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Experiences of Vulnerable Residential Customer Subpopulations with Critical Peak Pricing:

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CONSUMER BEHAVIOR STUDY ANALYSIS

Experiences of Vulnerable Residential Customer Subpopulations with Critical Peak Pricing

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Glossary of Acronyms, Abbreviations, and Terms

AMI	**Advanced Metering Infrastructure –** All components that allow two-way communication between meters and the electric utility's meter data management system to collect electricity usage and related information from customers and to deliver information to customers.
CBS	**Consumer Behavior Study**
CBSP	**Consumer Behavior Study Plan**
CEIC	**Cleveland Electric Illuminating Company**
CPP	**Critical Peak Pricing –** A time-based rate component that increases the price on electricity consumed for participating customers during the hours included in a declared critical event. This higher price is overlaid onto the existing retail rate. Critical events are called either on a day-ahead or in-day basis in response to forecasted or achieved, respectively, high wholesale market electricity prices, short-term system reliability problems, or both. The primary objective of this rate design is to promote reductions in the peak demand of electricity.
CPR	**Critical Peak Rebate –** A demand response program that pays participating customers for reducing electricity consumed in relation to a baseline during the hours included in a declared critical event. Critical events are called either on a day-ahead or in-day basis in response to forecasted or achieved, respectively, high wholesale market electricity prices, short-term system reliability problems, or both. The primary objective of this program design is to promote reductions in the peak demand of electricity.

DID	**Difference-in-Differences**
DOE	**Department of Energy**
DTE	**DTE Energy**
EAPR	**Energy Assistance Program**
FERC	**Federal Energy Regulatory Commission**
FOA	**Funding Opportunity Announcement**
GMP	**Green Mountain Power**
HEMS	**Home Energy Management System**
IHD	**In-Home Display**
IV	**Instrumental Variable regression**
kWh	**Kilowatt-hour**
LBNL	**Lawrence Berkeley National Laboratory**
LE	**Lakeland Electric**
MMLD	**Marblehead Municipal Light Department**
MP	**Minnesota Power**
NVE	**NV Energy**
OE	**DOE Office of Energy Delivery and Electricity Reliability**
OG&E	**Oklahoma Gas & Electric**
PCT	**Programmable Communicating Thermostat**
PURPA	**Public Utility Regulatory Policies Act**

RCT	**Randomized Controlled Trial –** A research strategy in which customers who volunteer to be exposed to a treatment are randomly assigned to treatment and control conditions.
RED	**Randomized Encouragement Design –** A research design in which two groups of customers are selected from the same population at random and one is offered a treatment while the other is not. Not all customers offered the treatment are expected to take it but, for analysis purposes, all those who are offered the treatment are considered to be in the treatment group.
SGIG	**Smart Grid Investment Grant**
SMUD	**Sacramento Municipal Utility District**
TAG	**Technical Advisory Group**
TOU	**Time-Of-Use –** A time-based rate program design that charges customers for electricity usage based on the block of time it is consumed. The price schedule is fixed and predefined, based on season, day of week, and time of day. The primary objective of this rate design is to promote overall shifting of electricity away from the peak period to other periods.
2SLS	**Two Stage Least Squares regression**
VEC	**Vermont Electric Cooperative**
VPP	**Variable Peak Pricing –** A time-based rate program design that charges customers for electricity usage based on the block of time it is consumed. The price schedule is variable and differs daily, based on bulk power system conditions during that period of the day. The primary objective of this

rate design is to promote targeted shifting of electricity away from the peak period to other periods.

Foreword

As far back as the 1890s, the electric industry has been debating the issue of how to efficiently and optimally charge customers for consuming electricity (Hausman and Neufeld, 1984). At that time, there were emerging and contentious discussions among economists about the merits of pricing this new commodity differentially based on time. The challenge with such pricing schemes revolved around metering—cost-effective technology did not exist at that time to allow electricity consumption to be tracked at the required level of detail. Thus, virtually all customers were charged for their electricity consumption at a rate that was time-invariant (i.e., flat).

By the 1970s, the debate had moved beyond issues of economic efficiency and instead turned towards more practical concerns about consumer behavior—could mass-market (i.e., residential and small commercial) customers actually manage their electricity consumption under time-based rate programs? The results of studies undertaken by the Federal Energy Administration, the predecessor to the U.S. Department of Energy (DOE), indicated such customers were, in fact, capable of managing their electricity consumption by moving it away from the expensive "peak" period to the less-expensive "off-peak" period (see Faruqui and Malko, 1983 for a meta-analysis of these experiments). In spite of this evidence, the lack of low-cost interval or period-based metering technology continued to limit the industry's ability to expand the application of time-based rate programs at the residential level through the end of the 20th century.

Over the past ten years, however, the costs of interval meters, the communication networks to connect the meters with utilities, and the back-office systems necessary to maintain and support them (i.e., advanced metering infrastructure or AMI) have dramatically decreased. The implementation of AMI and interval meters by utilities, which allows electricity consumption data to be captured, stored and reported at between 5 to 60-minute intervals in most cases, provides an opportunity for utilities and policymakers to once again seriously consider the merits of the widespread deployment of time-based rate programs. However, many regulators and other key policymakers have determined that more definitive answers to key policy questions must be addressed before they will fully support a paradigm shift in the way retail electricity providers charge residential and small commercial customers for consuming electricity.

The American Recovery and Reinvestment Act of 2009 included $3.4B for the Smart Grid Investment Grant (SGIG) program with the goal of creating jobs and accelerating the transformation of the nation's electric system by promoting investments in smarter grid technologies, tools and techniques (DOE, 2012). Among other topics, the Funding Opportunity Announcement (DE-FOA-0000058) identified interest in AMI projects that examined the impacts and benefits of time-based rate programs and enabling control and information technologies through the use of randomized controlled experimental designs.

Based on responses to this FOA, DOE decided to co-fund ten utilities to undertake eleven experimentally-designed Consumer Behavior Studies (CBS) that proposed to examine a wide range of the topics of interest to the electric utility industry. Each chosen utility was to design, implement and evaluate their own study in order to address questions of interest both to itself and to its applicable regulatory authority, whose approval was generally necessary for the study to proceed. The DOE Office of Energy Delivery and Electricity Reliability (OE), however, did set guidelines, both in the FOA and subsequently during the contracting period, for what would constitute an acceptable study under the Grant.

To assist in ensuring these guidelines were adhered to, OE requested that LBNL act as project manager for these Consumer Behavior Studies to achieve consistency of experimental design and adherence to data collection and reporting protocols across the ten utilities. As part of its role, LBNL formed technical advisory groups (TAG) to separately assist each of the utilities by providing technical assistance in all aspects of the design, implementation and evaluation of their studies. LBNL was also given a unique opportunity to perform a comprehensive, cross-study analysis that uses the customer-level interval meter and demographic data made available by these utilities due to SGIG-imposed reporting requirements, in order to analyze critical policy issues associated with AMI-enabled rates and control/information technology. LBNL will publish the results of these analyses in a series of research reports, of which this is one, that attempt to address critical policy issues relating to a variety of topics including customer acceptance, retention and load response to time-based rates and various forms of enabling control and information technologies.

Executive Summary

Ninety-eight percent of residential customers in the U.S. take service under flat or inclining block rates (FERC, 2012). Yet time-based rates provide an opportunity for customers and utilities alike to achieve a variety of benefits including: increased opportunity for customer bill management, lower utility power production costs, deferred future generation investments, and increased utilization of existing infrastructure (National Energy Technology Laboratory, 2008). Recent broad-based deployment of Advanced Metering Infrastructure (AMI) enables the opportunity for broader adoption of time-based rates, and the benefits that result have been sizable contributors to making the investments cost effective (National Energy Technology Laboratory, 2008).

However, some stakeholders have raised concerns about the assumptions underlying the benefits assessments in AMI business cases. Some contend AMI is not needed to implement time-based rates, although it may lower the cost of doing so and facilitate more diversity in the types of time-based rates that may be offered (Felder, 2010). Others infer that since less than 2% of residential customers at a national level take service under such rates (FERC, 2012), large groups of customers have consistently preferred stable and less volatile rate structures (Alexander, 2010). In addition, some observe that even mild forms of time-based rates (e.g., time-of-use) have sometimes drawn opposition from customers (Brand, 2010) which would potentially manifest itself in high attrition rates once customers are exposed to time-based rates. Furthermore, some have raised concerns that customer load response to such rates has been inconsistent, disappearing over time (AARP et al., 2010). Ultimately, if a very small share of customers take up these rates, and those who do either quickly leave or don't substantially and persistently respond to them, then the bill benefits that utilities promote in their AMI business case are unlikely to come to fruition.

Such concerns are especially acute for certain subpopulations of residential customers. Low income, elderly and chronically ill (i.e., vulnerable) customers are believed to not use as much energy as their counterparts and so have less load that can be shifted or reduced to capture bill savings (AARP et al., 2010). In addition, some assert that such vulnerable customers lack the know-how or wherewithal with which to curtail usage (Faruqui et al., 2010). Furthermore, vulnerable customers likely have more limited financial resources which may compel them to avoid high priced periods by reducing electricity for essential usage (e.g., life-sustaining medical equipment, air conditioning) causing them physical harm (AARP et al., 2010). Lastly, if these customers are on fixed or limited incomes, then they may be more adversely affected by higher bills, which might possibly result from certain forms of time-based rates.

Based on these concerns, a set of outstanding research questions can be identified:

1. Do vulnerable subpopulations exhibit usage patterns (either in terms of their average usage or flexibility of usage) that differ from those of non-vulnerable subpopulations?
2. Do vulnerable subpopulations participate and stay enrolled in time-based rates at different levels than non-vulnerable subpopulations?
3. Do vulnerable subpopulations exhibit load response to time-based rates at different levels than non-vulnerable subpopulations?
4. Do vulnerable subpopulations benefit financially from time-based rates at different levels than non-vulnerable subpopulations?
5. If vulnerable subpopulations do curtail usage in the peak period, is there evidence that they do so at the expense of comfort, wellbeing, or satisfaction to a greater extent than non-vulnerable subpopulations?

Unfortunately, there is limited existing literature that addresses these questions specifically with regard to vulnerable subpopulations. There have been a few pieces of empirical research that focus on the low-income community (see Faruqui et al., 2010; Smart Grid Consumer Collaborative, 2012), but little to no research has been published on the elderly or those with medical needs.

This report extends the existing empirical literature on the experiences of low-income customers exposed to critical peak pricing, and provides the first glimpses into the experiences of the elderly and those who reported being chronically ill. Specifically, we analyzed two of the time-based rate consumer behavior studies, which were co-funded by the Department of Energy as part of the Smart Grid Investment Grant program.

Although none of the SGIG-funded consumer behavior studies were explicitly designed to address the five outstanding research questions concerning certain vulnerable customer subpopulations articulated above, some were more conducive than others to contribute to our understanding. The following three criteria were used to determine which utility studies to include in this analysis:

1. The utility study had to include rate treatments that were similar in order to readily allow comparison. A high proportion of SGIG-funded consumer behavior studies included critical peak pricing (CPP) overlaid onto the utility's existing flat or inclining block rate. So the analysis was restricted to utility studies that included a CPP rate design.
2. A utility study had to be implemented in a way that readily enabled the inclusion of vulnerable customers. Most studies had qualification processes, screening criteria and/or geographic boundaries on the location of the study's participants that dramatically limited opportunities for vulnerable customers to be considered for enrollment.[i]
3. A utility study had to readily enable the identification of elderly, low-income and chronically ill customers in not just the control and treatment cells, but also in the pool of customers who eschewed the offer to participate in the study.[ii] Most utilities chose to collect demographic information via survey instruments at different points during and after their study. Because of this timing and the chosen approach taken for survey administration, most utilities had very limited success getting broad-based and high levels of survey responses from vulnerable populations of both participants and non-participants.

As such, only two of the eleven SGIG-funded consumer behavior studies had sufficient participation data, interval meter data, survey and other sources of demographic data to sufficiently analyze these outstanding research questions associated with vulnerable populations applied to a critical peak pricing rate design: Green Mountain Power (GMP) and Sacramento Municipal Utility District (SMUD). [iii]

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[i] For example, one utility study excluded all customers that were in arrears, which reduced the eligible pool of qualified customers by 30%. In another, the utility chose to run the study in an area that was considerably more affluent than the rest of the service territory.

[ii] This is needed in order to properly address the issue of participation – one must have information about those who accepted it as well as those who eschewed it to see if there is any difference between the two. In addition, this is needed in order to correctly estimate load response using a Randomized Encouragement Design (RED) estimation (for more detail on these methods see Appendix D).

[iii] Because neither SMUD nor GMP's study was designed to have the power to identify load responses of disaggregated customer groups, we chose to combine multiple similar treatment arms for both utilities in our analysis, in order to maximize the potential of identifying any differences in load response, enrollment rates, and bill impacts. In particular, while we analyzed SMUD's default rate treatment independently, we combined SMUD's voluntary CPP rate treatment arms, both of which faced exactly the same rates and critical events, but one of which was offered an in-home-display (IHD) and one of which was not. We similarly combined GMP's voluntary CPP rate treatment arms, both of which were exposed to exactly the same rates and experienced the same critical events, but one of which included an IHD and one of which did not. Appendix D provides tables showing the estimated results for these different treatment arms both

The experience of vulnerable customer subpopulations in GMP's and SMUD's consumer behavior studies suggests there may be some differences from those who would not be considered vulnerable, many of which are small in magnitude and not statistically significant. However, these results often differ both across the three vulnerable subpopulations, and across the two utilities included in this analysis. Returning to the questions initially posed, our research suggests that in general:

Key Finding #1

Do vulnerable subpopulations exhibit usage patterns that differ from those of non-vulnerable subpopulations?

In cases where differences were statistically discernable, the average peak period usage of elderly (GMP) and low-income (SMUD) customers was slightly lower, while it was higher for chronically ill (GMP) customers. In addition, there is evidence that all groups had instances of slightly lower load variability/flexibility than their non-vulnerable counterparts, though the differences were very small in magnitude, and not always statistically significantly different.

combined and disaggregated. Broadly speaking there were no outstanding differences between the combined treatments sufficient to limit the ability to make conclusions about the results when aggregated.

Key Finding #2

Do vulnerable subpopulations participate and stay enrolled in time-based rates at different levels than non-vulnerable subpopulations?

Vulnerable subpopulations participated in a CPP rate at similar levels in general as non-vulnerable subpopulations. Discernable differences were observed for chronically ill SMUD customers offered the voluntary CPP rate, and low-income customers defaulted onto the SMUD CPP rate, both of which participated at slightly lower levels than their non-vulnerable counterparts.[iv] In addition, the majority of vulnerable subpopulations stayed enrolled in the rate at roughly comparable levels as their non-vulnerable counterparts, with some slight differences that were statistically identifiable, but very small in magnitude.

Key Finding #3

Do vulnerable subpopulations exhibit load response to time-based rates at different levels than non-vulnerable subpopulations?

Vulnerable subpopulations were usually just as responsive on a proportional basis as their non-vulnerable counterparts over the entire study period, though exhibiting varying degrees of persistence. There were no differences in response level or persistence of response between vulnerable and non-vulnerable customers on the default rate. In the voluntary rates, the only case in which there was a statistically significant difference was for low-income customers, who exhibited a slightly lower load response as compared to their higher income counterparts. However, these voluntary low-income customers had a persistent load response between the first and second summer of the pilot, while higher income customer load response attenuated over time. Voluntary elderly customer load response in one instance attenuated between the two summers as well, while non-elderly load response did not.

[iv] Note that differences in participation rates do not reflect flaws in the initial randomization of households into control and treatment groups. These studies were designed to be evaluated using a Randomized Encouragement Design (RED).

Key Finding #4

Do vulnerable subpopulations benefit financially from time-based rates at different levels than non-vulnerable subpopulations?

Vulnerable subpopulations financially benefited at roughly similar proportional levels to their non-vulnerable counterparts. In the case of SMUD the rate was designed to be revenue neutral during the summer event season, but all customer groups actually experienced bill savings during this time period as a result of being on the rate. In addition, chronically ill customers financially benefited at even higher rates relative to their non-vulnerable counterparts. In the case of GMP, the rate was designed to be revenue neutral over the entire year, but events were only called during the summer. Bills were higher for all customer groups during the event season, and higher for elderly customers during the non-event season relative to both non-elderly customers, and relative to elderly customers in the control group.

This means that the estimation of load impacts and other outcomes can be accomplished even with imperfect compliance with treatment (i.e., customers not opting in or choosing to drop out do not invalidate the treatment estimates).

Key Finding #5

Do vulnerable subpopulations curtail usage at the expense of comfort, well-being, or satisfaction to a greater extent than non-vulnerable subpopulations

Using survey data available only from SMUD, we are able to analyze the responses of customers to questions regarding their comfort, the difficulty they faced in changing their usage, and their overall satisfaction with the rate. With respect to reported comfort and difficulty of changing behavior there were no differences between vulnerable and non-vulnerable subpopulations in the default treatment. In the voluntary treatment, chronically ill customers were more likely to report discomfort and elderly customers were less likely to indicate that behavior changes they undertook were difficult, relative to their respective non-vulnerable counterparts. However, overall satisfaction levels were extremely high across all subpopulations (with between 91% and 100% indicating they would want to remain on the rate), and low-income customers in the default treatment indicating statistically significantly higher levels of satisfaction than their higher income counterparts.

Here we look at the holistic experience of each of these vulnerable subpopulations more specifically.

Low Income Customers

Our results indicate that as a group, low-income customers participated in a CPP rate at slightly lower levels than their more affluent counterparts, particularly when the default enrollment approach was used. However, fewer low-income customers dropped out of the default CPP once the rate took effect, and comparable shares of customers from both groups chose to remain on the voluntary rate throughout the study. An analysis of energy usage patterns in the pre-treatment period indicated that low-income customers had lower average use levels (SMUD) and potentially less flexible peak loads (GMP), and once exposed to the CPP rate were somewhat less responsive on a proportional basis than their peers during CPP events when volunteering for the rate, though under a default enrollment approach the proportional load response was similar. In addition, voluntary low-income customers had a more persistent load response than their higher income counterparts. When taken together, low-income customers fared no better and no worse than other customers when it came to the bill impacts of CPP – they generally saw comparable proportional changes in their bills, which included bill savings in the case of SMUD's rate design, but higher expenditure during the event season on average in the case of GMP's rate design. Finally, low-income customers did not report any differing levels of discomfort or hardship in responding to SMUD's CPP rate, and when defaulted onto the rate were more likely to report high levels of satisfaction compared to their higher income counterparts.

Elderly Customers

In general elderly customers enrolled in CPP at similar rates, regardless of the enrollment approach, in comparison to their younger counterparts, and of those who actively volunteered similar proportions of elderly and non-elderly remained on the rate throughout the study. However, those defaulted onto the rate tended to drop out at higher rates than their younger counterparts. Furthermore, while elderly customers in GMP's pilot had lower average peak load usage and were slightly less flexible in this usage, there was no identifiable difference either in pre-treatment usage patterns between elderly and non-elderly in the SMUD study, or in the degree to which they responded to the CPP rate on average in either study, again on a proportional basis. There is some indication that elderly customers who volunteered for the rate may have attenuated their load response between the first and second summer, while non-elderly customers did not exhibit this result. In addition, they saw similar bill impacts, on a proportional basis, as their younger peers during the event season, though their bills were higher than both non-elderly treated households and elderly control households in the non-event season in GMP's pilot. Their survey responses indicated that on a whole they were happy with the rate. Elderly customers in both the default and voluntary rate reported lower levels of discomfort than their non-elderly counterparts, though the difference is not statistically significant. They were significantly more likely to report that the changes they made to their consumption were not difficult. Their overall level of satisfaction with the rate was equally as high as their non-elderly counterparts, with over 90% of respondents reporting both satisfaction with the rate and a willingness to continue on the rate going forward.

Chronically Ill Customers

As with the low-income subpopulations, a smaller proportion of customers with medical needs enrolled in the voluntary CPP rate, but they remained on the rate at roughly comparable levels throughout the study as those without such chronic health problems. However, those defaulted onto the rate dropped out at slightly higher rates than their non-ill counterparts. Despite having higher loads on average and potentially slightly less flexibility in some cases, chronically ill customers were just as responsive (regardless of the enrollment approach taken) on a proportional basis as their non-ill counterparts, and their load response was persistent between both summers. Chronically ill customers experienced comparable bill savings as their peers in general, though those who volunteered for SMUD's pilot actually experienced higher bill savings than their non-ill counterparts. On SMUD's study, chronically ill customers reported higher levels of discomfort, though this result is based on a very small sample size (only around 20 chronically ill customers responded to the survey) but their overall satisfaction with the rate was equally as high as all other subpopulations.

This analysis generally supports conclusions in the existing empirical research literature, discussed in more detail in this report, about the experiences of low-income customers (see Faruqui et al., 2010; Smart Grid Consumer Collaborative, 2012), and provides the first insights into the experiences of the elderly and those who reported being chronically ill on critical peak pricing. The results also suggest that the concerns of some, namely that low income, elderly and the chronically ill are less capable of managing their electricity consumption in response to a critical peak pricing rate design, were not realized in these two instances. In addition, in the case of SMUD's pilot, the level of satisfaction reported among survey respondents suggests that it is unlikely that customers were shifting or curtailing their energy use in response to critical events to an extent that was harmful to the vulnerable populations studied here. The only possible exception is chronically ill customers, who did report higher levels of discomfort. However, it's not clear to what extent these levels of discomfort were caused by the CPP rate, as overall levels of satisfaction with the rate reported by these same customers were very high.

In the end, this analysis focused on two studies whose primary objectives were not to analyze in great detail the experiences of low income, elderly or chronically ill customers, and therefore were not designed to do so. Our results are limited to those customers who qualified for these studies, resided in locales where the studies were implemented, and provided survey responses which enabled us to identify customers as vulnerable or not. Although our results accurately represent this sample of customers, our ability to extrapolate those results to the broader population is certainly limited. In addition, to the extent that identifiable differences in outcomes between vulnerable and non-vulnerable customers were found in this study, discussion of why these differences might exist was beyond the scope of this report.

To the degree policy-makers, utilities, and other stakeholders continue to demand more credible and precise estimates of load impacts and other key metrics that describe the experiences of vulnerable subpopulations, and desire a better understanding of why differences exist if present, this suggests a need to design and implement time-based rate studies utilizing experimental designs (sampling weights and sufficient sample sizes in particular) that are specifically targeted at these vulnerable subpopulations. Results from more concerted study on this topic would more definitively and concretely address the concerns of some in the electric industry. Furthermore, utilities undertaking future pricing studies focused on the most vulnerable customers should seek to more robustly collect demographic information from everyone, especially those who eschew the offer to participate in the study, in order to more accurately characterize the preferences and experiences of different customer subpopulations.

1. Introduction

Ninety-eight percent of residential customers in the U.S. take service under flat or inclining block rates (FERC, 2012). Yet time-based rates provide an opportunity for customers and utilities alike to achieve a variety of benefits including increased opportunity for customer bill management, lower utility power production costs, deferred future generation investments, and increased utilization of existing infrastructure (National Energy Technology Laboratory, 2008). Historically, implementation of time-based rates required replacement of a traditional electro-mechanical meter with a multi-register or interval meter that was accompanied by a monthly meter charge. The costs of individual meter upgrades were seen by many as a barrier to broader adoption of time-based rates. Recent broad-based deployment of Advanced Metering Infrastructure (AMI) removes this metering hurdle, thereby enabling the opportunity for broader adoption of time-based rates. Currently, utilities in the United States have installed more than 50 million smart meters, covering over 43% of U.S. homes (Institute for Electric Innovation, 2014).

However, before these AMI investments were undertaken, state regulators had to approve them. Utilities have justified the investment in AMI through a business case. This business case lays out the various technological components of the AMI system, along with an assessment of its costs and benefits (National Energy Technology Laboratory, 2008). Most AMI business cases include an estimate of benefits associated with the increased penetration of time-based rates now enabled by the introduction of two-way interval metering technology. Such calculations rely on assumptions about customer acceptance, retention and response to time-based rates.

Some stakeholders have raised concerns about the assumptions underlying such AMI benefits assessments. Some contend AMI is not needed to implement time-based rates, although it may lower the cost of doing so and facilitates more diversity in the types of time-based rates that may be offered (Felder, 2010). Others infer that since less than 2% of residential customers at a national level take service under such rates (FERC, 2012), large groups of customers have consistently supported stable and less volatile rate structures (Alexander, 2010). In addition, some observe that even mild forms of time-based rates (e.g., time-of-use) have sometimes drawn opposition from customers (Brand, 2010) which could potentially manifest itself in high attrition rates once customers are exposed to time-based rates. Furthermore, some have raised concerns that customer load response to such rates has been inconsistent, disappearing over time (AARP et al., 2010). Ultimately, if a very small share of customers take up these rates and those who do either quickly leave or don't substantially and persistently respond to them when staying, then the bill benefits that utilities promote in their AMI business case are unlikely to come to fruition.

Such concerns are especially acute for certain subpopulations of residential customers. Low income, elderly and chronically ill (i.e., vulnerable) customers are believed to use less energy than their counterparts and so have less load that can be shifted or reduced to capture bill savings (AARP et al., 2010). In addition, some assert that such vulnerable customers lack the know-how or wherewithal with which to curtail usage (Faruqui et al., 2010). Furthermore, vulnerable customers may be likely to have more limited financial resources, which may compel them to avoid high priced periods by reducing electricity for essential usage (e.g., life-sustaining medical equipment, air conditioning) causing them physical harm (AARP et al., 2010). Lastly, if these customers are on fixed or limited incomes, then they may be more adversely affected by higher bills that certain forms of time-based rates may introduce.

Based on these concerns, a set of research questions can be identified:

1. Do vulnerable subpopulations exhibit usage patterns (either in terms of their average usage or flexibility of usage) that differ from those of non-vulnerable subpopulations?
2. Do vulnerable subpopulations participate and stay enrolled in time-based rates at different levels than non-vulnerable subpopulations?
3. Do vulnerable subpopulations exhibit load response to time-based rates at different levels than non-vulnerable subpopulations?
4. Do vulnerable subpopulations benefit financially from time-based rates at different levels than non-vulnerable subpopulations?
5. If vulnerable subpopulations do curtail usage in the peak period, is there evidence that they do so at the expense of comfort, wellbeing, or satisfaction to a greater extent than non-vulnerable subpopulations?

Unfortunately, there is limited existing literature that specifically identifies customer acceptance and retention rates as well as estimates of load response to time-based rates for various vulnerable customer subpopulations. There is little to nothing published on the elderly or those with medical needs, but there have been a few pieces of research that focus on the low-income community. According to a national survey, low-income customers have a strongly stated interest in time-based rates (Smart Grid Consumer Collaborative, 2012) but there is little to no publicly available information about actual enrollment or retention estimates for such customers on existing time-based rate offerings. Faruqui et al. (2010) compiled load impact estimates from five different time-based rate evaluations, and found that while the magnitude of the responsiveness of low income customers relative to other customers varies there is nonetheless evidence that low income customers do respond to time-based rates. In addition, the authors performed a bill analysis that suggested a large percentage of such customers would immediately benefit due to their observed flatter than average load profiles.

The Department of Energy's (DOE) Smart Grid Investment Grant (SGIG) program provides an opportunity to contribute to this literature through an analysis of data collected as part of its consumer behavior study (CBS) effort.[1] The federal government co-funded eleven (11) electric utilities to design, implement and evaluate time-based rates provided to their residential customers under voluntary or default enrollment approaches. Each of the participating utilities were required to:

- Track and report on customer acceptance and retention levels throughout their studies;
- Utilize experimental designs that would provide greater opportunity for more precise and credible estimates of load impacts;
- Collect common demographic information from their study participants; and
- Submit customer-level interval meter data, participation data, and demographic and other survey data to Lawrence Berkeley National Laboratory (LBNL) for subsequent analyses.

Although none of the SGIG-funded consumer behavior studies were explicitly designed to address the five outstanding research questions concerning certain vulnerable customer subpopulations articulated above, some were more conducive than others to contribute to our understanding. The following three criteria were used to determine which utility studies to include in this analysis:

1. The utility study had to include rate treatments that were similar in order to readily allow comparison. A high proportion of SGIG-funded consumer behavior studies included critical peak pricing (CPP) overlaid onto the utility's existing flat or inclining block rate. So the analysis was restricted to utility studies that included a CPP rate design.

[1] See Appendix A for more details about the SGIG co-funded consumer behavior study effort.

2. A utility study had to be implemented in a way that readily enabled the inclusion of vulnerable customers. Most studies had qualification processes, screening criteria and/or geographic boundaries on the location of the study's participants that dramatically limited opportunities for vulnerable customers to be considered for enrollment.[2]
3. A utility study had to readily enable the identification of elderly, low-income and chronically ill customers in not just the control and treatment cells, but also in the pool of customers who eschewed the offer to participate in the study. [3] Most utilities chose to collect demographic information via survey instruments at different points during and after their study. Because of this timing and the chosen approach taken for survey administration, most utilities had very limited success getting broad-based and high levels of survey responses from vulnerable populations of both participants and non-participants.

As such, only two of the eleven SGIG-funded consumer behavior studies had sufficient participation data, interval meter data, survey and other sources of demographic data to sufficiently analyze these outstanding research questions associated with vulnerable populations applied to a critical peak pricing rate design: Green Mountain Power (GMP) and Sacramento Municipal Utility District (SMUD). [4]

This report contains the results of an analysis of the data collected as part of GMP and SMUD's consumer behavior studies that seeks to provide empirical evidence of whether or not vulnerable customer subpopulations have preferences, load profiles, load response capabilities, and bill impacts that differ from their non-vulnerable customer counterparts.

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[2] For example, one utility study excluded all customers that were in arrears, which reduced the eligible pool of qualified customers by 30%. In another, the utility chose to run the study in an area that was considerably more affluent than the rest of the service territory.

[3] This is needed in order to properly address the issue of participation – one must have information about those who accepted it as well as those who eschewed it to see if there is any difference between the two. In addition, this is needed in order to correctly estimate load response using a Randomized Encouragement Design (RED) estimation (for more detail on these methods see Appendix D).

[4] Because neither SMUD nor GMP's study was designed to have the power to identify load responses of disaggregated customer groups, we chose to combine multiple similar treatment arms for both utilities in our analysis, in order to maximize the potential of identifying any differences in load response, enrollment rates, and bill impacts. In particular, while we analyzed SMUD's default rate treatment independently, we combined SMUD's voluntary CPP rate treatment arms, both of which faced exactly the same rates and critical events, but one of which was offered an in-home-display (IHD) and one of which was not. We similarly combined GMP's voluntary CPP rate treatment arms, both of which were exposed to exactly the same rates and experienced the same critical events, but one of which included an IHD and one of which did not. Appendix D provides tables showing the estimated results for these different treatment arms both combined and disaggregated. Broadly speaking there were no outstanding differences between the combined treatments sufficient to limit the ability to make conclusions about the results when aggregated.

Specifically, this analysis augments the existing empirical literature on critical peak pricing about the experiences of low-income customers and provides the first glimpses into the experiences of the elderly and those who reported being chronically ill. For those states and utilities considering broader and more aggressive offering of critical peak pricing rates to residential customers, this analysis can contribute to the electric industry stakeholders' understanding of the degree to which perceived concerns about low income, elderly and/or chronically ill customers are, or are not, realized.

The report is organized as follows. In Chapter 2 we present the details of the studies included in the analysis. In Chapter 3, we provide the results of our analysis of customer preferences, load profiles, load response, bill impacts, and levels of satisfaction for different vulnerable and non-vulnerable customer subpopulations. Finally, in Chapter 4 we provide a summary of the major findings and conclusions from this analysis.

2. Study Overview

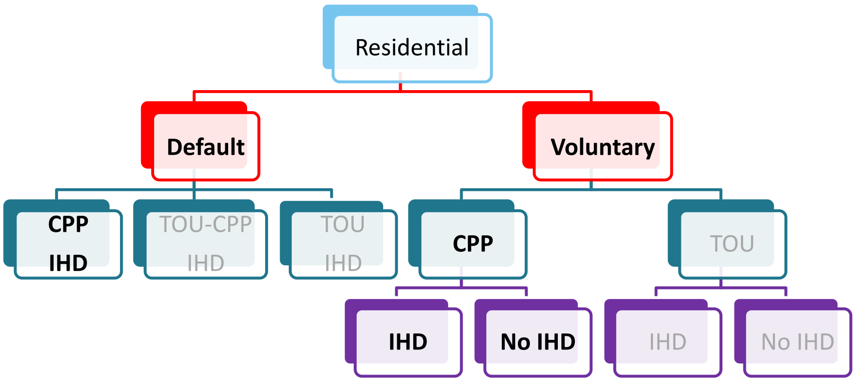
In this section we summarize the design and features of the consumer behavior studies conducted by GMP and SMUD. As previously mentioned, neither of these studies were explicitly designed to analyze the impacts of these rates on the specific subpopulations we study in detail here. This means we are limited in the conclusions we can draw, as the coverage of demographic information and overall sample sizes are not ideal for identifying the effects and differences that are of most interest. It is worth noting that neither SMUD nor GMP used any targeted messaging for any different customer groups in their recruitment process either.

2.1 SMUD's Consumer Behavior Study[5]

SMUD conducted one of the largest and most extensive consumer behavior studies under the SGIG program. One of the study's main goals was to better understand how the enrollment approach (voluntary vs. default) affected enrollment rates, drop-out rates, and electricity demand impacts. In addition, SMUD's study included evaluations of three rate treatments all in effect during the summer months (June through September) of 2012 and 2013: (1) a two-period TOU rate with a three-hour (4-7 p.m.) peak period, (2) CPP overlaid on an underlying inclining block rate, and (3) CPP overlaid on the TOU rate (see Figure 1 and Table 1). The CPP rate was designed and implemented with 12 critical events called each year between the hours of 4 PM and 7 PM (i.e., 48 hours in total) on summer weekdays, excluding holidays. For the purposes of this report, only the customers included in the CPP overlaid on the inclining block rate, including both enrollment approaches and treatments with or without the presence of an IHD offer, were analyzed. The default CPP with IHD treatment group was analyzed independently, while the Voluntary CPP with and without IHD treatment groups were combined in our analysis, in order to maximize our ability to identify effects when disaggregated by demographic subpopulations.[6]

[5] For more details about SMUD's consumer behavior study, see Appendix B

[6] Tables presenting the results of our analysis with the combined treatment groups broken out can be found in Appendix D.



Note: Those treatment arms depicted in gray were not analyzed here, while those with black text were included in this study.

Figure 1. SMUD's Consumer Behavior Study Experimental Design

Table 1. SMUD's CBS Summer 2012 Rate Design (¢/kWh)[7]

Period	CPP in ¢/kWh (Treatment)	Inclining Block in ¢/kWh (Control)
Non Critical Peak Base (< 700 kWh)	8.51	9.38
Non Critical Peak Base-Plus (> 700 kWh)	16.65	17.65
Critical Peak	75.0	N/A

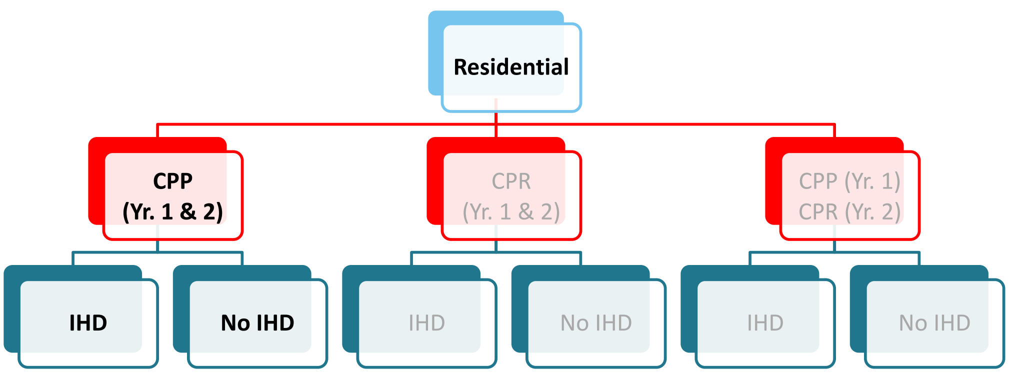
2.2 GMP's Consumer Behavior Study[8]

GMP conducted a consumer behavior study that focused exclusively on opt-in event-driven rate designs. One of the study's main goals was to better understand the timing and magnitude of changes in residential customers' peak demand due to exposure to either

[7] Table 1 shows the rates charged to SMUD's general population of customers on the CPP treatment rates. SMUD also included customers enrolled in the low-income rate, referred to as EAPR (Energy Assistance Program). These customers faced a lower fixed charge than non-EAPR customers, and were given a discount of 35% applied to electricity use charges for base use, and a discount of 30% applied to non-base use up to 600kWh, above which no discount was applied. This same discount structure applied to both time-based treatment rates and inclining block flat rates.

[8] For more details on GMP's consumer behavior study, see Appendix C

critical peak pricing (CPP) or critical peak rebate (CPR), as well as to observe customer preferences for different transition strategies towards these rates. As such, GMP's study included evaluations of two different event-driven rate treatments, all in effect for a 13 month period but broken into two epochs (Year 1: August 2012 – April 2013; Year 2: May 2013-September 2013) designed to call 10 critical peak events between 1 and 6 PM (i.e., 50 hours in total). However, only 4 critical events were called in Year 1[9], while all 10 were called in Year 2[10]. These two rates implemented by GMP were: (1) CPR overlaid on the existing flat rate, and (2) CPP overlaid on a slightly reduced flat rate (see Figure 2 and Table 2). For purposes of this report, only the customers included in the CPP overlaid on the flat rate for both year 1 (August 2012 – April 2013) and year 2 (May 2013 – September 2013) of the study, including both treatments with and without an IHD offer, are analyzed and discussed. The CPP with and without IHD treatment groups were combined in our analysis, in order to maximize our ability to identify effects when disaggregated by demographic subpopulations.[11]



Note: Those treatment arms depicted in gray were not analyzed here, while those with black text were included in this study.

Figure 2. GMP's Consumer Behavior Study Experimental Design

[9] Events in Year 1 were called on: 9/14, 9/21, 9/25, and 10/5 of 2012.

[10] Events in Year 2 were called on: 7/5, 7/15, 7/16, 7/17, 7/18, 7/19, 8/13, 8/21, 8/22, and 8/28 of 2013.

[11] Tables presenting the results of our analysis with the combined treatment groups broken out can be found in Appendix D.

Table 2. GMP's Summer 2012 CBS Rate Design (¢/kWh)[12]

Period	CPP in ¢/kWh (Treatment)	Flat in ¢/kWh (Control)
Non Critical Peak	13.948	15.546
Critical Peak	60.0	N/A

2.3 Definitions of Vulnerable Customer Subpopulations

Within the context of this analysis, we define each of the vulnerable customer subpopulations as follows[13]:

- **Low income:** Determined by reported income levels and the number of people living in the residence via utility-administered survey instruments, and a state-specific Low Income Home Energy Assistance Program (LIHEAP) cutoff definition;[14]
- **Elderly:** Determined by reported age of adults (those over 65 identified as elderly) living in the residence via utility-administered survey instruments; and
- **Chronically Ill:** Determined by reported existence of a chronic illness of individuals living in the residence via utility-administered survey instruments.

GMP and SMUD took different approaches to collecting demographic data via surveys from both their participating and non-participating customers. In the case of GMP, the utility administered the survey at the time customers were asked to enroll in the study, as a condition of participation, regardless of whether a customer was randomized into the

[12] GMP also offers a Low-Income Rate. According to the data provided by the utility, only a small subset of customers on the non-experimental flat rate were on the low-income version of that rate, but no customers were on the low-income version of the experimental CPP rate. GMP's low-income rate consisted of an inclining block rate structure with usage up to 600kWh charged at a lower rate (11.89 cents per kWh in the summer of 2012, for example), and usage beyond that point charged at the standard flat rate.

[13] The main data sources for identifying vulnerable customers were survey instruments administered by the CBS utilities. The survey instrument GMP administered to its customers during the enrollment process to collect demographic information can be found in Appendix 2 of the utility's interim evaluation report (Blumsack and Hines, 2013). A copy of SMUD's demographic survey instrument that was administered after the completion of the enrollment phase of the study can be found in Appendix B of the utility's interim evaluation report (Jimenez et al., 2013).

[14] The eligibility criteria for LIHEAP were found at http://dcf.vermont.gov/benefits/fuel-assistance and http://www.csd.ca.gov/Services/HelpPayingUtilityBills.aspx for Vermont and California, respectively.

control group or one of the treatment groups. As such, they were able to administer the survey to basically everyone associated with the study and get responses from just about all of them: greater than 99% coverage and response rates for both those not exposed to treatment (i.e., control group) and those in one of the treatment groups focused on in this analysis. In contrast, SMUD undertook its effort to collect demographic information after the completion of the recruitment phase of their study. They administered the survey to all their enrolled households, but to only a randomized subset of those households who eschewed treatment or were in the control group. This approach resulted in much lower coverage of the instrument for the eligible customer sample and also considerably lowers response rates: 1% coverage of those not exposed to treatment[15] and 45% coverage of those in one of the treatment groups analyzed in this study, with an overall response rate that was less than 40%.[16] The trade-off, however, was that while GMP had almost complete survey coverage of the households associated with the pilot, they had much smaller sample sizes overall as compared to SMUD. SMUD did not have survey responses for all customers associated with the pilot, but they had very large sample sizes, which allowed them to have very precisely estimated load impacts and other results in analyzing research questions for which survey responses were not necessary.

As Table 3 illustrates, based on SMUD's survey responses, over 30% of survey respondents reported income levels falling within the range we determined to be low-income[17] and a similar proportion reported that the household included members of an age we categorized as elderly, while much smaller shares of survey respondents (9-12%) reported having a chronic illness. GMP shows a considerably smaller share of survey respondents who reported income levels in the low-income range (15%) but had larger shares of both elderly (41%) and chronically ill (20%) residents.

[15] SMUD had a very large control group (around 40,000 customers). They only administered the survey to a small subset of the customers in the control group. That is why the coverage of the full non-participant population is so low, because the population itself is so large.

[16] Such limited coverage of the survey instrument may result in some of the subsequent reported metrics being different than they are for the entire study sample. However, if vulnerable and non-vulnerable customer subpopulations who answered the survey are reasonably representative of the broader study population, then the difference between the two groups should be representative of the broader study population even if their respective levels are not.

[17] Detail on how we defined the low income and elderly categories can be found at the beginning of Section 2.3.

Table 3. Percent of Survey Respondents Affiliated with the Identified Vulnerable Customer Subpopulation

	Low Income	Elderly	Chronically Ill
SMUD Voluntary Cells	39% (435/1119)	35% (407/1176)	9% (110/1209)
GMP Voluntary Cells	15% (69/463)	41% (230/560)	20% (111/558)
SMUD Default Cells	32% (80/248)	31% (80/262)	12% (31/264)
SMUD Control Cells	41% (87/211)	34% (78/227)	13% (31/233)
GMP Control Cells	16% (48/302)	42% (155/373)	25% (92/372)

Note: numbers in parentheses report the following: (# of households identified as vulnerable / # of households in total that responded to the relevant survey question).

2.4 Analysis Approach and Representation of Results

The analysis approach taken throughout this paper is as follows: for each vulnerable population category (i.e., elderly, low income, and chronically ill), customers are identified as either falling into that category or not. For each analysis to follow, outcomes of interest for customers that fall into a given "vulnerable" category (e.g., elderly) are compared to that category's "non-vulnerable" counterpart (e.g., non-elderly). We are only comparing elderly to non-elderly, low income to non-low income, and chronically ill to non-chronically ill.

Because this analysis covers so many results, it is challenging to summarize these results in ways that are digestible. In order to highlight the primary objective of the paper (the comparison of vulnerable to non-vulnerable subpopulations), we have devised a way of presenting results using a 45-degree plot. We present several different sets of results using this type of figure. Because of our reliance on this format, we take the time here to orient the reader to quickly and easily read and digest results from these plots.

Figure 3 shows a hypothetical example 45-degree plot. In this figure we would be comparing a given outcome (e.g., load impact of the CPP rate) between a given vulnerable and non-vulnerable population (e.g., elderly verses non-elderly, or low-income verses non-low income). The value of the outcome for the vulnerable population is plotted on the horizontal axis, and for the non-vulnerable population on the vertical axis. If a point lies on the line running from the lower-left to the upper-right of the figure, which is the 45-degree line, then the outcome is the same between the two subpopulations. The further from this line a point lies, the greater is the difference in the outcome between the vulnerable and non-vulnerable subpopulations. One final piece of information presented in these figures is indicated by the gray shaded bar area. This area is a graphical indication of whether the comparison between the vulnerable and non-vulnerable outcome is statistically significantly different from zero at some specified confidence level (i.e., 90%). Any points located inside the gray shaded area indicate results that, given our data, cannot be statistically distinguished between the vulnerable and non-vulnerable subpopulations of interest. Any points that are located outside of the gray shaded area indicate results for which the null hypothesis—that the outcomes are equal between the vulnerable and non-vulnerable subpopulation of interest—can be rejected with the specified level of confidence.

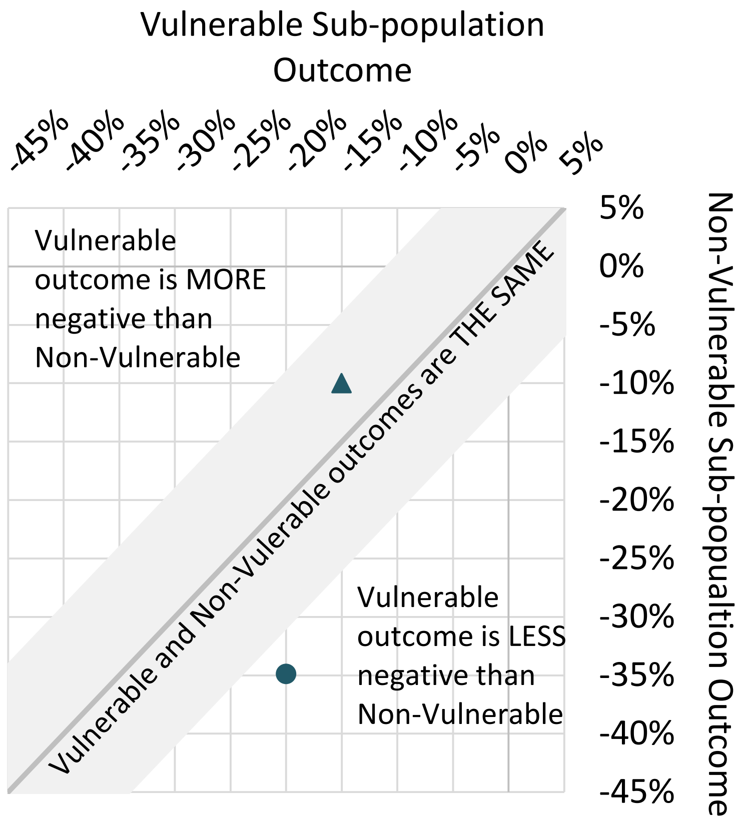


Figure 3. Hypothetical Example

To walk through a specific example, suppose the hypothetical outcome we are showing is peak period load impact, the triangle is indicating the hypothetical comparison between elderly and non-elderly, and the circle is indicating the hypothetical comparison between low-income and non-low income. These hypothetical results would indicate that elderly customers had a 15% load reduction in the peak period, while the load reduction for non-elderly was only 10%. However, the difference between these outcomes cannot be statistically distinguished from each other (indicated by the fact that the point lies inside the gray bar). On the other hand, low-income households exhibited a hypothetical peak period load reduction of 20% while for non-low income households it was 35%. In addition, the difference in hypothetical outcomes between the low-income and non-low income sub-populations was statistically significant.

By using this type of figure we are able to summarize very efficiently a large amount of information: the outcomes for a large number of comparisons (i.e., all the subpopulations of interest for different treatment groups in both utilities), the level of the outcome (e.g., the actual percent load reduction for all subpopulations), and the comparison between the vulnerable and non-vulnerable populations including results from tests of statistical significance.

3. Empirical Results

GMP's and SMUD's consumer behavior studies provide an opportunity to compare the experiences of vulnerable and non-vulnerable customer subpopulations when exposed to a critical peak pricing rate design. An analysis of the data collected during their studies provides information for policy and decision makers about the general usage patterns and usage flexibility, as well as customer acceptance, retention, demand response, and bill impacts from critical peak pricing, with respect to the different customer subpopulations. In addition, in the case of the SMUD study, we can also explore differences in reported satisfaction with the rate.

3.1 Average Load and Load Flexibility

In this section we present results summarizing differences in average load (i.e., average peak period electricity consumption) and load flexibility (as captured by both the coefficient of variation and the load factor).

We first present a comparison of average peak period electricity loads between the vulnerable and non-vulnerable subpopulations of interest. If vulnerable customers have smaller peak period loads in general than other customers, then they have less usage to reduce or shift to non-event periods. This might translate to less willingness to enroll in or remain on the rate, less load response, and potentially higher bills relative to what they would have paid on a non-time-based rate. In order to explore the foundational premise of this concern, an analysis of pre-treatment interval meter data of customers were identified based on the surveys as elderly, low-income or chronically ill in both SMUD's and GMP's studies. Such an analysis reveals that some but not all of these vulnerable customer subpopulations have average peak period loads that are less than their respective non-vulnerable counterparts. As shown in the two plots in column (a) of Figure 4, SMUD's low-income customers and GMP's elderly customers have smaller, on average, peak period electricity consumption than their non-vulnerable counterparts (i.e., their points lie in the upper-left area of the graph).[18] However, column (a) of Figure 4 also shows that those who responded to the survey in GMP's study indicating the presence of chronic illness in the household actually consume more peak period electricity, not less, than their healthier

[18] These differences are statistically significant at a 99.9% confidence level.

peers.[19] For the remaining subpopulations, the differences in average peak period load are very small, less than 5%, and not statistically significantly different between vulnerable and non-vulnerable groups.

Next we explore metrics of load flexibility to determine if these metrics differ significantly between vulnerable and non-vulnerable sub-populations. We explore this comparison because if vulnerable customers have more consistent loads that don't vary as much during the peak period, in comparison to their non-vulnerable counterparts, this might suggest they have less flexible loads with which to respond during critical events. Two metrics were constructed to assess this concern: coefficient of variation (CV)[20] in peak period consumption and a load factor[21] during the peak period.

In the former case (coefficient of variation), we see from the two figures in column (b) of Figure 4 that there is next to no difference in the dispersion of vulnerable and non-vulnerable customer subpopulations' peak period consumption levels. In fact, only households with elderly residents in GMP's study were found to have any measurable and statistically significant differences (99.9% confidence level) in that dispersion, relative to their non-elderly counterparts. This difference was very small in magnitude, however, but indicated that elderly customers had slightly less variability than their non-elderly counterparts (CV of 0.31 versus 0.34, respectively).

Generally speaking, a similar story holds when analyzing these study participants' peak period load factors (see panel (c) of Figure 4) where differences are relatively small. That being said, the load factors for SMUD's chronically ill (load factor of 0.35 versus 0.32), GMP's low income (load factor of 0.19 versus 0.17), and GMP's chronically ill (load factor of 0.19 versus 0.17) customer subpopulations do have statistically significant differences in their load factor (at a 95% confidence level at least) from their respective non-vulnerable comparison groups. All of these differences indicate that the peak consumption of chronically ill customers of both utilities, and low income customers in the SMUD study, were

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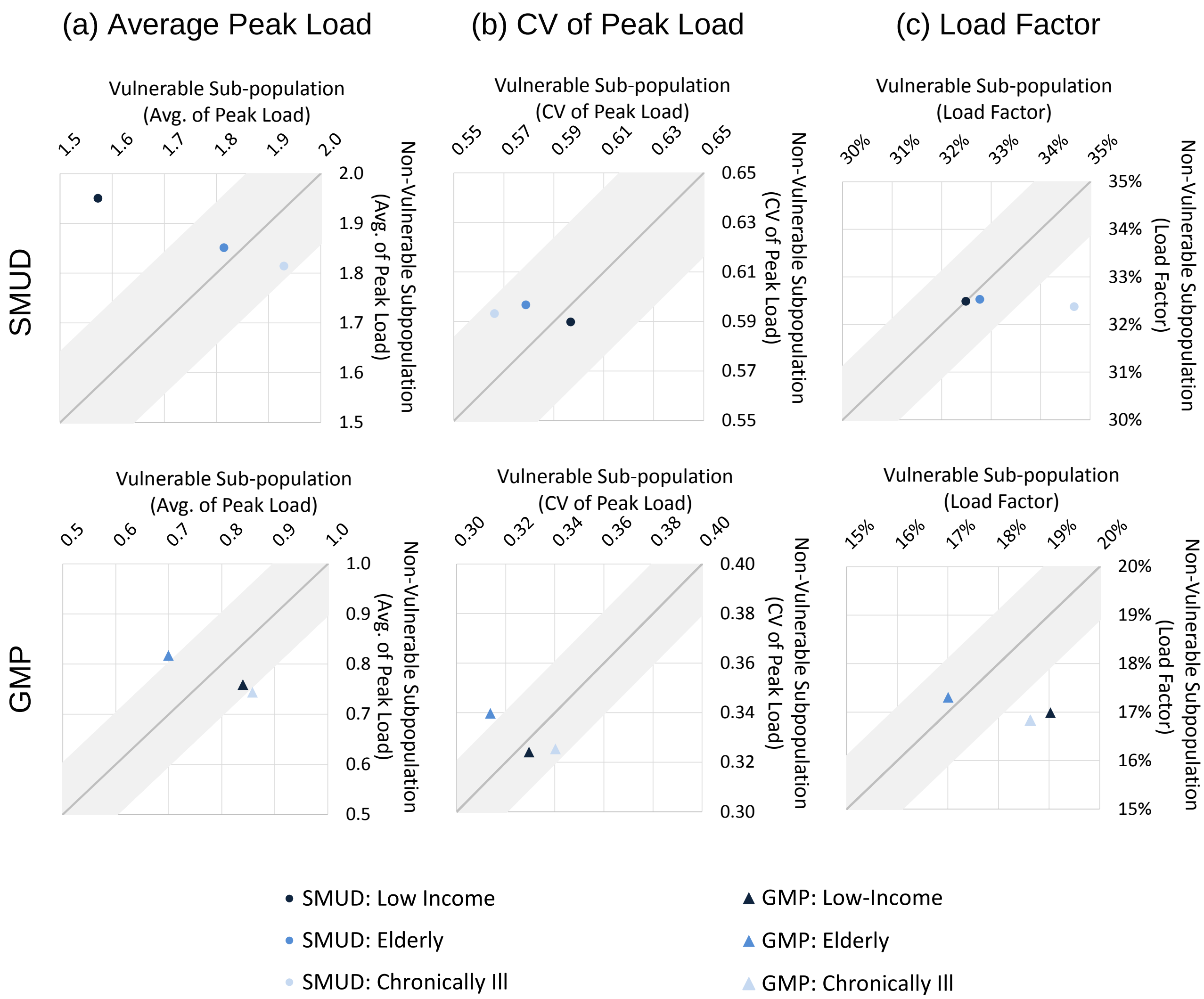
[19] This difference is statistically significant at a 99.9% confidence level.

[20] The coefficient of variation is a measure of dispersion that normalizes the variation around the mean of a sample of data. Specifically, it is calculated by taking the standard deviation of electricity consumption over a certain time period and dividing it by the mean of that same sample. The higher the CV the higher the dispersion of the data.

[21] The load factor is another measure of dispersion that compares the mean and maximum values of a sample of data. Specifically, it is calculated by taking the mean of electricity consumption over a certain time period and dividing it by the maximum of that same sample. The higher the load factor, the more constant the load.

on average significantly less variable than their respective non-ill or higher income counterparts with the load factor metric is used, though the differences are quite small in magnitude.



Note: For any of the points that lie in the gray bar area, the difference in relevant metric for the vulnerable population was not statistically significant (at a 90% confidence level at least) relative to the appropriate non-vulnerable counterpart population. The gray bar in and of itself is not the 90% confidence interval, but rather a graphical way of showing which estimates are statistically significant at the 90% confidence level and which are not.

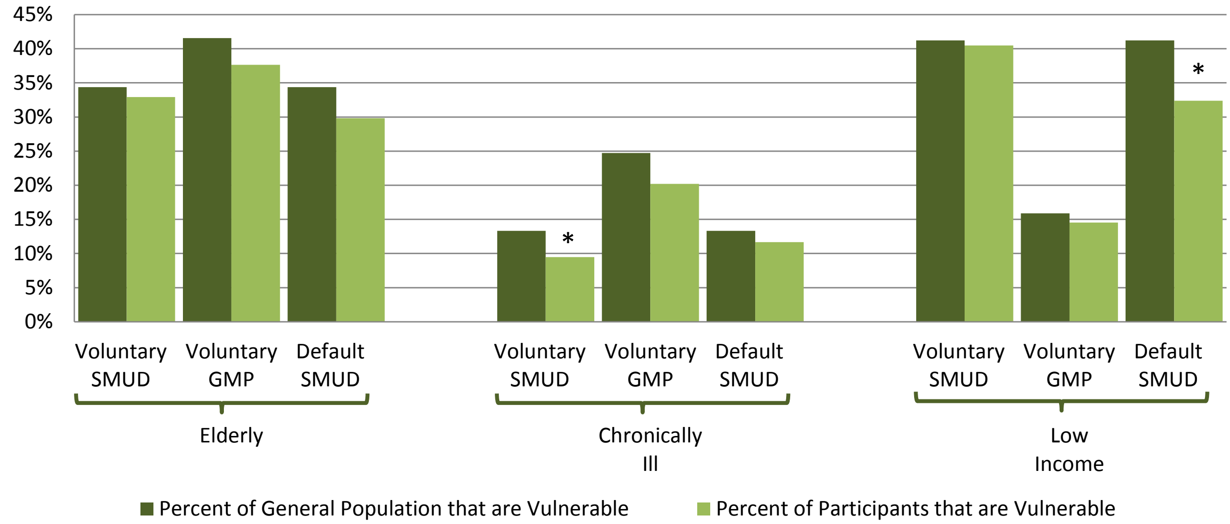
Figure 4. Average (a), Coefficient of Variation (b), and Load Factor (c) of Peak Period Load Absent Treatment for Vulnerable and Non-Vulnerable Populations

Overall, this analysis suggests that vulnerable customers have broadly similarly levels of consumption as well as similar degrees of consistency in consumption patterns as compared to their non-vulnerable counterparts. While low income and elderly customers may have slightly lower peak loads on average, chronically ill customers have slightly higher peak loads, and all differences are relatively small in magnitude. There is some evidence that all three vulnerable populations have slightly less variable/flexible loads than their respective non-vulnerable counterparts, but once again, the magnitude of these differences are relatively small. In the following sections we will document the degree to which these baseline pre-treatment differences might translate through to differences in how these populations accepted and performed on the critical peak pricing rate.

3.2 Enrollment and Retention

Concerns have been raised that vulnerable customers are less likely to want to take service under a time-based rate and are more likely to drop out once exposed. Results presented in Figure 5 and Figure 6 suggest this is not necessarily the case.

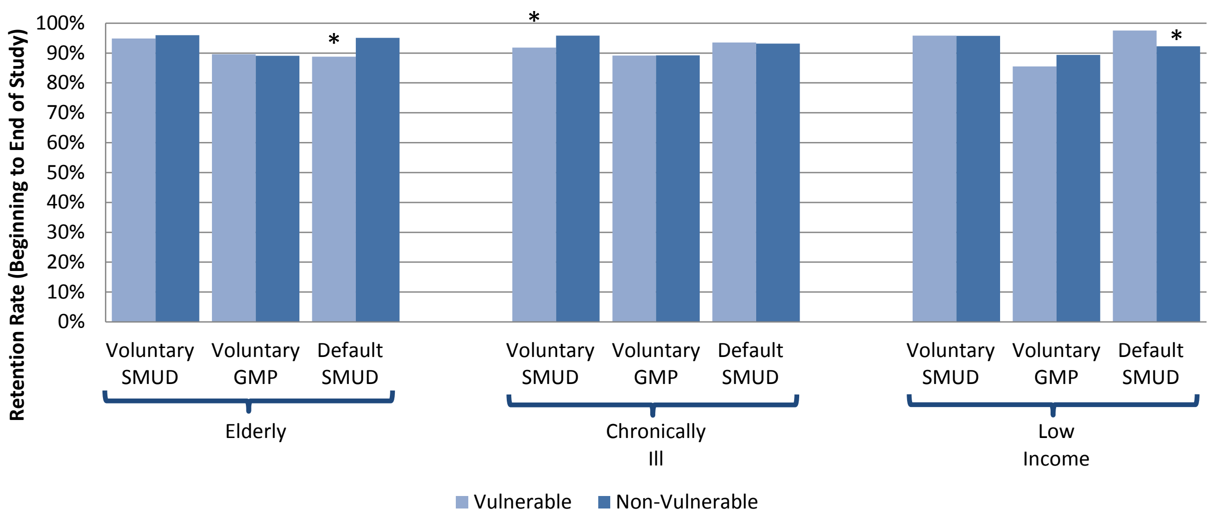
First, concerning enrollment experience, of those customers who responded to the demographic survey, we see that there is a tendency for vulnerable subpopulations to be somewhat less likely to participate in the study relative to their non-vulnerable counterparts (Figure 5). We can see this because the percent of the participant population that were identified as low-income, elderly, or chronically ill are slightly lower than the representation of this group in the general population (as measured by the control group). This difference is statistically significant (90% confidence level) in the case of chronically ill subpopulations for SMUD's voluntary treatment, and for low-income subpopulations in the default treatment group, but not statistically significant in any other case.



Note: These data are limited to those who responded to the survey. The percent of vulnerable households in the general population are based on those households from the control group that responded to the survey. * indicates that the difference between the percent of households facing treatment (i.e. opted in or didn't opt out) that are vulnerable versus the percent that are vulnerable in the general population are statistically significant at least at the 90% confidence level, all other differences are not statistically significant.

Figure 5. Vulnerable vs. Non-Vulnerable Representation in Groups Exposed to Treatment

Once customers began taking service under a CPP rate in one of these two consumer behavior studies, conditional on responding to the survey the vulnerable customer subpopulations did not drop out over the two-year study period at drastically different rates than their non-vulnerable counterparts (Figure 6). However, elderly customers were about twice as likely to drop out of a default CPP rate (11% vs. 5%, a difference that is statistically significant at a 90% confidence level); chronically ill customers were also twice as likely to drop out of SMUD's voluntary treatment (8% vs. 4%, a difference that is statistically significant at a 90% confidence level); and on the other hand low-income customers were less than half as likely to drop out of the same default CPP rate (3% vs. 8%, a difference that is statistically significant at a 90% confidence level) than higher income customers.



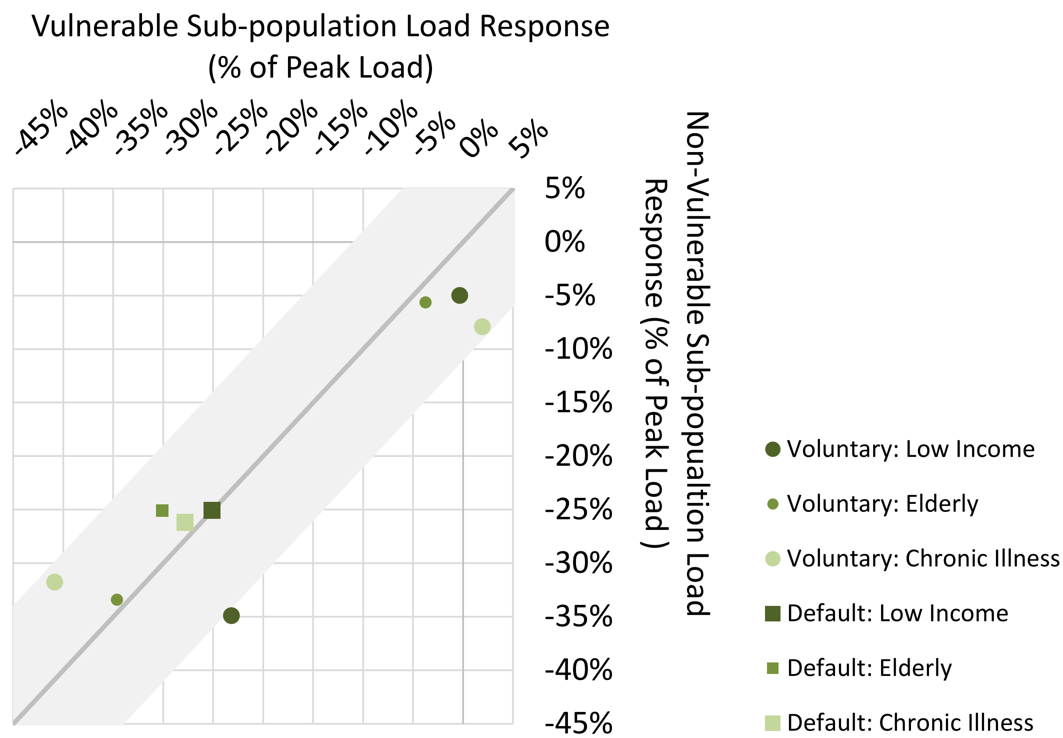
Note: * indicates that the difference in retention rate between the vulnerable and non-vulnerable study participants are statistically significant at least at the 90% confidence level, all other differences are not statistically significant.

Figure 6. Vulnerable vs. Non-Vulnerable Retention Experience

3.3 Load Response

Despite the fact that vulnerable customers seem to exhibit electricity consumption patterns that are not all that different from their non-vulnerable counterparts, it is still possible that the fact there are instances of them all exhibiting slightly less flexibility in their usage, based on one metric or another, could result in them being less able to respond to time-based rates. Load impacts during declared critical events for each customer subpopulation were estimated and then normalized relative to that customer subpopulation's average consumption level during those events (as exhibited by the control group) to produce a relative (i.e., percentage) load reduction. As shown in Figure 7, the load responses between the vulnerable and non-vulnerable subpopulations were relatively similar. In only one case was the difference between the vulnerable and non-vulnerable subpopulation statistically different (at a 99% confidence level): low income versus non-low income customers in one of the voluntary treatment groups. In this case, the low-income customers exhibited a peak period load response of 23% on average, while higher income customer load response was 35% on average.[22]

[22] It's important to note here that there is a correlation between customers on SMUD's low-income rate (EAPR), and those designated as low income through our definition based on the survey data and LIHEAP categories. In the case of SMUD, 67% of customers designated as low income were on the EAPR rate. While the ratio of critical peak period rate to base rate was similar for EAPR and non-EAPR (9.0 vs. 8.8, respectively), the absolute level of the critical peak period rate was



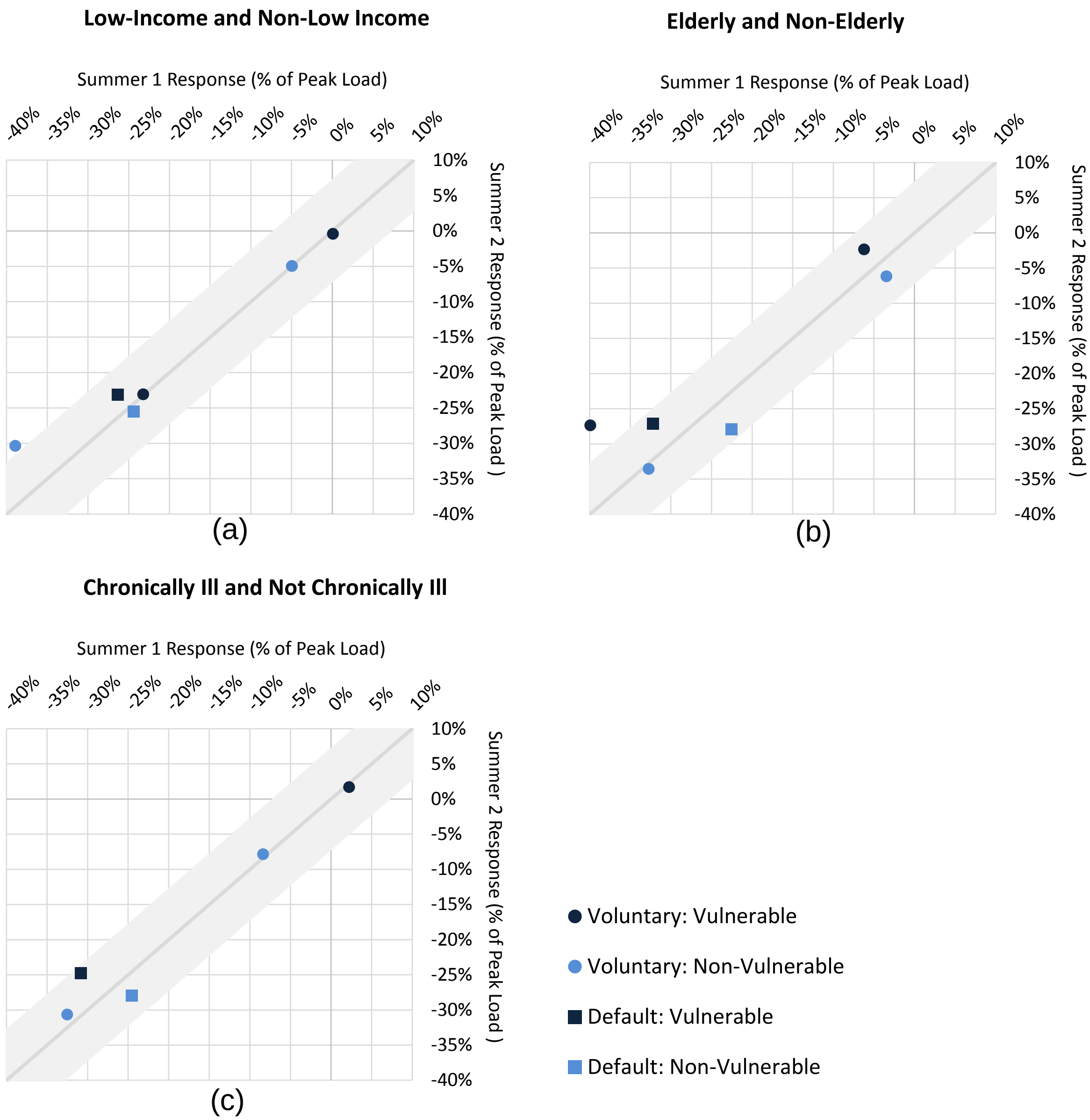
Note: The markers in this graph indicate the estimated load response as a percent of average consumption. For any of the points that lie in the gray bar area, the difference between the estimated load response for the vulnerable population was not statistically significant (at a 90% confidence level) relative to the relevant non-vulnerable counterpart population. The gray bar in and of itself is not the 90% confidence interval, but rather a graphical way of showing which estimates are statistically significant at the 90% confidence level and which are not.

Figure 7. Load Response of Vulnerable and Non-Vulnerable Customer Subpopulations

Concerns have also been raised that customers in general, but especially vulnerable customer subpopulations, are unable to maintain their initial levels of load response as they continue taking service under time-based rates. Figure 8 shows average load response during declared events by customer subpopulation over time. With respect to age, elderly customers do appear to become less responsive as they gain experience with the rate, though the change between the first (40%) and second summer (27%) peak-period load response was only statistically significant (at a 90% confidence level) in the case of one of the voluntary treatments, and is not statistically significant in the case of the other voluntary treatment group. In contrast, for both chronically ill and low-income customers, none of the changes between the first and second summer load response were statistically significantly

lower for EAPR versus non-EAPR customers ($0.50 vs. $0.75, respectively). Depending on how customers respond to rates and what aspects of the rates are salient, this may be one important reason why the low-income customers on SMUD's voluntary rate were less responsive on a proportional basis than higher income customers.

different. However, higher income customers did reduce their load response on average from the first summer (39%) to the second summer (30%) in the case of one of the voluntary treatment groups, a change that was statistically significant at a 90% confidence level.



Note: The markers in this graph indicate the estimated load response as a percent of average consumption. For any of the points that lie in the gray bar area, the difference between the estimated load response in the first summer of the pilot was not statistically significant (at a 90% confidence level) relative to the second summer. The gray bar in and of itself is not the 90% confidence interval, but rather a graphical way of showing which estimates are statistically significant at the 90% confidence level and which are not.

Figure 8. First vs. Second Summer Event Response for Vulnerable vs. Non-Vulnerable Customer Subpopulations

These results indicate that vulnerable customers are not necessarily more likely to diminish the degree to which they respond to the rate over time as compared to their non-vulnerable counterparts. There appear to be cases where this may be true, but other instances where the opposite is the case.

3.4 Bill Impacts

As is true with any customers, vulnerable customers, if unable or unwilling to respond to CPP rates, may see higher bills than they otherwise would if on a flat or inclining block rate, especially during periods when critical events are dispatched. However, rate design plays an important role in an assessment of how customers, or particular customer subpopulations, are affected; so results are separately reported for SMUD and GMP.

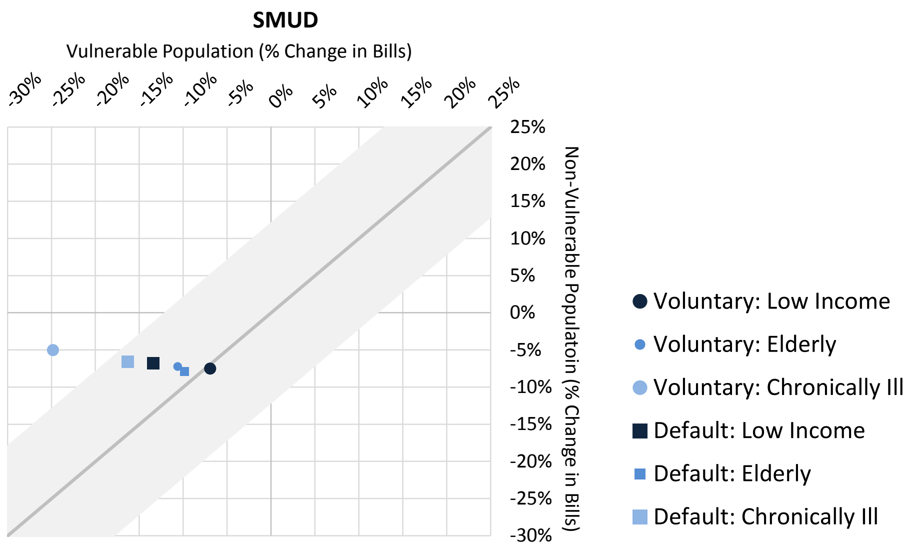
In both utilities' studies, the CPP rates were designed to be revenue neutral for the class-average customer's load shape over some defined period of time - the four summer months for SMUD and the entire year for GMP. Since the higher rate in effect during critical events produces substantially higher revenue for the utility, it must be offset with a rate discount during the other non-event hours in the period of time covered by the rate design.

Given SMUD's rate design, an analysis of their customers' bill experiences is limited to the four summer months.[23] As shown in Figure 9, every vulnerable and counterpart non-vulnerable subpopulation on the CPP rate, regardless of enrollment approach, saw lower bills on average (a finding that was robust at a 95% confidence level or more in all cases). In general the experiences of vulnerable and non-vulnerable subpopulations were similar in this regard. This was a positive outcome for SMUD because, given the significant load responses exhibited by all sub-populations presented previously, it indicated that people benefited financially from the pilot rate in large part because they responded to the rate, and not just because only structural winners[24] enrolled. In addition, there was a tendency for all the vulnerable subpopulations to experience even higher bill savings relative to their non-vulnerable counterparts, however there was only one case where the difference between subpopulations was statistically significant (at a 99% confidence level). This case indicates

[23] As a point of interest, we did perform the analysis for SMUD during the non-summer months and found no bill impacts for any of the customer subpopulations relative to the control group.

[24] Structural winners are customers that would benefit from the piloted rate not because they changed their behavior as a result of the rate, but simply by virtue of their habitual usage pattern (e.g., lower on-peak use and higher off-peak use vis-à-vis the class-average customer).

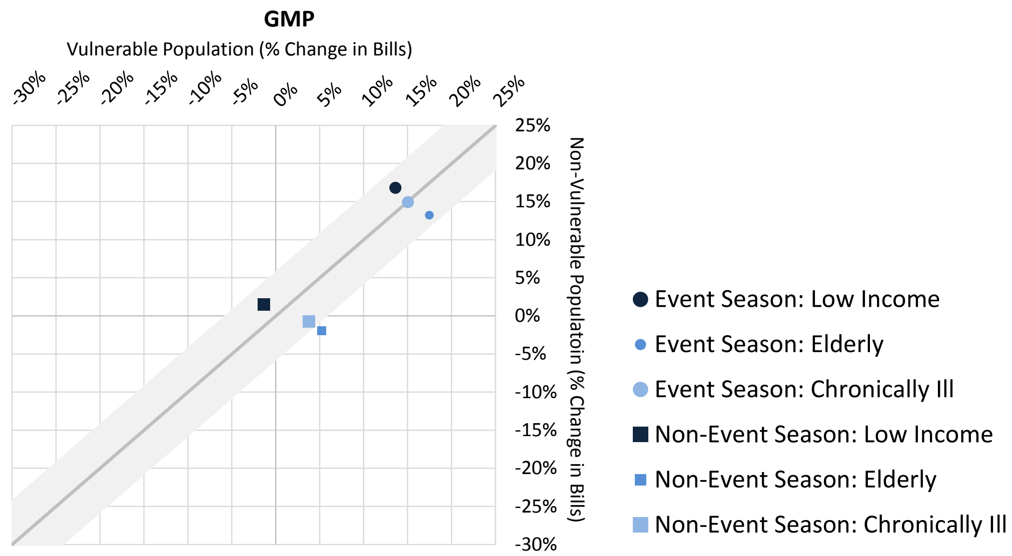
that chronically ill customers on SMUD's voluntary rate actually experienced higher expenditure savings (25% reductions on average) compared to their non-ill counterparts (5% reductions on average).



Note: The markers in these graphs indicate the estimated bill impacts from the treatment rates as a percent of average consumption. For any of the points the lie in the gray bar area, the difference between the estimated load response for the vulnerable population was not statistically significant (at a 90% confidence level) relative to the non-vulnerable counterpart population. The gray bar in and of itself is not the 90% confidence interval, but rather a graphical way of showing which estimates are statistically significant at the 90% confidence level and which are not. The estimates for SMUD were done during the event season only, as that was when the experimental rates were in effect.

Figure 9. SMUD Bill Impacts by Vulnerable vs. Non-Vulnerable Subpopulations (Event season only)

GMP's rate design was in effect for the entire 13 month study period, although critical events were only called during a limited number of months (September and October in 2012 and July and August in 2013). A comparison of bill impacts during months when events were called and when they were not called reveals a different story than at SMUD. In the case of GMP's rate, customer bills were higher on average for both vulnerable and non-vulnerable subpopulations (this result was robust at a 99.9% confidence level for all groups). This is shown in Figure 10, where customer bills during the event season are 10-20% higher for all customer subpopulations relative to the control group. However, the savings from the non-event rates during the non-event season were not enough to counteract the losses (i.e., higher bills) experienced during the event season. All customer subpopulations experienced no sizable changes (all within +/-5%) in their bills relative to the control group during the non-event season, on average. The only case where the bill effects in the non-event season were statistically significant were for elderly customers, who saw a statistically significant (5%, at a 99% confidence level) increase in their bills relative to the elderly customers in the control group, and relative to non-elderly treatment customers, who saw no statistically significant change in their bills.



Note: The markers in these graphs indicate the estimated bill impacts from the treatment rates as a percent of average consumption. For any of the points the lie in the gray bar area, the difference between the estimated load response for the vulnerable population was not statistically significant (at a 90% confidence level) relative to the non-vulnerable counterpart population. The gray bar in and of itself is not the 90% confidence interval, but rather a graphical way of showing which estimates are statistically significant at the 90% confidence level and which are not. The estimates for GMP were done during both the event season and the non-event season separately, as GMP's rates were in effect throughout the year.

Figure 10. GMP Bill Impacts by Vulnerable and Non-Vulnerable Populations (Event vs. Non-Event Season)

It's not entirely clear why the bill impacts for GMP had these outcomes. GMP had a deeper non-event discount than SMUD, and a lower critical event volumetric rate. One possible explanation is that the average peak period energy use for GMP customers was much smaller than SMUD (see Figure 4) and, potentially in part because of this fact, the load response exhibited by GMP customers was very small and not significant (see Figure 7). The fact that customers on GMP's rate did not change their consumption significantly during events may have been a factor in their higher bills while on the rate.

3.5 Customer Satisfaction

GMP did not provide data from any customer satisfaction surveys they may have conducted. SMUD, on the other hand, did provide data from their end-of-pilot customer satisfaction survey. Here we compare levels of comfort and satisfaction as indicated by the survey responses of vulnerable and non-vulnerable subpopulations. These results are presented in Figure 11.

First, panel (a) and (b) of Figure 11 show the results of two questions regarding the level of comfort and ease of response to critical events reported by survey respondent. Panel (a) shows the percent of respondents who answered the question "I sometimes feel uncomfortable inside my home on summer afternoons and evenings because it is too expensive to run my air conditioner" with one of the following options: "No opinion," "Somewhat disagree," or "Strongly disagree."[25] The heights of the bars, therefore, represent the percent of households who reported that they were generally comfortable. Here we see that, across all subpopulations, the response was at or below 50%. While there is some variation across response rates of vulnerable and non-vulnerable subpopulations, the difference is only statistically significant in one case: chronically ill residents in the voluntary treatment reported feeling uncomfortable at a somewhat higher rate than those who did not indicate the presence of a resident with a chronic illness.

Second, in a previous question, respondents were asked what actions they took to reduce energy use in the peak period. They were then asked the question "How difficult were these changes to make?" Panel (b) shows the percent of households that responded "Not difficult at all"[26] to this question. Broadly speaking, all subpopulations responded that these actions were not difficult the majority of the time with the exception of chronically ill customers in the default treatment group. The only instance in which the difference in response was statistically significant was for elderly customers in the voluntary treatment, who were more likely to say that the changes were not difficult to make than non-elderly respondents.

Even given the majority of households that reported being uncomfortable some of the time, the results presented in panel (c) and (d) of Figure 11 provide a more holistic view of the attitudes around the critical peak pricing rate. The results presented in panel (c) reflect

[25] All response options were: "Strongly agree," "Somewhat agree," "No opinion," "Somewhat disagree," or "Strongly disagree."

[26] All response options were: "Not difficult at all," "Somewhat difficult," and "Very difficult."

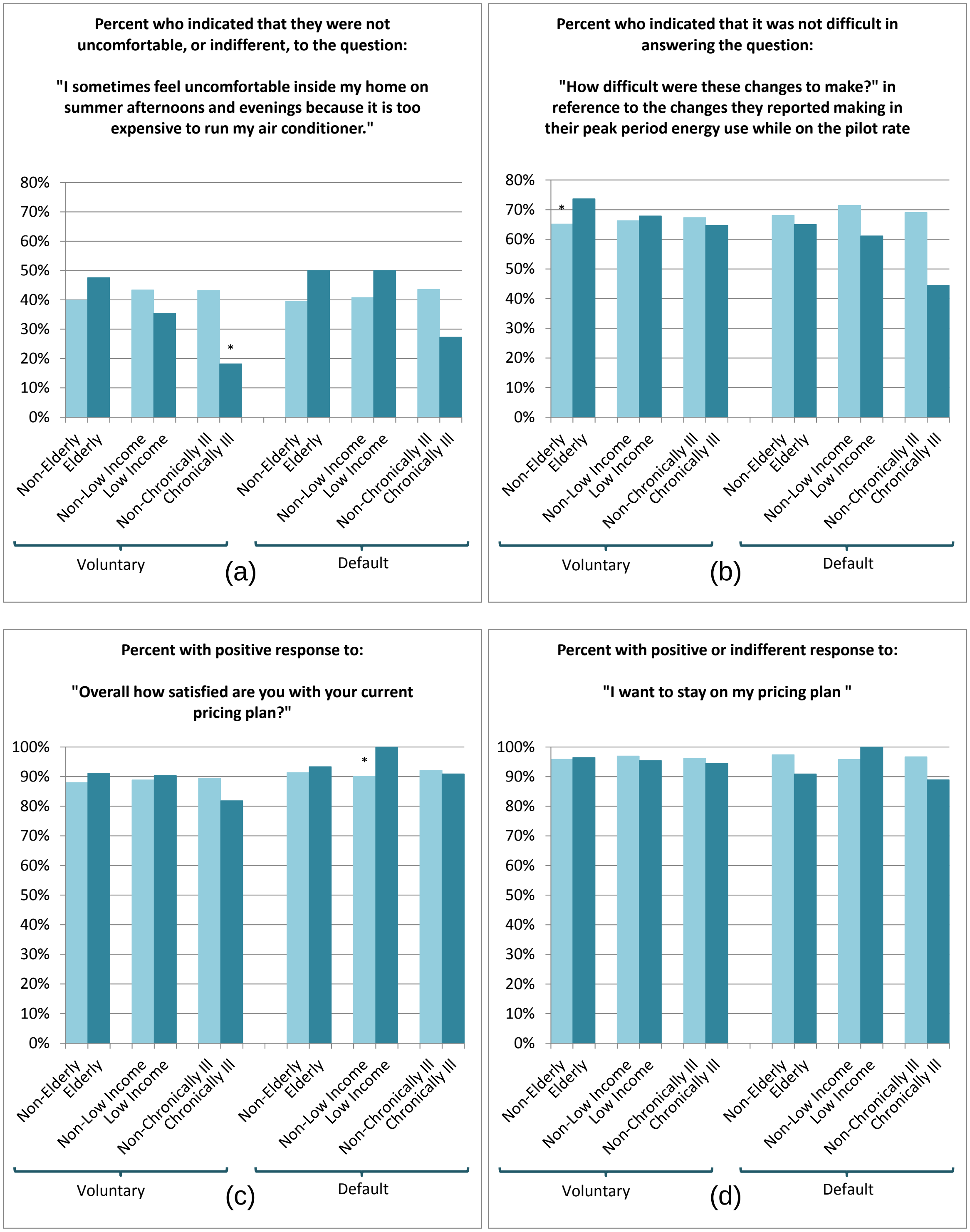
responses when customers were asked: "Overall how satisfied are you with your current pricing plan?" and show the percent of respondents that answered this question with: “Very satisfied” or “Somewhat satisfied.”[27] These results suggest that, conditional on having responded to both the demographic survey[28] and customer satisfaction survey, all sub-populations were generally satisfied with the critical peak pricing rate. Favorable responses ranged between 88% and 100% and the only difference between vulnerable and non-vulnerable populations that was statistically significant indicated that low income customers on the default treatment were actually significantly more satisfied with the rate than their higher income counterparts. Panel (d) presents results from respondents who were posed the statement “I want to stay on my pricing plan,” and shows the percent of respondents who answered: “Strongly agree,” “Somewhat agree,” or “No opinion.”[29] Again, these results indicate a high degree of favorability or indifference (between 91% and 100%) across all subpopulations, with no statistically significant differences between the vulnerable and non-vulnerable groups.

While we are only able to look at a relatively narrow subset of customers in this analysis, there is no indication that any particular customer subpopulation was highly dissatisfied. This suggests that, in the case of SMUD’s pilot, not only were vulnerable sub-populations able to manage their electricity use and respond to this rate, they were able to do so to the point of experiencing bill savings, and they did not feel the need to do so up to the point that they were unduly harmed or made highly dissatisfied with the rate.

[27] All response options were: “Very satisfied,” “Somewhat satisfied,” “Somewhat dissatisfied,” and “Very dissatisfied.”

[28] The number of customers in this analysis include between 347 and 411 customers in SMUD’s voluntary treatments and between 94 and 111 in SMUD’s default treatment, depending on the demographic group and survey question, as response rates varied from question to question.

[29] All response options were: “Strongly agree,” “Somewhat agree,” “No opinion,” “Somewhat disagree,” or “Strongly disagree.”



Note: The bars show the percent of favorable survey responses. * indicates the response rates between the vulnerable and non-vulnerable subpopulations is different with a confidence of 90% or higher. All other differences are not statistically significantly.

Figure 11. SMUD Satisfaction Survey Results

4. Discussion and Conclusions

The experience of vulnerable customer subpopulations in the consumer behavior studies conducted by Green Mountain Power and Sacramento Utility District suggests there may be some differences from those who would not be considered vulnerable, many of which are small in magnitude and not statistically significant. However, these results often differ both across the three vulnerable subpopulations, and across the two utilities included in this analysis. Returning to the questions initially posed in the introduction, our research suggests that in general:

Key Finding #1

Do vulnerable subpopulations exhibit usage patterns that differ from those of non-vulnerable subpopulations?

In cases where differences were statistically discernable, the average peak period usage of elderly (GMP) and low-income (SMUD) customers was slightly lower, while it was higher for chronically ill (GMP) customers. In addition, there is evidence that all groups had instances of slightly lower load variability/flexibility than their non-vulnerable counterparts, though the differences were very small in magnitude, and not always statistically significantly different.

Key Finding #2

Do vulnerable subpopulations participate and stay enrolled in time-based rates at different levels than non-vulnerable subpopulations?

Vulnerable subpopulations participated in a CPP rate at similar levels in general as non-vulnerable subpopulations. Discernable differences were observed for chronically ill SMUD customers offered the voluntary CPP rate, and low-income customers defaulted onto the SMUD CPP rate, both of which participated at slightly lower levels than their non-vulnerable counterparts.[30] In addition, the majority of vulnerable subpopulations stayed enrolled in the rate at roughly comparable levels as their non-vulnerable counterparts, with some slight differences that were statistically identifiable, but very small in magnitude.

Key Finding #3

Do vulnerable subpopulations exhibit load response to time-based rates at different levels than non-vulnerable subpopulations?

Vulnerable subpopulations were usually just as responsive on a proportional basis as their non-vulnerable counterparts over the entire study period, though exhibiting varying degrees of persistence. There were no differences in response level or persistence of response between vulnerable and non-vulnerable customers on the default rate. In the voluntary rates, the only case in which there was a statistically significant difference was for low-income customers, who exhibited a slightly lower load response as compared to their higher income counterparts. However, these voluntary low-income customers had a persistent load response between the first and second summer of the pilot, while higher income customer load response attenuated over time. Voluntary elderly customer load response in one instance attenuated between the two summers as well, while non-elderly load response did not.

[30] Note that differences in participation rates do not reflect flaws in the initial randomization of households into control and treatment groups. These studies were designed to be evaluated using a Randomized Encouragement Design (RED).

Key Finding #4

Do vulnerable subpopulations benefit financially from time-based rates at different levels than non-vulnerable subpopulations?

Vulnerable subpopulations financially benefited at roughly similar proportional levels to their non-vulnerable counterparts. In the case of SMUD the rate was designed to be revenue neutral during the summer event season, but all customer groups actually experienced bill savings during this time period as a result of being on the rate. In addition, chronically ill customers financially benefited at even higher rates relative to their non-vulnerable counterparts. In the case of GMP, the rate was designed to be revenue neutral over the entire year, but events were only called during the summer. Bills were higher for all customer groups during the event season, and higher for elderly customers during the non-event season relative to both non-elderly customers, and relative to elderly customers in the control group.

This means that the estimation of load impacts and other outcomes can be accomplished even with imperfect compliance with treatment (i.e., customers not opting in or choosing to drop out do not invalidate the treatment estimates).

Key Finding #5

Do vulnerable subpopulations curtail usage at the expense of comfort, wellbeing, or satisfaction to a greater extent than non-vulnerable subpopulations

Using survey data available only from SMUD, we are able to analyze the responses of customers to questions regarding their comfort, the difficulty they faced in changing their usage, and their overall satisfaction with the rate. With respect to reported comfort and difficulty of changing behavior there were no differences between vulnerable and non-vulnerable subpopulations in the default treatment. In the voluntary treatment, chronically ill customers were more likely to report discomfort and elderly customers were less likely to indicate that behavior changes they undertook were difficult, relative to their respective non-vulnerable counterparts. However, overall satisfaction levels were extremely high across all subpopulations (with between 91% and 100% indicating they would want to remain on the rate), and low-income customers in the default treatment indicating statistically significantly higher levels of satisfaction than their higher income counterparts.

Here we look at the holistic experience of each of these vulnerable subpopulations more specifically.

Low Income Customers

Our results indicate that as a group, low-income customers participated in a CPP rate at slightly lower levels than their more affluent counterparts, particularly when the default enrollment approach was used. However, fewer low-income customers dropped out of the default CPP once the rate took effect, and comparable shares of customers from both groups chose to remain on the voluntary rate throughout the study. An analysis of energy usage patterns in the pre-treatment period indicated that low-income customers had lower average use levels (SMUD) and potentially less flexible peak loads (GMP), and once exposed to the CPP rate were somewhat less responsive on a proportional basis than their peers during CPP events when volunteering for the rate, though under a default enrollment approach the proportional load response was similar. In addition, voluntary low-income customers had a more persistent load response than their higher income counterparts. When taken together, low-income customers fared no better and no worse than other customers when it came to the bill impacts of CPP – they generally saw comparable proportional changes in their bills, which included bill savings in the case of SMUD's rate design, but higher expenditure during the event season on average in the case of GMP's rate design. Finally, low-income customers did not report any differing levels of discomfort or hardship in responding to SMUD's CPP rate, and when defaulted onto the rate were more likely to report high levels of satisfaction compared to their higher income counterparts.

Elderly Customers

In general elderly customers enrolled in CPP at similar rates, regardless of the enrollment approach, in comparison to their younger counterparts, and of those who actively volunteered similar proportions of elderly and non-elderly remained on the rate throughout the study. However, those defaulted onto the rate tended to drop out at higher rates than their younger counterparts. Furthermore, while elderly customers in GMP's pilot had lower average peak load usage and were slightly less flexible in this usage, there was no identifiable difference either in pre-treatment usage patterns between elderly and non-elderly in the SMUD study, or in the degree to which they responded to the CPP rate on average in either study, again on a proportional basis. There is some indication that elderly customers who volunteered for the rate may have attenuated their load response between the first and second summer, while non-elderly customers did not exhibit this result. In addition, they saw similar bill impacts, on a proportional basis, as their younger peers during the event season, though their bills were higher than both non-elderly treated households and elderly control households in the non-event season in GMP's pilot. Their survey responses indicated that on a whole they were happy with the rate. Elderly customers in both the default and voluntary rate reported lower levels of discomfort than their non-elderly counterparts, though the difference is not statistically significant. They were significantly more likely to report that the changes they made to their consumption were not difficult. Their overall level of satisfaction with the rate was equally as high as their non-elderly counterparts, with over 90% of respondents reporting both satisfaction with the rate and a willingness to continue on the rate going forward.

Chronically Ill Customers

As with the low-income subpopulations, a smaller proportion of customers with medical needs enrolled in the voluntary CPP rate, but they remained on the rate at roughly comparable levels throughout the study as those without such chronic health problems. However, those defaulted onto the rate dropped out at slightly higher rates than their non-ill counterparts. Despite having higher loads on average and potentially slightly less flexibility in some cases, chronically ill customers were just as responsive (regardless of the enrollment approach taken) on a proportional basis as their non-ill counterparts, and their load response was persistent between both summers. Chronically ill customers experienced comparable bill savings as their peers in general, though those who volunteered for SMUD's pilot actually experienced higher bill savings than their non-ill counterparts. On SMUD's study, chronically ill customers reported higher levels of discomfort, though this result is based on a very small sample size (only around 20 chronically ill customers responded to the survey) but their overall satisfaction with the rate was equally as high as all other subpopulations.

This analysis generally supports conclusions in the existing empirical literature about the experiences of low-income customers, and provides the first insights into the experiences of the elderly and those who reported being chronically ill on critical peak pricing. The results also suggest that the concerns of some, namely that low income, elderly and the chronically ill are less capable of managing their electricity consumption in response to a critical peak pricing rate design, were not realized in these two instances. In addition, in the case of SMUD's pilot, the level of satisfaction reported among survey respondents suggests that it is unlikely that customers were shifting or curtailing their energy use in response to critical events to an extent that was harmful to the vulnerable populations studied here. The only possible exception is chronically ill customers, who did report higher levels of discomfort. However, it's not clear to what extent these levels of discomfort were caused by the CPP rate, as overall levels of satisfaction with the rate reported by these same customers were very high.

In the end, this analysis focused on two studies whose primary objectives were not to analyze in great detail the experiences of low income, elderly or chronically ill customers, and therefore were not designed to do so. Our results are limited to those customers who qualified for these studies, resided in locales where the studies were implemented, and provided survey responses which enabled us to identify customers as vulnerable or not. Although our results accurately represent this sample of customers, our ability to extrapolate those results to the broader population is certainly limited. In addition, to the extent that identifiable differences in outcomes between vulnerable and non-vulnerable customers were found in this study, discussion of why these differences might exist was beyond the scope of this report.

To the degree policymakers, utilities, and other stakeholders continue to demand more credible and precise estimates of load impacts and other key metrics that describe the experiences of vulnerable subpopulations, and desire a better understanding of why differences exist if present, this suggests a need to design and implement time-based rate studies utilizing experimental designs (sampling weights and sufficient sample sizes in particular) that are specifically targeted at these vulnerable subpopulations. Results from more concerted study on this topic would more definitively and concretely address the concerns of some in the electric industry. Furthermore, utilities undertaking future pricing studies focused on the most vulnerable customers should seek to more robustly collect demographic information from everyone, especially those who eschew the offer to participate in the study, in order to more accurately characterize the preferences and experiences of different customer subpopulations.

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Appendix A. Background on SGIG Consumer Behavior Studies

In 2009, Congress saw an opportunity to advance the electricity industry's investment in the US power system's infrastructure by including the Smart Grid Investment Grant (SGIG) as part of the American Recovery and Reinvestment Act (Recovery Act). To date, DOE and the electricity industry have jointly invested over $7.9 billion in 99 cost-shared SGIG projects that seek to modernize the electric grid, strengthen cybersecurity, improve interoperability, and collect an unprecedented level of data on smart grid and customer operations enabled by these investments. The SGIG program includes more than 60 projects that involve AMI deployments with the aim of improving operational efficiencies, lowering costs, improving customer services, and enabling expanded implementation of time-based rate programs.[31]

In selecting project applications for SGIG awards, DOE was interested in working closely with a subset of utilities willing to conduct comprehensive consumer behavior studies that applied randomized and controlled experimental designs. DOE's intent for the studies was to encourage the utilities to produce robust statistical results on the impacts of time-based rates, customer information systems, and customer automated control systems on peak demand, electricity consumption, and customer bills. The intent was to produce more robust and credible analysis of impacts, costs, benefits, and lessons learned and assist utility and regulatory decision makers in evaluating investment opportunities involving time-based rates. Of the SGIG projects investing in AMI and implementing time-based rate programs, there were ten utilities that were interested in working with DOE to participate in the CBS program.

A.1 Scope of the CBS Projects

The ten CBS utilities set out to evaluate a variety of different time-based rate programs and customer systems. Concerning the former, the CBS utilities planned to study TOU, CPP, critical peak rebates (CPR), and variable peak pricing (VPP).[32] Many also planned to include some form of customer information system (e.g., IHDs) and/or customer automated control system (e.g., PCTs). Several CBS utilities evaluated multiple combinations of rates and

[31] When the SGIG program is completed in 2015, SGIG will have helped to deploy more than 15 million new smart meters, which represents about 23% of the 65 million smart meters that industry estimates will be installed nationwide. At that point, smart meter deployment is estimated to comprise about 45% of the electric meters in the United States.

[32] Technically, CPR is not a time-based rate; it is an incentive-based program. However, for simplicity of presentation, it is classified with the other event-driven time-based rate programs.

customer systems, based on the specific objectives of their SGIG projects and consumer behavior studies. For example, one utility evaluated treatment groups with a CPP rate layered on top of a flat rate, in combination with and without IHDs. Another evaluated VPP as well as CPP layered on top of a TOU rate in combination with and without PCTs.

Table A-1. Scope of CBS Projects

	CEIC	DTE	GMP	LE	MMLD	MP	NVE	OG&E	SMUD	VEC
Rate Treatments										
CPP		●	●		●	●	●	●	●	
TOU Pricing		●		●		●	●	●	●	
VPP								●		●
CPR	●		●							
Non-Rate Treatments										
IHD	●	●	●					●	●	
PCT	●	●					●	●		
Education							●			
Recruitment Approaches										
Opt-In	●	●	●	●	●	●	●	●	●	●
Opt-Out				●					●	

Utility Abbreviations: Cleveland Electric Illuminating Company (CEIC), DTE Energy (DTE), Green Mountain Power (GMP), Lakeland Electric (LE), Marblehead Municipal Light Department (MMLD), Minnesota Power (MP), NV Energy (NVE), Oklahoma Gas and Electric (OG&E), Sacramento Municipal Utility District (SMUD), Vermont Electric Cooperative (VEC)

A.2 DOE Guidance on CBS Projects

DOE's goal for all of the consumer behavior studies was for them to produce load impact results that achieve internal and ideally external validity.[33] To help ensure that this goal was met, DOE published ten guidance documents for the CBS utilities. The guidelines were intended to help the utilities better understand DOE's expectations of their studies to achieve these goals, including their design, implementation, and evaluation activities.

Specifically, several of the DOE guidance documents addressed how to appropriately apply experimental methods such as randomized controlled trials and randomized encouragement designs to more precisely estimate the impact of time-based rates on electricity usage patterns, and identify the key drivers that motivated changes in behavior.[34] The guidance documents identified key statistical issues such as the desired level of customer participation, which is critical for ensuring that sample sizes for treatment and control groups were large enough for estimates of customer response to have the desired level of accuracy and precision. Without sufficient numbers of customers in control and treatment groups, it would be difficult to determine whether or not differences in the consumption of electricity were due to exposure to the treatment or random factors (i.e., internal validity).

To make best use of the guidance documents, DOE assigned a Technical Advisory Group (TAG) of industry experts to each CBS utility to provide technical assistance. The TAGs helped customize the application of the guidance documents as each of the utility studies was different and had their own goals and objectives, starting points, levels of effort, and regulatory and stakeholder interests. These latter factors, in conjunction with the DOE guidance documents, determined how each utility study was designed and implemented. For

[33] Internal validity is the ability to confidently identify the observed effect of treatments, and determine unbiased estimates of that effect. External validity is the ability to confidently extrapolate study findings to the larger population from which the sample was drawn.

[34] The experimental designs were intended to ensure that measured outcomes could be determined to have been caused by the program's rate and non-rate treatments, and not random or exogenous factors such as the local economic conditions, weather or even customer preferences for participating in a study. Most of the studies decided to use a *Randomized Controlled Trial* experimental design, which is a research strategy involving customers that volunteer to be exposed to a particular treatment and are then randomly assigned to either a treatment or a control group. A few studies chose to use a *Randomized Encouragement Design*, which is a research strategy involving two groups of customers selected from the same population at random, where one is offered a treatment while the other is not. Not all customers offered the treatment are expected to take it, but for analysis purposes, all those who are offered the treatment are considered to be in the treatment group. For more information, see Cappers et al. (2013)

example, several utilities had prior experience with time-based rates and used the studies to evaluate needs for larger-scale roll-outs. Others had little or no experience and used the studies to learn about customer preferences and assess the relative merits of alternative rates and technologies.

Each CBS utility was required to submit a comprehensive and proprietary Consumer Behavior Study Plan (CBSP) that was reviewed by the TAG and approved by DOE. In its CBSP, each utility documented the proposed study elements, including the objectives, research hypotheses, sample frames, randomization methods, recruitment and enrollment approaches, and experimental designs. The CBSP also provided details surrounding the implementation effort, including the schedule for regulatory approval and recruitment efforts, methods for achieving and maintaining required sample sizes, and methods for data collection and analysis.[35]

Each CBS utility was also required to comprehensively evaluate their own study and document the results, along with a description of the methods employed to produce them, in a series of evaluation reports that were reviewed by the TAG, approved by DOE, and posted on Smartgrid.gov. Each utility was expected to file an interim evaluation report after the first year of the study and a final evaluation report at the end of the study.

[35] In several cases, utilities encountered problems during implementation (e.g., insufficient numbers of customers in certain treatment groups) that required the study's initial design as described in the CBSP to be altered to maintain a high probability of achieving as many of the study's original objectives as possible. For several utilities this meant reductions in the number of treatment groups included in the studies.

Appendix B. Background on SMUD's Consumer Behavior Studies

B.1. Overview

Sacramento Municipal Utility District (SMUD) is a summer peaking municipal electric utility with ~625,000 customers in its ~900 square mile service territory that covers much of the Sacramento, CA metropolitan area. SMUD's SGIG project (SmartSacramento) includes a consumer behavior study that evaluates customer acceptance and response to enabling technology combined with various time-based rates under different recruitment methods. The utility is targeting AMI-enabled residential customers across the entire service territory to participate in the study.

B.2. Goals and Objectives

This study focuses on evaluating the timing and magnitude of changes in residential customers' peak demand patterns due to exposure to varying combinations of enabling technology, different recruitment methods (i.e., opt-in vs. opt-out), and several time-based rates. SMUD is also interested in learning about customer acceptance of the different time-based rates under the alternative recruitment methods.

B.3. Treatments of Interest

Rate treatments include the implementation of three time-based rate programs in effect from June through September (see Table B-1): a two-period TOU rate that includes a three-hour on-peak period (4 - 7 p.m.) each non-holiday weekday; a CPP overlaid on their underlying tiered rate; and a TOU with CPP overlay (TOU w/CPP).

Customers participating in any CPP rate treatments receive day-ahead notice of critical peak events, called when wholesale market prices are expected to be very high and/or when system emergency conditions are anticipated to arise. CPP participants will be exposed to 12 critical peak events during each year of the study.

Control/information technology treatments include the deployment of IHDs. SMUD is offering IHDs to all opt-out customers in any given treatment group and to more than half of the opt-in customers in the treatment group. All participating customers receive web portal access, customer support and a variety of education materials.

Table B-1. SMUD Summer 2012 CBS Rate Design (¢/kWh)

Period	CPP	Inclining Block (Control)
Non Critical Peak Base (< 700 kWh)	8.51	9.38
Non Critical Peak Base-Plus (> 700 kWh)	16.65	17.65
Critical Peak	75.0	N/A

B.4. Experimental Design

Due to the variety of treatments, the study includes three different experimental designs: randomized controlled trial (RCT) with delayed treatment for the control group, randomized encouragement design (RED) and within-subjects design (see Figure B-1).

In all three cases, AMI-enabled residential customers in SMUD's service territory are initially screened for eligibility and then randomly assigned to one of the seven treatments or the RED control group.

For the two treatments that are included in the RCT "Recruit and Delay" study design, customers receive an invitation to opt in to the study where participating customers receive an offer for a specific treatment. Upon agreeing to join the study, customers are told if they are to begin receiving the rate in the first year of the study (i.e., June 2012) or in the summer after the study is complete (i.e., June 2014).

For two of the three treatments that are included in the RED, customers are told that they have been assigned to a specific identified treatment but have the ability to opt out of this offer. Those who do not opt out receive the indicated treatment for the duration of the study. Those who opt out are nonetheless included in the study's evaluation effort but do not receive the indicated treatment. For one of the three RED treatments, customers receive an invitation to opt in to the study where participating customers receive a specific treatment. Customers that opt in are then assigned to receive the treatment in year 1 of the study (i.e., 2012).

For the two treatments that are included in the within-subject design, customers are told they have been assigned to either the Block w/CPP treatment or the TOU w/CPP treatment with technology.[36] In the former case, customers only have the ability to opt in to this specific treatment. In the latter case, customers only have the ability to opt out of this specific treatment.

[36] The within-subjects method was designed to use no explicit control group; instead it estimates the effects of the treatment for each participant individually, using observed electricity consumption behavior both before and after becoming a participant in the study as well as on critical peak event and non-event days. However, the control group selected for the RED design may be used as a control group.

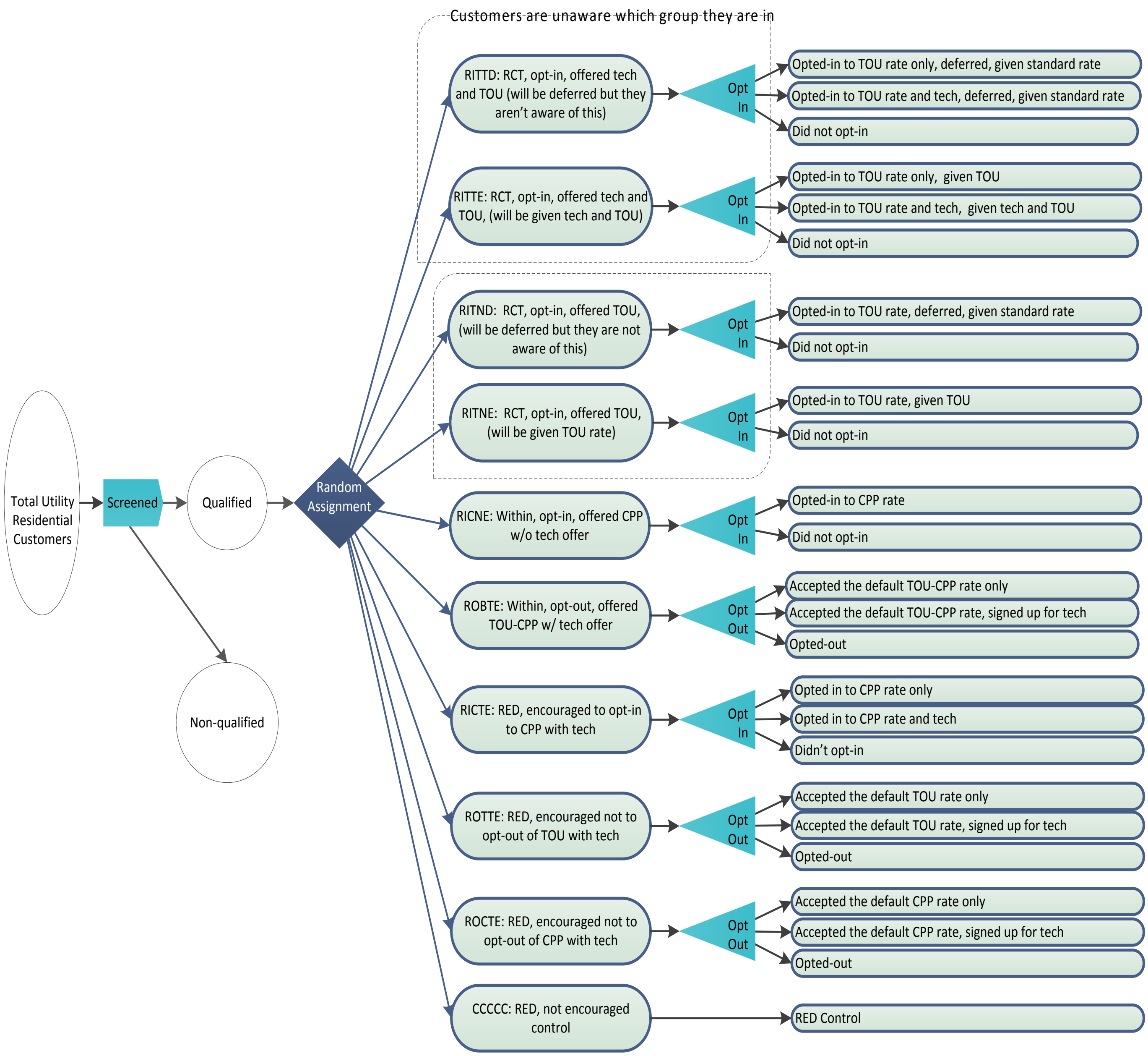

Figure B-1. SMUD Recruitment Process

Appendix C. Background Information on GMP's Consumer Behavior Study

C.1. Overview

Green Mountain Power (GMP) is a summer peaking investor-owned electric utility with ~250,000 customers in its service territory that covers most of Vermont. GMP is one of 20 utility participants in the Vermont SGIG project (named eEnergy Vermont) and one of two utilities performing consumer behavior studies. The GMP study evaluates customer acceptance and response to different time-based rates coupled with information feedback treatments under different transition strategies towards more time-based rates. The utility is targeting AMI-enabled residential customers in the Rutland area for participation in the study; a county with a slightly older and lower-income population than the rest of the state.

C.2. Goals and Objectives

This study focuses primarily on the timing and magnitude of changes in residential customers' peak demand due to exposure to either CPP or CPR. GMP is also interested in understanding customer preferences for different transition strategies towards more time-based rates.

C.3. Treatments of Interest

Rate treatments include the application of time-based rates and rebate designs (see Table C-1). The utility is implementing a critical peak rebate that provides a payment to customers for reducing electric load during declared critical peak events, while the price charged by GMP for electricity consumed stays at the customers' existing flat rate (Flat w/CPR). In addition, GMP is implementing a CPP rate design that slightly lowers the customers' existing standard flat rate but augments it with a substantially higher price overlay during declared critical peak events (Flat w/CPP). Both the Flat w/CPR and Flat w/CPP rates are in effect year-round and critical peak events, which can be called on weekdays between the hours of 1 and 6 p.m., are declared based on wholesale market conditions, coincident with the ISO New England annual system peak, which has traditionally occurred in the summer.

Control/information technology treatments include the deployment of IHDs. This technology acts as a means for viewing site-level electricity consumption information but also provides the customer with notification of a declared critical event. All participating customers receive direct notification (e.g., email, text, voice message) of peak events, web portal access to interval meter data, customer support and a variety of education materials.

Table C-1. GMP's Summer 2012 CBS Rate Design (¢/kWh)

Period	CPP	Flat (Control)
Flat	13.948	15.546
Critical Peak	60.000	N/A

C.4. Experimental Design

The design for the pilot is a randomized controlled trial with denial of treatments for the control group and pre-recruitment assignment (see Figure C-1). AMI-enabled customers in the Rutland, VT area who meet certain eligibility criteria are randomly assigned to either one of the two control groups (differing by customers' awareness about the study and critical peak events) or one of the six treatment groups. In addition, there is one unaware control group of customers who were never contacted; this group consists of customers that might have qualified for the study (based on their rate category) but were not selected for recruitment into one of the other treatment or control cells. These customers, except those assigned to the unaware control group, receive an invitation to opt in to the study where participating customers could receive one of several treatments, with the understanding that this treatment is limited in supply, but are not notified of their assignment at this time. Customers who opt in are then screened and surveyed to ensure that they qualify to potentially receive a treatment. Those who do are then notified of their assignment to one of the treatment or control cells. Customers assigned to the Flat w/CPP treatment cell must opt-in (agree) to this rate change. Customers assigned to the Flat w/CPR treatment cell or one of the control cells are simply told of their assignment, and so may opt-out if they choose. The pilot transitions customers in two treatment groups from the Flat w/CPR in year one of the study (2012) to a Flat w/CPP rate design in year two (2013), while the remaining customers are exposed to their specific rate treatments for two full years (2012 and 2013).

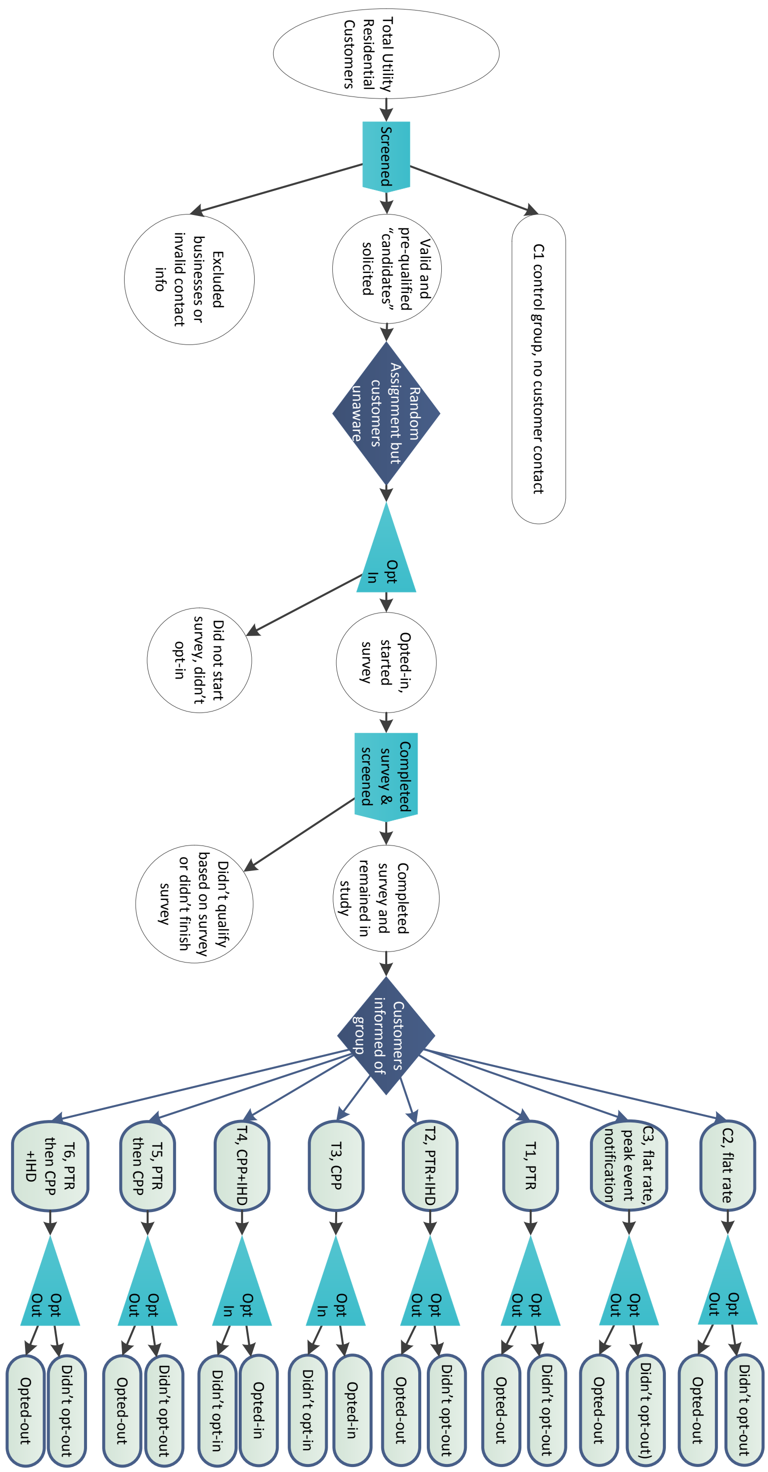

Figure C-1. GMP Recruitment Process

Appendix D. Econometric Model Methodology and Estimates

D.1. Average Peak Period Load Impacts

A separate regression is run to determine the marginal impacts of the CPP rates on critical event days for each vulnerable subpopulation (low income, elderly, or chronically ill) relative to their non-vulnerable counterparts, and for each utility (SMUD and GMP).

In the equations that follow, T_{it} is an indicator variable equal to one starting on the date the treatment rates took effect and for all hours thereafter for each utility (June 1st, 2012 in the case of SMUD, and August 25th, 2012 in the case of GMP) if household i was actually enrolled in treatment and remained in treatment at time t, zero otherwise. A_{it} is an indicator variable equal to one starting the date the treatment rates took effect for each utility if household i was encouraged to be in one of the treatment groups (random assignment to treatment), zero otherwise. Finally P_t is an indicator variable equal to one starting on the date the treatment rates took effect for each utility, zero otherwise. The estimation was done using two-stage least squares (2SLS), where terms including the indicator T_{it} were instrumented for using analogous terms constructed using the indicator A_{it}. More specifically, given a particular vulnerable population (V_i) (e.g., low income), the regression used to estimate the marginal impact of being a treated member of that vulnerable population relative to a treatment household that is not a member of that vulnerable population includes the terms T_{it} and ($T_{it} * V_i$). These terms are instrumented for with the terms A_{it} and ($A_{it} * V_i$) by running the first stage regressions shown in equations (1) and (2) below, and then including the predicted values from those regressions, $\widehat{T_{it}}$ and $(\widehat{T_{it} * V_i})$, in the final stage regression shown in equation (3), below.

$$T_{it} = \eta_1 A_{it} + \eta_2 (A_{it} * V_i) + \eta_3 (P_t * V_i) + \gamma_i + \tau_t + \varepsilon_{it} \quad (1)$$

$$(T_{it} * V_i) = \delta_1 A_{it} + \delta_2 (A_{it} * V_i) + \delta_3 (P_t * V_i) + \gamma_i + \tau_t + \varepsilon_{it} \quad (2)$$

$$y_{it} = \beta_1 \hat{T}_{it} + \beta_2 (\widehat{T_{it} * V_i}) + \beta_3 (P_t * V_i) + \gamma_i + \tau_t + \varepsilon_{it} \quad (3)$$

The variable y_{it} is hourly electricity consumption for household i in hour t; γ_i is a household fixed effect; τ_t is an hour of sample fixed effect; and ε_{it} is the error term assumed to be distributed IID normal across households, conditional on the covariates. In order to account for serial correlation across time observations within households, we cluster the standard errors of the estimates at the household level. The data used are peak hour consumption (4 pm to 7 pm for SMUD and 1 pm to 6pm for GMP) during critical event days in both treatment summers (2012 and 2013), and on counterfactual days similar (in terms of temperature) to event days, identified in the pre-treatment period (during the summer of 2011 for SMUD, and between from May 1st through August 25th, 2012 in the case of GMP). Households in both the treatment groups and the control group are included. Coefficient β_1 captures the average hourly treatment effect per household of non-vulnerable customers, and β_2 captures the marginal difference in treatment effect between the non-vulnerable and vulnerable treated households.

The estimates generated using this methodology for SMUD voluntary treatment groups (both with and without IHD combined) are shown in Table D-1 The results for SMUD's default treatment group is shown in Table D-2, and for GMP's voluntary treatment groups (both with and without IHD combined) are shown in Table D-3.

Table D-1. SMUD Average Peak Period Load Impacts for Voluntary Treatments Combined

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
$\boldsymbol{\beta_1}$: Treatment Effect of Non-VP	-0.781***	-0.907***	-0.813***	-0.750***
standard errors	(0.0734)	(0.113)	(0.0868)	(0.0797)
p-value	0.0000	0.0000	0.0000	0.0000
$\boldsymbol{\beta_2}$: Marginal Treatment Effect of VP		0.445**	0.0185	-0.232
standard errors		(0.144)	(0.165)	(0.198)
p-value		0.0020	0.9110	0.2430
$\boldsymbol{\beta_3}$: Change Between Pre- and Treatment Period of VP		0.0828	0.094	0.162
standard errors		(0.085)	(0.0934)	(0.104)
p-value		0.3300	0.3140	0.1180
VP Percent Load Impact		-23%	-35%	-41%
Non-VP Percent Load Impact	-33%	-35%	-33%	-32%
N	177543	163440	172539	177288
Average Peak Period Energy Use of Control Households on Critical Event Days				
VP		1.99	2.30	2.40
Non-VP		2.60	2.43	2.36
All Survey Respondents	2.36	2.36	2.36	2.36

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level are in the parentheses.

Table D-2. SMUD Average Peak Period Load Impacts for Default Treatments

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	-0.624***	-0.652***	-0.611***	-0.618***
standard errors	(0.0836)	(0.117)	(0.103)	(0.092)
p-value	0.0000	0.0000	0.0000	0.0000
β_2: Marginal Treatment Effect of VP		0.151	-0.0825	-0.0566
standard errors		(0.166)	(0.178)	(0.209)
p-value		0.3640	0.6430	0.7860
β_3 : Change Between Pre- and Treatment Period of VP		0.0823	0.0942	0.163
standard errors		(0.0852)	(0.0936)	(0.104)
p-value		0.3340	0.3150	0.1180
VP Percent Load Impact		-25%	-30%	-28%
Non-VP Percent Load Impact	-26%	-25%	-25%	-26%
N	62265	57300	61023	62043
Average Peak Period Energy Use of Control Households on Critical Event Days				
VP		1.99	2.30	2.40
Non-VP		2.60	2.43	2.36
All Survey Respondents	2.36	2.36	2.36	2.36

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level are in the parentheses.

Table D-3. GMP Average Peak Period Load Impacts for Voluntary Treatments Combined

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	-0.0517	-0.0512	-0.0619	-0.0756**
standard errors	(0.0268)	(0.032)	(0.0355)	(0.029)
p-value	0.0543	0.1110	0.0816	0.0093
β_2: Marginal Treatment Effect of VP		0.0474	0.0261	0.0997
standard errors		(0.083)	(0.0541)	(0.0715)

p-value		0.5680	0.6300	0.1640
β_3 : Change Between Pre- and Treatment Period of VP		-0.0323	-0.00508	-0.06
standard errors		(0.0484)	(0.0336)	(0.0439)
p-value		0.5050	0.8800	0.1720
VP Percent Load Impact		0%	-4%	2%
Non-VP Percent Load Impact	-5%	-5%	-6%	-8%
N	124437	101697	124297	123877
Average Peak Period Energy Use of Control Households on Critical Event Days				
VP		1.16	0.93	1.26
Non-VP		1.03	1.10	0.96
All Survey Respondents	1.05	1.05	1.05	1.05

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level are in the parentheses.

D.2. Disaggregated Average Peak Period Load Impacts of SMUD and GMP Voluntary Treatment Groups

For the primary analysis we combined the two voluntary treatment groups included for SMUD, and the two voluntary treatment groups included for GMP. These groups faced the exact same rates and critical events, but one treatment group in each utility was offered an in-home-display (IHD) and the other was not. We combined the IHD and non-IHD voluntary treatment groups in order to maximize the power and increase the likelihood of identifying any differences between the vulnerable and non-vulnerable populations that might exist. Here we show the results of these groups separated out.

Table D-4. SMUD Average Peak Period Load Impacts for Voluntary Treatment without IHD

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	-0.552**	-0.634	-0.787**	-0.520**
p-value	0.0025	0.0569	0.0014	0.0070
β_2: Marginal Treatment Effect of VP		0.227	0.382	-0.17
p-value		0.5370	0.2980	0.7680
β_3 : Change Between Pre- and Treatment Period of VP		0.0826	0.0944	0.163
p-value		0.3330	0.3140	0.1170

VP Percent Load Impact		-20%	-18%	-29%
Non-VP Percent Load Impact	-23%	-24%	-32%	-22%
N	58209	53076	55935	58083
Average Peak Period Energy Use of Control Households on Critical Event Days				
VP		1.99	2.30	2.40
Non-VP		2.60	2.43	2.36
All Survey Respondents	2.36	2.36	2.36	2.36

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level.

Table D-5. SMUD Average Peak Period Load Impacts for Voluntary Treatment with IHD

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	-0.806***	-0.933***	-0.814***	-0.776***
p-value	0.0000	0.0000	0.0000	0.0000
β_2: Marginal Treatment Effect of VP		0.464***	-0.0349	-0.225
p-value		0.0006	0.8230	0.2360
β_3 : Change Between Pre- and Treatment Period of VP		0.0829	0.094	0.162
p-value		0.3300	0.3140	0.1190
	-0.806***	-0.933***	-0.814***	-0.776***
VP Percent Load Impact		-24%	-37%	-42%
Non-VP Percent Load Impact	-34%	-36%	-33%	-33%
N	148293	136623	144729	148164
Average Peak Period Energy Use of Control Households on Critical Event Days				
VP		1.99	2.30	2.40
Non-VP		2.60	2.43	2.36
All Survey Respondents	2.36	2.36	2.36	2.36

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level.

Table D-6. GMP Average Peak Period Load Impacts for Voluntary Treatment without IHD

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	-0.0479	-0.0446	-0.0759	-0.0701*
p-value	0.1070	0.2020	0.0547	0.0272
β_2: Marginal Treatment Effect of VP		0.0395	0.0689	0.088
p-value		0.6490	0.2480	0.2760
β_3 : Change Between Pre- and Treatment Period of VP		-0.0323	-0.00503	-0.06
p-value		0.5050	0.8810	0.1720
VP Percent Load Impact		0%	-1%	1%
Non-VP Percent Load Impact	-5%	-4%	-7%	-7%
N	99893	81903	99753	99333
Average Peak Period Energy Use of Control Households on Critical Event Days				
VP		1.16	0.93	1.26
Non-VP		1.03	1.10	0.96
All Survey Respondents	1.05	1.05	1.05	1.05

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level.

Table D-7. GMP Average Peak Period Load Impacts for Voluntary Treatment with IHD

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	-0.0594	-0.0653	-0.0359	-0.0860*
p-value	0.1020	0.1540	0.4360	0.0343
β_2: Marginal Treatment Effect of VP		0.0643	-0.0717	0.128
p-value		0.6300	0.3380	0.1380
β_3 : Change Between Pre- and Treatment Period of VP		-0.0322	-0.00516	-0.06
p-value		0.5070	0.8780	0.1730
VP Percent Load Impact		0%	-11%	3%
Non-VP Percent Load Impact	-6%	-6%	-3%	-9%
N	74982	60407	74842	74702
Average Peak Period Energy Use of Control Households on Critical Event Days				

VP		1.16	0.93	1.26
Non-VP		1.03	1.10	0.96
All Survey Respondents	1.05	1.05	1.05	1.05

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level.

D.3. Average Hourly Peak Period Load Impacts Disaggregated Across the Two Treatment Summers

The treatment effects across the two summers were separated using a regression analysis similar to that described in equations (1), (2) and (3), but allowing for heterogeneity between the two summers. The estimation of these effects is show in equations (4), (5), (6) and (7). Households in both the treatment groups and the control group are included. A separate regression is run for each vulnerable population (low income, elderly and chronically ill), each treatment group (Voluntary and Default), and each utility (SMUD and GMP). The three first stage regressions are show in equation (4), (5) and (6). The term S_t is an indicator variable equal to one if date t is in the second summer of the study, zero otherwise. Predicted values from the first stage regressions are used in the final regression shown in equation (7) to estimate the final treatment effects.

$$T_{it} = \eta_1 A_{it} + \eta_2 (A_{it} * V_i) + \eta_3 (A_{it} * S_t) + \eta_4 (A_{it} * V_i * S_t) + \eta_5 (P_t * V_i) + \eta_6 (V_i * S_t) + \gamma_i + \tau_t + \varepsilon_{it} \quad (4)$$

$$(T_{it} * V_i) = \delta_1 A_{it} + \delta_2 (A_{it} * V_i) + \delta_3 (A_{it} * S_t) + \delta_4 (A_{it} * V_i * S_t) + \delta_5 (P_t * V_i) + \delta_6 (V_i * S_t) + \gamma_i + \tau_t + \varepsilon_{it} \quad (5)$$

$$(T_{it} * V_i * S_t) = \delta_1 A_{it} + \delta_2 (A_{it} * V_i) + \delta_3 (A_{it} * S_t) + \delta_4 (A_{it} * V_i * S_t) + \delta_5 (P_t * V_i) + \delta_6 (V_i * S_t) + \gamma_i + \tau_t + \varepsilon_{it} \quad (6)$$

$$y_{it} = \beta_1 \widehat{T_{it}} + \beta_2 (\widehat{T_{it} * V_i}) + \beta_3 (\widehat{T_{it} * S_t}) + \beta_4 (\widehat{T_{it} * V_i * S_t}) + \beta_5 (P_t * V_i) + \beta_6 (V_i * S_t) + \gamma_i + \tau_t + \varepsilon_{it} \quad (7)$$

The coefficient β_1 is the estimate of the average hourly per-household treatment effect of non-vulnerable households in the first summer; β_2 is an estimate of the marginal difference in treatment effect between vulnerable and non-vulnerable households in the first summer; β_3 is an estimate of the marginal difference in treatment effect between the first and second summer of the pilot for the non-vulnerable households, and finally β_4 is an estimate of the marginal difference in the change in treatment effect between the two summers of vulnerable households relative to non-vulnerable households. Results from this analysis are shown in Table D-8, Table D- 9, and Table D-10.

Table D-8. SMUD Average Peak Period Load Impacts for Voluntary Treatment Combined Disaggregated between Summer 1 and Summer 2

	Low Income	Elderly	Chronic Illness
$\boldsymbol{\beta_1}$: Summer 1 Treatment Effect of Non-VP	-1.012***	-0.797***	-0.768***
standard errors	(0.131)	(0.0996)	(0.0893)
p-value	0.0000	0.0000	0.0000
$\boldsymbol{\beta_2}$: Marginal Summer 1 Treatment Effect of VP	0.549***	-0.123	-0.335*
standard errors	(0.161)	(0.176)	(0.2)
p-value	0.000663	0.486	0.0948
$\boldsymbol{\beta_3}$: Marginal Summer 2 Treatment Effect of Non-VP (relative to Summer 1)	0.223*	-0.0286	0.0447
standard errors	(0.132)	(0.0949)	(0.0889)
p-value	0.0907	0.763	0.615
$\boldsymbol{\beta_4}$: Marginal Summer 2 Treatment Effect of VP (relative to Summer 2 and non-VP)	-0.22	0.309*	0.224
standard errors	(0.159)	(0.179)	(0.18)
p-value	0.166	0.0835	0.215
$\boldsymbol{\beta_5}$: Marginal Difference Between Pre and Summer1 Energy Use of Control VP	0.125	-0.0327	0.0661
standard errors	(0.098)	(0.112)	(0.12)
p-value	0.202	0.77	0.582
$\boldsymbol{\beta_6}$: Marginal Difference Between Summer 1 and Summer 2 Energy Use of Control VP	0.0833	-0.246**	-0.187*
standard errors	(0.0998)	(0.11)	(0.0964)
p-value	0.404	0.0253	0.0525
Percent Load Impact: VP Summer 1	-23%	-40%	-46%

Percent Load Impact: Non-VP Summer 1	-39%	-33%	-33%
Percent Load Impact: VP Summer 2	-23%	-27%	-35%
Percent Load Impact: Non-VP Summer 2	-30%	-34%	-31%
Average Peak Period Energy Use of Control Households on Critical Event Days (both summers combined)			
VP	1.99	2.30	2.40
Non-VP	2.60	2.43	2.36
All Survey Respondents	2.36	2.36	2.36
Observations	164106	173229	178011
R-squared	0.567	0.568	0.568

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level in parentheses.

Table D- 9. SMUD Average Peak Period Load Impacts for Default Treatment Combined Disaggregated between Summer 1 and Summer 2

	Low Income	Elderly	Chronic Illness
β_1: Summer 1 Treatment Effect of Non-VP	-0.634***	-0.549***	-0.580***
standard errors	(0.132)	(0.112)	(0.101)
p-value	0.0000	0.0000	0.0000
β_2: Marginal Summer 1 Treatment Effect of VP	0.109	-0.198	-0.164
standard errors	(0.19)	(0.204)	(0.252)
p-value	0.568	0.332	0.515
β_3: Marginal Summer 2 Treatment Effect of Non-VP (relative to Summer 1)	-0.0377	-0.131	-0.0801
standard errors	(0.113)	(0.0831)	(0.0809)
p-value	0.738	0.116	0.323
β_4: Marginal Summer 2 Treatment Effect of VP (relative to Summer 2 and non-VP)	0.0928	0.245	0.226
standard errors	(0.15)	(0.177)	(0.2)

p-value	0.536	0.167	0.259
$\boldsymbol{\beta_5}$: Marginal Difference Between Pre and Summer1 Energy Use of Control VP	0.125	-0.0324	0.0668
standard errors	(0.0981)	(0.112)	(0.12)
p-value	0.204	0.772	0.579
$\boldsymbol{\beta_6}$: Marginal Difference Between Summer 1 and Summer 2 Energy Use of Control VP	0.0824	-0.246**	-0.187*
standard errors	(0.0999)	(0.11)	(0.0966)
p-value	0.41	0.0258	0.0536
Percent Load Impact: VP Summer 1	-26%	-32%	-31%
Percent Load Impact: Non-VP Summer 1	-24%	-23%	-25%
Percent Load Impact: VP Summer 2	-23%	-27%	-25%
Percent Load Impact: Non-VP Summer 2	-26%	-28%	-28%
Average Peak Period Energy Use of Control Households on Critical Event Days (both summers combined)			
VP	1.99	2.30	2.40
Non-VP	2.60	2.43	2.36
All Survey Respondents	2.36	2.36	2.36
Observations	57300	61023	62043
R-squared	0.593	0.594	0.592

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level in parentheses.

Table D-10. GMP Average Peak Period Load Impacts for Voluntary Treatment Combined Disaggregated between Summer 1 and Summer 2

	Low Income	Elderly	Chronic Illness
$\boldsymbol{\beta_1}$: Summer 1 Treatment Effect of Non-VP	-0.051	-0.038	-0.0801**
standard errors	(0.0437)	(0.0475)	(0.0397)
p-value	0.244	0.424	0.0441
$\boldsymbol{\beta_2}$: Marginal Summer 1 Treatment Effect of VP	0.0526	-0.0205	0.108
standard errors	(0.124)	(0.0725)	(0.0888)
p-value	0.672	0.777	0.223
$\boldsymbol{\beta_3}$: Marginal Summer 2 Treatment Effect of Non-VP (relative to Summer 1)	-0.000415	-0.0347	0.00585
standard errors	(0.0627)	(0.0655)	(0.0525)
p-value	0.995	0.596	0.911
$\boldsymbol{\beta_4}$: Marginal Summer 2 Treatment Effect of VP (relative to Summer 2 and non-VP)	-0.00583	0.0663	-0.0116
standard errors	(0.16)	(0.0991)	(0.134)
p-value	0.971	0.503	0.931
$\boldsymbol{\beta_5}$: Marginal Difference Between Pre and Summer1 Energy Use of Control VP	-0.00983	-0.048	-0.00817
standard errors	(0.0553)	(0.043)	(0.0588)
p-value	0.859	0.265	0.889
$\boldsymbol{\beta_6}$: Marginal Difference Between Summer 1 and Summer 2 Energy Use of Control VP	0.0718	-0.142**	0.168*
standard errors	(0.107)	(0.0646)	(0.0889)
p-value	0.504	0.0284	0.0586
Percent Load Impact: VP Summer 1	0%	-6%	2%
Percent Load Impact: Non-VP Summer 1	-5%	-3%	-8%
Percent Load Impact: VP Summer 2	0%	-2%	2%
Percent Load Impact: Non-VP Summer 2	-5%	-6%	-8%

Average Peak Period Energy Use of Control Households on Critical Event Days (both summers combined)			
VP	1.16	0.93	1.26
Non-VP	1.03	1.10	0.96
All Survey Respondents	1.05	1.05	1.05
Observations	101697	124297	123877
R-squared	0.49	0.478	0.478

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level in parentheses.

D.4. Bill Impacts

In this analysis we estimate the effect on average expenditure as a result of the CPP pricing, relative to the control group expenditure. The actual bill savings were estimated using a DID 2SLS regression. The same estimating strategy was used as was described in equations (1), (2), and (3) above. Now, however, the y_{it} variable is the expenditure of household i in month t. The expenditure was converted from bill cycles to calendar months in order to avoid any systematic discrepancies generated based on differences in bill period start and stop dates across control and treatment groups. This conversion was done by pro-rating the total bill amount, averaged across all dates in that bill cycle, to each day within that bill cycle. These prorated daily expenditure amounts were then aggregated back up to the calendar month level. The results from this analysis were reported as a percent of average expenditure for the Control group. The analysis for SMUD was done during the summer months (June, July, August, and September) using data from 2011, 2012 and 2013. The results from this analysis are shown in Table D-11 and Table D-12 (for the Voluntary and Default treatment groups, respectively). The analysis for GMP was done separately for event months (September and October of 2012 and July and August of 2013) and non-event months. The results from this analysis can be seen in Table D-13 and Table D-14.

Table D-11. SMUD Average Event-Season Monthly Expenditure Impacts for Voluntary Treatment Combined

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	-7.565**	-9.667*	-8.186**	-5.431
standard errors	(3.277)	(5.236)	(3.767)	(3.550)
p-value	0.0211	0.0651	0.0299	0.126
β_2: Marginal Treatment Effect of VP		4.661	-2.304	-18.83**
standard errors		(6.646)	(7.188)	(8.889)
p-value		0.483	0.749	0.0343
β_3 : Change Between Pre- and Treatment Period of VP		0.386	1.195	6.614
standard errors		(4.202)	(4.501)	(5.664)
p-value		0.927	0.791	0.243
VP Percent Expenditure Impact		-7%	-11%	-25%
Non-VP Percent Expenditure Impact	-7%	-8%	-7%	-5%
N	16,549	15,237	16,083	16,525
Average Monthly Expenditure of Control Households:				
VP		72	99	98
Non-VP		129	113	108
All Survey Respondents	107	107	107	107

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level.

Table D-12. SMUD Average Event-Season Monthly Expenditure Impacts for Default Treatment

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	-8.206***	-8.740*	-8.943**	-7.102**
standard errors	(3.015)	(4.570)	(3.584)	(3.261)
p-value	0.00672	0.0564	0.0129	0.0299
β_2: Marginal Treatment Effect of VP		-0.959	-0.780	-8.844
standard errors		(6.255)	(6.536)	(8.706)
p-value		0.878	0.905	0.310

$\boldsymbol{\beta_3}$: Change Between Pre- and Treatment Period of VP		0.377	1.197	6.614
standard errors		(4.209)	(4.508)	(5.672)
p-value		0.929	0.791	0.244
VP Percent Expenditure Impact		-13%	-10%	-16%
Non-VP Percent Expenditure Impact	-8%	-7%	-8%	-7%
N	5,765	5,311	5,652	5,745
Average Monthly Expenditure of Control Households:				
VP		72	99	98
Non-VP		129	113	108
All Survey Respondents	107	107	107	107

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level.

Table D-13. GMP Average Event-Season Monthly Expenditure Impacts for Voluntary Treatment Combined

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
$\boldsymbol{\beta_1}$: Treatment Effect of Non-VP	15.53***	17.96***	15.16***	15.09***
standard errors	(2.040)	(2.416)	(2.829)	(2.225)
p-value	0.0000	0.0000	0.0000	0.0000
$\boldsymbol{\beta_2}$: Marginal Treatment Effect of VP		-3.597	0.835	2.655
standard errors		(7.459)	(3.943)	(5.364)
p-value		0.630	0.832	0.621
$\boldsymbol{\beta_3}$: Change Between Pre- and Treatment Period of VP		1.027	-5.017**	1.266
standard errors		(3.241)	(2.081)	(2.882)
p-value		0.751	0.0161	0.660
VP Percent Expenditure Impact		14%	17%	15%
Non-VP Percent Expenditure Impact	15%	17%	13%	15%
N	7,489	6,136	7,473	7,457
Average Monthly Expenditure of Control Households:				
VP		106	92	118
Non-VP		107	115	101
All Survey Respondents	105	105	105	105

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level.

Table D-14. GMP Average Non-Event Season Monthly Expenditure Impacts for Voluntary Treatment Combined

	All (Survey respondents only)	Low Income	Elderly	Chronic Illness
β_1: Treatment Effect of Non-VP	0.317	1.558	-2.288	-0.780
standard errors	(1.843)	(2.153)	(2.617)	(1.965)
p-value	0.864	0.469	0.382	0.691
β_2: Marginal Treatment Effect of VP		-3.046	6.819**	4.970
standard errors		(7.457)	(3.461)	(5.017)
p-value		0.683	0.0491	0.322
β_3 : Change Between Pre- and Treatment Period of VP		2.466	-6.118***	-1.950
standard errors		(4.523)	(2.139)	(3.131)
p-value		0.586	0.00432	0.534
VP Percent Expenditure Impact		-1%	5%	4%
Non-VP Percent Expenditure Impact	0%	1%	-2%	-1%
N	21,695	17,740	21,649	21,603
Average Monthly Expenditure of Control Households:				
VP		109	87	112
Non-VP		104	116	101
All Survey Respondents	103	103	103	103

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard errors clustered at the household level.

D.5. Pre-Treatment Average Peak Consumption and Variability in Peak Consumption

In order to look at differences in consumption patterns between vulnerable and non-vulnerable populations the following analysis was performed. In the pre-treatment period the average peak consumption, the load factor, and the coefficient of variation (CV) of peak usage were calculated for each household and averaged across the vulnerable and non-vulnerable customer groups. A t-test was conducted to identify if differences in these metrics between the vulnerable and non-vulnerable groups was statistically significant. Table D-15 shows the summary statistics from this analysis for SMUD, and Table D-16 shows these same statistics for GMP.

Table D-15. SMUD Average, CV, and Load Factor of Peak kWh Usage

	Low Income	t-test of difference between Low Income and Non-Low Income	Elderly	t-test of difference between Elderly and Non-Elderly	Chronic Illness	t-test of difference between Chronically Ill and Non-Chronically Ill
Average kWh usage						
VP	1.57		1.81		1.93	
	[1.02]	-0.378***	[1.23]	-0.0375	[1.18]	0.115
Non-VP	1.95	(0.000)	1.85	(0.532)	1.81	(0.217)
	[1.20]		[1.13]		[1.15]	
CV of hourly usage						
VP	0.60		0.58		0.57	
	[0.24]	0.0069	[0.25]	-0.0186	[0.23]	-0.0278
Non-VP	0.59	(0.585)	0.60	(0.137)	0.59	(0.156)
	[0.24]		[0.24]		[0.25]	
Load factor						
VP	0.32		0.33		0.35	
	[0.13]	-0.0001	[0.13]	0.0024	[0.12]	0.0230*
Non-VP	0.32	(0.992)	0.33	(0.718)	0.32	(0.023)
	[0.13]		[0.12]		[0.13]	
Number of Vulnerable Households	604		567		171	
Total Number of Households	1582		1669		1711	

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard deviation in brackets, p-values in parentheses.

Table D-16. GMP Average, CV, and Load Factor of Peak kWh Usage

	Low Income	t-test of difference between Low Income and Non-Low Income	Elderly	t-test of difference between Elderly and Non-Elderly	Chronic Illness	t-test of difference between Chronically Ill and Non-Chronically Ill
Average kWh usage						
VP	0.84		0.70		0.86	
	[0.46]	0.0804	[0.40]	-0.118***	[0.52]	0.114**
Non-VP	0.76	(0.084)	0.82	(0.000)	0.74	(0.002)
	[0.55]		[0.59]		[0.53]	
CV of hourly usage						
VP	0.32		0.31		0.34	
	[0.14]	-0.00732	[0.15]	-0.0265**	[0.14]	0.0149
Non-VP	0.33	(0.618)	0.34	(0.005)	0.33	(0.183)
	[0.22]		[0.22]		[0.22]	
Load factor						
VP	0.19		0.17		0.19	
	[0.11]	0.0204*	[0.09]	-0.00352	[0.08]	0.0180**
Non-VP	0.17	(0.016)	0.17	(0.518)	0.17	(0.005)
	[0.10]		[0.10]		[0.10]	
Number of Vulnerable Households	116		383		204	
Total Number of Households	761		929		925	

Notes: * p<0.05, ** p<0.01, *** p<0.001, VP= Vulnerable Population, standard deviation in brackets, p-values in parentheses.

D.6. Enrollment

Because in the case of SMUD not everyone in the group of customers that eschewed treatment were surveyed, the way that we are able to assess whether vulnerable or non-vulnerable populations enrolled at different rates requires looking at the frequency of occurrence of vulnerable populations in the control group and comparing it to the similar frequency of occurrence in the group that enrolled in treatment. If the rate of occurrence of vulnerable households in the treatment group is higher than in the control group, the assumption is that that populations enrolled at a higher rate than their non-vulnerable counterparts, and vice versa. To test whether this difference is statistically significant the test statistics and p-values from a two-sample test of proportions testing the difference in proportion of vulnerable households between the control and treated groups are presented. Results of this analysis for SMUD's voluntary treatment groups combined (Table D-17), SMUD's default treatment group (Table D-18) and GMP's voluntary treatment groups combined (Table D-19) are presented below.

Table D-17. SMUD Enrollment Numbers for Voluntary Treatment Groups (Combined)

	Control Group				CPP Voluntary Group				
	Non-VP	VP	Total	Percent of Treatment Status Group That Are Vulnerable	Non-VP	VP	Total	Percent of Treatment Status Group That Are Vulnerable	Two sample test of proportions comparing control to treated groups z-stat (p-value)
	Elderly								
Not Exposed to Treatment	149	78	227	34%	196	126	322	39%	0.414
Exposed to Treatment					573	281	854	33%	(0.679)
Total	149	78	227	34%	769	407	1176	35%	
	Chronically Ill								
Not Exposed to Treatment	202	31	233	13%	306	27	333	8%	1.711
Exposed to Treatment					793	83	876	9%	(0.087)
Total	202	31	233	13%	1099	110	1209	9%	
	Low Income								
Not Exposed to Treatment	124	87	211	41%	200	106	306	35%	0.202
Exposed to Treatment					484	329	813	40%	(0.840)
Total	124	87	211	41%	684	435	1119	39%	

Table D-18. SMUD Enrollment Numbers for Default Treatment Group

	Control Group				CPP Default Group				
	Non-VP	VP	Total	Percent of Treatment Status Group That Are Vulnerable	Non-VP	VP	Total	Percent of Treatment Status Group That Are Vulnerable	Two sample test of proportions comparing control to treated groups z-stat (p-value)
	Elderly								
Not Exposed to Treatment	149	78	227	34%	3	4	7	57%	1.071
Exposed to Treatment					179	76	255	30%	(0.284)
Total	149	78	227	34%	182	80	262	31%	
	Chronically Ill								
Not Exposed to Treatment	202	31	233	13%	6	1	7	14%	0.546
Exposed to Treatment					227	30	257	12%	(0.585)
Total	202	31	233	13%	233	31	264	12%	
	Low Income								
Not Exposed to Treatment	124	87	211	41%	5	2	7	29%	1.954
Exposed to Treatment					163	78	241	32%	(0.051)
Total	124	87	211	41%	168	80	248	32%	

Table D-19. GMP Enrollment Numbers for Voluntary Treatment Groups (Combined)

	Control Group				CPP Voluntary Group				
	Non-VP	VP	Total	Percent of Treatment Status Group That Are Vulnerable	Non-VP	VP	Total	Percent of Treatment Status Group That Are Vulnerable	Two sample test of proportions comparing control to treated groups z-stat (p-value)
	Elderly								
Not Exposed to Treatment	218	155	373	42%	30	49	79	62%	1.165
Exposed to Treatment					300	181	481	38%	(0.244)
Total	218	155	373	42%	330	230	560	41%	
	Chronically Ill								
Not Exposed to Treatment	280	92	372	25%	64	14	78	18%	1.576
Exposed to Treatment					383	97	480	20%	(0.115)
Total	280	92	372	25%	447	111	558	20%	
	Low Income								
Not Exposed to Treatment	254	48	302	16%	53	11	64	17%	0.497
Exposed to Treatment					341	58	399	15%	(0.619)
Total	254	48	302	16%	394	69	463	15%	

D.7. Attrition

Table D-20 shows the attrition rates of vulnerable and non-vulnerable households once they were enrolled in treatment by study and enrollment method. In order to test whether vulnerable households dropped out at statistically significantly different rates, the test statistics and p-values from a two-sample test of proportions testing the difference between the attrition rate of vulnerable and non-vulnerable subpopulations are presented.

Table D-20. Attrition Rates

	SMUD	GMP	SMUD
Enrollment Method	CPP Voluntary	CPP Voluntary	CPP Default
	Elderly		
Attrition Rate Vulnerable	5%	10%	11%
Attrition Rate Non-Vulnerable	4%	11%	5%
z-statistic for test of difference (p-value)	-0.896 (0.371)	0.179 (0.858)	-1.858 (0.063)
	Chronically Ill		
Attrition Rate Vulnerable	8%	11%	6%
Attrition Rate Non-Vulnerable	4%	11%	7%
z-statistic for test of difference (p-value)	-1.918 (0.055)	-0.022 (0.982)	0.086 (0.931)
	Low Income		
Attrition Rate Vulnerable	4%	14%	3%
Attrition Rate Non-Vulnerable	4%	11%	8%
z-statistic for test of difference (p-value)	0.083 (0.934)	-0.930 (0.352	1.618 (0.106)

D.8. Survey Responses

Table D-21 through Table D-24 show survey responses from SMUD's customer satisfaction survey. The test statistics and p-values from a two-sample test of proportions testing the difference between the favorable response rate of vulnerable and non-vulnerable subpopulations are presented.

Table D-21. Survey Response Rates: Comfort

Question: I sometimes feel uncomfortable inside my home on summer afternoons and evenings because it is too expensive to run my air conditioner.

Answers Considered Favorable: Strongly disagree, Somewhat disagree, No opinion

Answers Considered Not Favorable: Somewhat agree, Strongly agree

SMUD		
Enrollment Method	CPP Voluntary	CPP Default
	Elderly	
Favorable Response Rate Vulnerable	48%	50%
Favorable Response Rate Non-Vulnerable	40%	40%
z-statistic for test of difference (p-value)	-1.438 (0.1504)	-0.994 (0.3204)
	Chronically Ill	
Favorable Response Rate Vulnerable	18%	27%
Favorable Response Rate Non-Vulnerable	43%	44%
z-statistic for test of difference (p-value)	2.313 (0.0207)	1.040 (0.2985)
	Low Incomes	
Favorable Response Rate Vulnerable	35%	50%
Favorable Response Rate Non-Vulnerable	43%	41%
z-statistic for test of difference (p-value)	1.337 (0.1812)	-0.830 (0.4067)

Table D-22. Survey Response Rates: Difficulty Adjusting

Question: How difficult were these changes to make?

Answers Considered Favorable: Not difficult at all

Answers Considered Not Favorable: Somewhat difficult, Very difficult

SMUD		
Enrollment Method	CPP Voluntary	CPP Default
	Elderly	
Favorable Response Rate Vulnerable	74%	65%
Favorable Response Rate Non-Vulnerable	65%	68%
z-statistic for test of difference (p-value)	-1.600 (0.1097)	0.258 (0.7965)

	Chronically Ill	
Favorable Response Rate Vulnerable	65%	44%
Favorable Response Rate Non-Vulnerable	67%	69%
z-statistic for test of difference (p-value)	0.225 (0.8223)	1.488 (0.1367)
	Low Incomes	
Favorable Response Rate Vulnerable	68%	61%
Favorable Response Rate Non-Vulnerable	66%	71%
z-statistic for test of difference (p-value)	-0.267 (0.7896)	0.847 (0.3972)

Table D-23. Survey Response Rates: Satisfaction

Question: Overall how satisfied are you with your current pricing plan?

Answers Considered Favorable: Very satisfied, Somewhat satisfied

Answers Considered Not Favorable: Somewhat dissatisfied, Very dissatisfied

SMUD		
Enrollment Method	CPP Voluntary	CPP Default
	Elderly	
Favorable Response Rate Vulnerable	91%	93%
Favorable Response Rate Non-Vulnerable	98%	91%
z-statistic for test of difference (p-value)	-0.931 (0.352)	-0.339 (0.7349)
	Chronically Ill	
Favorable Response Rate Vulnerable	82%	91%
Favorable Response Rate Non-Vulnerable	89%	92%
z-statistic for test of difference (p-value)	1.117 (0.2641)	0.136 (0.8922)
	Low Incomes	
Favorable Response Rate Vulnerable	90%	100%
Favorable Response Rate Non-Vulnerable	89%	90%
z-statistic for test of difference (p-value)	-0.387 (0.6991)	-1.666 (0.0957)

Table D-24. Survey Response Rates: Desire to Stay

Question: I want to stay on my pricing plan.

Answers Considered Favorable: Strongly agree, Somewhat agree, No opinion

Answers Considered Not Favorable: Somewhat disagree, Strongly disagree

SMUD		
Enrollment Method	CPP Voluntary	CPP Default
	Elderly	
Favorable Response Rate Vulnerable	96%	91%
Favorable Response Rate Non-Vulnerable	96%	97%
z-statistic for test of difference (p-value)	-0.263 (0.7925)	1.348 (0.1775)
	Chronically Ill	
Favorable Response Rate Vulnerable	94%	89%
Favorable Response Rate Non-Vulnerable	96%	97%
z-statistic for test of difference (p-value)	0.362 (0.7175)	1.130 (0.2585)
	Low Incomes	
Favorable Response Rate Vulnerable	95%	100%
Favorable Response Rate Non-Vulnerable	97%	96%
z-statistic for test of difference (p-value)	0.672 (0.5016)	-1.002 (0.3164)