RESOURCES
for the FUTURE

Different Prices for Different Slices: A Meta-Analysis of Time-Based Electricity Rates

Jenya Kahn-Lang, Yuqi Zhu, Karen Palmer, and Peter Cappers

Working Paper 25-04
February 2025

About the Authors

Jenya Kahn-Lang is an economist and a fellow at Resources for the Future (RFF). Her research primarily examines market barriers to an equitable climate transition and associated policy solutions. Her expertise is in the electric power sector, with research and consulting experience covering utility regulation, retail electricity markets, wholesale electricity market design, distributed energy resources, retail rate design, and fuel switching.

Yuqi Zhu is a Senior Research Associate who joined RFF in 2022 after receiving his master's degree in public policy from the Harvard Kennedy School. Prior to graduate school, he worked in corporate development at Liberty Media, a media and communications holding company in Denver.

Karen Palmer is a senior fellow at RFF and an expert on the economics of environmental, climate and public utility regulation of the electric power sector. Her work seeks to improve the design of environmental and technology regulations in the sector and the development of new institutions to help guide the ongoing transition of the electricity sector. To these ends, she explores climate policy design, analyzes efficient ways to promote use of renewable and other clean sources of electricity, and investigates new market designs, new approaches to electricity pricing and regulatory reforms to pave the way for long-term decarbonization of electricity supply and electrification of the energy economy.

Peter Cappers is a Staff Scientist and Strategic Advisor to the Electricity Markets and Policy Department at Berkeley Lab. With over 20 years of experience, Cappers has provided research and technical assistance to territorial, state, federal, and international regulators and policymakers on electric utility regulation, business models, pricing and rate design, demand response, renewable energy, and energy efficiency market and policy issues.

Acknowledgements

The work described in this study was funded by the US Department of Energy's Office of Energy Efficiency and Renewable Energy under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231. The abstract and introduction of this paper were written with the assistance of ChatGPT. All results, literature review, and errors are our own.

Different Prices for Different Slices: A Meta-Analysis of Time-Based Electricity Rates

Jenya Kahn-Lang*
Resources for the Future

Yuqi Zhu†
Resources for the Future

Karen Palmer‡
Resources for the Future

Peter Cappers§
Lawrence Berkeley National Laboratory

December 31, 2024

Abstract

With many US regions trying to meet aggressive electric power sector decarbonization goals, utilities and policymakers have renewed interest in time-based electricity rates as a tool to manage peak demand, encourage energy conservation, and shift consumption patterns. We conduct a rigorous meta-analysis of the literature on US residential time-based rates. We focus on the impacts on peak demand and on-peak usage. By reviewing the diverse utility experiences, we identify key factors influencing rate design effectiveness and provide insight into enrollment and demand response heterogeneity. We also highlight gaps in research and discuss areas where additional exploration could improve rate design policies.[1]

*jkahn-lang@rff.org
†yzhu@rff.org
‡Palmer@rff.org
§pacappers@lbl.gov

[1]The work described in this study was funded by the US Department of Energy's Office of Energy Efficiency and Renewable Energy under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231. The abstract and introduction of this paper were written with the assistance of ChatGPT. All results, literature review, and errors are our own.

1 Introduction

As part of a transition to a high-renewable electricity grid, residential time-based rate designs may be a useful and efficient tool for encouraging demand-side flexibility. These rate designs incentivize consumers to reduce energy use during high-cost periods with little renewable generation, thereby contributing to grid reliability and efficiently lowering generation costs. Despite many utility pilots and significant research on these rate designs, questions remain about the extent and nature of consumer response.

We seek to answer two broad research questions:

1. What insights from past utility experiences with residential time-based rates can inform future rate design implementation?

2. What are the key remaining gaps in our understanding of residential time-based rate enrollment and response?

Through a meta-analysis of the literature, this paper provides new insights into the drivers of heterogeneity in customer responses to time-based rates and identifies critical areas where more research is needed to inform rate design and energy policy. We review over 100 utility evaluation reports and journal articles and draw conclusions from the 140 analyses across 39 papers that pass our quality and eligibility screens.

On average, we estimate that time-based rates lead to a 16 percent reduction in peak demand per participant, but this response is highly heterogeneous. Individual estimates range from *increases* in peak demand to reductions of over 50 percent. This large heterogeneity persists when we isolate the studies that follow methodological best practices, suggesting that the heterogeneity is coming from true differences across rate designs and pilot characteristics. We explore the drivers of this heterogeneity and find significant variation from specific rate design elements, accompanying interventions, recruitment strategies, and customer demographics.

This paper contributes to two key areas of the synthesis literature on time-based rates. First, we add statistical rigor. A large literature documents suggestive drivers of customer response to time-based rates (e.g., Star et al. 2010; Joskow 2012; Gyamfi et al. 2013; Baatz 2017; Siddiqui 2021). However, most of the literature is qualitative, frequently citing only a few papers to support each finding. Only a few studies (Faruqui and Palmer 2012; Faruqui and Sergici 2013; Davis et al. 2013; Nicolson et al. 2018),[2] report the precision of their estimates

[2]Two of these studies present variations on the same analysis.

or otherwise specify uncertainty. Similarly, only a couple of the meta-analyses (Davis et al. 2013; DOE 2016) document careful attention to the evaluation design and implementation quality underlying the estimates in the papers they consider. In contrast, we conduct a rigorous meta-analysis that evaluates these factors for each study *and* quantifies the precision of our estimates.

Second, we build on the literature on the key drivers of this response heterogeneity. In particular, we provide new findings in areas of the literature that have ongoing debate, offer insights into mechanisms to explain the impacts of known drivers, and identify some new drivers of this heterogeneity that were not previously studied, to our knowledge, which include the timing of the high-priced period for time-of-use rates and solar photovoltaic ownership. These characteristics may be increasingly important as the power sector becomes more decarbonized.

2 Background

Time-based electricity rate designs differ from traditional, time-invariant designs in that prices vary with the timing of consumption. Per-kilowatt-hour (kWh) energy price or per-kilowatt (kW) demand prices may vary by time of day, day of the week, or day of the year. As a result, time-based rate designs can better align retail prices with fluctuating wholesale supply costs. Utilities are increasingly using these rate designs as a tool to encourage more efficient electricity consumption. In particular, time-based rates may reduce peak demand, shift usage toward low-cost hours, or incentivize energy efficiency investments or electricity conservation.

Our review examines the following five types of time-based rates:

- **Time-of-use (TOU)**: TOU rates feature energy or demand charges that vary across specific, predetermined periods, usually defined by certain hours of the day and days of the week, such as weekdays from 4 to 8 p.m. Although the terms utilities use to describe these periods vary, we define the highest- and lowest-priced periods as "on-peak" and "off-peak," respectively, throughout this analysis.

- **Real-time pricing (RTP)**: Under RTP, energy charges vary hourly, with prices typically indexed to wholesale market prices. Most frequently, utilities set these hourly prices a day in advance, enabling the prices to reflect dynamic information about market conditions.

- **Critical peak pricing (CPP)**: CPP is a type of "event rate" where the retail energy price is especially high during a small number of hours of the year. These periods are called "events" or "critical peak periods" and typically occur when the grid faces its highest demand.

- **Peak-time rebates (PTR)**: PTRs, also known as Critical Peak Rebates, are event rates. They use a reward-based structure and offer financial rebates to consumers who reduce their usage below a predefined baseline during events.

- **Variable Peak Pricing (VPP)**: VPP combines elements of TOU and event rates. Like TOU rates, these rates offer consistent on-peak and off-peak periods. However, the utility sets on-peak rates dynamically while maintaining a constant off-peak rate.

A synthesis literature on the impacts of time-based rates generally finds that they lead to peak demand *and* on-peak usage reductions. However, the estimated magnitude of these impacts varies widely. One focus of this literature has been to identify some of the key drivers of this impact heterogeneity. We summarize the status of knowledge on these drivers in the following paragraphs.

The synthesis literature that examines the factors influencing customer responsiveness to time-based electricity rates agrees on several key drivers of impact heterogeneity. A consensus exists that providing control technologies, such as programmable thermostats, improves the effectiveness of time-based rate designs in reducing peak demand (Faruqui and George 2002; Faruqui and Sergici 2008; Faruqui and Wood 2008; Faruqui and Sergici 2010; Newsham and Bowker 2010; Stromback et al. 2011; Faruqui et al. 2012; Faruqui and Palmer 2012; Joskow 2012; U.S. Department of Energy 2016; Dutta and Mitra 2017; Harding and Sexton 2017). Similarly, a smaller body of literature shows that providing customers with real-time usage feedback, such as through in-home displays, can enhance peak demand reductions and lower overall consumption (Stromback et al. 2011; Joskow 2012; Davis et al. 2013). Broad agreement also exists that event-based rates, such as CPP and PTR, lead to greater peak demand reductions compared to TOU rates (Faruqui and George 2002; Faruqui and Wood 2008; Newsham and Bowker 2010; Stromback et al. 2011; Faruqui and Palmer 2012; Joskow 2012). However, Stromback et al. (2011) point out that TOU rates have the relative benefit of reducing on-peak usage throughout the year.

More limited evidence exists for the effect of other design choices, especially design aspects that may impact both enrollment and the average customer response. For instance, Newsham and Bowker (2010) and DOE (2016) find that

CPP designs outperform PTR designs in reducing peak demand per customer, although DOE (2016) show that PTR designs may yield higher customer retention rates. Similarly, opt-out enrollment models achieve substantially higher participation rates than opt-in models (DOE 2016; Nicolson et al. 2018) but may also be associated with smaller demand reductions per customer (DOE 2016). Nicolson et al. (2018) also find suggestive evidence that bill protection increases take-up, but they conclude that more research is needed and do not analyze resulting effects on electricity usage.

Still other potential drivers of heterogeneity in the responsiveness to time-based rates yield mixed results across studies. For example, although some studies report greater reductions in peak demand or on-peak usage as the peak-to-off-peak price ratio increases (Stromback et al. 2011; Faruqui and Palmer 2012; DOE 2016), Newsham and Bowker (2010) find no clear relationship between this ratio and peak demand reductions. Evidence is also mixed on whether low-income households have a smaller response than high-income households, with some studies finding a smaller response and others finding no significant difference (Faruqui et al. 2012; Faruqui and Tang 2023). Collectively, these findings highlight the need for further research to clarify these relationships and the underlying mechanisms driving heterogeneity among them.

Few studies focus on off-peak usage impacts. However, there is some evidence that consumers primarily respond to time-based rates by reducing their usage rather than shifting it to off-peak periods (Stromback et al. 2011). Whether these rates increase or decrease off-peak usage on net remains an open question.

Although most of the synthesis literature pays limited attention to the studies' identification methods, evidence indicates that selection and spillover bias may be common. Davis et al. (2013) find that participant selection into the study and into specific treatment groups are the most common known risks of bias among the studies they analyze. Using a randomized control trial, Todd et al. (2019) show that a common method of assessing the impacts of event rates suffers from spillover bias.

3 Methods

3.1 Literature Selection

We systematically collected and reviewed a comprehensive set of utility evaluation reports and peer-reviewed academic literature. We restricted our search to literature published since January 2000 on rate pilots or full-scale implementations in the United States. This section outlines our literature search protocol and inclusion and exclusion criteria.

We used a multistage approach to collect utility evaluation reports. We began by gathering evaluation reports on time-based rate pilot programs known to us. We then supplemented this set with eligible reports listed in Enright and Faruqui (2015) and Sergici et al. (2023). We identified additional utilities with large residential enrollment in time-based rates, defined as at least 10,000 participating customers or 5 percent of their residential customer base, using the Energy Information Administration's 2015 and 2022 EIA-861 Forms. For these utilities, we used Google Search to conduct targeted searches for evaluation reports on time-based rate programs using the utility's name, keywords, such as "residential evaluation report" and "pilot," and rate terms, such as "time-of-use," "real-time pricing," "critical peak pricing," "peak-time rebate," and "variable peak pricing." For each utility, we only included the most recent evaluation report on a given pilot or rate.

We also collected relevant academic literature. Our initial set of articles again included known research and those cited in Enright and Faruqui (2015) and Sergici et al. (2023). To identify further studies, we searched the Google Scholar and EconLit databases using the keywords "electricity," "residential," "impact," and similar rate terms as those used for utility reports. We restricted our search to papers published this century and stopped after the fourth result page. We focused on ex-post impacts based on observed data and excluded analyses of simulated or hypothetical rate impacts and papers older than five years that had fewer than 25 citations. Although we collected synthesis papers to put our results in context, we do not directly include any content from these papers in our meta-analysis.

We further pared down the reports and journal articles based on analysis quality. We first excluded analyses of fewer than 500 customers due to concerns about external validity. We then reviewed the analysis designs in detail for internal validity, assessing each on bias due to spillover effects and selection. We removed any analyses without sufficient information on methods to assess quality. We then scored each remaining analysis on how well we thought it identified a causal relationship between the rate design and assessed impacts using a three-tiered rating system.

We excluded analyses that received the lowest score because we deemed them too biased to be informative. These analyses generally fell into two categories. The first was studies that compare customers who opted for the rate design to those who did not, due to concerns about selection bias. In particular, we may worry that customers who opted in would be more likely to have relatively low usage during high-priced periods irrespective of their rate design. Second, we excluded studies that compared the usage of customers on event rates during and outside of the events, as the rate design could have spillover effects on the non-event hours that could bias results upward (e.g., due to usage shifting from event to non-event hours) or downward (e.g., due to purchasing a more efficient air conditioning system that would reduce usage on event *and* non-event days).

We included studies with the two highest scores, "high" and "medium" quality, in our meta-analysis. A high rating reflects best practices for assessing causal inference. In practice, we exclusively awarded this score to randomized encouragement designs and randomized control trials. We assigned a medium score to methods designed to avoid bias due to spillover effects and limit bias due to selection; common approaches included creating a control group by matching participants to customers with similar characteristics who were not approached, comparisons of participants' usage before and after the rate design change, and difference-in-differences designs that combine these two approaches.

Some studies had differing quality designations across treatment arms, which is the unit of analysis in this meta-analysis. We define a treatment arm by the utility, rate, eligible customer population, analytical method, enrollment strategy, accompanying interventions, and choice of full, partial, or no bill protection. Each arm has a unique value for each of these categories, and many studies have multiple arms. For a few studies, we excluded some arms from our analysis and kept others due to differing quality designations.

3.2 Analytical Methods

The statistical portion of the meta-analysis has two key goals: 1) combine estimates from many studies to provide a total or average estimate for the effect of time-based rates on each key outcome, and 2) explore observable sources of rate and program heterogeneity in these estimates. This section summarizes our analytical approaches and our rationales for choosing them.

For the first objective, the most straightforward approach would arguably be to calculate a simple average of the effect estimates across studies, treating each study equally. However, this approach implicitly assumes that each study estimate is equally reliable and that any differences in estimates arise purely from random sampling variation. In practice, however, we may be more confident in some estimates due to sampling error variance, methodological rigor, or other differences across the studies. Many of these differences are fundamentally unobservable and cannot be captured by variables we include in our analysis.

To account for sample error variance differences across studies, we calculate a weighted mean of study estimates, where the weights are proportional to each study's sample size. This approach captures the fact that mean estimates from larger studies have lower variances than those from smaller studies due to the Law of Large Numbers Theorem. When direct variance estimates are unavailable, sample size serves as a reasonable proxy, in line with best practices for meta-analysis (Nelson and Kennedy 2009).

To address concerns about differences in methodological rigor, we report weighted averages for two groups: medium- and high-quality studies together and high-quality studies alone. These classifications follow the definitions in Section 3.1. We also display each individual estimate from medium- and high-quality studies to show the heterogeneity in these estimates.

Similarly, a direct approach to the second goal may be to group studies based on an observable characteristic of interest (e.g., bill protection), calculate the mean within each group, and compare these means across groups. The implicit assumption behind this approach is that the study estimates are comparable in all ways besides the specific grouping characteristics. Although this assumption may be appropriate when comparing treatment arms of a randomized control trial, it may be a strong assumption when comparing across a small number of studies.

Therefore, for characteristics with sufficient within-study variation, we isolate this variation by using paper fixed effects to control for differences across studies. We define a characteristic as having sufficient within-study variation if at least eight papers have variation in it across treatment arms. Unfortunately, the within-study variation for many characteristics of interest is insufficient to use this approach. For these characteristics, we analyze outcome differences without paper fixed effects and implicitly assume that the characteristics we aim to analyze are uncorrelated with any other relevant variation across the studies, such as climate, customer populations, and outreach approaches. If 5–7 papers have variation in a characteristic across treatment arms, we also check robustness to including paper fixed effects.

Formally, for each heterogeneity dimension, we estimate β in the following models:

$$Y_{as} = \alpha + \beta^T D_{as} + \delta_p + \varepsilon_{as}, \quad \varepsilon_{as} \sim \mathcal{N}(0, \sigma_{as}^2)$$

and

$$Y_{as} = \alpha + \beta^T D_{as} + \varepsilon_{as}, \quad \varepsilon_{as} \sim \mathcal{N}(0, \sigma_{as}^2)$$

, where Y_{as} is the outcome of interest for treatment arm a of study s, D_{as} is a matrix of the treatment characteristics of interest, δ_p are paper fixed effects, and ε_{as} is a normally distributed random error term with Huber-White heteroskdasticity-robust standard errors. We weight each observation by our prediction of σ_{as}^{-2} based on study sample size.

Our primary outcomes of interest for the heterogeneity analysis are reductions in mean peak demand and on-peak usage per participating customer. We use the definitions of peak demand and on-peak usage reported in the individual studies. For example, peak demand may reflect the total usage in the hour with the highest system-wide demand or capture usage across all event periods. In addition, some studies report peak demand impacts separately for the summer and winter seasons. In these cases, we use the reductions for the utility's peak season. For all the utilities in our analysis except for one, the peak season is summer.

Similarly, our approach addresses variation in how studies present on-peak usage reductions: for summer only, by season, or for the full year. For characteristics that do not vary by season, such as control technology, we restrict our analysis to the full-year results in our main specification. We also consider summer-only results for robustness. For those that do vary by season, such as the on-to-off-peak premium, we consider summer and winter results as separate observations. We exclude studies that only report full-year results, except for those that have the same rate features in the summer and winter.

For the recruitment strategy characteristics, we analyze three additional outcomes: enrollment as a share of eligible customers, aggregate peak demand reductions, and aggregate on-peak usage reductions. These aggregate reductions are measured with respect to the baseline peak demand and on-peak usage across the full eligible customer base.

We report all peak demand and electricity usage outcomes as reductions, so a positive β implies a more effective intervention. Most characteristics of interest, such as accompanying provision of a control technology, are binary. In this case, $\alpha = 0$, and β can be interpreted as the additional percentage point reduction in usage from providing a control technology. For continuous characteristics, such as the on-peak-to-off-peak premium, β can be interpreted as the incremental percentage point reduction in usage from a one-unit increase in the characteristic. For categorical characteristics, such as rate type, we report all the outcomes relative to those of studies with one specific characteristic category (e.g., a CPP rate design).

Some dimensions of heterogeneity in our analysis may be correlated. We are limited in our ability to control for many potentially correlated sources of heterogeneity, given our sample size. However, when a specific control intuitively seems especially relevant, we check the robustness of our results to adding it. This may provide some support for the hypothesis that the correlations reflect causal relationships.

We also check that our results are robust to additional alternative specifications. We explore robustness to weighting all studies equally for all characteristics and restricting the analysis to high-quality studies for characteristics with at least six papers for each relevant level of the characteristic. For characteristics with fixed effects in the preferred specification, we also check robustness to excluding these paper fixed effects.

4 Results

4.1 Summary of Included Studies

After our initial screen for papers that met our criteria, we reviewed 75 in detail; 51 were utility evaluation reports on rate pilots or full-scale implementations, and 24 were academic studies on rate pilots or experiments. We excluded 10 reports and three studies due to large concerns about methods, and we removed another 10 reports and 13 studies because a closer read showed they did not meet our screening criteria. We additionally dropped some treatment arms from our analysis due to methodological concerns. Our final sample included 140 treatment arms across 39 papers, covering 31 utility service territories. See Table A21 for a full list of included papers.

Figure A1 displays the geographic footprint of the electric utilities included in this analysis. The utilities span the US Census Divisions and climate regions used in Energy Information Administration's Residential Energy Consumptions Survey. The figure suggests especially high representation in the Northeast, Midwest, West Coast, and Mid-Atlantic regions. Although our meta-analysis includes utilities in the South Central Division, two southern utilities remained unnamed and are not included in the figure. Our sample also includes one utility each in Florida and New Mexico with small geographic footprints.

Table 4.1 provides a summary of the prevalence of each analyzed characteristic across included studies. The first two columns list the characteristics, and the last four columns display the number of papers or treatment arms in the meta-analysis that include estimates of each of the key outcomes—peak demand reduction and on-peak usage reduction—by characteristic. The on-peak usage reduction values reflect full-year estimates. Many of the papers include multiple treatment arms to test different rate designs, enrollment approach, or other characteristics.

Table 4.1 suggests that the results of this meta-analysis are most useful for understanding the peak demand impacts of TOU rates, event rates, and rate designs that incorporate TOU and event components. Most designs are TOU or a combination of TOU and an event rate. Only two papers evaluate real-time pricing. In addition, more papers report peak demand outcomes than on-peak usage outcomes. For each characteristic value, excluding rate type, at least seven papers and 15 treatment arms report peak demand response. The values for on-peak usage results are generally smaller. However, there are still at least five treatment arms with each characteristic value, excluding rate type, and most characteristics have at least 12 arms for each value. We are careful in interpreting results about uncommon rate types.

Table 1: Summary Statistics: Characteristics of Included Studies

Characteristic		# of Papers with Peak Demand	# of Treatment Arms with Peak Demand	# of Papers with On-Peak Usage	# of Treatment Arms with On-Peak Usage
Rate Type	TOU	9	28	17	45
	CPP	6	9	-	-
	PTR	7	13	-	-
	RTP	2	2	-	-
	TOU+CPP/VPP	12	40	7	12
	TOU+PTR	2	4	1	3
Enrollment Approach	Opt In	26	81	18	48
	Opt Out	9	15	4	12
Control Technology	Yes	12	26	3	7
	No	23	70	19	53
Real-Time Usage Info	Yes	11	31	3	5
	No	19	65	17	55
Other Extra Usage Info	Yes	7	28	4	17
	No	21	68	16	43
Bill Protection	Yes	10	43	5	31
	No	17	53	15	29
NEM Customers Excluded	Yes	9	36	8	30
	No	20	60	13	30
Low-Income Outcomes	Yes	7	19	9	22
	No	23	77	13	38
Summer On-Peak Period	Evening Only	-	-	4	14
	Afternoon Only	-	-	6	12
	Afternoon & Evening	-	-	11	34

We planned to include many characteristics in our meta-analysis that we could not due to data availability. Notably, few studies reported participant retention over time, peak demand or usage reductions more than a couple of years after switching to the time-based rate, or any impacts on technology adoption or durable good investments. In addition, most of the studies evaluate the impacts of rate design pilots as opposed to full-scale implementations. As a result, our results overwhelmingly reflect short-term responses from pilot studies.

4.2 Overall Response

Overall, we estimate that time-based rates lead to a 16 percent reduction in peak demand per participant, on average, although this result is highly uncertain. The left chart in Figure A2 displays the weighted average estimates and 95 percent confidence intervals across all medium- and high-quality studies and for high-quality studies only. The 95 percent confidence intervals show that we cannot reject reductions as high as 40 percent. At the other extreme, we also cannot reject that the rates have no effect at all. Restricting to high-quality studies reduces the estimate to 12 percent, but the large uncertainty persists.

Turning to the individual study estimates, we find that the peak demand response is highly heterogeneous across studies. The right chart in Figure A2 presents each individual peak demand response estimate. We display estimates in chronological order by publication date and combine treatment-arm-specific estimates from the same paper on the the same x-axis value. The size of each point reflects the weight assigned to that estimate for the aggregation, and the color reflects whether we classified the analysis methods as medium or high quality. Even isolating the high-quality studies, estimates range from *increases* in peak demand to peak demand reductions of over 50 percent. Looking across time, this heterogeneity has not diminished and appears to have increased. We also observe substantial variation across treatment arms within and across papers. These findings suggest that the heterogeneity may be coming from true differences across rate designs or other pilot characteristics as opposed to differences in methods across studies.

We perform a similar weighted averaging exercise for estimates of usage reductions by TOU period. The daily usage reduction estimates are smaller, in percentage terms, than the peak demand response, although this difference is not significant. We estimate on-peak usage reductions of about 3 percent in the summer and 1 percent in the winter. We estimate a 1 percent increase in off-peak usage, and the vast majority of individual study estimates also indicate an off-peak usage increase, suggesting that some of the on-peak usage reductions may come from shifting usage to off-peak hours. However, all of these estimates have large uncertainty, and we cannot rule out no response with 95 percent confidence in any of these periods. See Figures A3, A4, and A5 for individual study estimates.

We also analyze price elasticity estimates, which reflect the relationship between the responses and the size of the price change. Unfortunately, only nine papers report own-price elasticity estimates; we estimate a weighted average own-price elasticity of -0.075, which also has large uncertainty. We cannot reject a value twice as large or perfect inelasticity. See Figure A6 for individual study estimates.

The following sections explore some key drivers of the peak demand and on-peak usage response heterogeneity: across rate design elements, accompanying interventions, recruitment strategies, and customer demographics.

4.3 Sources of Response Heterogeneity

4.3.1 Rate Design Elements

Price Premiums

As discussed in Section 2, one key driver of time-based rate response heterogeneity frequently discussed in the literature is the differential between the highest- and lowest-priced periods. Figure A7 shows a scatterplot and best-fit line of the relationship between individual treatment arm estimates of the TOU on-peak usage reductions and the difference between the on- and off-peak TOU prices in the utility's peak season. Consistent with much of the literature, we find larger responses with a larger price difference. On average, we estimate that a $0.10/kWh higher on-peak price premium increases expected on-peak response by 1.3 percentage points. For comparison, recall that the overall on-peak usage response is only about 2–3 percent. These results are robust to controlling for the length of the on-peak period (see Figure A8).

In contrast, we find no trend in the relationship between peak demand reductions and the event price premium over nonevent hours. As shown in Figure A10, the slope of the best-fit line is negative and not significantly different from zero. This result departs from some findings in the synthesis literature and is consistent with others.

Notably, all the event price premiums in this meta-analysis were over $0.30/kWh, and most of the on-to-off-peak price premiums were smaller than $0.30/kWh. It is, therefore, difficult to isolate the effect of the event nature from the price premium magnitude. If we restrict the TOU analysis to rates with price premiums over $0.30/kWh, we find a small and insignificant positive slope.

We find similar results when we analyze price *ratios*. Many utility rates have rate riders, which are supplemental charges on top of the base rate that often vary within a year. Some studies exclude these rate riders when describing the time-based rates. Price ratios are more sensitive than price premiums to including or excluding rate riders in the study results. However, most—if not all—studies in the literature with similar analyses focus on price ratios. See Figures A9 and A12 for responses by price ratio.

These findings contribute to the mixed literature on households' sensitivity to price ratios across periods. The TOU ratio results are consistent with Faruqui and Palmer (2012) and Faruqui and Sergici (2013) and contrary to the results of Newsham and Bowker (2010). In contrast, the low price sensitivity to critical peak ratios is consistent with the results of Newsham and Bowker (2010) and Gillan (2017) and contrary to the finding of Faruqui and Sergici (2013).

Many TOU rates have three tiers, with on-, off-, and mid-peak periods. In contrast to the on-to-off-peak price ratio results, we find that on-peak usage reductions *decrease* with the on-to-mid peak price ratio controlling for the on-to-off-peak price ratio (see Figure A11). This result may suggest that consumers primarily respond to three-tiered TOU rates by shifting usage from the on- and mid-peak periods to the off-peak period as opposed to shifting usage from the on-peak to the mid-peak periods. However, more research is needed to better understand consumer behavior in response to three-tier TOU rate designs.

On-Peak Period Timing

Although we do not find analyses of TOU period definitions in the literature, the on-peak period *timing* may also influence consumer response. Table A1 shows the incremental on-peak usage reduction when the on-peak period occurs in the afternoon only or in the afternoon *and* evening relative to in the evening only. We classify periods that end by 4 PM as "Afternoon Only" and those that begin no earlier than 6 PM as "Evening Only." We estimate more than a 6 percentage point improvement in the response if the on-peak period occurs in the afternoon versus the evening. Notably, this estimate is double the overall estimate of the weighted average on-peak usage response. Although our preferred specification excludes paper fixed effects due to sample size concerns, a robustness check with these fixed effects supports this finding. These within-study estimates are much noisier, but we still observe smaller on-peak usage reductions with evening-only on-peak periods.

Rate Type

We also compare peak demand impacts across types of time-based rates. Table A2 presents estimates of average peak demand reductions by rate type relative to CPP-only rates along with 95 percent confidence intervals. A negative result suggests that a rate type is less effective at reducing demand than a CPP rate, on average, at least among the analyzed studies. As discussed, differences across rate designs may arise due to rate features that often coincide with the rate design, such as price differentials.

We find that CPP rates are significantly more effective at reducing peak demand when they are not combined with a TOU or VPP component. We estimate that CPP rates reduce peak demand by 8 percentage points more than VPP or combined TOU and CPP rates, although this point estimate is smaller and insignificant when studies are weighted equally. This difference may be related to the complexity of the rate signal, as VPP and TOU+CPP rates typically have many more unique prices and more price changes over the course of a day or year than CPP-only rates.

For the other rate types, the 95 percent confidence intervals are relatively large, but the relationships are directionally consistent with the literature. Point estimates suggest that CPP rates are also more effective at reducing peak demand than the other rate designs. However, these estimates are noisy, and we cannot reject that TOU, PTR and TOU+PTR rates have impacts as large as CPP rates. We are especially cautious in making conclusions about RTP and PTR rates, given the small sample sizes for these rate types. As shown in Table 4.1, the PTR and RTP estimates are based on only four treatment arms across two papers and only two treatment arms across two papers, respectively. However, the point estimate for the PTR rates is consistent with the loss aversion and time-based rates literature, suggesting that penalties for usage during events induce a greater response than payments for additional usage reductions. The negative and significant estimate for RTP rates is consistent with the VPP and TOU+CPP results in showing a negative relationship between rate complexity and participants' peak demand response.

4.3.2 Accompanying Interventions

Control Technologies

Consistent with the literature, we find that offering a control technology, such as a smart thermostat, along with the rate design is associated with large, significant improvements in response. Tables A3 and A4 show the resulting additional on-peak usage and peak demand reductions, respectively. We estimate a 5 percentage point increase in the on-peak usage reduction and a 22 percentage point increase in the peak demand response. For both outcomes, the magnitudes of the impacts are larger than the average overall estimated response discussed in Section 4.2.

A small number of pilot studies targets customers who already have control technologies and do not directly provide these technologies. The additional on-peak reductions of such studies are of a similar magnitude to the effect of offering control technologies along with TOU rates. This may suggest that the impact of offering control technologies comes from the technologies enabling a response to the TOU rates as opposed to a direct response of adopting the technologies. In contrast, we find a significantly smaller effect on peak demand reductions among studies that target customers with control technologies relative to studies that offer the technologies along with the rate. Although we are hesitant to draw any conclusions about the impact of targeting marketing to control technology owners, given the small number of studies in this analysis that did so, these results suggest that exploring differences in efficacy when customers are offered control technologies along with the rate design change versus when customers already own them may be useful for understanding the impacts of full-scale time-based rate implementation.

Information Provision

Consistent with the literature, we also find that providing usage information or feedback can substantially improve on-peak response. We estimate that providing real-time usage information increases on-peak reductions by about 6 percentage points. Similarly, providing less frequent usage information that is still more detailed than the information on a customer's typical monthly bill increases on-peak reductions by about 5 percentage points.

However, we do not find a similar effect on peak demand. Although the 95 percent confidence intervals are large, we do not observe significantly larger peak demand reductions among participants who received real-time or other usage information not typically available to customers. The point estimates in our preferred specification suggest a smaller reduction, if anything. We cannot draw many conclusions from these results, given the large uncertainty, but the discrepancy in the on-peak and peak demand results suggests a direction for future research. In particular, it may be valuable to explore whether the primary impact of granular usage information is a short-term effect on investments or habits as opposed to ongoing monitoring and adjustment.

4.3.3 Recruitment Strategy

Opt-Out

We also see important variation in recruitment strategy. We find that the choice of an opt-out or opt-in recruitment design has ramifications for enrollment and response. Table A7 shows that opt-out designs increase enrollment by about 80 percentage points. This result is consistent with consumers being inattentive to their rate options or having imperfect information about their usage.[3]

However, the average response per participant is also significantly lower with opt-out designs. As shown in Tables A8 and A9, opt-out designs decrease the average participant on-peak and peak demand responses by about 4 and 9 percentage points, respectively. This result is also consistent with an inattention mechanism. Participants who are inattentive to their rate options may also be less attentive to their rate designs than participants who always choose the same rate design regardless of which is their default option.

In aggregate, we find evidence that opt-out designs increase system-wide peak demand reductions, but the net effect on on-peak usage is ambiguous. We estimate that aggregate peak demand reductions across all customers are about 3 ($t = 2.3$) percentage points larger, suggesting that some participants who choose the time-based rate because it is the default still respond to the rate design by reducing demand during peak events. However, we cannot reject that these complier participants have no daily response to TOU rates.

Bill Protection

Similarly, another common strategy to encourage higher enrollment under either an opt-in or opt-out enrollment design is to offer bill protection. Most commonly, utilities do so by charging each participant the lower of their bill under the time-based rate design and their hypothetical bill under their previous rate design. This approach guarantees that participants do not see a bill increase from the time-based rate.

Bill protection may also have unintended consequences on consumers' incentives to modify their consumption behavior. Under perfect information, a consumer whose bill would increase under time-based rates without bill protection would have no marginal incentive to reduce their on-peak usage or peak demand, and the incentives of a consumer whose bill would decrease without bill protection would be unaffected. However, in practice, consumers may have poor information about their usage, the bill protection policy, and how much they would have to change their consumption to observe a bill reduction.

On average, across all studies, we estimate that offering bill protection increases participant enrollment in time-based rates by 23 percentage points. However, this estimate is highly uncertain, and we cannot reject that bill protec-

[3] Alternative explanations also exist. For example, customers may find contacting their electric utility to be prohibitively costly.

tion has no effect on enrollment. Notably, this enrollment impact is significantly lower than for switching from an opt-in to an opt-out recruitment strategy.

Offering bill protection does, however, significantly reduce the average response of participating customers. On average, we estimate a 2.5 percentage point decrease in on-peak usage reductions per participant, which is about half of the estimated average on-peak usage effect of time-based rates overall. We also estimate that bill protection leads to an 11 percentage point decrease in average peak demand reductions per participant, which is about two thirds of the overall average peak demand estimate.

Combining these enrollment and response impacts, point estimates suggest that bill protection may erode aggregate savings, although some of these estimates are uncertain. Considering only opt-in enrollment designs, we estimate that bill protection has no significant impact on aggregate on-peak usage reductions and diminishes peak demand reductions by 1.5 percentage points ($t = -2.6$). Point estimates suggest that bill protection diminishes aggregate reductions more for opt-out enrollment designs, although this difference is only significant for on-peak usage reductions.

4.3.4 Customer Demographics

Low-Income Customers

We weigh in on the discussion in the literature of whether low-income customers respond differently to time-based rates than other customers. As discussed, the literature is mixed on this point. Some researchers show that low-income participants respond comparably to other participants, but other researchers show that they exhibit an especially small response. Some papers in this meta-analysis reported average responses specifically for low-income participants or low-income subsidy recipients. We explore low-income customer response by comparing these estimates to estimates for the larger participant population.

We find that low-income households exhibit significantly smaller peak demand reductions than other households. We estimate a difference of 12 percentage points. Although our preferred specification excludes paper fixed effects due to sample size concerns, a robustness check with these fixed effects supports the directional finding. Isolating differences within studies, we estimate a 5 percentage point smaller response ($t = 1.64$).

We also find that low-income households exhibit significantly smaller on-peak usage reductions, although the estimates are restricted to the winter season and not as large as the peak demand results. We estimate a 1 percentage point smaller on-peak usage response over the year. When we restrict the analysis to the summer season, the on-peak reductions for low-income participants and the general participant population are similar in magnitude and not significantly different.

As an initial exploration of potential mechanisms for these results, we consider the interaction between income group and control technology provision. Our results suggest that low-income households may benefit more from control technologies, although these results are not statistically significant. We do not find that low-income customers have a significantly different peak demand response than the general participant population when receiving control technologies. If anything, point estimates suggest that they may have an especially large response.[4]

Although these results suggest that variation in providing control technologies may help explain the lack of consensus in the literature, more research is needed to understand the low-income customer experience with time-based rates. These results suggest a few specific directions for further research. One key direction is exploring current discrepancies in control technology ownership and strategies for reducing the barriers to low-income households' adoption. Another is the role of heating and cooling. Differences in baseline heating and cooling may explain the seasonality of the on-peak usage results and the large difference in the magnitudes of the on-peak usage reduction and peak demand results.

Solar Customers

We also explore whether customers who generate their own electricity from solar photovoltaic (PV) systems and are compensated for some or all of this generation at their retail rate have a notable response to time-based rates. Most US customers with solar PV have compensation tied to their retail rate, through a mechanism broadly referred to as "net energy metering" (NEM). Although no studies in this meta-analysis reported results separately for customers with solar PV or NEM, some pilots excluded customers with NEM from participating. We compare responses across studies that allowed participants with NEM and those that did not, as shown in Tables A19 and A20. We include studies that explicitly say that they excluded NEM customers and studies that state they excluded customers in solar programs or solar customers. All of these utilities have some form of NEM (NC Clean Energy Technology Center 2024).

We find evidence that NEM customers exhibit a smaller on-peak usage re-

[4]Sample sizes were too small to conduct this analysis for on-peak usage reductions.

duction than the average participant, but we do not see a significant difference in peak demand response. We estimate that studies that excluded NEM customers exhibited a 4 percentage point larger reduction in on-peak usage than studies that did not. Restricting to the summer season, this estimate increases to 8 percentage points. Although we do not know the share of NEM customers in the studies that are open to them, we consider these estimates a lower bound on the NEM customer-specific impacts.

These results are consistent with incomplete net metering, such as "net billing." In these cases, the marginal compensation for solar generation may be lower than the retail rate when generation exceeds the customer's usage over some period (e.g., 15 minutes, all on-peak hours in one month). Customers with solar PV may have a lower incentive to reduce their usage during periods with a positive probability that their solar generation will exceed their usage.

An important caveat is the possibility of selection into excluding NEM customers from a pilot. For instance, utilities with a lot of NEM customers may be more likely to exclude them, and a utility's share of NEM customers may be correlated with income or air conditioning use.[5] Although it is encouraging that the results are directionally intuitive, more research is needed to understand the relationship between solar ownership and response to time-based rates.

5 Conclusion

This meta-analysis shows that time-based rates have highly heterogeneous impacts on electricity consumption. Plausible estimates of peak demand effects include reductions of up to 40 percent and no effect at all. Similarly, for rates with TOU components, we cannot reject summer on-peak usage effects of 12 percent or 0. Plausible estimates for the corresponding effect on off-peak usage range from reductions of 7 percent to increases of 4 percent.[6]

We investigate some key sources of this response heterogeneity, including variation in the rate design, accompanying interventions, recruitment strategy, and customer demographics. We build on the literature by focusing our analysis on studies with plausibly causal estimates of the impacts of time-based rates and carefully considering the precision of the estimates. We also analyze dimensions of heterogeneity not studied in the literature.

We find that rate design and the relative rate levels have implications for

[5]In our data set, the correlations between excluding NEM customers and the on-peak TOU period occurring in the afternoon only and in the evening only are -0.06 and 0.12, respectively.

[6]We use a significance level of $\alpha = 0.05$ for these determinations.

a time-based rate's efficacy in promoting peak demand and on-peak usage reductions. Specifically, we show that the on-peak usage response increases with the on-to-off-peak TOU price premium. In contrast, we find no evidence that the peak demand response increases with the event price premium. On-peak usage reductions for TOU rates are also larger when the on-peak period is in the afternoon. We also find important variation in peak demand reductions across rate types, and these patterns are consistent with customers exhibiting a relatively smaller response when their rate structure is more complex.

Consistent with the literature, we observe that providing control technologies and usage information improves response. However, we do not find evidence that usage information affects the peak demand response despite a significant impact on on-peak usage. This discrepancy may suggest that habit formation or technology investment drives the on-peak information effect.

In addition, we find that opt-out recruitment designs and offering bill protection increase enrollment yet reduce the average on-peak usage and peak demand response per participating customer. On net, we estimate that opt-out designs increase aggregate peak demand reductions. Our results suggest that bill protection may erode aggregate peak demand reductions, although utilities often only implement bill protection as a transitional measure.

We also find some important differences in response across customer demographics. We estimate that low-income households have a smaller peak demand and on-peak usage response than other households, on average. We also deduce that customers with net metered solar PV systems exhibit a smaller on-peak TOU response than other participants, on average. We do not find a significant difference in the peak demand reductions of these solar customers.

Our results suggest some key remaining gaps in the literature that research could address. First is the limited information on the long-run effects of permanent, full-scale, time-based rate offerings. Our results predominantly reflect short-run effects of pilot rates. We found only three studies on full-scale rate implementations that met our criteria, and only two of these and one pilot study reported outcomes beyond a few years after the rate introduction. Relatedly, data on participant retention outcomes proved scarce. We also did not find any ex-post analyses of the impact of time-based rates on technology adoption or use, which may be one indicator of long-lasting effects.

Second, our results offer some insights into where the reductions are coming from, but they are far from conclusive. Too few of the studies explored mechanisms for us to systematically analyze their results. Research focusing on the behavior that leads to these reductions may be valuable. For example, to what extent are the reductions foregone usage versus shifting of usage from higher- to lower-priced hours? Are the reductions due to changes in behavior or in technology adoption and use? Answering these questions could improve understanding of how burdensome this adjustment is for participants and whether these responses are likely to persist.

Finally, related questions remain about why some of the key dimensions of response heterogeneity outlined in this paper exist and the implications for rate design and policy. Uncovering these underlying drivers may improve predictions of how the response to time-based rates will change with widespread adoption of emerging technologies and a decarbonizing power sector. Further analysis on the systematic differences in experiences with time-based rates across customers may also help utilities more effectively and efficiently target marketing of time-based rates and tailor rate designs to their customer populations.

References

Allcott, H. 2009. *Real Time Pricing and Electricity Markets*. Working Paper.

Baatz, B. 2017. *Rate Design Matters: The Intersection of Residential Rate Design and Energy Efficiency*. Technical report. American Council for an Energy-Efficient Economy.

Bell, E., G. Jiang, A.-E. Smith, and A. Hauser. 2024. *Residential Time-of-Use Pricing Pilot Third Annual Evaluation Report*. Technical report. Resource Innovations in partnership with Apex Analytics.

Bell, E., A. Savage, and D. Lesperance. 2021. 2020 *Load Impact Evaluation of Southern California Edison's Default Time-of-Use Pilot*. Technical report. Nexant.

Bleything, S., S. Blumsack, P. Hines, and L. Morris. 2015. *Vermont Electric Cooperative Consumer Behavior Study Year 2 Final Report: The Effect of Variable Peak Pricing on Electricity Demand*. Technical report. Vermont Energy Investment Corporation.

Blumsack, S., and P. Hines. 2015. Load Impact Analysis of Green Mountain Power Critical Peak Events, 2012 and 2013. Technical report.

Bollinger, B.K., and W.R. Hartmann. 2020. Information vs. Automation and Implications for Dynamic Pricing. *Management Science* 66(1): 290–314.

Braithwait, S.D., D.G. Hansen, and D.A. Armstrong. 2012. *2011 Impact Evaluation of San Diego Gas & Electric's Peak-Time Rebate Pilot Program Ex-Post and Ex-Ante Report*. Technical report. Christensen Associates Energy Consulting.

Braithwait, S. D., D.G. Hansen, and D.A. Armstrong. 2016. 2015 *Load Impact Evaluation of Pacific Gas and Electric Company's Residential Time-Based Pricing Programs: Ex-Post and Ex-Ante Report*. Technical report. Christensen Associates Energy Consulting.

Braithwait, S. D., D.G. Hansen, and M.T. Clark. 2017. 2016 *Load Impact Evaluation of San Diego Gas and Electric's Voluntary Residential Critical Peak Pricing (CPP) and Time-of- Use (TOU) Rates*. Technical report. Christensen Associates Energy Consulting.

Charles River Associates. 2005. Impact Evaluation of the California Statewide Pricing Pilot. Technical report.

Davis, A. L., T. Krishnamurti, B. Fischhoff, and W. Bruine de Bruin. 2013. Setting a standard for electricity pilot studies. *Energy Policy* 62: 401–9.

DNV. 2023. Schedule 1G, Residential Service (Experimental) Rate 2023 Annual Program Evaluation. Technical report.

Dominion Energy Services, Inc. 2017. *Dominion Energy Virginia's Final Annual Report to the State Corporation Commission of Virginia on Its Dynamic Pricing Pilot*. Technical report.

DTE Energy. 2014. *SmartCurrents Dynamic Peak Pricing Pilot Final Evaluation Report*. Technical report. Technical report.

Dutta, G., and K. Mitra. 2017. A Literature Review on Dynamic Pricing of Electricity. *Journal of the Operational Research Society* 68(10): 1131–45.

eMeter Strategic Consulting. 2010. *PowerCentsDC Program Final Report*. Technical report.

Enright, T., and A. Faruqui. 2015. *A Bibliography of Dynamic Pricing and Time-of-Use Rates Version 6.0*. Technical report. Brattle Group.

Faruqui, A., and S.S. George. 2002. The Value of Dynamic Pricing in Mass Markets. *Electricity Journal* 15(6): 45–55.

Faruqui, A., R. Hledik, and J. Palmer. 2012. *Time-Varying and Dynamic Rate Design*. Technical report. Brattle Group and the Regulatory Assistance Project.

Faruqui, A., and J. Palmer. 2012. The Discovery of Price Responsiveness—A Survey of Experiments Involving Dynamic Pricing of Electricity. SSRN 2020587.

Faruqui, A., and S. Sergici. 2008. *The Power of Experimentation: New Evidence on Residential Demand Response*. Brattle Group Discussion Paper.

Faruqui, A., and S. Sergici. 2010. Household Response to Dynamic Pricing of Electricity: A Survey of 15 Experiments. *Journal of Regulatory Economics* 38: 193–225.

Faruqui, A., and S. Sergici. 2013. Arcturus: International Evidence on Dynamic Pricing. *Electricity Journal* 26(7): 55–65.

Faruqui, A., S. Sergici, and L. Akaba. 2013. Dynamic Pricing of Electricity for Residential Customers: The Evidence from Michigan. *Energy Efficiency* 6: 571–84.

Faruqui, A., and Z. Tang. 2023. Time-Varying Rates Are Moving from the Periphery to the Mainstream of Electricity Pricing for Residential Customers in the United States. Forthcoming chapter, *Handbook on Electricity Regulation*.

Faruqui, A., and L. Wood. 2008. Quantifying the Benefits of Dynamic Pricing In the Mass Market. Technical report. Brattle Group, Prepared for the Edison Electric Institute.

Fowlie, M., C. Wolfram, P. Baylis, A.C. Spurlock, A. Todd-Blick, and P. Cappers. 2021. Default Effects and Follow-On Behaviour: Evidence From An Electricity Pricing Program. *Review of Economic Studies* 88(6): 2886–934.

GDS Associates, Inc. 2013. *Marblehead Municipal Light Department Energy-Sense CPP Pilot Final Evaluation Report*. Technical report.

George, S., E. Bell, A. Savage, and B. Messer. 2018. *California Statewide Opt-In Time-of-Use Pricing Pilot Final Report*. Technical report. Nexant.

George, S., M. Sullivan, L. Schellenberg, and A. Lemarchand. 2015. *Dynamic Pricing PECO Smart Time Pricing Pilot Final Report*. Technical report. Nexant.

Gillan, J.M. 2017. *Dynamic Pricing, Attention, and Automation: Evidence from a Field Experiment in Electricity Consumption*. Working Paper.

Guidehouse. 2021. Evergy Missouri Residential Time-of-Use Rate Evaluation Final Impacts for Missouri Metro and West Jurisdictions. Technical report.

Gyamfi, S., S. Krumdieck, and T. Urmee. 2013. Residential Peak Electricity Demand Response—Highlights of Some Behavioural Issues. *Renewable and Sustainable Energy Reviews* 25: 71–7.

Hansen, D.G., and D.A. Armstrong. 2020. *Load Impact Evaluation of Pacific Gas and Electric Company's Residential Default Time-of-Use Pricing Pilot*. Technical report. Christensen Associates Energy Consulting.

Harding, M., and C. Lamarche. 2016. Empowering Consumers Through Data and Smart Technology: Experimental Evidence on the Consequences of Time-of-Use Electricity Pricing Policies. Jo*urnal of Policy Analysis and Management* 35(4): 906–31.

Harding, M., and S. Sexton. 2017. Household Response to Time-Varying Electricity Prices. *Annual Review of Resource Economics* 9(June): 337–59.

Jiang, G., A. Hauser, R. Peterson, E. Bell, and A. Savage. 2023. *Innovative Pricing Pilot Evaluation Wave 1, Wave 2, & Wave 3 Final Report*. Technical report. Resource Innovations in partnership with Apex Analytics.

Joskow, P.L. 2012. Creating a Smarter US Electricity Grid. *Journal of Economic Perspectives* 26(1): 29–48.

Kirkeide, L. 2012. Effects of Three-Hour On-Peak Time-of-Use Plan on Residential Demand during Hot Phoenix Summers. *Electricity Journal* 25(4): 48–62.

Lakeland Electric. 2015. *Lakeland Electric Consumer Behavior Study Final Evaluation Report*. Technical report.

Leidos. 2014. *Final Report NHEC Dynamic Pricing Pilot*. Technical report.

Marrin, K., K. Chiccarelli, A. Duer, A. Nguyen, and T. Williams. 2017. *2016 Evaluation of OG&E's SmartHours Program in Oklahoma*. Technical report. Applied Energy Group.

Navigant. 2019. *Residential Energy Time-of-Use (RE-TOU) Trial Evaluation Report 2: Findings from October 2018 to July 2019*. Technical report.

NC Clean Energy Technology Center. 2024. Database of State Incentives for Renewables & Efficiency.

Nelson, J.P., and P.E. Kennedy. 2009. The Use (and Abuse) of Meta-Analysis in Environmental and Natural Resource Economics: An Assessment. *Environmental and Resource Economics* 42(3): 345–77.

Newsham, G.R., and B.G. Bowker. 2010. The Effect of Utility Time-Varying Pricing and Load Control Strategies on Residential Summer Peak Electricity Use: A Review. *Energy Policy* 38(7): 3289–96.

Nguyen, A., C. Williamson, K. Parmenter, K. Marrin, and T. Williams. 2013. *SmartGridCity Pricing Pilot Program Impact Evaluation Results, 2011–2013*. Technical report. EnerNOC, Inc.

Nicolson, M.L., M.J. Fell, and G.M. Huebner. 2018. Consumer Demand for Time of Use Electricity Tariffs: A Systematized Review of the Empirical Evidence. *Renewable and Sustainable Energy Reviews* 97(2018): 276–89.

NV Energy. 2015. *Nevada Dynamic Pricing Trial Final Report: An Evaluation of NV Energy's Choose When You Use Program*. Technical report.

Potter, J.M., S.S. George, and L.R. Jimenez. 2014. *SmartPricing Options Final Evaluation: The Final Report on Pilot Design, Implementation, and Evaluation of the Sacramento Municipal Utility District's Consumer Behavior Study*. Technical report. Sacramento Municipal Utility District.

Reeves, S., J. Stewart, M. Izawa, and Z. Horvath. 2018. *Flex Pricing and Behavioral Demand Response Pilot Program Evaluation Report*. Technical report. CADMUS.

Seiden, K., C. Olig, D. Max, and M. Sherman. 2017. *National Grid Smart Energy Solutions Pilot Final Evaluation Report*. Technical report. Navigant.

Sergici, S., A. Faruqui, N. Powers, S. Shetty, and Z. Tang. 2021. *PC44 Time of Use Pilots: End-of-Pilot Evaluation*. Technical report. Brattle Group.

Sergici, S., A. Faruqui, and S. Tang. 2023. *Do Customers Respond to Time-Varying Rates: A Preview of Arcturus 3.0*. Brattle Group.

Siddiqui, O. 2021. *Benchmarking Study of U.S. Regulated Utility Real Time Pricing Programs, Architecture and Design*. Electric Power Research Institute Technical Update 3002021204.

Star, A., M. Isaacson, D. Haeg, L. Kotewa, and CNT Energy. 2010. *The Dynamic Pricing Mousetrap: Why Isn't the World Beating Down Our Door*? 2010 ACEEE Summer Study on Energy Efficiency in Buildings.

Stromback, J., C. Dromacque, and M.H. Yassin. 2011. *The Potential of Smart Meter Enabled Programs to Increase Energy and Systems Efficiency: A Mass Pilot Comparison*. VassaETT, prepared for European Smart Metering Industry Group.

Todd, A., P. Cappers, A. Spurlock, and L. Jin. 2019. Spillover as a Cause of Bias in Baseline Evaluation Methods for Demand Response Programs. *Applied Energy* 250: 344–57.

US Department of Energy. 2016. *Final Report on Customer Acceptance, Retention, and Response to Time-Based Rates from the Consumer Behavior Studies*. Smart Grid Investment Grant Program November 2016.

Violette, D., J. Erickson, and M. Klos. 2007. *Final Report for the MyPower Pricing Segments Evaluation*. Technical report. Summit Blue Consulting, LLC.

Wakefield, M., G. Horst, B. Neenan, S. Braithwait, D. Hansen, M. Hilbrink, and L. Kirsch. 2011. The *Effect on Electricity Consumption of the Commonwealth Edison Customer Applications Program: Phase 2 Final Analysis Technical Update*. Technical report. Electric Power Research Institute.

Wang, W., T. Ida, and H. Shimada. 2020. *Default Effect Versus Active Decision: Evidence from a Field Experiment in Los Alamos*. *European Economic Review* 128: 103498.

Williamson, C., and J. Shishido. 2012. *OG&E Smart Study Together Impact Results Auxiliary Final Report—Summer 2011*. Technical report. Global Energy Partners, An EnerNOC Company.

Appendices

A Figures

Figure A1: Utility Service Areas Represented in the Meta-Analysis

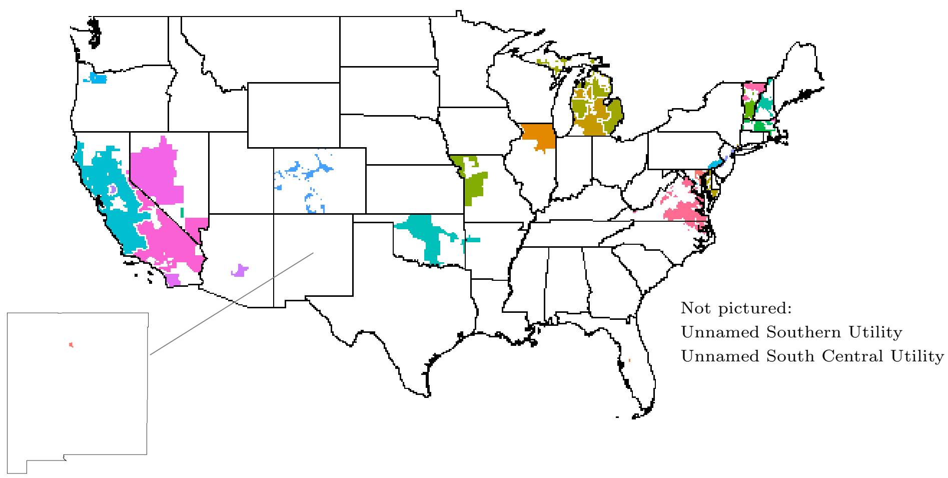
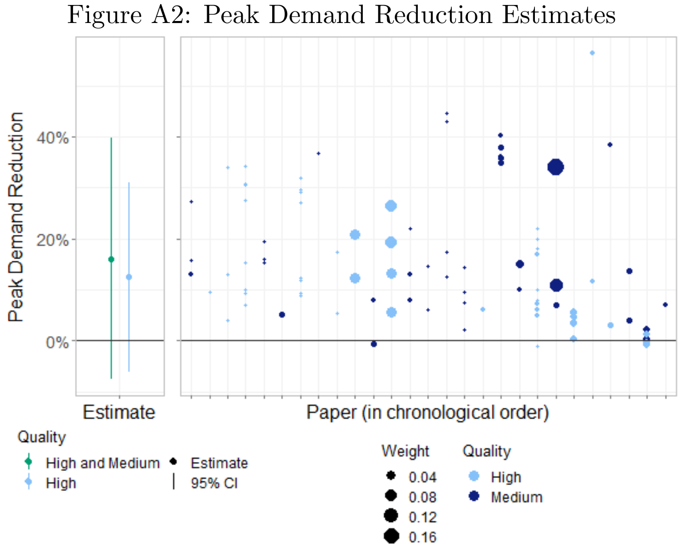
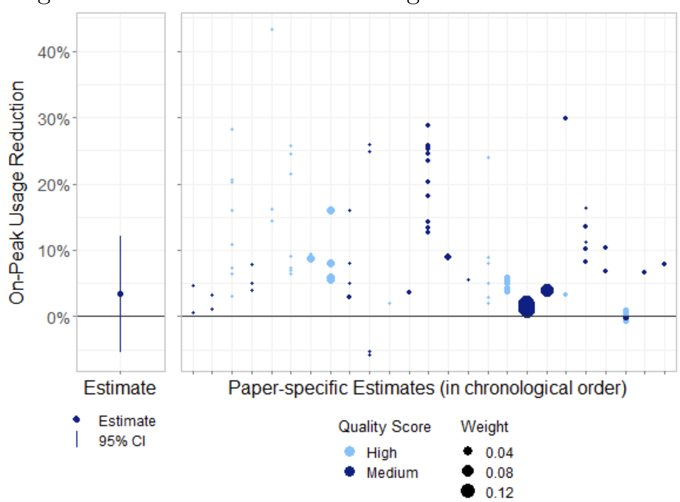


Figure A2: Peak Demand Reduction Estimates



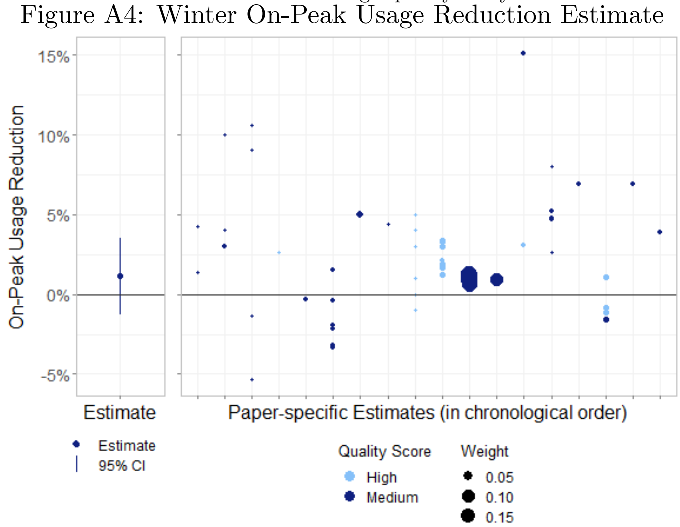
The left chart plots estimates and 95 percent confidence intervals of the mean reduction in peak demand reported in all included studies and the subset of high-quality studies, weighted by treatment arm sample size. The right chart shows individual treatment arm estimates of peak demand reduction in chronological order by study analysis start year. The size of the points reflect treatment arm sample size, and the colors denote medium- and high-quality analysis classifications.

Figure A3: Summer On-Peak Usage Reduction Estimate



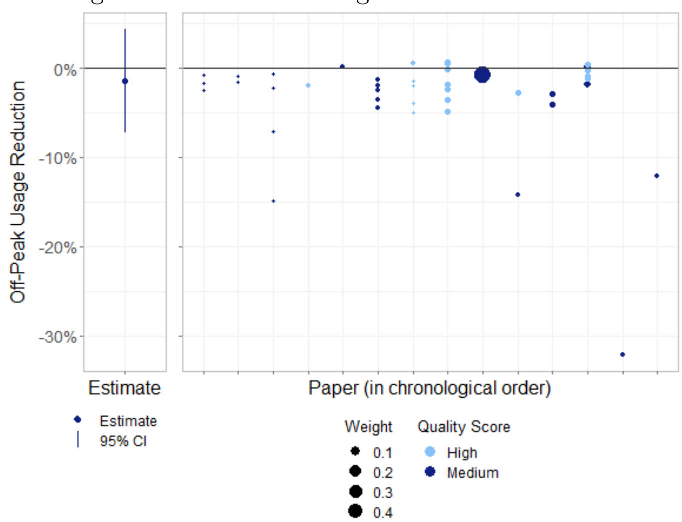
The left chart plots an estimate and 95 percent confidence interval of the mean reduction in on-peak summer usage reported in all included studies, weighted by treatment arm sample size. The right chart shows individual treatment arm estimates of on-peak summer usage reduction in chronological order by study analysis start year. The size of the points reflect treatment arm sample size, and the colors denote medium- and high-quality analysis classifications.

Figure A4: Winter On-Peak Usage Reduction Estimate



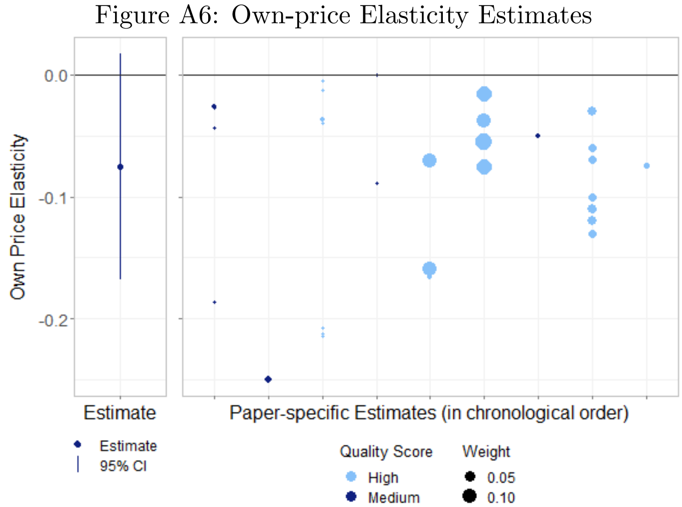
The left chart plots an estimate and 95 percent confidence interval of the mean reduction in on-peak winter usage reported in all included studies, weighted by treatment arm sample size. The right chart shows individual treatment arm estimates of on-peak winter usage reduction in chronological order by study analysis start year. The size of the points reflect treatment arm sample size, and the colors denote medium- and high-quality analysis classifications.

Figure A5: Off-Peak Usage Reduction Estimate



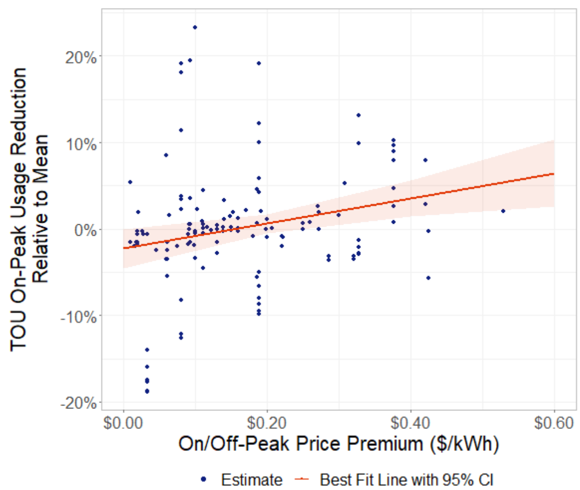
The left chart plots an estimate and 95 percent confidence interval of the mean reduction in off-peak usage across all included studies, weighted by treatment arm sample size. The right chart shows individual treatment arm estimates of off-peak usage reduction in chronological order by study analysis start year. The size of the points reflect treatment arm sample size, and the colors denote medium- and high-quality analysis classifications.

Figure A6: Own-price Elasticity Estimates



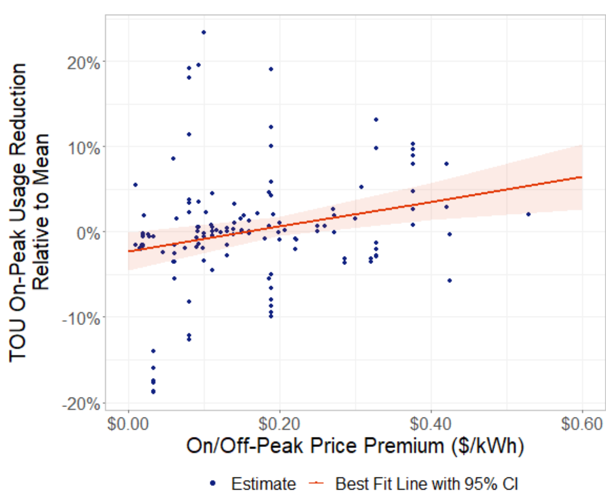
The left chart plots an estimate and 95 percent confidence interval of the mean own-price elasticity across all included studies, weighted by treatment arm sample size. The right chart shows individual treatment arm estimates of off-peak usage reduction in chronological order by study analysis start year. The size of the points reflect treatment arm sample size, and the colors denote medium- and high-quality analysis classifications.

Figure A7: TOU On-Peak Usage Reduction by On-to-Off-Peak Price Premium



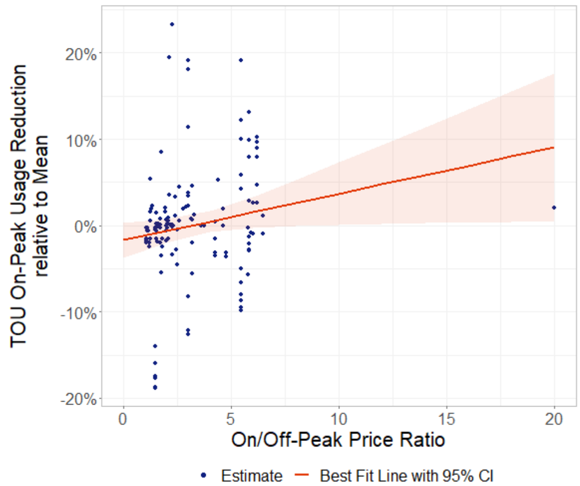
This figure plots residuals from a weighted least squares regression of on-peak usage reduction on paper fixed effects against the on-to-off-peak TOU price premium. The best linear fit line and 95 percent confidence interval under Huber-White robust standard errors are shown in reddish orange.

Figure A8: TOU On-Peak Usage Reduction by On-to-Off-Peak Premium with Length Control



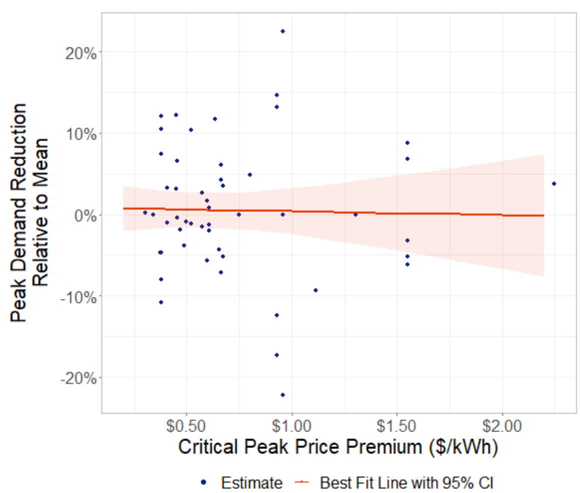
This figure plots residuals from a weighted least squares regression of on-peak usage reduction on paper fixed effects and on-peak period length against the on-to-off-peak TOU price premium. The best linear fit line and 95 percent confidence interval under Huber-White robust standard errors are shown in reddish orange.

Figure A9: TOU On-Peak Usage Reduction by On-to-Off-Peak Ratio



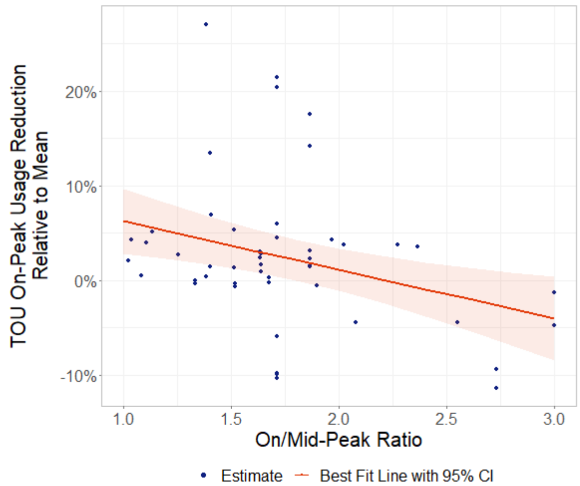
This figure plots residuals from a weighted least squares regression of on-peak usage reduction on paper fixed effects against the on-to-off-peak TOU price ratio. The best linear fit line and 95 percent confidence interval under Huber-White robust standard errors are shown in reddish orange.

Figure A10: Peak Demand Reduction by Critical Peak Price Premium



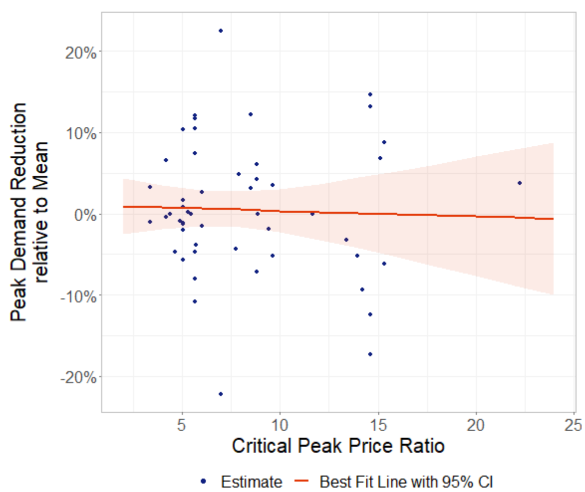
This figure plots residuals from a weighted least squares regression of peak demand reduction on paper fixed effects against the critical peak price premium. The best linear fit line and 95 percent confidence interval under Huber-White robust standard errors are shown in reddish orange.

Figure A11: TOU On-Peak Usage Reduction by On-to-Mid-Peak Ratio



This figure plots residuals from a weighted least squares regression of peak demand reduction on the on-to-off-peak TOU price premium against the mid-to-off-peak TOU price premium. The best linear fit line and 95 percent confidence interval under Huber-White robust standard errors are shown in reddish orange.

Figure A12: Peak Demand Reduction by Critical Peak Price Ratio



This figure plots residuals from a weighted least squares regression of peak demand reduction on paper fixed effects against the on-to-off-peak TOU price ratio. The best linear fit line and 95 percent confidence interval under Huber-White robust standard errors are shown in reddish orange.

B Regression Result Tables

Table A1: On-Peak Usage Reduction by On-Peak Period Timing

	On-Peak Usage Reduction		
	(1)	(2)	(3)
Afternoon Only	0.062***	0.047	0.047***
	(0.015)	(0.032)	(0.016)
Afternoon & Evening	0.035***	0.065**	0.050***
	(0.013)	(0.026)	(0.013)
Constant	x		x
Paper Fixed Effects		x	
Weighted by Sample Size	x	x	
Observations	145	145	145
Adjusted R^2	0.110	0.654	0.058

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A2: Peak Demand Reduction by Rate Type

	Peak Demand Reduction		
	(1)	(2)	(3)
TOU	−0.077	−0.140***	−0.150***
	(0.080)	(0.041)	(0.053)
PTR	−0.077*	−0.047	−0.073*
	(0.041)	(0.075)	(0.041)
RTP	−0.226***	−0.136***	−0.231***
	(0.062)	(0.038)	(0.063)
TOU+CPP/VPP	−0.078***	0.028	−0.028
	(0.008)	(0.066)	(0.040)
TOU+PTR	−0.057	−0.079**	−0.075
	(0.058)	(0.039)	(0.054)
Constant		x	
Paper Fixed Effects	x		x
Weighted by Sample Size	x	x	
Observations	96	96	96
Adjusted R^2	0.428	0.374	0.468

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A3: Peak Demand Reduction by Control Technology

	Peak Demand Reduction			
	(1)	(2)	(3)	(4)
Control Technology	0.218***	0.218***	0.196***	0.169***
	(0.015)	(0.015)	(0.033)	(0.028)
Targeted Control Technologies		0.005		
		(0.013)		
Constant			x	
Paper Fixed Effects	x	x		x
Weighted by Sample Size	x	x	x	
Observations	96	96	96	96
Adjusted R^2	0.754	0.751	0.451	0.653

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A4: On-Peak Usage Reduction by Control Technology

	On-Peak Usage Reduction				
	(1)	(2)	(3)	(4)	(5)
Control Technology	0.046***	0.035	0.021	0.072***	0.163***
	(0.016)	(0.022)	(0.015)	(0.024)	(0.027)
Targeted Control Technologies		0.036***			
		(0.009)			
Constant	x	x	x		x
Paper Fixed Effects				x	
Weighted by Sample Size	x	x		x	x
Season	Year-round	Year-round	Year-round	Summer	Summer
Observations	60	57	60	94	94
Adjusted R^2	0.021	0.166	0.007	0.766	0.165

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A5: Peak Demand Reduction by Additional Usage Information

	Peak Demand Reduction	
	(1)	(2)
Real-Time Usage Info via In-home Display	−0.007	0.031
	(0.058)	(0.027)
Other Real-Time Usage Info	−0.058	0.023
	(0.059)	(0.043)
Additional Usage Info	0.018	0.041
	(0.045)	(0.030)
Constant	x	x
Weighted by Sample Size	x	
Observations	96	96
Adjusted R^2	−0.025	−0.002

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A6: On-Peak Usage Reduction by Additional Usage Information

	On-Peak Usage Reduction			
	(1)	(2)	(3)	(4)
Real-Time Usage Info	0.056***	0.051***	0.018	0.068***
	(0.008)	(0.012)	(0.016)	(0.018)
Additional Usage Info	0.049***	0.042***	0.013	0.063***
	(0.008)	(0.012)	(0.012)	(0.013)
Constant	x		x	x
Control Technology Fixed Effects		x		
Rate Type Fixed Effects		x		
Weighted by Sample Size	x	x		x
Season	Year-round	Year-round	Year-round	Summer
Observations	60	60	60	94
Adjusted R^2	0.145	0.199	−0.008	0.262

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A7: Enrollment by Default Participation Status

	Enrollment (% of eligible)		
	(1)	(2)	(3)
Opt Out	0.800***	0.706***	0.787***
	(0.020)	(0.027)	(0.053)
Constant		x	
Paper Fixed Effects	x		x
Weighted by Sample Size	x	x	
Observations	102	102	102
Adjusted R^2	0.995	0.936	0.981

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A8: Peak Demand Reduction by Default Participation Status

	Peak Demand Reduction		
	(1)	(2)	(3)
Opt Out	−0.094***	−0.109**	−0.054***
	(0.028)	(0.043)	(0.018)
Constant		x	
Paper Fixed Effects	x		x
Weighted by Sample Size	x	x	
Observations	96	96	96
Adjusted R^2	0.509	0.153	0.444

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A9: On-Peak Usage Reduction by Default Participation Status

	On-Peak Usage Reduction		
	(1)	(2)	(3)
Opt Out	−0.039***	−0.051***	−0.077***
	(0.007)	(0.008)	(0.014)
Constant	x	x	x
Weighted by Sample Size	x		x
Season	Year-round	Year-round	Summer
Observations	60	60	94
Adjusted R^2	0.509	0.213	0.434

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A10: Aggregate Peak Demand Reduction by Default Participation Status

	Aggregate Peak Demand Reduction		
	(1)	(2)	(3)
Opt Out	0.031**	0.024*	0.031**
	(0.013)	(0.014)	(0.013)
Constant		x	
Paper Fixed Effects	x		x
Weighted by Sample Size	x	x	
Observations	66	66	66
Adjusted R^2	0.632	0.085	0.632

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A11: Aggregate On-Peak Usage Reduction by Default Participation Status

	On-Peak Usage Reduction		
	(1)	(2)	(3)
Opt Out	0.002	0.002	0.016**
	(0.003)	(0.003)	(0.007)
Constant	x	x	x
Weighted by Sample Size	x		x
Season	Year-round	Year-round	Summer
Observations	49	49	66
Adjusted R^2	0.023	0.023	0.140

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A12: Enrollment by Bill Protection

	Enrollment (% of eligible)	
	(1)	(2)
Any Bill Protection	0.232*	0.207***
	(0.140)	(0.067)
Constant	x	x
Weighted by Sample Size	x	
Observations	102	102
Adjusted R^2	0.101	0.063

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A13: Peak Demand Reduction by Bill Protection

	Peak Demand Reduction		
	(1)	(2)	(3)
Any Bill Protection	-0.108^{**}	-0.016	-0.114^{***}
	(0.045)	(0.026)	(0.030)
Constant	x	x	x
Weighted by Sample Size	x		x
Quality 1 Papers Only			x
Observations	96	96	55
Adjusted R^2	0.158	-0.007	0.308

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A14: On-Peak Usage Reduction by Bill Protection

	On-Peak Usage Reduction		
	(1)	(2)	(3)
Any Bill Protection	-0.025^{**}	-0.029^{***}	-0.051^{***}
	(0.011)	(0.011)	(0.016)
Constant	x	x	x
Weighted by Sample Size	x		x
Season	Year-round	Year-round	Summer
Observations	60	60	94
Adjusted R^2	0.258	0.102	0.245

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A15: Aggregate Peak Demand Reduction by Bill Protection

	Aggregate Peak Demand Reduction		
	(1)	(2)	(3)
Any Bill Protection	-0.015^{**}	-0.019^{**}	-0.015^{**}
	(0.006)	(0.008)	(0.006)
Opt Out	0.049^{*}		0.049^{*}
	(0.027)		(0.027)
Any Bill Protection x Opt Out	-0.033		-0.033
	(0.030)		(0.030)
Constant	x	x	x
Weighted by Sample Size	x	x	
Observations	66	66	66
Adjusted R^2	0.217	0.075	0.217

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A16: Aggregate On-Peak Usage Reduction by Bill Protection

	Aggregate On-Peak Usage Reduction			
	(1)	(2)	(3)	(4)
Any Bill Protection	−0.0002	−0.001	−0.0002	−0.003
	(0.001)	(0.001)	(0.001)	(0.003)
Opt Out	0.016***		0.016***	0.049***
	(0.001)		(0.001)	(0.010)
Any Bill Protection x Opt Out	−0.015***		−0.015***	−0.047***
	(0.003)		(0.003)	(0.010)
Constant	x	x	x	x
Weighted by Sample Size	x	x		x
Season	Year-round	Year-round	Year-round	Summer
Observations	49	49	49	66
Adjusted R^2	0.210	−0.011	0.210	0.527

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A17: Peak Demand Reduction by Income Group

	Peak Demand Reduction			
	(1)	(2)	(3)	(4)
Low Income	−0.116***	−0.075**	−0.054	−0.061*
	(0.040)	(0.030)	(0.033)	(0.034)
Control Technology		0.196***		
		(0.034)		
Low Income x Control Tech.		0.094		
		(0.107)		
Constant	x	x		x
Paper Fixed Effects			x	
Weighted by Sample Size	x	x	x	
Observations	115	115	115	115
Adjusted R^2	0.141	0.509	0.477	0.022

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A18: On-Peak Usage Reduction by Income Group

	On-Peak Usage Reduction			
	(1)	(2)	(3)	(4)
Low Income Only	−0.012***	0.017	−0.012	0.000
	(0.003)	(0.012)	(0.008)	(0.001)
Low Income Excluded		0.022***		
		(0.008)		
Constant		x		
Paper Fixed Effects	x		x	x
Weighted by Sample Size	x	x		x
Season	Year-round	Year-round	Year-round	Summer
Observations	82	80	82	46
Adjusted R^2	0.813	0.045	0.393	0.957

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A19: Peak Demand Reduction by Net Energy Metering (NEM) Customer Exclusion

	Peak Demand Reduction		
	(1)	(2)	(3)
NEM Customers Included	0.029	−0.063	−0.017
	(0.066)	(0.041)	(0.028)
Constant	x	x	x
Weighted by Sample Size	x	x	
Quality 1 Papers Only		x	
Observations	96	55	96
Adjusted R^2	0.003	0.037	−0.006

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

Table A20: On-Peak Usage Reduction by Net Energy Metering (NEM) Customer Exclusion

	On-Peak Usage Reduction			
	(1)	(2)	(3)	(4)
NEM Included	-0.043^{***}	-0.083^{***}	-0.069^{***}	-0.022^{**}
	(0.005)	(0.014)	(0.021)	(0.011)
On-Peak Includes Afternoon			0.042	
			(0.028)	
NEM Included x On-Peak I. Afternoon			0.036	
			(0.035)	
Constant	x	x	x	x
Weighted by Sample Size	x	x	x	
Season	Year-round	Summer	Summer	Year-round
Observations	60	77	77	60
Adjusted R^2	0.455	0.495	0.560	0.052

*p<0.1, **p<0.05, ***p<0.01. Huber-White heteroskedasticity-robust standard errors in parentheses.

C List of Included Papers

Table A21: Papers Included in Meta-Analysis

Citation	Utilities
Charles River Associates (2005)	Pacific Gas and Electric, Southern California Edison, San Diego Gas and Electric
Violette et al. (2007)	Public Service Electric and Gas
Allcott (2009)	Commonwealth Edison
eMeter Strategic Consulting (2010)	Potomac Electric Power Company
Wakefield et al. (2011)	Commonwealth Edison
Williamson and Shishido (2012)	Oklahoma Gas & Electric
Kirkeide (2012)	Salt River Project
Braithwait et al. (2012)	San Diego Gas and Electric
Faruqui et al. (2013)	Consumers Energy
Nguyen et al. (2013)	Xcel Energy
GDS Associates, Inc. (2013)	Marblehead Municipal Light Department
DTE Energy (2014)	DTE Electric
Potter et al. (2014)	Sacramento Municipal Utility District
Leidos (2014)	New Hampshire Electric Cooperative
Lakeland Electric (2015)	Lakeland Electric
NV Energy (2015)	Sierra Pacific Power, Nevada Power
Bleything et al. (2015)	Vermont Electric Cooperative
Blumsack and Hines (2015)	Green Mountain Power
George et al. (2015)	PECO Energy
Harding and Lamarche (2016)	Unnamed South Central Utility
Braithwait et al. (2016)	Pacific Gas and Electric
Dominion Energy Services, Inc. (2017)	Dominion Energy
Gillan (2017)	Pacific Gas and Electric, Southern California Edison, San Diego Gas and Electric
Marrin et al. (2017)	Oklahoma Gas & Electric
Seiden et al. (2017)	Nantucket Electric Company d/b/a National Grid
Braithwait et al. (2017)	San Diego Gas and Electric
Reeves et al. (2018)	Portland General Electric
George et al. (2018)	Pacific Gas and Electric, Southern California Edison, San Diego Gas and Electric
Navigant (2019)	Xcel Energy
Bollinger and Hartmann (2020)	Unnamed Southern Utility
Hansen and Armstrong (2020)	Pacific Gas and Electric
Wang et al. (2020)	Los Alamos Department of Public Utilities
Bell et al. (2021)	Southern California Edison
Guidehouse (2021)	Evergy
Fowlie et al. (2021)	Sacramento Municipal Utility District
Sergici et al. (2021)	Baltimore Gas and Electric, Potomac Electric Power Company, Delmarva Power & Light
DNV (2023)	Dominion Energy
Jiang et al. (2023)	Consolidated Edison
Bell et al. (2024)	Commonwealth Edison