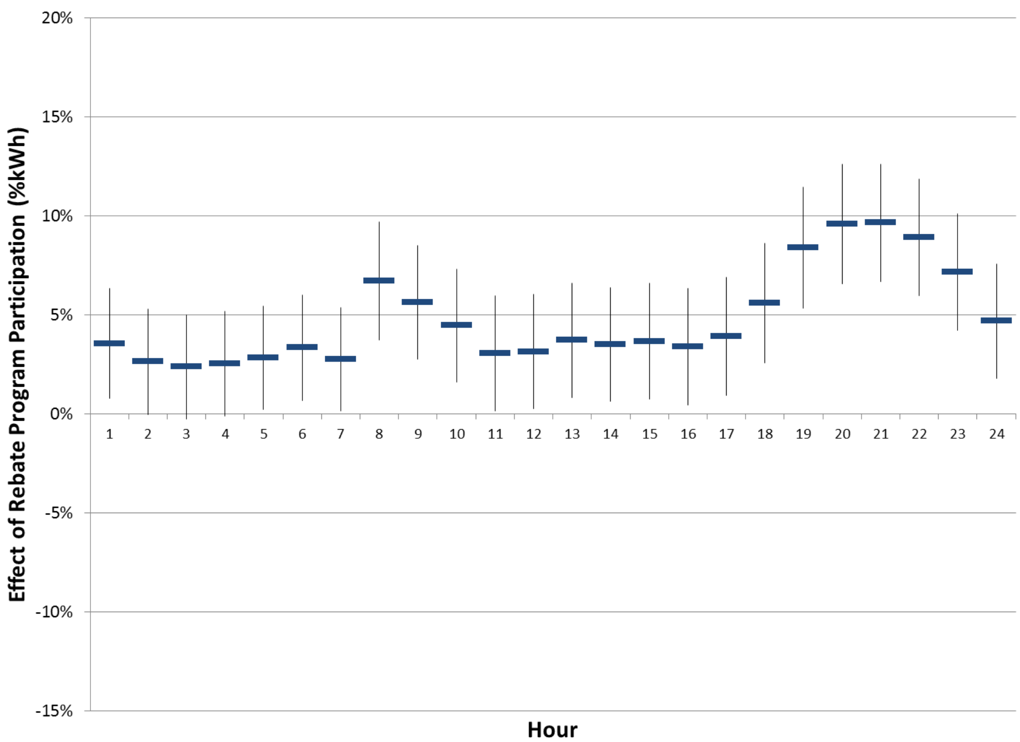

Figure 28: Hourly energy effect following household participation in the PG&E efficiency rebate program on Weekdays from the unbalanced panel, 2008-2011

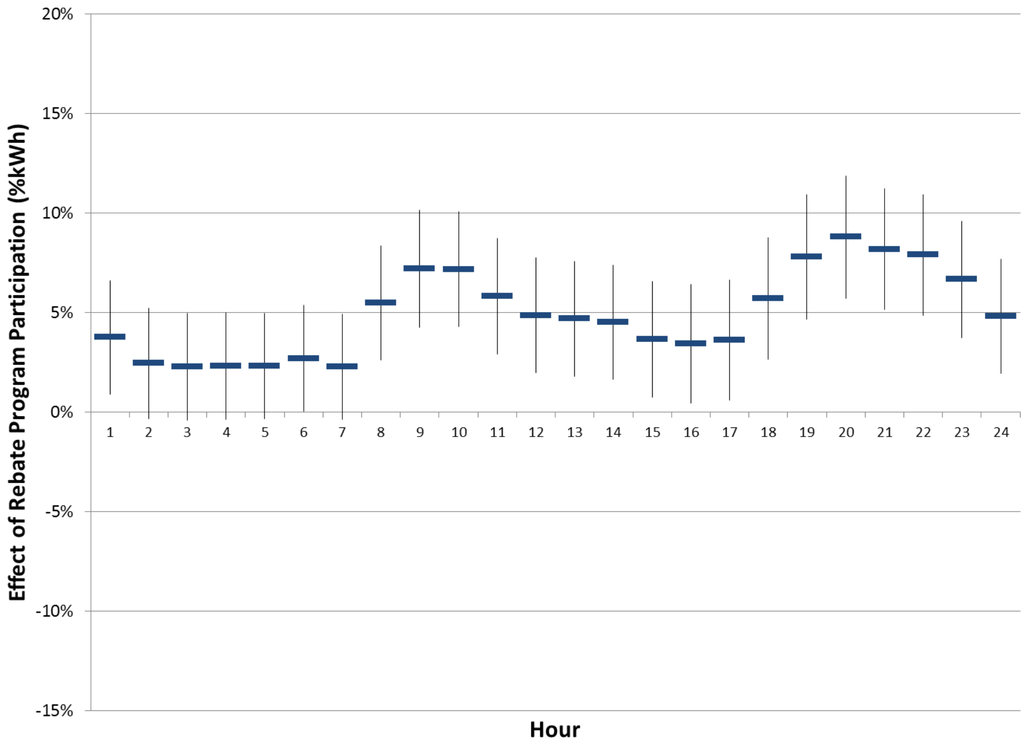

Figure 29: Hourly energy effect following household participation in the PG&E efficiency rebate program on Weekends from the unbalanced panel, 2008-2011

Estimating the hourly effects using the following equation, which removes the interaction terms between the rebate program and PG&E's other demand-side programs allows us to more directly estimate the total effect of the rebate program. Figure 30 shows the results of these 24 estimates of the coefficient associated with participation in the rebate program. The results here are not substantively different from the estimates shown in Figure 14.

$$\ln\left(kWh_{i,t}\right) = (\alpha + u_i) + \beta_j\left(Temp_{i,t}\right)_j + \gamma\left(RebateDummy_{i,t}\right) + \delta_k(TimeDummies_t)_k + \zeta(TimeTrend_t) + \varphi_q\left(Program_{i,t}\right)_q + \varepsilon_{i,t} \quad (6)$$

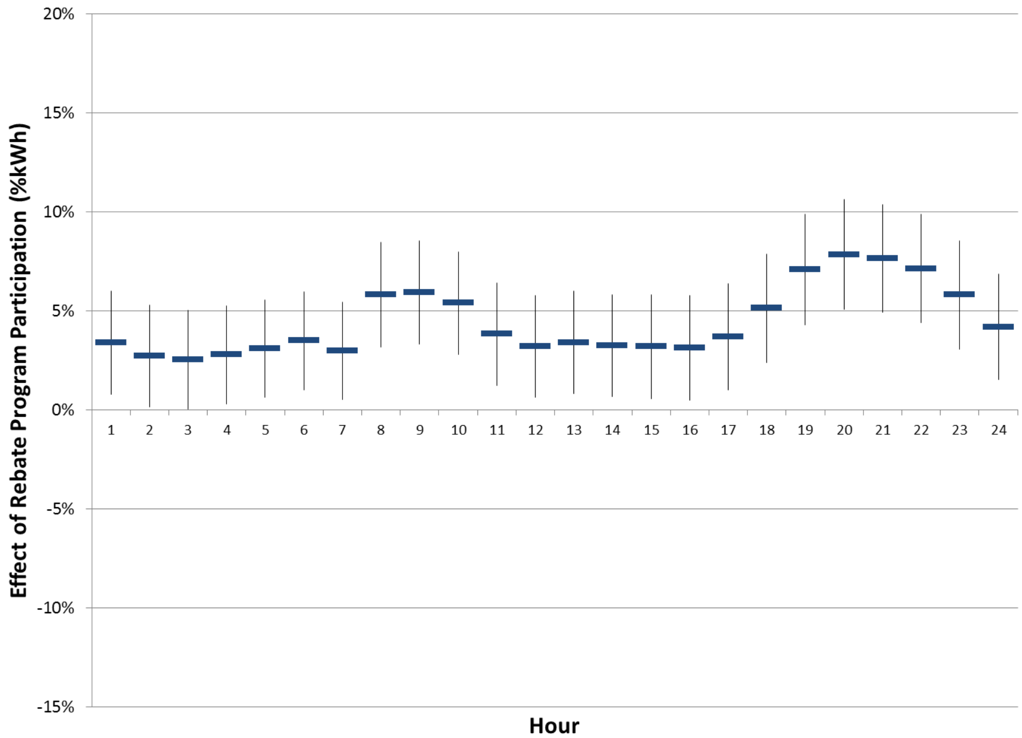

Figure 30: Hourly energy effect following household participation in the PG&E efficiency rebate program from the unbalanced panel, 2008-2011

SECTION 6: DISCUSSION AND POLICY CONCLUSIONS

We find that participation in this particular energy efficiency rebate program is associated with a subsequent increase in energy consumption, which suggests that the program is instead behaving as an equipment purchase subsidy. This, in turn, leads the household to consume additional energy services. This unintended consequence is inconsistent with the policy objectives that policymakers were targeting with the creation of this program. Certainly it is the case that enabling the consumption of additional energy services in the household does likely provide a marginal increase in utility to participating households and thus has some social value. However this should be weighed against the various pathways in which social value is created through the absolute reduction in household electricity consumption.

Past implementation and evaluation for other programs has shown that efficiency rebate programs can deliver energy consumption reductions, and that well-designed DSM programs contribute as an important and cost-effective component of integrated resource planning. However, in this program, we find that the rebate program is likely to have led to an increase in energy usage. To be clear, we do not suggest that efficiency rebate programs cannot deliver absolute energy consumption reductions generally. Nor do we claim that well-designed DSM programs cannot contribute as an important and cost-effective component of integrated resource planning. On the contrary, we are convinced that the empirical evidence has demonstrated that policy interventions designed to improve household energy efficiency, through either technological or behavioral means, can reduce aggregate system demand and generate net social value. In this program we identify the need for care to be taken in the design of these programs. We suspect, with a larger sample size, that we would find a negative and statistically significant coefficient estimate for the energy effect of the appliance recycling program. Indeed, this is an analysis that PG&E could likely readily complete using their full customer information database, rather than the sample of that dataset that we use here. If this were to be the case, a ready adjustment to the program can be made to require the permanent retirement of an older version of the equipment for which a rebate is issued.

We acknowledge that this analysis may suffer from self-selection bias; i.e., the households that participate in the program are not randomly assigned but instead voluntarily opt-in. The ideal comparison that we would like to make is between a household's energy consumption following participation in the program and what that household would have consumed in the absence of the program's existence. Would the household have made an equipment purchase if the rebate was not available? If so, did the program encourage a shift towards a more efficient version of the purchase that was made? An answer of 'no' to the first of these questions would mean that the program is in fact increasing counterfactual energy consumption while an answer of 'no' to the second would mean that the program is having no net effect. A 'yes' to both would suggest that the program is operating as intended. The dataset we use was not collected with these questions in mind. The analysis we have produced however suggests that these questions require answers.

A step towards producing the required analysis would be to incorporate household-level demographic information with this dataset. This would enable the formation of more appropriate comparison groups using a propensity score matching method. As the data are, characteristics upon which the propensity for a household to participate in the rebate program are available only at the neighborhood (US Census blockgroup) level, therefore neighborhood location becomes the controlling characteristic for assessing participation likelihood. Household-specific demographics (ideally, including information about the building structure in addition to the occupants) would enable the creation of participation scores based on the observed rates of participation for similarly situated households. That would allow a comparison of the energy consumption patterns of households that participated in the program with households that were scored as similarly likely to participate in the program but which nevertheless did not. Another way to improve these data would be to disaggregate rebate type in greater detail. We find a statistically significant positive influence of the 'appliance' portion of the rebate program, but without greater detail on the types of these appliances we cannot draw further conclusions. Ideally, we would like to test the energy effect of different appliance types to identify more specifically the types of rebate participation are associated with specific changes in energy consumption patterns.

Acknowledgements for Chapter 3

Support for this work was provided by the Steinbrenner Center for Environmental Education and Research at Carnegie Mellon University, enabled by a grant from the Colcom Foundation, and by the Center for Climate and Energy Decision Making. Helpful discussions and comments were received from Nathaniel Horner, Alex Davis, Karen Palmer, Pedro Ferreira, Fallaw Sowell, Granger Morgan, Scott Matthews and David Dzombak. Data were provided by PG&E, facilitated by the Wharton Customer Analytics Initiative at the Wharton Business School, University of Pennsylvania.

CHAPTER 4: LIGHT-DUTY VEHICLE FUEL CONSUMPTION TRENDS: A POPULATION TURNOVER ANALYSIS

CHAPTER ABSTRACT

Two key projections – that of driving age adults and that of the vehicle parc[10] – will influence fuel use in the United States. This work applies the implications of these projections as a part of the design of fuel efficiency policies, to track aggregate fuel consumption outcomes. Due to the long-lived nature of on-road vehicles, policies that affect the efficiency of new vehicles sold can take an extended period before meaningful effects on overall fuel consumption can be observed. As a result, even aggressive policies for increasing the fuel economy of light-duty vehicles are necessarily relatively ineffective short-term solutions. However, long-term trends in fuel economy combined with trends in the adult driving population, suggest that the U.S. could be entering a new period in which reliance on foreign fossil fuels is waning. Indeed, it is possible that the U.S. has already reached "peak consumption" in terms of volume of motor fuels and will not again require the quantity of gasoline and diesel that it did in the mid-2000's.

SECTION 1: INTRODUCTION

There is considerable debate in the literature as to the appropriate policy response for the objective of reducing fuel consumption, reducing greenhouse gas emissions, and doing so in a cost-effective way, from the transportation sector. Much of this debate centers around the relative merits of the use of a command and control regulatory scheme, such as the corporate average fuel economy (CAFE) standard, or a market based scheme, such as fuel taxes or other price signals. Most research on consumers' valuation of vehicle fuel economy, in relation to the

[10] The population of operational vehicles in a country is often referred to as the "vehicle parc" for that country. That term will be used in the discussion which follows.

purchase of a new vehicle, suggests that a typical consumer is willing to invest in fuel economy at a rate equal to between two and four years of discounted anticipated fuel savings (Jenn et al., 2013). In fact, a telephone survey of new vehicle purchasers found "no household that analyzed their fuel costs in a systematic way in their automobile or gasoline purchases" (Turrentine and Kurani 2007). This poses a public policy problem[11], as the social value of vehicle fuel economy is equal to at least the discounted value of the fuel savings (and emissions avoided) over the lifetime of the vehicle. This is often described in the literature as high implicit (and largely irrational) discount rates (Brown, 2001; Dreyfus and Viscusi, 1995; Gately, 1980; Hausman, 1979; Houston, 1983; Meier and Whittier, 1983; Ruderman et al., 1987; Min et al., 2014) and has, in the U.S., led to CAFE standards as the preferred policy option.

Despite this, work by Greene and German (2007), citing work by Gal (2006), suggests that the consumer may, instead, be rationally under-valuing fuel economy. As behavioral research has shown, status quo bias (or endowment effect) results in a consumer preferring an initial framing to an equivalent alternative (e.g., Kahneman et al., 1990). From this (as Gal labels it) "inertia," it follows that a consumer will require a premium to leave the status quo. Further, in the face of an uncertain alternative payout, a consumer will not have a clear preference and the choice between the status quo and an alternative becomes "fuzzy." The premium required for a change from the status quo in the face of an imprecise, or fuzzy, preference increases as the consumer now requires the premium for change as well as a premium to overcome the uncertainty of the risky alternative. In the absence of such a premium, "inertia" will keep the consumer at the status quo.

[11] For contradictory evidence, see Keefe, Griffin and Graham (2008) who found that the costs and benefits associated with newer technologies to improve vehicle fuel economy are largely similar from the consumer and social perspectives.

This uncertain payout, put in the context of vehicle fuel economy, is the present value of a stream of future fuel savings. Uncertainty in future fuel savings is a function of imperfect information about the actual attributes of the vehicle (i.e., the fuel economy the consumer will experience will likely be at least somewhat different from the listed vehicle fuel economy), unknown future travel demand (how many miles the vehicle will actually be driven), and uncertainty in the future price of fuel. The combined effect of these uncertainties could increase the imprecise, or fuzzy, preference of the consumer between making an investment in fuel economy or not.

Thus, even if the consumer knows to expect a relatively high fuel price (as a result of a higher oil price, or from a carbon tax or other policy instrument), the underlying uncertainty in the base price of the fuel, along with the other uncertainties identified, can result in an uncertain value of an investment in fuel economy. The consumer may then defer choice in the absence of a clear premium for action, and under invest in fuel economy – preferring instead the certain upfront savings in the vehicle purchase price. This logic would imply that there is, at the least, a delay between a change in fuel prices and a response by the consumer in their vehicle purchase decision.

However, CAFE standards work slowly to reduce aggregate fuel consumption, and consumers often prefer other vehicle characteristics that detract from the fuel economy that can be achieved, even in the presence of high fuel prices. Studies by Glazer and Lave (1994) and Lin, et al., (1997) have found that significant lags exist between changes in fuel prices and fuel economy preferences from both the consumer and producer perspectives. A study (Clerides and

Zachariadis 2008) which performed a cross-sectional time series analysis of 18 countries, found that fuel standards could be supplanted by higher fuel prices only if fuel prices “remain at high levels for more than a decade.” While that study concluded that increases in fuel taxes would likely have a larger impact in U.S. than they would in Europe or Japan due to the relative difference in fuel prices (and taxes) that already exist, “new car fuel economy becomes less sensitive to fuel prices after the adoption of standards” – suggesting that the present existence of fuel economy standards would dampen any policy-induced price effect. In a study specific to the U.S., Greene (1990) found that CAFE standards had a significant influence on many auto manufacturers over the period from 1978 to 1989, and were possibly as much as two times as important as gasoline prices over that period.[12]

While fuel economy standards were static for a period of about 20 years until 2012, it is not the case that the relevant technologies had been dormant over that time. Indeed, fuel efficiency on a per unit weight basis was constantly improving. The fact that fuel efficiency has not also increased on a per vehicle basis reflects the fact that consumers value other vehicle attributes that compete with fuel economy (such as size, acceleration, towing capacity, air conditioning) more.

There is also considerable evidence in the literature to contradict the discussion above that consumers do not demonstrate an adequate response to fuel prices. There are several studies that present evidence that, if the policy objective is to reduce gasoline consumption, a gasoline tax is a less costly policy option, in terms of total welfare, than a CAFE standard (e.g., (CBO 2003),

[12] However, Greene goes on to make the interesting observation that an increase in fuel prices might have a larger effect on fuel economy than a similar decrease in price. The argument goes that if increased fuel prices induce technology improvements, a subsequent fall in prices would return fuel economy to some level that is higher than the initial fuel economy achieved prior to the technological innovations.

(Austin, D. and T. Dinan 2005), (West, S. and R. Williams III 2005) and (Murphy, F. and E. Rosenthal 2006)). Kleit (1990) argues that the effect of CAFE standards on energy savings is ambiguous, and even if savings are present, the costs are "prohibitive".

Part of the assessment to conclude that gasoline taxes are less costly involves the "rebound effect" that CAFE standards induce. As fuel economy is exogenously increased due to CAFE standards, the marginal cost of driving decreases on a per mile basis encouraging an increase in total driving (Azevedo, 2014; Sorrell, 2007; Sorrell and Dimitropoulos, 2007; Thomas and Azevedo, 2013a; Thomas and Azevedo, 2013b; Thomas and Azevedo, 2014). This rebound effect causes a reduction in the amount of fuel that would have otherwise been saved from the fuel economy standard, and also presents additional costs associated with additional travel demand. "The difference between fuel economy standards and a gasoline tax is exacerbated when incorporating the welfare effects of the rebound effect, like additional congestion and pollution" (Fischer, C. 2008). Although a study by Small and Van Dender (2007) has estimated a low (relative to previous studies), and declining over time with increased per capita income, rebound effect (2.2% in the short-run and 10.7% in the long-run), these ancillary costs are avoided (indeed reduced) with fuel taxes as the alternative.

In a study conducted after the oil-shocks of the 1970's to determine household decision-making between 4, 6 and 8 cylinder vehicles, Greenlees (1980) found "strong cross-elasticity of small car demand with respect to the price of gasoline." That study calculated "a ten percent increase in fuel price is estimated to yield an increase of just over eight percent in the proportion of small (four and six cylinder) cars purchased." Similarly, Khan (1986) found an impact of a shock in gasoline prices on the value of vehicles in the used-car market that was relative to their rate of fuel consumption. Those results were "consistent with the view that different types of automobiles are very good substitutes for each other, but that there do not exist close substitutes for automobile services" – a "high cross-elasticity of demand for different types of automobiles, but a lower elasticity of demand for automobile services"

These results suggest that consumers do, at least on some level, incorporate fuel costs in their vehicle purchase decisions, and that aggregated decision-making manifests itself in the market. Atkinson (1981) finds that consumers exhibit "substantial price responsiveness" to fuel prices and an analysis from the same time period found that consumers base "expectations about future gasoline prices based on experience within the last three months as well as trends over the past sixteen months" (quote from Greene, 1990, citing EEA, 1983). While these studies are all somewhat dated at this point, there is an argument to be made that the fuel prices in the mid-2000's were more similar to those of the late 1970's and early 1980's, than to those of the late 1990's and so these arguments cannot simply be dismissed without first demonstrating that the dynamic of the market has shifted and that the guidance suggested by these conclusions can no longer be considered valid. Some, in fact, do make such an argument. Hughes, Knittel and Sperline (2006) argue that the short-run price elasticity for gasoline has changed considerably between the early 2000's compared with the late 1970's. Their study concludes that "gasoline taxes would need to be significantly large today in order to achieve an equivalent reduction in gasoline consumption" and "policies and technologies designed to improve fuel economy are likely becoming relatively more attractive as a means to reduce fuel consumption."

If, for the moment, the argument that an increased gasoline tax is the least costly option to reduce fuel consumption is accepted, it follows that if the objective is to reduce greenhouse gas emissions a carbon tax transmitted to the consumer as a fuel tax would similarly be the least costly policy choice. This is mentioned to suggest that since the debate between standards and taxes appears to remain open, the debate on the appropriate policy prescription remains relevant despite recently enacted legislation to increase CAFE standards. Indeed, a 1999 analysis that compared the efficacy of fuel economy regulation and fuel taxes (Greene, D., J. Kahn and R. Gibson 1999) failed to reject the hypothesis that consumers respond equivalently to a change in fuel cost per mile that is caused either by a change in fuel price by or a change in vehicle fuel economy.

This study examines the impact that fuel economy standards will have in the United States (US) using a demographic analysis of on-road vehicles, and demographic projection of the people who drive them. The objective is to create a model to estimate the fuel consumption effects of CAFE standards, and to formulate a basic model that can be used as a tool for examining future policy proposals or the performance of existing policies in light of new information about transportation behavior. The findings suggest that in the near-term fuel consumption levels are expected to remain constant – but even in the more conservative of the two scenarios considered, fuel consumption levels are poised for a long-term decline. This has important policy implications taken in the context of improved oil recovery techniques that could lead to increased domestic liquid fuels production.

SECTION 2: MODEL DESCRIPTION

A four-part accounting model is created in this analysis. In the description that follows, each of the four modules is described in turn along with the assumptions that are made in the base case of the model run. Similarly, those terms that can be treated as variable inputs are identified and the range of plausible values these variables could take are discussed. Doing so allows for the construction of a model which can, in future iterations, be used to examine the consequence of potential future policy or market characteristics. Figure 31 diagrams the basic structure of the model and the four modules.

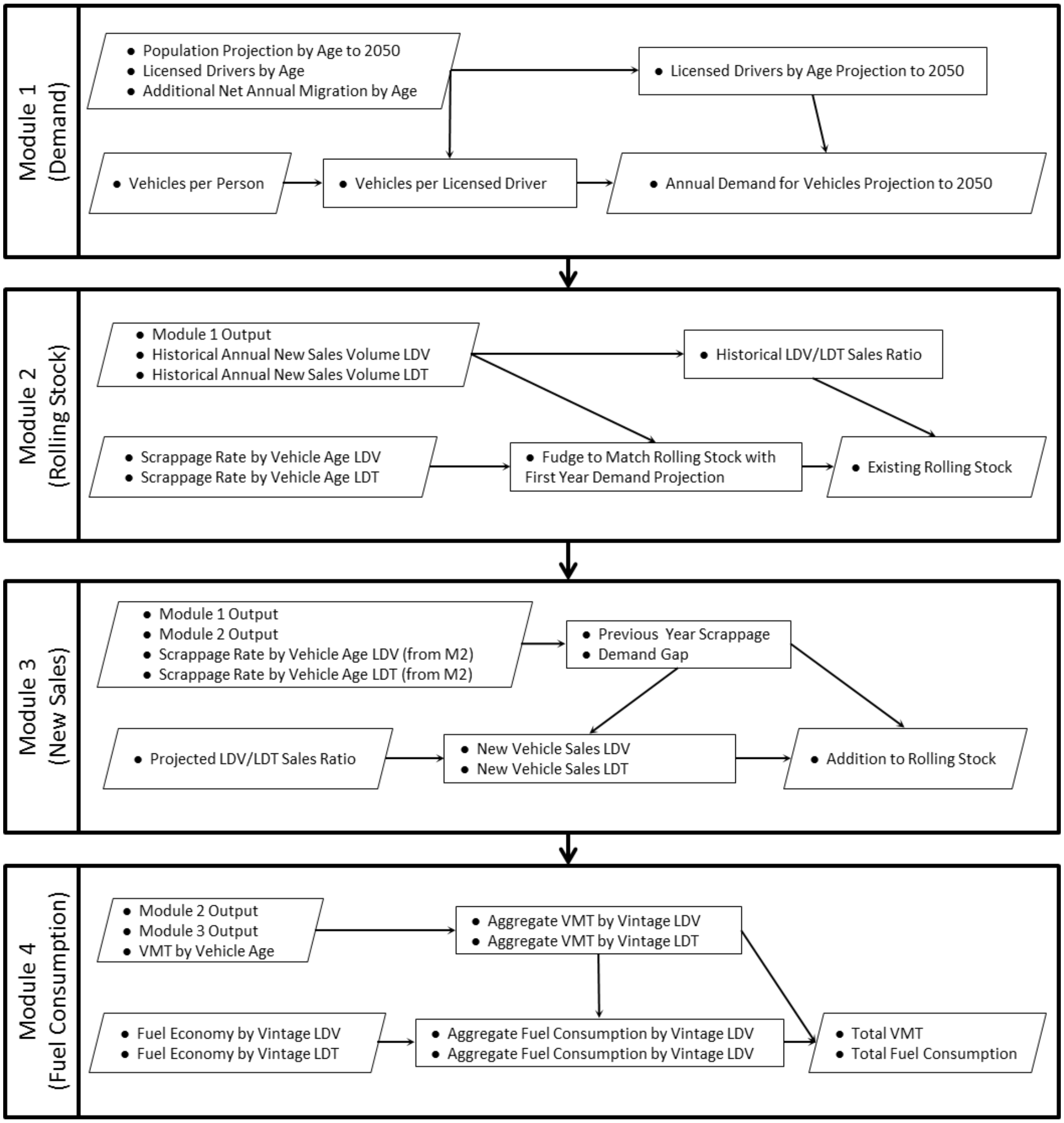

Figure 31: Model Diagram

<u>MODULE 1 – DEMAND</u>

The purpose of the first module is to estimate the number of future populations of US adults who will contribute to aggregate vehicle miles traveled (VMT) in light-duty vehicles (LDVs) and light-duty trucks (LDTs)[13]. The population estimate from which the number of future drivers is calculated comes from the Census (Census, 2008). In this model a necessary simplifying assumption is made that population growth is an independent exogenous input that is not correlated with patterns of mobility over the range of population values considered. The number of licensed drivers is based on Federal Highway Administration (FHWA) (2011) data for 2010 both scenarios. This population profile is treated as a constant for all years of the forecast. In the URBAN scenario, however, the number of licensed drivers among the youngest generation never exceeds 80% of that population as they percolate through the age tables. The the number of licensed drivers is shown in Figure 32. The base-case for the model assumes that licensing percentages remain at current levels as age-cohorts traverse the age table over time.

[13] LDVs are standard consumer cars (including sports cars, but not exotic makes like Ferrari or Lamborghini). LDTs are trucks under 8,500 lbs and include cross-over vehicles, SUVs, minivans, and pickups.

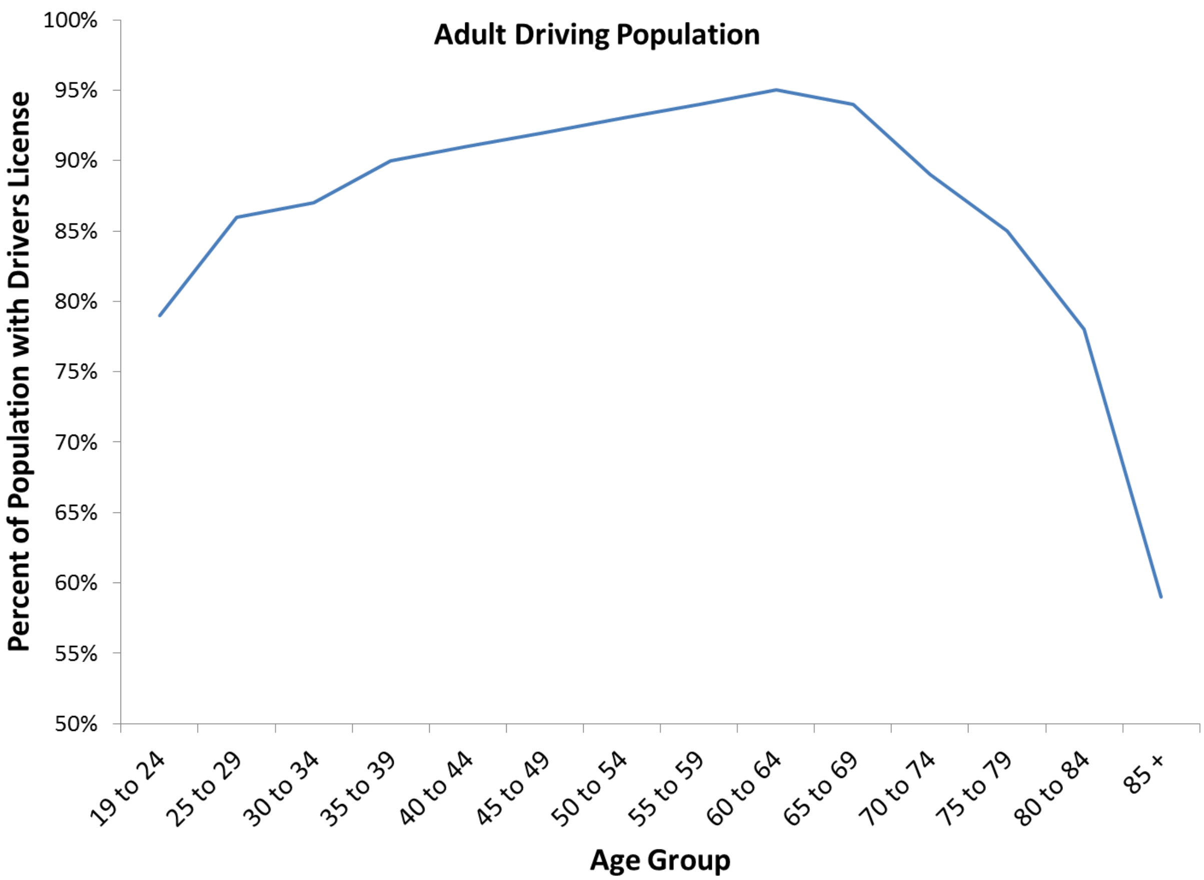

Figure 32: Fraction of the adult population with driver's licenses. Data are from Table DL-22 of FHWA, 2011

A key assumption that will impact fuel consumption is the rate of vehicle ownership among the population. The assumption made for the base-case is that vehicle ownership, on a per capita basis, has plateaued in the United States, and will remain roughly constant throughout the period of analysis. Several studies support this assumption (see eg., Dargay et al 2007 and Wang et al 2007) and show that light-duty vehicle ownership in the US is around 800 vehicles per 1,000 people (see e.g., ORNL 2012, Table 8.1). The logic supporting the assumption that ownership rates have leveled off are that vehicle ownership rates (as with most capital intensive consumer durables) follow a saturation pattern described by a Gompertz function of per capita income (Dargay et al., 2007). At low levels of income (as in the developing world), the population simply cannot afford the good due to the "lumpy" nature of a highly capital intensive purchase

(Chamon et al 2008). As incomes rise, the population reaches an income level at which the income elasticity for the good increases rapidly (described by the derivative of the Gompertz function – see Figure below). Once the population exceeds the per capita income threshold for the good, elasticity declines as the good becomes a new 'necessity' for the population and ownership saturation for the good levels off (Storchmann, 2005). The United States is above the income threshold necessary for vehicle ownership to be in this high-saturation stable condition.

$V_t = \gamma e^{\alpha e^{\beta GDP_t}}$ Gompertz function[14]

$\eta_t = \alpha \beta GDP_t e^{\beta GDP_t}$ Gompertz derivative, income elasticity of demand

An argument could be made that by bifurcating portions of the population according to income levels, that we could separately apply the saturation levels predicted by the Gompertz function to each income group – and therefore make projections about growth in vehicle ownership as these populations become more wealthy (perhaps especially important among low-income immigrant populations). This is exactly the type of analysis made by those who forecast growth in vehicle markets for the developing world (see eg, Wilson et al 2004, Chamon et al 2008, O'Neill and Stupnytska 2009, Lescaroux 2010). Indeed, by examining the National Household Transportation Survey (2009), we can see that vehicle ownership rates do follow income levels in a manner that can be fit using a Gompertz function. From the 2009 National Household Transportation Survey, probabilities for individual level vehicle ownership rates were determined by income group. These probabilities were calculated by taking a weighted mean of the vehicles per person within each household. Further, the income reported from each household was divided by the number of household members; creating a per capita household

[14] The parameters α and β define the shape and steepness of the Gompertz curve. The parameter γ represents the saturation level for vehicle ownership (since the Gompertz function naturally varies from 0 to 1), and is typically expressed in terms of number of vehicles per 1000 people.

GDP metric. In cases in which a household owned more than one vehicle per person, the probability of ownership was limited to one. By doing so, the calculation is not a strict vehicle ownership rate derived from the NHTS but is instead simply a probability of ownership per capita. Restricting these data to a probability, rather than an ownership rate, was done to limit the effect of households with a very large vehicle ownership rate from skewing the dataset.

The ownership probabilities for each income group were used to fit a Gompertz curve, using the maximum ownership probability found (about 96%) as the saturation rate, and solving for alpha and beta by minimizing the sum of squared errors between the predicted Gompertz curve and the observed ownership probabilities. For each income group, the median income point was selected for purposes of per capita GDP in the solving for the best Gompertz fit. Additionally, a 'zero-zero' point was added to the calculation of the sum of squared errors to force the curve toward zero probability at no income.

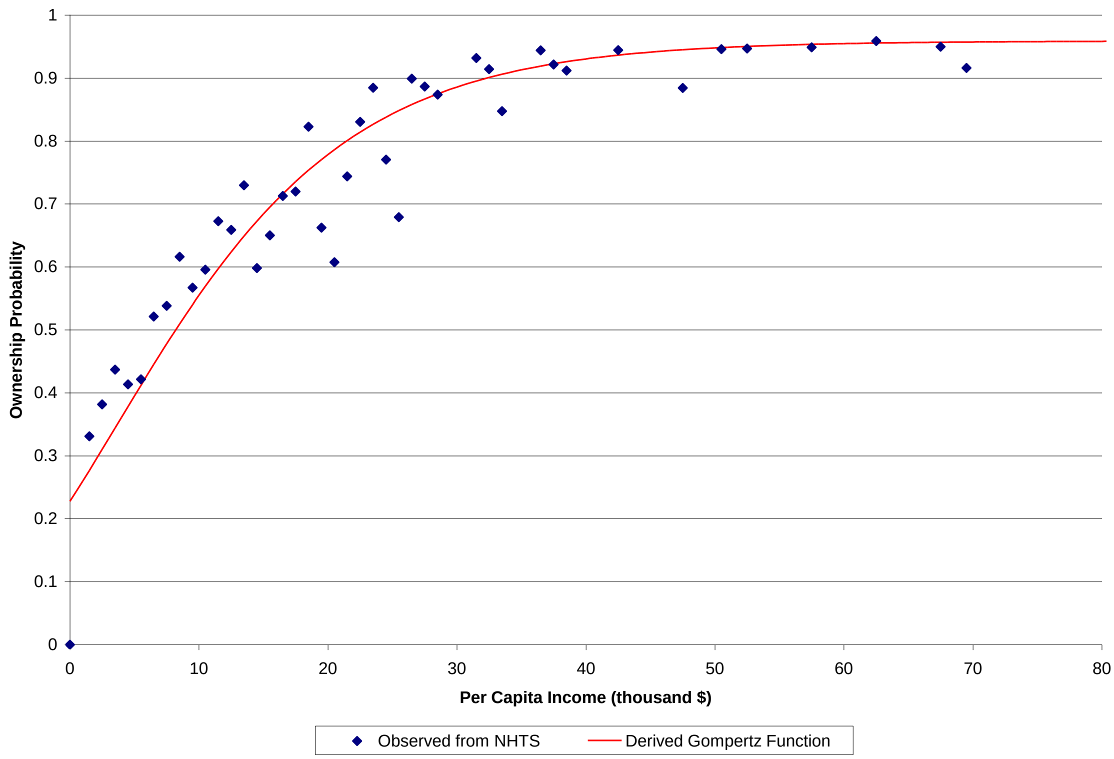

Figure 33: Probability of vehicle ownership as a function of per capita income for the United States from the National Household Transportation Data (NHTS 2009) micro data-set and best-fit Gompertz distribution.

We make the simplifying assumption that ownership saturation is constant—and remains constant as population changes. That is, the size of the vehicle parc changes on a constant basis with population change. However, the portion of the population that is licensed is explicitly considered, and will modify aggregate ownership accordingly to be consistent with the demographic projection. This is done by scaling current ownership rates expressed as a function of total population to be expressed in terms of licensed drivers. This differs from previous work. For example, the Transportation module of the National Energy Modeling System (NEMS) uses a population projection but does not employ a detailed age distribution of the population to describe the evolution of the population of licensed drivers (EIA, 2013). Recalculating vehicle saturation, we find that assuming 800 vehicles per 1,000 people implies a vehicle ownership rate of about 1,200 vehicles per 1,000 licensed drivers in 2010. Figure 34 shows the implication of that rate being held constant for the licensed driver population.

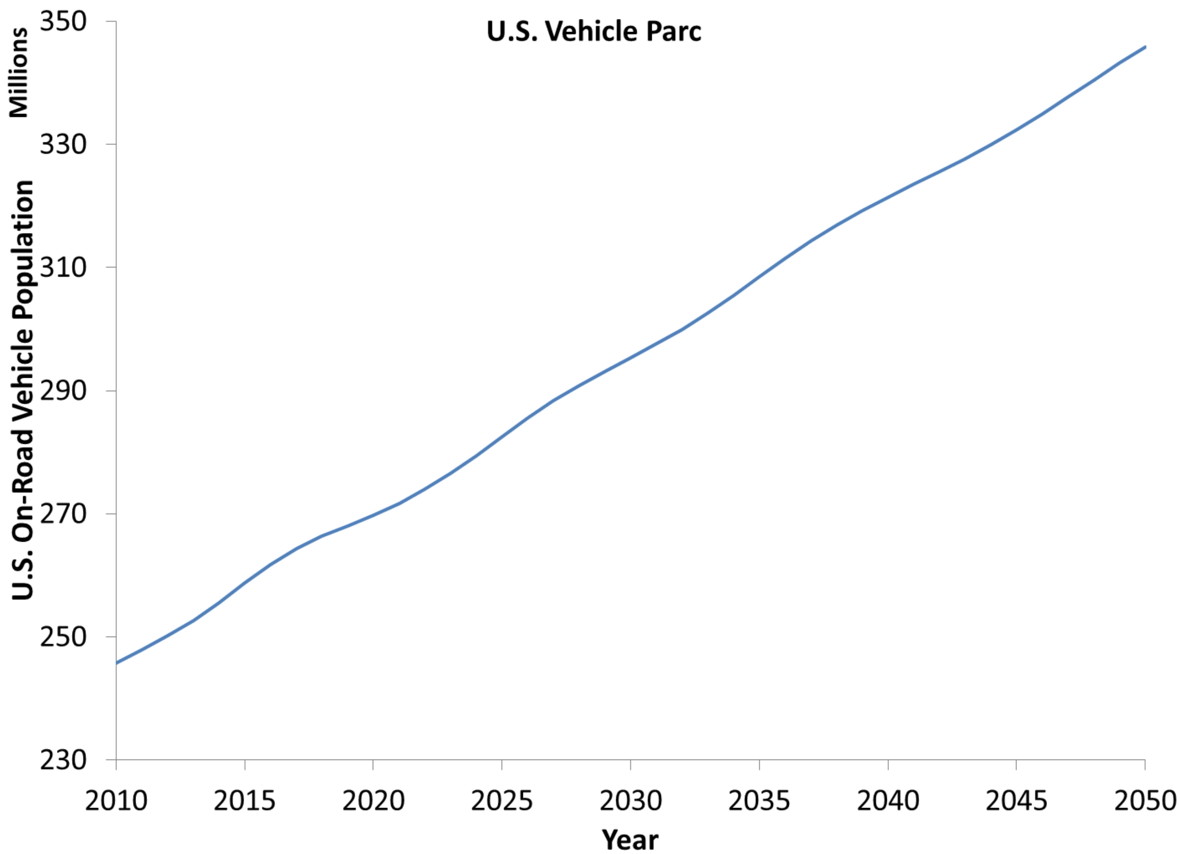

Figure 34: Projection for the U.S. Vehicle Parc holding ownership rates per licensed driver constant.

The total number of vehicles forecast in Module 1 informs the projection of vehicle turnover, and overall vehicle parc fuel economy levels. In the module described next, vehicle retirement is considered. Rates of vehicle retirement and additions to the adult driving population determine demand for new vehicle sales. It is the retirement of old inefficient vehicles coupled with new vehicle sales, and their regulatory-driven high fuel economy levels, that propel greater levels of fuel economy overall.

MODULE 2 – ROLLING STOCK

To model of the characteristics of the vehicle parc, historical data on vehicle sales and fuel economy is included. Historical sales figures for LDVs and LDTs are sourced from ORNL (2012, Tables 4.5 and 4.6). To move forward with historical sales records, the module accounts for changes scrappage rates as a function of vehicle age – treated separately for LDVs and LDTs. Vehicle survival functions follow an S-shaped Weibull distribution of the function form shown below (EPA 2001, Appendix E)[15] with survival rate values for LDVs and LDTs taken from (EPA 2010)[16]. Module 2 applies this survival function for each year of the forecast to each vintage of vehicles that are added to the model. As a result, a matrix of 72 years of scrappage by 72 years of new vehicle sales (1979 through 2050) are calculated for both LDVs and LDTs, with values for vintage-age survival population calculated for each.

$Survival = c \times e^{(-((age/b)^{a}))}$ Weibull distribution[17]

Both modules 1 and 2 are essentially bottom-up demographic accounting models, and because they use different sets of assumptions to arrive at the size of the vehicle parc in the year 2010 (the base year of the analysis) there is disagreement in the models for the population of the parc in that year. To reconcile this disagreement, the historical sales values built into module 2 are "fudged" so that the vehicle parc in 2010 is equivalent to that in module 1. The reason for the disagreement is likely mostly due to the particular survival parameter values employed in module 2 (for which there is substantial uncertainty) so it seems reasonable that module 2s should be adjusted in order to reach model agreement. The "fudge" procedure is to multiply

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[15] This model makes the assumption that vehicle survival rates are constant, and that vehicles do not become more durable over time. This assumption is dubious, but lacking data suggesting otherwise (or the resources for a more in-depth analysis of the nature of changes in this relationship) the simplifying assumption is necessary.

[16] For simplicity of calculation, it is also assumed that zero percent of vehicles survive beyond 50 years of life. This differs from the source cited for very old vehicles.

[17] The term *c* is a scaling term (ranging from 0 to 1 when used to define survival fractions), *e* is the base of the natural logarithm (≈2.718), *b* is a term which is roughly analogous to the midpoint of the distribution, and *a* defines the steepness of the curve.

historical LDV and LDT sales by a percentage increase parameter, for which module 2 solves. The solved solution sets the total parc of module 2 equal to the parc of module 1 by varying only this single percentage change parameter. By varying sales values rather than survival rates, the single parameter avoids skewing values which differ by orders of magnitude since sales values are all within the same order (and so the result of a percentage change parameter affecting a value near zero much less than a value that is in the millions is not present). One of the main reasons this adjustment is necessary is the constant survival rate assumption – that is, that newer vintages of vehicles have the same survival characteristics as older vintages. This is a simplifying assumption for model implementation, but is certainly incorrect: vehicles manufactured in the 2000's have longer expected lifetimes than vehicles manufactured in the 1980's, for example. This phenomenon is not captured by the model.

MODULE 3 – NEW SALES

Module 3 makes an assumption regarding future sales rates between LDVs and LDTs, which diverges from the assumptions made by EPA (2001) and EIA (2012, Table 39), and assumes a constant sales ratio of 1:1 (that is, 50% LDVs and 50% LDTs) for the period of analysis[18]. New vehicle demand is determined by first taking the value of the parc from module 1 as the size of the parc that is demanded by the market and determining the number of new vehicles sales that are required to meet that demand based on the increase in the size of the parc required and the scrappage of the existing vehicle fleet in that year, calculated in module 2. The demand for new vehicles is distributed between LDVs and LDTs evenly (as the rationale above explains). Note that because historically LDVs have sold at higher rates than LDTs, the distribution between the

[18] EPA (2001) assumes that LDTs continue to gain market share over time. EIA (2012) assumes that LDTs lose their market share gains back to LDVs. The EIA (2012) position is a recent change for that annual publication, which in previous years was in agreement with EPA (see e.g., EIA 2008). Because the assumption made here is different from both, these results are not directly comparable with forecasts made by either of those agencies.

two in the parc will trend towards a higher fraction of LDTs than is currently present (that is, trending toward a 50/50 split) as new vehicles enter and persist in the fleet.

Because new vehicle additions to the model are calculated based on calculated demand from module 1, the analysis does not forecast or consider the impact of economic shocks or temporary dislocations. Boom and bust cycles are a pattern of U.S. economic history, and will undoubtedly continue, but forecasting this is outside the scope of this analysis. Periods of slower economic activity typically lead to lower new vehicle sales, and an increase in the average age of the parc as vehicles are scrapped less to make up for the decrease in supply. This means that those periods of low economic growth are associated with higher fuel consumption (*ceteris paribus*) per mile of vehicle travel. Typically the period that follows a decline in sales experiences some degree of "catch up" in sales which are then associated with lower fuel consumption per mile of vehicle travel. This modeling approach assumes that these countervailing effects roughly cancel each other out.

MODULE 4 – FUEL CONSUMPTION

Total fuel consumption is a function of the size of the vehicle parc, the fuel economy of the vehicles in the parc, and the VMT of the vehicles in the parc. Historical sales weighted fuel economy for LDVs and LDTs are sourced from ORNL (2012, Tables 4.21 and 4.22). Fuel economy projections in module 4 are taken from Corporate Average Fuel Economy (CAFE) standards, the regulatory-driven fuel economy requirement for all auto-manufacturers each year. Module 4 assumes the CAFE standard is binding – that is, the auto-makers 'just-meet' the standard, they do not exceed it in any years (this could be perceived as a reflection of the fact that consumers tend to prefer horsepower to fuel economy and any technological capacity to exceed the fuel economy standard would be diverted to delivering added horsepower instead). Currently CAFE standards are set to increase for LDVs and LDTs each year through 2025. After 2025, module 4 assumes that CAFE remains at 2025 levels, and remains a binding standard[19]. Future CAFE values are taken from the regulatory announcement (Federal Register, 2012). As a simplifying assumption, module 4 does not degrade on-road fuel economy as a function of vehicle age. In reality, we can expect some modest deterioration of achieved fuel economy performance as vehicles get older, and maintenance for some in the parc are substandard.

Vehicle VMT does vary in an important way with vehicle age, and module 4 captures this dynamic. New vehicles are typically the most intensively used of the vehicle parc, and this declines with vehicle age. VMT per vehicle by vehicle age is taken from ORNL (2012, Table 8.10). There are two effects related to VMT that module 4 does not capture: the rebound effect that results in higher rates of travel demand as vehicles become more fuel efficient, and the income effect of people spending more on travel as incomes rise. The rebound effect is probably relatively small (and shrinking with increasing income (see e.g., Small and VanDender, 2007)). The trend toward more travel demand as a function of rising average incomes is a historically important trend which is not accounted for, but which is likely decreasing in its importance over time as marginal travel demand becomes valued less highly (market saturation) and the effect of marginal income has a lower effect (decreasing income elasticity of demand). Nevertheless, this is a trend which the model excludes, and which could have a modest effect on the results.

[19] There is some difference between vehicle fuel economy measured under test procedures for CAFE purposes and achieved on-road fuel economy. In this work, I have assumed test fuel economy to be equivalent to achieved fuel economy. Since I do this for both the historical and projected fuel consumption values and since the conclusions I draw are based on fractional, not absolute, change in fuel consumption, the key findings would not be affected.

Figure 35 below shows projections for total VMT and fuel demand for the base-case scenario.

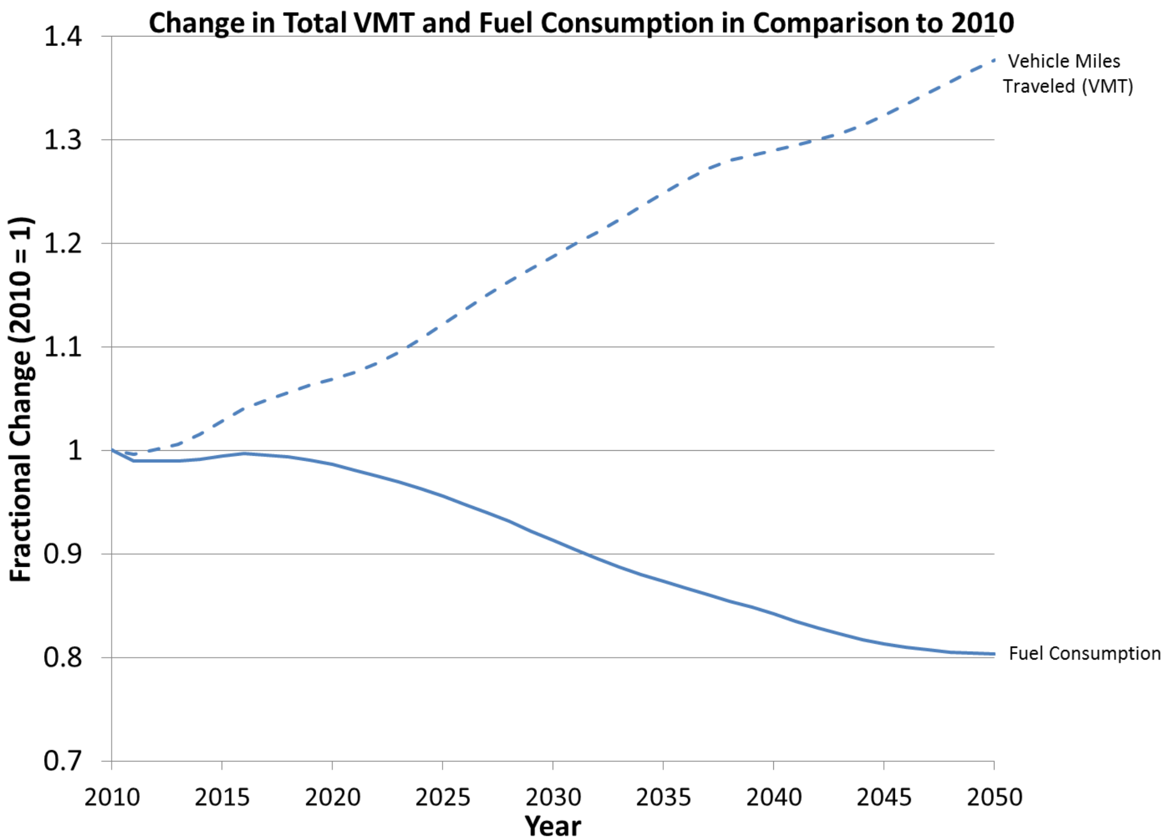

Figure 35: VMT and Fuel Consumption Projections relative to 2010.

As the figure shows, both scenarios project that near term fuel consumption is relatively flat. Once vehicles subject to the new CAFÉ standards begin to enter the parc in significant numbers however, the overall fuel consumption begins to drop for both scenarios. Despite the fact that total VMT is increasing over the scenario shows a drop in total fuel demand over the projection period. This suggests that long term-trends regarding fuel economy standards and vehicle ownership saturation will result in a downward trend in total fuel demand – though this will not begin to be realized until the late 2010's or the early 2020's.

The policy implications for this finding relate to the national dependence on foreign sources of fossil fuels, and for aggregate emissions of greenhouse gases. Over the past several years, U.S. domestic production of crude has increased (EIA, 2012b), and many suspect that production could continue to increase with the use of enhanced oil recovery techniques in shale formations. The confluence of increased domestic production and decreased demand could have significant implications for the balance of trade of the U.S., security concerns about supply from politically unstable world regions, and supply shortages as the developing world shifts to middle-income status and starts to drive at significantly higher rates.

Acknowledgments for Chapter 4

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CHAPTER 5: SUMMARY OF CONCLUSIONS AND POLICY RECOMMENDATIONS

The analyses described above examine the expected or observed energy effects of selected policies to improve energy efficiency. As identified in the introduction to this dissertation, energy efficiency is not the end product of these policies, but is a vehicle through which policy objectives can be achieved. The policy recommendations included bear this relationship between energy efficiency and ultimate policy objectives in mind.

In Chapter 2, I found that despite considerable uncertainty, it is highly likely that the efficiency programs examined are indeed cost-effective policies. However, reporting on these programs could be improved considerably in order to better direct future efficiency interventions. Subsets of the overall program could be more or less cost-effective than the program in aggregate. Identifying those interventions that produce a large benefit relative to their costs is a critical step toward maximizing the social benefit that these programs generate. Concretely, a straightforward first step that DSM operators can do is to report the full stream of expected annual energy savings over the expected lifetime of installed equipment or the estimated current year energy savings by vintage of past installations. This avoids underselling the value generated by efficiency investments by focusing only on first-year energy savings, and it also makes comparisons between investments with different expected lifetimes more comprehensive. Second, DSM operators should produce disaggregated efficiency intervention data so that regulators (and the public) can examine the types of investments being made with public moneys. In addition to the obvious transparency justification, doing so allows comparison of cost-effectiveness between technology and intervention types more readily and helps regulators to identify efficiency investments that are yielding the greatest benefit-cost ratios.

Next, reflecting on the large uncertainty range in the disaggregation method, it is clear that the parameters of which TRM estimates are composed contain substantial uncertainty. Depending on the policy objective of the regulator, the range of possible energy savings may be more or less important relative to the central estimate. In the case of Vermont, where avoiding the need for installing additional electrical system capacity is primary, understanding the range of possible energy outcomes can be just as important since that regulatory environment is risk-averse to hitting system constraints. In Pennsylvania, where there are net electricity exports but greater concerns about emissions close to population centers, maximizing the expected value of energy savings may be relatively more important. Incorporating these uncertain parameters in the calculation of estimated energy savings is a relatively straightforward (and inexpensive) way to provide this relevant information to policy makers. Finally, estimates of the benefits of energy efficiency improvements are usually calculated exclusively in terms of the price of energy avoided. But this is only one portion of the value that energy efficiency improvements generate, and fails to incorporate the unpriced avoided externality benefits associated with emissions reduction and capacity constraints eased (where marginal pricing may be an inaccurate assessment of costs avoided). While estimating these values are likely to include substantial uncertainty, the range of possible values do not include zero and thus their exclusion necessarily results in an underestimate of the total value of efficiency interventions.

In Chapter 3 I find, counterintuitively, that household energy consumption *increases* by an average of around seven percent following participation in PG&E's efficiency rebate program. I hypothesize that the reason for this is likely because consumers are treating the program as an equipment subsidy program rather than as an equipment replacement program. That is, following participation in the program, the household does not dispose of an existing inefficient piece of equipment to be replaced by the new efficient version but instead starts consuming new energy services from the new equipment in addition to continuing past energy consumption patterns. If this is the case, the policy fix is relatively simple—require equipment recycling in addition to proof of purchase of qualifying new equipment. The conclusions of Chapter 3 also help us to reinterpret the findings in Chapter 2. Chapter 3 shows that there are often unintended outcomes from a policy implementation. A TRM-style calculation of the energy effects of the interventions made in the PG&E efficiency rebate program would show a positive energy reduction because it would likely not consider the possibility that the new energy consuming equipment would operate in parallel with the old. This highlights the critical importance of *ex post* examinations of aggregate energy consumption to ensure that anticipated program benefits are actually being realized. As data from smart-meters become more readily available to DSM operators it is becoming more straightforward to perform these kinds of analyses systematically. Policymakers should be made aware that this type of analysis is possible and require it as a part of DSM program design.

Chapter 4 examines how long term trends in demographics and vehicle turnover influence aggregate fuel demand from LDVs in the transportation sector. I show how, despite considerable continued population growth, increasing CAFE standards will likely result in substantially lower demand for transportation fuels in the long-term. CAFE standards are a slow working policy instrument however, and demand over the medium term (<10 years) will not see major changes. It is important to note that the NHTSA CAFE standard is a footprint based standard that allows larger vehicles to meet a less stringent level of fuel economy (in addition to providing different standards for cars and light trucks). This is done to reconcile with NHTSA's primary responsibility toward vehicle safety—although some research shows that this size-based method may be counterproductive (Gayer, 2004). Because research shows that consumer vehicle-size purchase decisions are influenced by fuel prices, it is plausible to believe that fuel (or carbon) taxes can be complementary to a binding CAFE standard that is based on vehicle footprint.

This research also present several avenues for lines of future work. Building on the work of Chapter 2, a logical next step would be to perform similar analyses for other types of residential demand side efficiency interventions besides lighting. As federal lighting efficiency standards come into effect, lighting interventions will be a less prominent option among those available to DSM operators. Characterizing the uncertainty associated with other technology types will be important moving forward as these programs seek out new cost-effective measures to improve household energy efficiency. Similarly, building out from the two states selected for the case-study examination, performing similar analyses for the largest segments of DSM programs in other states seems to be a straightforward extension.

As identified in the conclusion to Chapter 3, that analysis can be replicated where smart-meter data can be made available in a way that allows DSM operators to associate household participation in efficiency programs with energy consumption data. Doing similar analyses across multiple jurisdictions will being to provide a better understanding of how efficiency programs translate to energy savings in practice. Since a goal of performing this kind of analysis should be to deliver efficiency improvements in the most cost-effective way possible, a natural next step is to use household participation data to better predict participation in efficiency programs. Doing so would allow DSM operators to better target marketing materials towards households that are both likely to participate and that fit the profile of households from which valuable electricity demand reduction is available. Smart meter data can also be used to discover which interventions produce the most valuable electricity savings. Examining changes to the load shape profile of households following different types of efficiency interventions would allow DSM operators to better understand which types of technologies or behaviors reduce the most valuable (peak load) electricity demand, rather than just the greatest overall quantity. Further, pairing changes in the load shape profile of household electricity consumption can allow a more precise estimate of the emissions avoided by those interventions. This can be done by comparing the timing of reduced demand with the marginal generator in each time period. Finally, greater detail in the data on the types of interventions associated with each rebate in the PG&E case would create a better understanding of which types of appliances (for example) are associated with the most cost-effective demand reduction.

A logical next step for building on the work described in Chapter 4 would be to construct a series of plausible alternate future scenarios to examine the range of possible outcomes, and the policy choices that could lead to those futures. Further, performing a series of sensitivity analyses to determine the factors that, when varied across plausible future values, have the greatest impact on total fuel consumption could contribute to future policy decision-making. As a model validation exercise, it would be useful to do a comparison of this model to the NEMS transportation sub-module. Doing so with runs both that incorporate both standard population characterization and the more detailed population treatment included in this work would highlight the differences that including that characterization have in the policy outcomes of interest.

CHAPTER 6: REFERENCES

Anderson, C.; Claxton, J. (1982) Barriers to consumer choice of energy efficient products. *Journal of Consumer Research, 9* (2), 163-170.

Arimura, T.H., Li, S., Newell, R. G, & Palmer, K., (2011). "Cost-Effectiveness of Electricity Energy Efficiency Programs." *National Bureau of Economic Research Working Paper Series* No. 17556.

Ashe, M., Chwastyk, D., de Monasterio, C., Gupta, M., & Pegors, M., (2012). "2010 U.S. Lighting Market Characterization." edited by U.S. Department of Energy Office of Energy Efficiency & Renewable Energy. Washington DC: Navigant Consulting.

Atkinson, S. (1981): *Rising Gasoline Prices and Federal Automobile Efficiency Standards: Their Impact on Consumer Choice*. United States: American Petroleum Institute, Washington, DC.

Auffhammer, M., Blumstein, C., & Fowlie, M. (2008). Demand-side management and energy efficiency revisited. *The Energy Journal, 29*(3).

Austin, D., and T. Dinan (2005): "Clearing the Air: The Costs and Consequences of Higher Cafe Standards and Increased Gasoline Taxes," *Journal of Environmental Economics and Management*, 50, 562-582.

Azevedo IL, Morgan MG, Palmer K, & Lave L (2013) Reducing U.S. Residential Energy Use and CO_2 Emissions: How much, How Soon, and at What Cost? *Environmental Science & Technology* 47:2502-2511.

Azevedo, I.L. (2009). Energy Efficiency in the U.S. Residential Sector: An Engineering and Economic Assessment of Opportunities for Large Energy Savings and Greenhouse Gas Emissions Reductions. Ph.D. thesis, Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA.

Azevedo, I.L. (2014) “Consumer End-Use Energy Efficiency and Rebound Effects” *Annual Review of Environment and Resources (forthcoming)*. Vol 39.

Bebbington, M, Lai, C., and Zitikis, R., (2008). Lifetime Analysis of Incandescents Lamps: The Menon-Agrawal Model Revisited. R&RATA #1 (Vol. 1).

Blumstein, C.; Stoft, S. E. (1995). Technical efficiency, production functions and conservation supply curves. *Energy Policy, 23, 9,* 765-768.

Brown M & Levine M (1997) Scenarios of U.S. Carbon Reductions: Potential Impacts of Energy Technologies by 2010 and Beyond. (Lawrence Berkeley National Laboratory and Oak Ridge National Laboratory, Berkeley, CA and Oak Ridge, TN).

Brown, M. A. (2001). Market failures and barriers as a basis for clean energy policies. *Energy Policy, 29*, 1197-1207

Brown, M.A.; Levine, M.D.; Romm, J.P.; Rosenfeld, A.H.; Koomey, J. (1998). Engineering-economic studies of energy technologies to reduce greenhouse gas emissions: opportunities and challenges. *Annual Revision Energy Environ, 23,* 287-385.

Brown, R.; Borgeson, S.; Koomey, J.; Biermayer, P. (2008). *U.S. Building-sector Energy Efficiency Potential*. Lawrence Berkeley National Laboratory: 2008.

CBO (2003): "The Economic Costs of Fuel Economy Standards Versus a Gasoline Tax," *Congressional Budget Office*.

Census. (2008) 2008 National Population Projections. U.S. Department of Commerce. http://www.census.gov/population/projections/data/national/2008.html

Chamon, M., Mauro, P. & Okawa, Y. (2008) Mass car ownership in the emerging market giants. *Economic Policy,* 23**,** 243-296.

Clerides, S., and T. Zachariadis (2008): "The Effect of Standards and Fuel Prices on Automobile Fuel Economy: An International Analysis," *Energy Economics*, 30, 2657-2672.

Crabtree, G.; Glicksman, L.; Goldstein, D.B.; Goldston, D.; Greene, D.; Kammen, D.M.; Levine, M.; Lubell, M.; Richter, B.; Savitz, M.; Sperling, D. (2008). *Energy Future – Think Efficiency. How America can look within to achieve energy security and reduce global warming*. American Physical Society: 2008. Available at: http://www.aps.org/energyefficiencyreport/ (accessed Jul 11, 2012).

Danielsen, A., and J. Hilliard (1983): "Oil Price Increases as Leading Indicators of New Car Sales," *Resources and Energy*, 5, 155-170.

Dargay, J. M. (2001) The effect of income on car ownership: evidence of asymmetry. *Transportation Research Part A: Policy and Practice,* 35**,** 807-821.

Dargay, J., Gately, D. & Sommer, M. (2007) Vehicle Ownership and Income Growth, Worldwide: 1960-2030. *Energy Journal,* 28**,** 143-170.

Davis LW, Fuchs A, & Gertler PJ (2012) Cash for Coolers. in *NBER Working Paper Series* (National Bureau of Economic Research, Cambridge, MA).

Dietz T, Gardner GT, Gilligan J, Stern P, & Vandenbergh MP (2009) Household actions can provide a behavioral wedge to repidly reduce US carbon emissions. *PNAS* 106(44):18452-18456.

Dreyfus, M.K. & Viscusi, W.K., (1995) "Rates of time preferences and consumer valuations of automobile safety and fuel efficiency" *Journal of Law and Economics*, 38, 79-105

Duquesne (2010). Final Annual Report to the Pennsylvania Public Utility Commission for the period June 1, 2009 to May 31, 2010, Duquesne Light Company, prepared by Navigant Consulting, Inc.

Duquesne (2011). Final Annual Report to the Pennsylvania Public Utility Commission for the period June 1, 2010 to May 31, 2011, Duquesne Light Company, prepared by Navigant Consulting, Inc.

Efficiency Vermont (2011a). Technical Reference User Manual (TRM): Measure Savings Algorithms and Cost Assumptions. TRM User Manual No. SV 2011.

Efficiency Vermont (2012a), personal communication. 2011 Prescriptive Lighting Micro-Data

Efficiency Vermont (annually, 2004 – 2012), Annual Reports 2003 – 2011. Burlington, VT. Submitted to the Vermont Department of Public Service and the Efficiency Vermont Contract Administrator. Available at http://www.efficiencyvermont.com/about_us/information_reports/annual_reports.aspx

EIA (2012a), State Electricity Profiles 2010, U.S. Energy Information Administration, Assistant Administrator for Energy Statistics, Office of Electricity, Renewables, and Uranium Statistics, U.S. Department of Energy. DOE/EIA-0348(01)/2. Available from http://www.eia.gov/electricity/state/

EIA (2012b). State Historical Tables for 2011: Retail Sales of Electricity by State by Sector by Provider, 1990-2011. From Electric Power Annual and Form-861. Available at http://www.eia.gov/electricity/data.cfm

EIA (2013a) Frequently Asked Questions: How much electricity is used for lighting in the United States. Updated January 9, 2013. Available at http://www.eia.gov/tools/faqs/faq.cfm?id=99&t=3

EIA (2013b) Electric Power Annual 2012. http://www.eia.gov/electricity/annual/

EIA. (2008) Annual Energy Outlook 2008. Energy Information Administration, Department of Energy. Available at http://www.eia.gov/oiaf/archive/aeo08/index.html

EIA. (2012a) Annual Energy Outlook 2012. Energy Information Administration, Department of Energy. Available at http://www.eia.gov/forecasts/aeo/data.cfm

EIA. (2012b) Petroleum Supply Annual. Energy Information Administration, Department of Energy. Available at http://www.eia.gov/dnav/pet/pet_crd_crpdn_adc_mbbl_a.htm

Energy and Environmental Analysis. (1983): "Consumer Expectations for Future Gasoline Prices," United States, Pages: 30.

Energy Information Administration (2004-2010): Monthly U.S. Retail Gasoline Prices.

Energy Information Administration (2004-2010): Refinery Operable Utilization Rates.

EnergyStar (2012). Learn About Light Output. Accessed September, 2012. Available at http://www.energystar.gov/index.cfm?c=cfls.pr_cfls_lumens

EPA (2010) How Consumers Value Fuel Economy: A Literature Review. *EPA-420-R-1-008.* Washington, D.C., Environmental Protection Agency.

EPA. (2001) Fleet Characterization Data for MOBILE6: Development and Use of Age Distributions, Average Annual Mileage Accumulations Rates, and Projected Vehicle Counts for Use in MOBILE6. U.S. Environmental Protection Agency, Air and Radiation, Office of Transportation and Air Quality. Prepared by Tracie R. Jackson. Document M6.FLT.007 EPA420-R-01-047. Available at http://www.epa.gov/otaq/models/mobile6/m6tech.htm

EPA. (2010) MOVES2010 Highway Vehicle: Population and Activity Data. U.S. Environmental Protection Agency, Office of Transportation and Air Quality, Assessment and Standards Division. Document EPA-420-R-10-026. Available at http://www.epa.gov/otaq/models/moves/movesback.htm

EPA. (2014). Clean Power Plan Proposed Rule. June 2, 2014. http://www2.epa.gov/sites/production/files/2014-05/documents/20140602proposal-cleanpowerplan.pdf

Evergreen Economics. (2013) Needs Assessment for the Energy Savings Assistance and the California Alternate Rates for Energy Programs: Volume 1: Summary Report. December 16, 2013. Available at www.cpuc.ca.gov/PUC/energy/Low+Income/

Federal Register. (2012) 2017 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions and Corporate Average Fuel Economy Standards. Environmental Protection Agency and Department of Transportation, National Highway Traffic Safety Administration. Federal Register, Vol 77 No 199 Book 2 of 2, Pages 62623-63200. October 15, 2012. Available at http://www.nhtsa.gov/staticfiles/rulemaking/pdf/cafe/2017-25_CAFE_Final_Rule.pdf

FHWA. (2011) Highway Statistics 2010. U.S. Department of Transportation, Federal Highway Administration. http://www.fhwa.dot.gov/policyinformation/statistics/2010/

Fischer, C. (2008): "Comparing Flexibility Mechanisms for Fuel Economy Standards," *Energy Policy*, 36, 3116-3124.

Foster, B., A. Chittum, S. Hayes, M. Neubauer, S. Nowak, S. Vaidyanathan, K. Farley, K. Schultz, & T. Sullivan (2012). The 2012 State Energy Efficiency Scorecard. American Council for an Energy-Efficient Economy, Washington, D.C. Report Number E12C. http://www.aceee.org/sites/default/files/publications/researchreports/e12c.pdf

Friedrich, K., Eldridge, M., York, D., Witte, P., & Kushler, M. (2009). Saving Energy Cost-Effectively: A National Review of the Cost of Energy Saved Through Utility-Sector Energy Efficiency Programs (Vol. U092, pp. 31). Washington, DC: American Council for an Energy-Efficient Economy.

Gal, D. (2006): "A Psychological Law of Inertia and the Illusion of Loss Aversion," *Judgment and Decision Making*, 1, 23-32.

GAO (2008) Refinery Outages Can Impact Petroleum Product Prices, but No Federal Requirements to Report Outages Exist. *GAO-09-87.* Washington, D.C., Government Accountability Office.

Gately, D., (1980) "Individual discount rates and the purchase and utilization of energy-using durables: Comment." *Bell Journal of Economics*, 11, 373-374

Gayer, T. (2004): "The Fatality Risks of Sport-Utility Vehicles, Vans, and Pickups Relative to Cars," *Journal of Risk and Uncertainty*, 28, 103-133.

Gillingham K, Newell RG, & Palmer K (2009) Energy Efficiency Economics and Policy. *RFF Discussion Paper* RFF DP 09-13.

Glazer, A., & Lave, C. (1994) "How Regulations Can Succeed Where Taxes Do Not: An Examination of Automobile Fuel Efficiency." University of California at Irvine, Department of Economics.

Goldman, C.A., Hoffman, I.M., Billingsley, M., & Barbose, G.L., (2012). On a Rising Tide: The Future of U.S. Utility Customer-Funded Energy Efficiency Programs. Lawrence Berkeley National Laboratory. ACEEE Summer Study on Energy Efficiency in Buildings. Available at http://www.aceee.org/files/proceedings/2012/start.htm

Goldstein DB (2008) Extreme Efficiency: How Far Can We Go If We Really Need To? *ACEEE Summer Study on Energy Efficiency in Buildings*.

Golove, W. & Eto, J. (1996). Market Barriers to Energy Efficency: A critical reappraisal of the rationale for public policies to promote energy efficiency, Lawrence Berkeley National Laboratory, Energy Environment Division: 1996.

Green, DL. (1990) "Cafe or Price?: An Analysis of the Effects of Federal Fuel Economy Regulations and Gasoline," *Energy Journal*, 11, 37.

Greene, D., and J. German (2007): "Fuel Economy: The Case for Market Failure, Presentation at the Asilomar 2007 Conference on Transportation and Climate Policy."

Greene, D., J. Kahn, and R. Gibson (1999): "Fuel Economy Rebound Effect for Us Household Vehicles," *Energy Journal*, 20, 1-31.

Greenlees, J. S. (1980): "Gasoline Prices and Purchases of New Automobiles," *Southern Economic Journal*, 41(1), p167.

Greenspan, A., and D. Cohen (1996): "Motor Vehicle Stocks, Scrappage, and Sales," *Review of Economics and Statistics*, 81, 369-383.

Hausman, J.A. (1979). "Individual discount rates and the purchase and utilization of energy-using durables." *Bell Journal of Economics*, 10, 33-54

Heffner, G., (Global Energy Associates). (2009). Demand Response Valuation Frameworks Paper. Ernest Orlando Lawrence Berkeley National Laboratory. LBNL-2489E. Available at http://drrc.lbl.gov/sites/drrc.lbl.gov/files/lbnl-2489e.pdf

Hopper, N., Goldman, C., & Schlegel, J. (2006). Energy Efficiency in Western Utility Resource Plans: Impacts on Regional Resource Assessment and Support for WGA Policies (pp. 50). Berkeley, CA: Ernest Orlando Lawrence Berkeley National Laboratory, prepared for Western Interstate Energy Board Committee on Regional Electric Power Cooperation & Office of Electricity Delivery and Energy Reliability, Department of Energy.

Houston, D.A. (1983) "Implicit discount rates and the purchase of untried, energy-saving durable goods." *Journal of Consumer Research*, 10, 236-246.

Hughes, J., C. Knittel, and D. Sperling (2006): "Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand," *University of California Energy Institute, Center for the Study of Energy Markets*.

Ito, K. (2013) Asymmetric Incentives in Subsidies: Evidence from a Large-Scale Electricity Rebate Program. In *NBER Working Paper Series* (National Bureau of Economic Research, Cambridge, MA).

Itron (2008). California Residential Efficiency Market Share Tracking: Lamps 2007. San Diego, CA. Prepared for Southern California Edison.

IWG. (1997). Interlaboratory Working Group. *Scenarios of U.S. Carbon Reductions: Potential impacts of energy-efficient and low-carbon technologies by 2010 and beyond*. Oak Ridge National Laboratory and Lawrence Berkeley National Laboratory, ORNL-444, LBNL-40533: 1997.

IWG. (2000). Interlaboratory Working Group. *Scenarios for a Clean Energy Future*. Oak Ridge National Laboratory and Lawrence Berkeley National Laboratory, ORNL/CON-476, LBNL-44029: 2000.

Jackson, T. (1995) Joint implementation and cost-effectiveness under the framework convention on climate change. *Energy Policy, 23, 2,* 117-138.

Jacobs, P., Evans, B., Hall, N., Horowitz, P., Ridge, R., Peach, G., & Prahl, R., (2010). New York Standard Approach for Estimating Energy Savings from Energy Efficiency Programs: Residential, Multi-Family, and Commercial/Industrial Measures. Prepared for New York Department of Public Service. Prepared by New York Evaluation Advisory Contractor Team, TecMarket Works. Available at http://www.dps.ny.gov/EEPS_Evaluation.html

Jenkins C, Neme C, & Enterline S (2011) Energy efficiency as a resource in the ISO New England Forward Capacity Market. *Energy Efficiency* 4:31-42.

Jenn, A., Azevedo, I.L., & Ferreira, P. (2013) "Impact of federal incentives on the adoption of hybrid electric vehicles in the United States." *Energy Economics*, 40, 936-942

Keefe, R., J. P. Griffin, and J. D. Graham (2008): "The Benefits and Costs of New Fuels and Engines for Light-Duty Vehicles in the United States," *Risk Analysis*, 28, 1141-1154.

Khan, J. E. (1986): "Gasoline Prices and the Used Automobile Market: A Rational Expectations Asset Price Approach," MIT Press, 323-339.

Kleit, A. (1990): "The Effect of Annual Changes in Automobile Fuel Economy Standards," *Journal of Regulatory Economics*, 2, 151-172.

Koomey, J.; Atkinson, C.; Meier, A.; Mahon, J. E.; Boghosian, S.; Atkinson, B.; Turiel, I.; Levine, M.; Nordman, B.; Chan, P. (1991). *The Potential for Electricity Efficiency Improvements in the U.S. Residential Sector*. Lawrence Berkeley National Laboratory, LBL-20477: 1991.

Lescaroux, F. O. & Reach, O. (2008) The Impact of Automobile Diffusion on the Income Elasticity of Motor Fuel Demand. *Energy Journal,* 29**,** 41-60.

Lin, C., J. Chiou, and B. Liu (1997): "Product Quality, Gasoline Prices, and Japanese Shares in the US Automobile Market," *International Journal of Bussiness*, 2, 61-80.

Loughran, D. S., & Kulick, J. (2004). Demand-Side Management and Energy Efficiency in the United States. *The Energy Journal, 25*(1), 19-43.

Lutzenhiser L (1993) Social and Behavioral Aspects of Energy Use. *Annu. Rev. Energy Environ.* 18:247-289.

Lutzenhiser L, *et al.* (2009) Behavioral Assumptions Underlying California Residential Sector Energy Efficiency Programs. in *CIEE Behavior and Energy Program* (California Institute for Energy and Environment, Oakland, CA).

McKinsey (2007). *Reducing the U.S. Greenhouse Gas Emissions: How much at what cost?* U.S. greenhouse gas abatement mapping initiative, McKinsey & Company

McKinsey (2009) Pathways to a Low-Carbon Economy: Version 2 of the Global Greenhouse Gas Abatement Cost Curve. McKinsey & Company

Meier, A. (1982), *Supply Curves of Conserved Energy*; Lawrence Berkeley National Laboratory, 1982. LBL-14686.

Meier, A.K. & Whitier, J. (1983) "Consumer discount rates implied by purchases of energy-efficient refrigerators." *Energy*, 8, 957-962

Messenger, M., Bharvirkar, R., Golemboski, B., Goldman, C. A., Shiller, S., (2010). Review of Evaluation, Measurement and Verification Approaches Used to Estimate the Load

Impacts and Effectiveness of Energy Efficiency Programs. Ernest Orlando Lawrence Berkeley National Laboratory, Environmental Technologies Division. LBNL-3277E

MetEd (2010). Annual Report to the Pennsylvania Public Utility Commission for the period June 2009 to May 2010 Program Year 1, Metropolitan Edison Company.

MetEd (2011). Annual Report to the Pennsylvania Public Utility Commission for the period June 2010 to May 2011 Program Year 2, Metropolitan Edison Company.

Min, J., Azevedo, I.L., Michalek, J, & Bruine de Bruin, W. (2014). "Labeling energy cost on light bulbs lowers implicit discount rates." *Ecological Economics*, 97, 42- 50.

Moezzi M, Iyer M, Lutzenhiser L, & Woods J (2009) Behavioral Assumptions in Energy Efficiency Potential Studies. in *CIEE Behavior and Energy Program* (California Institute for Energy and Environment, Oakland, CA).

Murphy, F., and E. Rosenthal (2006): "Allocating the Added Value of Energy Policies," *The Energy Journal (Cambridge, MA)*, 27, 143-156.

Nadel, S.; Shipley, A.; Elliott, R. N. (2004). *The Technical, Economic and Achievable Potential for Energy-Efficiency in the U.S. – A Meta-Analysis of Recent Studies*. American Council for an Energy Efficient Economy, American Council for an Energy Efficient Economy

NAS (1992) Policy Implications of Greenhouse Warming: Mitigation, adaptation, and the science base. The National Academies of Science

Navigant Consulting, Inc. (2002). U.S. Lighting Market Characterization. Volume I: National Lighting Inventory and Energy Consumption Estimate. Washington, DC. Prepared for Building Technologies Program, Office of Energy Efficiency and Renewable Energy, U.S. Department of Energy

NEEP (2012). Northeast Residential Lighting Strategy. Prepared for the Northeast Energy Efficiency Partnerships (NEEP) by Energy Futures Group, D&R International, Ecova, and Optimal Energy.

NHTS. (2011) National Household Travel Survey: Micro Data. U.S. Department of Transportation, Federal Highway Administration. http://nhts.ornl.gov/download.shtml

Nowak, S., Kushler, M., Sciortino, M., York, D., & Witte, P. (2011). Energy Efficiency Resource Standards: State and Utility Strategies for Higher Energy Savings (pp. 102). Washington, DC: American Council for an Energy-Efficient Economy.

NRC (2010) *Realistic prospects for energy efficiency in the United States;* National Research Council, National Academies Press 329pp.: 2010.

O'Neill, J. & Stupnytska, A. (2009) The Long-Term Outlook for the BRICs and the N-11 Post Crisis. *Global Economics Paper No: 192.* Goldman Sachs.

ORNL. (2012) Transportation Energy Data Book: Edition 31. Oak Ridge National Laboratory, U.S. Department of Energy. Available at http://cta.ornl.gov/data/index.shtml

OTA, (1991). *Changing by Degrees: Steps to reduce greenhouse gases*. Office of Technology Assessment, OTA-0-489, 1991.

PA PUC (2012). Technical Reference Manual. Pennsylvania Public Utility Commission. Available at http://www.puc.state.pa.us/filing_resources/issues_laws_regulations/act_129_information/technical_reference_manual.aspx

Pacala, S. & Socolow, R. (2004). Stabilization wedges: solving the climate problem for the next 50 years with current technologies. *Science,* 305**,** 968-972.

Parfomak, P. W. & L. B. Lave (1996). "How many kilowatts are in a negawatt? Verifying 'ex post' estimates of utility conservation impacts at the regional level." *The Energy Journal* 17(4).

PECO (2010). Annual Report to the Pennsylvania Public Utility Commision for the Period June 2009 through May 2010 Program Year One, PECO Energy Company, prepared by Navigant Consulting, Inc.

PECO (2011). Annual Report to the Pennsylvania Public Utility Commission for the Period June 2010 through May 2011 Program Year Two, PECO Energy Company, prepared by Navigant Consulting, Inc.

PENELC (2010). Annual Report to the Pennsylvania Public Utility Commission for the period June 2009 to May 2010 Program Year 1, Pennsylvania Electric Company.

PENELC (2011). Annual Report to the Pennsylvania Public Utility Commission for the period June 2010 to May 2011 Program Year 2, Pennsylvania Electric Company.

PennPower (2010). Annual Report to the Pennsylvania Public Utility Commission for the period June 2009 to May 2010 Program Year 1, Pennsylvania Power Company.

PennPower (2011). Annual Report to the Pennsylvania Public Utility Commission for the period June 2010 to May 2011 Program Year 2, Pennsylvania Power Company.

PPL (2010). PY1 Final Annual Report to the Pennsylvania Public Utility Commission for the period June 1, 2009 to May 31, 2010 Program Year 1, PPL Electric and The Cadmus Group, Inc.

PPL (2011). PY2 Final Annual Report to the Pennsylvania Public Utility Commission for the period June 1, 2010 to May 31, 2011 Program Year 2, PPL Electric and The Cadmus Group, Inc.

Renshaw, E. (1992): "Identifying No Growth Years in the Us Economy—Using Increases in Crude Oil Prices," *Energy Economics*, 14, 132-135.

Rosenfeld, A.; Atkinson, C.; Koomey, J.; Meier, A.; Mowris, R.; Price, L. (1991). A *Compilation of Supply Curves of Conserved Energy*. LBL #31700. Berkeley, Calif.: Center for Building Science, Lawrence Berkeley Laboratory: 1991.

Rosenfeld, A.; Atkinson, C.; Koomey, J.; Meier, A.; Mowris, R.; Price, L. (1993). Conserved energy supply curves for U.S. buildings. *Contemporary Policy Issues*, *11*, 45-68.

Rosenfeld, A.H. (1999). The art of energy efficiency: Protecting the environment with better technology. *Annual Review, Energy & Environment*, *24*, 33-82.

Rubin, E.S.; Cooper, R.N.; Frosh, R.A.; Lee, T.H.; Marland, G.; Rosenfeld, A.H., Stine, D.D. (1992). Realistic mitigation options for global warming. *Science*, *257*, 148-149, 261-266.

Rudermand, H., Levine, M.D., & McMahon, J.E. (1987) "The behavior of the market for energy efficiency in residential appliances including heating and cooling equipment" *Energy Journal*, 8, 101-124

Rufo M & Coito F (2002) California's Secret Energy Surplus: The Potential for Energy Efficiency. (The Energy Foundation and The Hewlett Foundation, Oakland, CA).

Schiller, S.R., Goldman, C.A., & Galawish, E., (2011). National Energy Efficiency Evaluation, Measurement and Verification (EM&V) Standard: Scoping Study of Issues and Implementation Requirements. Ernest Orlando Lawrence Berkeley National Laboratory. LBNL-4265E. Available at http://emp.lbl.gov/sites/all/files/lbnl-4265e.pdf

Sedano, R. (2011). Who Should Deliver Ratepayer-Funded Energy Efficiency? A 2011 Update, The Regulatory Assistance Project.

Seligman C, Darley JM, & Becker L, J. (1977) Behavioral Approaches to Residential Energy Conservation. *Energy and Buildings* 1:325-337.

Siler-Evans, K., Azevedo, I. L., & Morgan, M. G. (2012). Marginal Emissions Factors for the U.S. Electricity System. *Environmental Science & Technology, 46*(9), 4742-4748.

Small, K., and K. Van Dender (2007): "Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect," *Energy Journal*, 28, 25.

Smith, V. K. & Moore, E.M. (2010). Behavioral economics and benefit cost analysis. *Env. and Resource Econ*. *46*, 17-234.

Sorrell, S. (2007) "The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency." Sussex Energy Group, UK Energy Research Centre. Available at http://aida.econ.yale.edu/~nordhaus/homepage/documents/UK_ReboundEffectReport.pdf

Sorrell, S. & Dimitropoulos, J. (2007) "UKREC Review of Evidence for the Rebound Effect Technical Report 2: Econometric Studies" UK Energy Research Centre, Working Paper. Available at http://www.ukerc.ac.uk/support/ReboundEffect

Storchmann, K. (2005) Long-run Gasoline Demand for Passenger Cars: The Role of Income Distribution. *Energy Economics,* 27**,** 25-58.

Sweeney, J.L. (2002). The California Electricity Crisis. Hoover Institution. ISBN-10: 0817929118

Tellus (1997). Policies and Measures to Reduce CO_2 Emissions in the United States: An analysis of options for 2005 and 2010. Tellus Institute: 1997.

Thomas, B.A. & Azevedo, I.L. (2013a) “Estimating direct and indirect rebound effects for U.S. households with input-output analysis Part 1: Theoretical framework.” *Ecological Economics*, 86, 199-210.

Thomas, B.A. & Azevedo, I.L. (2013b) “Estimating direct and indirect rebound effects for U.S. households with input-output analysis Part 2: Simulation.” *Ecological Economics*, 86, 188-198

Thomas, B.A. & Azevedo, I.L. (2014) “Should policy-makers allocate funding to vehicle electrification or end-use energy efficiency as a strategy for climate change mitigation and energy reduction? Rethinking electric utilities efficiency programs.” *Energy Policy (accepted).*

Tolouei, R., and H. Titheridge (2009): "Vehicle Mass as a Determinant of Fuel Consumption and Secondary Safety Performance," *Transportation Research Part D: Transport and Environment*, 14, 385-399.

Turrentine, T., and K. Kurani (2007): "Car Buyers and Fuel Economy?," *Energy Policy*, 35, 1213-1223.

Ürge-Vorsatz, D.; Novikova, A.; Köppel, S; Boza-Kiss, B. (2009). Bottom–up assessment of potentials and costs of CO_2 emission mitigation in the buildings sector: Insights into the missing elements. *Energy Efficiency*, *2*, 293-316.

VEIC (2011). Mid-Atlantic Technical Reference Manual: Version 2. Prepared for the Northeast Energy Efficiency Partnerships by the Vermont Energy Investment Corporation. July 2011. Available at http://neep.org/emv-forum/forum-products-and-guidelines

VT PSB (2013) See the Public Service Board website http://psb.vermont.gov/projects/EEU/rfpsandcontracts.

Wang, M., Huo, H., Johnson, L. & He, D. Q. (2007) Projection of Chinese motor vehicle growth, oil demand, and CO2 emissions through 2050. *Transportation Research Record***,** 69-77.

Wasi N & Carson RT (2011) The Influence of Rebate Programs on the Demand for Water Heaters: The Case of New South Wales. in *UC Center for Energy and Environmental Economics Working Paper Series* (UCE^3, Berkeley, California).

West, S., and R. Williams III (2005): "The Cost of Reducing Gasoline Consumption," *American Economic Review*, 95, 294-299.

WestPenn (2010). Annual Report to the Pennsylvania Public Utility Commission for the period June 2009 to May 2010 Program Year 1, West Penn Power Company.

WestPenn (2011). Annual Report to the Pennsylvania Public Utility Commission for the period June 2010 to May 2011 Program Year 2, West Penn Power Company.

Whitfield, S. C., Rosa, E. A., Dan, A., & Dietz, T. (2009). The Future of Nuclear Power: Value Orientations and Risk Perception. *Risk Analysis, 29*(3), 425-437.

Wilson, D., Purushothaman, R. & Fiotakis, T. (2004) The BRICs and Global Markets: Crude, Cars and Capital. *Global Economics Paper No: 118.* Goldman Sachs.

World Resouce Institute (WRI), Carbon Emissions Flow Chart. Available at: http://www.wri.org/resources/charts-graphs/us-greenhouse-gas-emissions-flow-chart.

Wüstenhagen, R., Wolsink, M., & Bürer, M. J. (2007). Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy, 35*(5), 2683-2691.