PC44 Time of Use Pilots: Year One Evaluation

PREPARED BY

Sanem Sergici

Ahmad Faruqui

Nicholas Powers

Sai Shetty

Jingchen Jiang

PREPARED FOR

Maryland Joint Utilities

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THE Brattle GROUP

AUTHORS

Sanem Sergici, Ph.D. Dr. Sanem Sergici is a Principal in The Brattle Group's Boston, MA office specializing in program design and evaluation in the areas of rate design, energy efficiency, demand response, and electrification. Dr. Sergici has been at the forefront of the design and impact analysis of innovative retail pricing, enabling technology, and behavior-based energy efficiency pilots and programs in many states and regions including District of Columbia, Connecticut, Florida, Illinois, Maryland, Michigan, Ontario, CA and New Zealand. She has led numerous studies that were instrumental in regulatory approvals of Advanced Metering Infrastructure (AMI) investments and smart rate offerings for electricity customers. She has expertise in resource planning; economic analysis of distributed energy resources (DERs); their impact on the distribution system operations and assessment of emerging utility business models and regulatory frameworks.

Sanem.Sergici@brattle.com

Ahmad Faruqui, Ph.D. Dr. Ahmad Faruqui's consulting practice focuses on ways to enhance customer engagement. He advises clients on matters related to rate design, load flexibility, energy efficiency, demand response, distributed energy resources, demand forecasting, decarbonization, and electrification. He has worked for over 150 clients on five continents, and provided expert testimony and appeared before regulatory bodies, governments, and legislative councils. Dr. Faruqui has authored or coauthored more than 100 papers on energy economics in peer-reviewed and trade journals and is the co-editor of four books on industrial structural change, customer choice, and electricity pricing.

Ahmad.Faruqui@brattle.com

Nicholas Powers, Ph.D. Dr. Powers has broad experience in applying econometric analysis to more a variety of economic questions in the electric and other industries. His electricity experience includes several key analyses of price effects, market power, and anticompetitive behavior. In addition, he conducts econometric analysis of innovative pricing programs in the electric industry. He has supported expert testimony in three separate litigation proceedings arising from the California electricity crisis of 2000–2001. He has also overseen the statistical analyses in several New Source Review cases and performed damages and other analyses in energy-related litigation proceedings. Dr. Powers also has extensive experience estimating cartel impacts in large-scale price-fixing cases and conducting analysis for and submitting expert reports in regulatory proceedings in other industries.

Nicholas.Powers@brattle.com

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Executive Summary

As part of the Maryland Public Service Commissions' PC44 proceedings, three investor-owned utilities in Maryland –BGE, Pepco, and DPL—are running pilots with time-of-use (TOU) rates. The utilities are henceforth going to be referenced as the Joint Utilities (JUs). The JUs designed the pilots through a Work Group process that was created by the Commission. Customers began transferring to the TOU rates beginning in April of 2019. This report contains the results from an impact evaluation of the first year of the pilot, which began in June 2019 and ran through May 31, 2020. The year was divided into two periods, summer and the rest of the year, which was labeled non-summer. While there is a long history in the US of running TOU pilots, the PC44 pilots have several unique features that make them stand out:

- They include TOU rates with quite sizeable differentials between peak and off-peak periods. The ratio of peak to off-peak prices ranges from 4 to 6 across the three JUs, providing customers a strong incentive to save money by consuming power during the substantially less expensive off-peak period.
- The peak periods are relatively short, allowing customers to respond more easily by reducing peak usage and shifting some of it to off-peak periods. In the summer, the peak period runs from 2 PM to 7 PM on weekdays. All weekend hours are off-peak as were all the hours on holidays. In the non-summer, the peak period runs from 6 AM to 9 AM.
- The TOU rates apply to charges for generation, transmission and distribution, and not just to the generation as is often the case with TOU pilots.
- The pilots are designed to separately measure the impact of TOU rates on low and moderate income (LMI) customers and non-LMI customers, by creating designated treatment cells for these groups.
- The pilots feature a quasi-experimental design. Specifically, customers were randomly chosen for recruitment; recruited customers then had the opportunity to opt in to the pilot. Using a large pool of eligible customers that were not targeted for recruitment, we select a "matched control group" by utilizing a widely used technique called "propensity score matching" in order to minimize pre-pilot differences between the treatment and customer groups.
- During the recruitment phase, customers who were randomly chosen for recruitment in the pilot were provided with a personalized estimate of their potential savings under the TOU rate, based on their load profiles. Based on their pre-pilot consumption patterns, about two-thirds of the customers who chose to participate would have seen a decrease in their bills even without changing their behavior. We call these customers "structural winners" in this report.
- The pilots were designed not only to yield information on the impact of the specific TOU rates being tested but also to yield econometric models that can be used to predict the impact of alternative

TOU rates. These models also yield estimates of two types of elasticities that are often of interest to analysts: (1) the elasticity of substitution, which measure the extent to which load shifting takes place between peak and off-peak periods; and (2) the daily price elasticity, which measures the change in daily usage induced by change in daily prices.

- Treatment customers were provided online messages on a weekly basis. These e-mails reminded treatment customers about the timing of the peak period and also provided tips on how to curtail peak loads and to shift some of that load to the off-peak period. This tool, known as "behavioral load shaping" was combined with the TOU rate price signal to facilitate changes in behavior. The impacts quantified in the pilot are the combined effect of pricing and the information treatment.
- We analyzed the load data econometrically using a widely-used technique known as panel data regression analysis. A panel data has repeated time series information on individual customers as well as cross-sectional information across customers. Essentially, this approach allows us to: (a) compare the usage of treatment customers before and during the pilot period; (b) compare the usage of control group customers before and during the pilot period; and (c) net out the latter change from the former change, yielding the "difference-in-differences," which is the estimate of the impact of TOU rates on peak and off-peak usage.

An unexpected development in the non-summer season was the outbreak of COVID-19. In Maryland, the pandemic broke out in March 2020 and affected all customers in the pilots, whether they were on TOU rates or on standard rates. We leveraged the econometric model to identify the impact of COVID-19 on customer behavior.

Results

Customer enrollment rates in the pilots ranged from 0.5% to 1.9% across the JU's. About two-thirds of the customers who enrolled would have experienced bill reductions by switching to TOU rates without changing their load behavior. This was true of both the LMI and non-LMI customers.

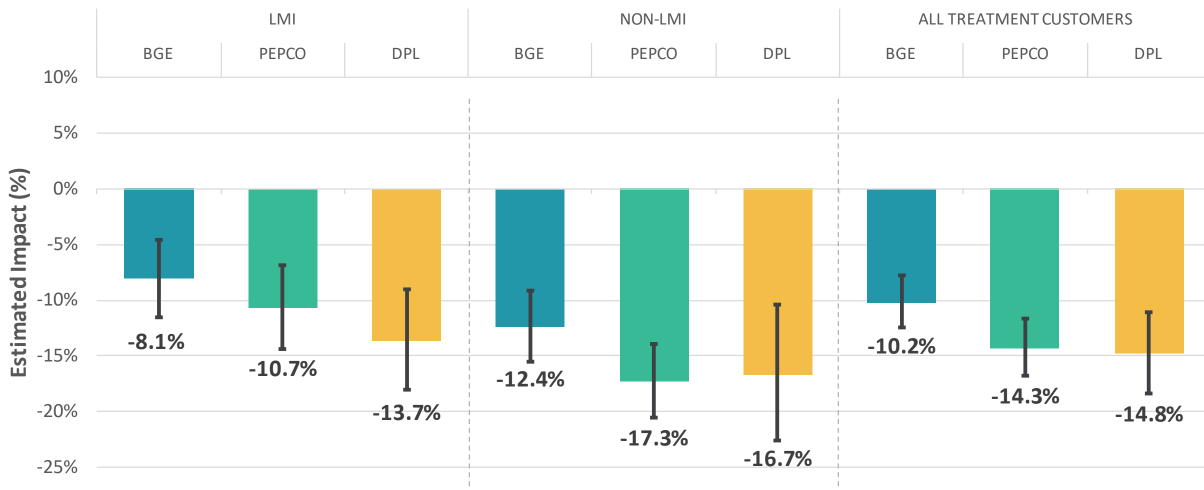
Intuitively, we would expect that the TOU rates would induce customers to lower their consumption in peak hours, relative to what they would have consumed on a flat rate, and to shift some of that consumption to the off-peak hours. It is difficult to predict in advance what would happen to daily consumption. Behavioral messaging would further stimulate a change in customer behavior.

SUMMER IMPACTS

The summer results are presented below. The Figure ES.1 shows the summer weekday peak impacts by utility, initially by LMI and non-LMI customers, and then for all treatment customers combined. The peak impacts for the combined customer group range from -10.2% to -14.8%. Peak demand falls in all cases and the magnitude of the reduction is statistically significant in all cases.

What is also noteworthy is that the demand response of LMI customers is statistically significant for each of the JUs. Furthermore, the magnitude of the LMI impact cannot be statistically distinguished from that of non-LMI customers, with the exception of Pepco. **This provides conclusive evidence that LMI customers respond to the TOU prices by as much or nearly as much as non-LMI customers.**

FIGURE ES.1: SUMMER WEEKDAY PEAK IMPACTS



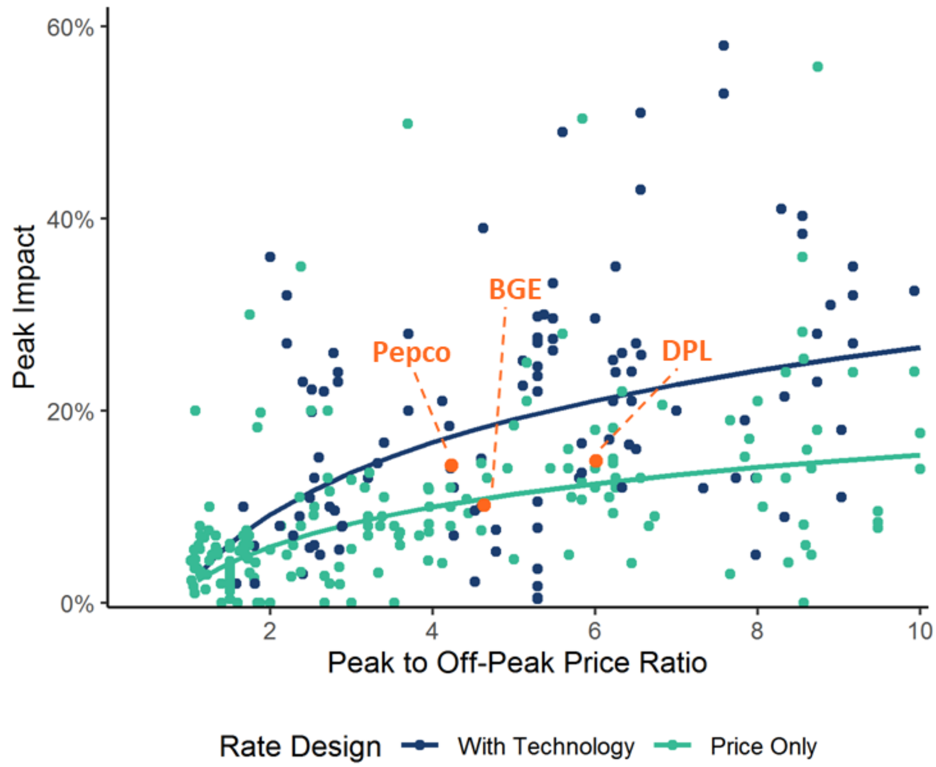
Note: The error bands in each bar show confidence bands. There is a 95% chance that the actual impact lies within the bands.

Surprisingly, off-peak usage does not appear to rise on weekdays, as we would expect, in response to the lower prices. Furthermore, on weekends, usage during the hours that correspond to the peak period is lower. These unexpected off-peak and weekend effects could be "spillover effects" from the BLS messaging tool, or customers may be using the same schedule for their smart thermostats during both the weekdays and weekends, resulting in a reduction in peak period hours even during weekends.

We also detect statistically significant weekday conservation impacts for all three JUs in the range of -2.8% to -4.9%. These results do not significantly differ between LMI and non-LMI customers.

The summer reductions in peak periods, when correlated with the price ratios in the PC44 TOU pilots, line up well with the results of other pricing pilots in the Arcturus database that Brattle has developed over the years. Figure ES.2 below shows this comparison.

FIGURE ES.2: SUMMER PEAK IMPACTS FROM OTHER TIME VARYING PRICING PILOTS AND PC44 TOU IMPACTS

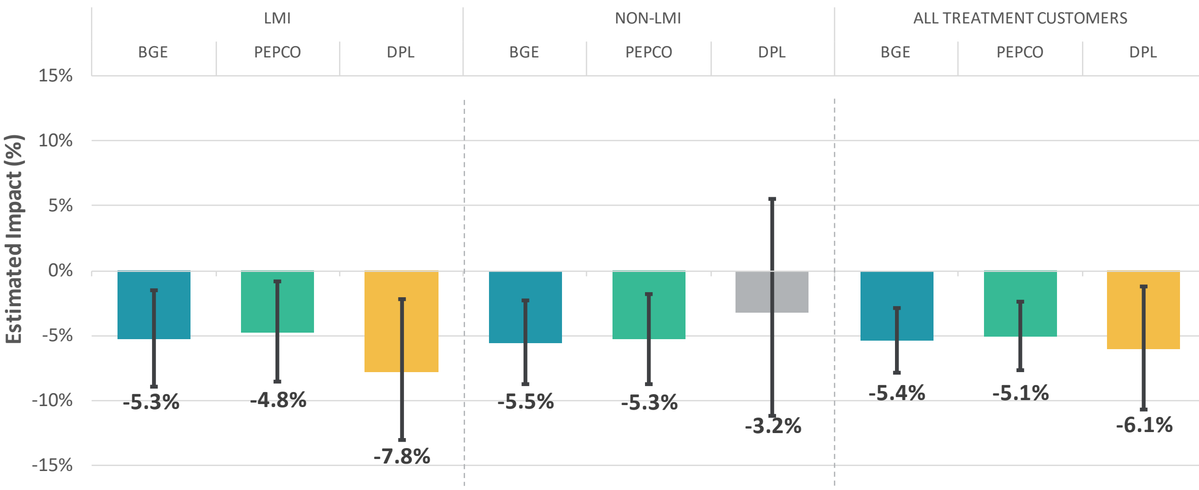


Note: The PC44 data points are based on the results for all customers (combined LMI and non-LMI effects).

NON-SUMMER IMPACTS

The non-summer results are presented below. For all three utilities, we detect economically and statistically significant peak load reductions that range from -5.1% to -6.1% for the combined sample. The non-summer impacts are generally smaller than the summer impacts, which has also been observed in other pilots which had two seasons in them. Demand response of LMI customers is statistically significant for each of the JUs. The magnitude of the impact cannot be statistically distinguished from that of non-LMI customers. Accordingly, a key summer result is also confirmed in the non-summer months: **LMI customers respond to the TOU prices at comparable magnitudes to non-LMI customers.**

FIGURE ES.3: NON-SUMMER WEEKDAY PEAK IMPACTS



COVID-19 IMPACTS

COVID-19 tended to lead to flatter load shapes and higher consumption levels in all three utilities for the control group customers who were not on TOU rates. This strikes us as being intuitively plausible since customers were sheltering in place during the pandemic. **Non-summer peak impacts remained largely similar for BGE and Pepco during COVID-19 months, while they were lower for DPL**. All JUs revealed a larger tendency to conserve load during COVID months, as exhibited by large daily price elasticities.

SUBGROUP IMPACTS

We also analyze customers' response to TOU rates by subgroup. We find that impacts were generally similar between NEM and non-NEM customers, and between structural winners and others. The latter finding is particularly important in the sense that customers who would observe bill savings on the TOU rates (due to their favorable load profiles) even without changing their usage did not tune out the price signals. On the contrary, they achieved peak load reductions as large as those of other customers who did not have similarly favorable load profiles. **This contradicts a commonly held belief that opt-in pilots will only attract "structural winners" and that once on the rate, these customers will not respond to the price signals.**

BILL IMPACTS

Finally, we find that on average, customers on the TOU rates enjoyed bill savings in the range of 5% to 10% across the three JUs. These bill savings were not generally uniform across seasons or JUs. For example, while Pepco TOU customers enjoyed substantial bill savings in the summer but smaller bill savings in the non-summer period; TOU customers at BGE and DPL both experienced bill increases in the summer but considerable savings in the non-summer period. We find that on average, both LMI and non-LMI customers enjoyed bill savings on an annual basis.

I. Introduction

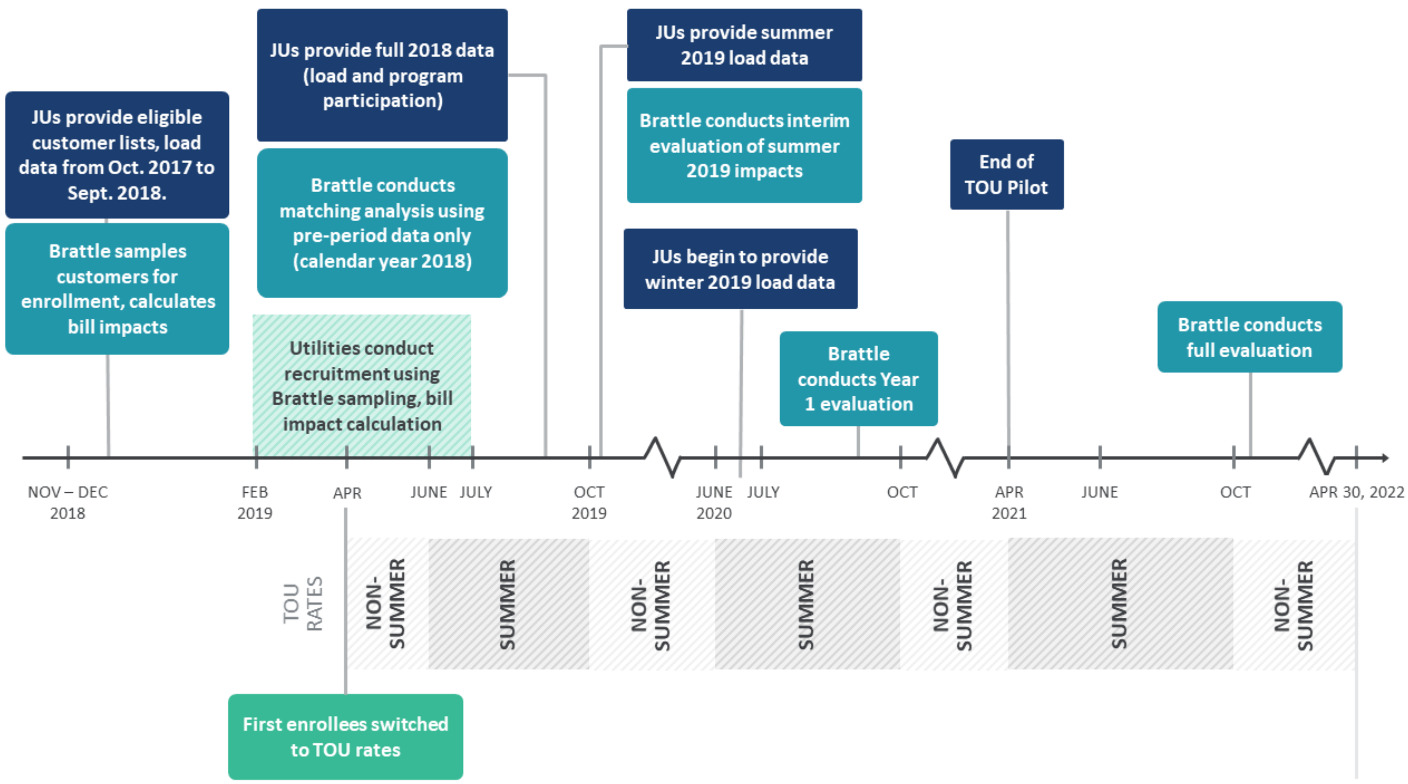
This report presents the results of the first year of the PC44 Time-of-Use ("TOU") pilots. The Maryland Public Service Commission ("PSC" or "the Commission") initiated Public Conference 44 ("PC44") on September 26, 2016 for the purposes of ensuring that the "electric distribution systems in Maryland are customer-centered, affordable, reliable, and environmentally sustainable."[1] In furtherance of that goal, the Commission instituted a Rate Design Work Group ("Work Group") to "explore time-varying rates for traditional electric service…and considering pilot programs for driving desired results through performance-based compensation."[2] It was the Commission's hope that these pilots would "more effectively reintroduce time-varying rates to Maryland customers, and better reach the potential to incent the real-time, peak shaving behavior now enabled by the deployment of Advanced Metering Infrastructure available to more than 80 percent of Maryland electric customers."[3] The PC44 TOU pilots were designed in a collaborative Work Group process that took place in late 2018 and early 2019. Customers began transferring to the TOU rates beginning in April of 2019. The Year 1 analysis covers June 1, 2019 through May 31, 2020. A timeline with key pilot milestones, as well as milestones for the evaluation, measurement, and verification ("EM&V") of the pilot, is presented in Figure 1: Pilot Timeline.

[1] PC 44 Notice, September 26, 2016, p. 1.

[2] PC 44 Notice, September 26, 2016, p. 3.

[3] ML# 217978, p. 2.

FIGURE 1: PILOT TIMELINE



A. Purpose

As described in the Evaluation, Measurement, and Verification Plan filed with the Commission for these PC44 TOU pilots, this is the first of two reports evaluating those pilots.[4] The objective of this evaluation report is to assess whether the customers participating in the pilots have modified their electricity consumption in response to the price signals conveyed by the TOU rates, in a statistically significant manner. In this report, we present the results of our evaluation of the impacts of the TOU rates on pilot customers, relative to comparable customers who have not enrolled in the pilot ("control group"). We evaluate a variety of impacts, including:

- peak load reductions;
- load impacts during off-peak times;
- overall conservation impact;
- substitution elasticities, which measure the extent to which pilot customers substitute away from consumption in high-priced peak hours;

4 Sanem Sergici, Ahmad Faruqui, and Nicholas Powers, "Evaluation, Measurement and Verification Plan for the PC44 Time-of-Use Rate Pilots." June 15, 2018, p. 2. ("EM&V Plan")

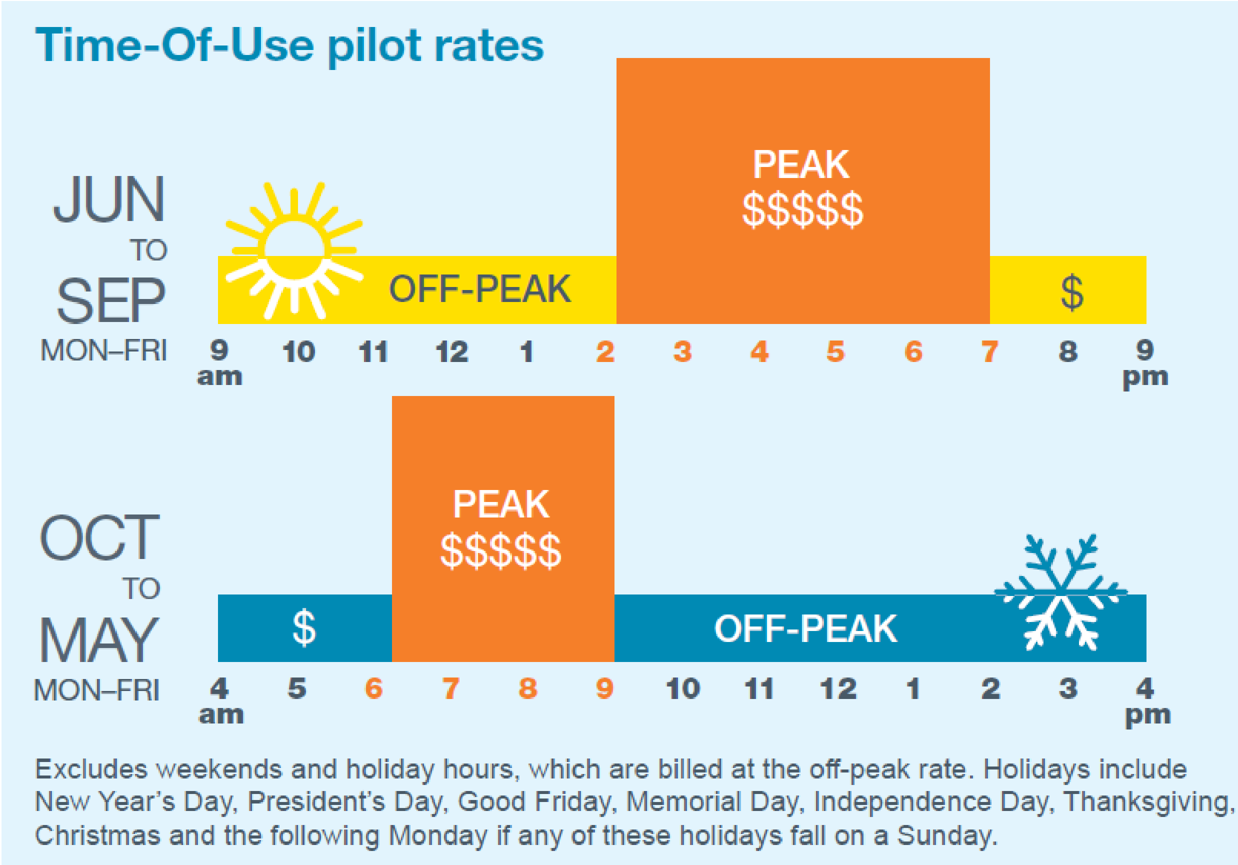
- demand elasticities, which measures the extent to which customers conserve in response to higher average prices; and
- load impacts for various sub-groups.

B. Pilot Overview, Including Key Differences From Previous Pilots

Three Maryland utilities are conducting the PC44 TOU pilots: Baltimore Gas & Electric ("BGE"); Pepco Maryland ("Pepco"), and Delmarva Power & Light Maryland ("DPL"). We refer to the three utilities as the Joint Utilities ("JUs") for the rest of this report. While each JU is conducting its own TOU pilot, the three pilots share the same fundamental design features:

- opt-in enrollment by eligible customers who were randomly selected for recruitment into the pilot;
- a seasonal rate structure, in which summer rates apply from June to September and non-summer or "non-summer" rates apply from October to May;
- season-specific definition of peak hours, in which the peak is from 2 PM to 7 PM on non-holiday weekdays in the summer months, and from 6 AM to 9 AM on non-holiday weekdays in the non-summer months. In both seasons, all other hours, including weekends, are off-peak;
- the peak and off-peak rates as set by each utility vary, but are designed to be revenue neutral on an annual basis in the absence of load shifting.

FIGURE 2: SEASONS AND PEAK HOURS



Source: BGE recruitment letter

The PC44 pilots differ from previous TOU pilots in several key ways:

1. Unlike the majority of previous TOU pilots that imposed higher peak prices only on the energy supply portion of enrolled customers' bills, both the energy and the delivery portions of rates faced by customers participating in the PC44 TOU pilot are higher in the peak than in the off-peak. As a result, most of the customers' bill is subject to the TOU peak and off-peak prices, potentially strengthening their incentives to respond to the price signals.

2. All-in peak rates faced by enrolled customers are between 4 and 6 times the off-peak rates, as summarized in Figure 3, and represent meaningful incentives for customers to shift their usage from peak to off-peak periods.

FIGURE 3: RATES DURING THE FIRST YEAR OF THE PILOT

	Summer (June 2019 - September 2019)				Non-Summer (October 2019 - May 2020)			
	Peak	Off-Peak	Peak to Off-Peak Ratio	Default "R" Rate	Peak	Off-Peak	Peak to Off-Peak Ratio	Default "R" Rate
BGE	$0.343	$0.074	4.63	$0.108	$0.360	$0.080	4.52	$0.115
Pepco	$0.406	$0.096	4.22	$0.163	$0.426	$0.105	4.07	$0.139
DPL	$0.493	$0.082	6.01	$0.135	$0.501	$0.086	5.82	$0.137

Note: Rates for each period are simple averages of all variable components of rates in each month, as provided by the JUs. Variable rates include all applicable volumetric charges for transmission, distribution, generation, administrative credits, receipt taxes, stabilization adjustments, procurement adjustments, and county surcharges. The default "R" rate column refers to the flat volumetric rate tariff that applies to the majority of residential customers who have not opted to purchase energy from a third-party supplier.

3. The Maryland Public Service Commission was particularly interested in assessing the impacts of TOU rates on low-to-moderate income ("LMI") customers in addition to average residential customers. Accordingly, the pilot designs involved separate treatment groups for LMI customers to ensure that the JUs recruited a sufficient number of LMI customers to enable estimation of statistically significant impacts for that category of customers.

4. Recruitment materials provided detailed and *individualized* information on predicted customer bill impacts under the TOU rates, based on each customer's 2018 load data and various load response assumptions including no load response, 5% peak load shifting and 10% peak load shifting. This implies that PC44 customers made an informed decision to participate in the pilot by reviewing different bill impact scenarios. It is reasonable to expect that "structural winners", or customers with flatter load profiles, will participate in the pilot at higher rates. Since JUs indicated that any future full-scale opt-in TOU program would also include a similar bill comparison element, this recruitment feature does not violate the external validity of the results.

5. Motivated by the Commission's interest in determining whether TOU rates can help lower customer bills, enrolled customers also received weekly e-mails as part of a behavioral load shaping ("BLS") tool. These e-mails provided regular reminders to pilot customers as to the timing of the peak, and provided tips for how customers could shift or conserve their load. As a result, we cannot attribute the customer impact solely to a price response; instead, we interpret the impacts to be the combined effect of the two components. Since JUs indicated that any future full-scale opt-in TOU program would always include a similar informational element, estimation of a combined treatment impact is instructive in this context.

II. Methodology

In this section, we provide an overview of the methodology we used to analyze the results from the first year of the pilot. The pilot design approach that we use is known as "random sampling with a matched control group". Under this pilot design approach, the selection of pilot participants depends in part on randomization, in that the utility randomly selects which customers are offered the opportunity to participate in the pilot.

Under this approach, the analysis proceeds in two stages. First, we undertake a matching stage to ensure that the control group that serves as the benchmark against which we measure pilot impacts is as comparable as possible to the enrolled or "treatment" group. In the second stage, we conduct the impact evaluation by comparing the outcomes of the pilot group to those of the control group, using regression analysis.

This approach is known as a "quasi-experimental" approach. The ability to identify a control group that is similar to the treatment group on a variety of observable dimensions significantly mitigates concerns that there are systematic differences between the two groups that might bias the resulting impact estimates. Furthermore, this approach avoids the potential for either negative customer experience risks or higher recruitment costs associated with other approaches that were considered, such as recruit-and-deny and randomized encouragement design approaches.[5]

In the remainder of this section, we provide a summary of pilot eligibility and the recruitment process. We then describe in additional detail on the matching process. Finally, we describe the regression-based approaches used to evaluate the impacts of the pilot. We cover details of a more technical nature in the Appendix.

A. Summary of Eligibility and Recruitment

In November and December of 2018, each of the three utilities provided lists of eligible customer IDs. Consistent with the criteria specified in the EM&V Plan, we requested that the utilities determine eligible customers as follows:[6]

[5] EM&V plan, pp. 7-10.

[6] EM&V Plan, pp. 10-11.

- only residential customers who had been at the current address and for whom the utilities had consistent AMI data dating back to at least January 1, 2018 could be included;7
- customers with medical needs flags were excluded;
- participants in virtual net energy metering or Community Solar programs were excluded;
- customers who had been included in the control group of other programs (such as Opower Home energy reports) were excluded;
- BGE customers participating in the Prepaid Pilot Program were also excluded.

To ensure that there was no personally identifiable information ("PII"), the utilities created unique identifiers that were anonymized and different from any identifier used internally. In addition to this identifier, each utility provided the zip code of the premise of each eligible customer ID. BGE also provided household-level income estimates, as provided by a third-party data supplier, for roughly 73% of BGE customers; for the remaining customers, the household income variable reflected zip-code averages from U.S. Census data.

In its PC44 Workgroup Order, the Commission specified that "the pilots should be designed with a separate LMI sample to collect statistically significant results."[8] Following guidance from the JUs, we classify customers with annual household income below $74,000 as LMI customers.[9] Given the importance of LMI customers to this pilot, and the possibility that targeted LMI customers would be less likely to enroll than other customers, the recruitment plan for BGE and Pepco targeted customers who were more likely to be LMI customers.[10] In the case of DPL, a much higher share of the households in the service territory has household incomes below the LMI threshold.[11] Accordingly, we used simple random sampling when selecting the DPL customers for recruitment.

For each utility, we sampled "waves" of customers for recruitment, pursuant to discussion with each of the JUs regarding their recruitment strategies and costs. As part of this sampling process, we set aside

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7 In fact, the list BGE provided included some customers who moved into their premises after January 1, 2018. Some of these customers were subsequently randomly selected to receive recruitment materials, and 325 targeted customers with move-in dates after January 1, 2018 thus enrolled in the pilot. Many of these customers nevertheless had accumulated a full year of AMI data at the same residence prior to the start of the pilot. We include in our analysis all enrolled customers with move-in dates after January 1, 2018, truncating the pre-period data to ensure that only the enrolled customer's data is included in the impact evaluation.

8 Maryland Public Service Commission, Letter Order RE: Public Conference 44 – Rate Design Workgroup, dated May 7, 2018.

9 This LMI threshold, provided by the JUs, is equal to 80% of the median state income of $92,500 in 2017. See "Income Limits 2017," Maryland Department of Housing and Community Development, at p. 2. https://dhcd.maryland.gov/HousingDevelopment/Documents/prhp/2017_MD_Income_Limits.pdf.

10 As customers' LMI status was unknown unless and until they enrolled in the pilot, we could not generally observe whether eligible customers fell into this group. As explained above, BGE had provided third-party data for most of its eligible customers. For the remainder, and for Pepco, we relied on zip-code level data. All things equal, the lower median household income in a zip code, the higher the likelihood that a randomly selected household would be an LMI household.

11 According to U.S. Census data provided by the utilities, 59.4% of the eligible customers live in zip codes where the median household income is below the LMI threshold.

for each utility a large pool of potential control customers in order to ensure that the matching process would generate a balanced control group.

- For BGE, 100,000 customers were sampled into 2 recruitment waves, leaving a control customer pool of over 600,000 customers.
- For Pepco, 303,634 customers were sampled into 9 recruitment waves, leaving a control customer pool of 20,000 customers.
- For DPL, 100,000 customers were samples across 6 recruitment waves, leaving a control customer pool of 13,300 customers.

The utilities sent the recruitment letters, beginning in early February 2019. BGE and DPL recruited for all waves in February 2019, whereas Pepco's recruitment effort lasted through mid-April. The recruitment letters included, for each customer, a summary of the bill impacts, based on the: (1) the prevailing tariffs for that customer's rate class as of the end of 2018; (2) the tariff for the pilot rates; and (3) that customer's 2018 load data. The BGE letters provided bill impacts for three scenarios:

- no load response
- in both seasons, the customer would shift 5% of their pre-pilot peak load to off-peak (but would not reduce their total load)
- in both seasons, the customer would shift 10% of their pre-pilot peak load to off-peak (but would not reduce their total load).

The letters that Pepco and DPL sent to targeted customers provided bill impacts for two scenarios:

- no load response
- in both seasons, the customer would shift 8% of their pre-pilot peak load to off-peak (but would not reduce their total load).

In the discussion that follows, we refer to customers who would see their bills decrease without any load response as "Structural Winners." These customers, based on their pre-recruitment consumption patterns, would see bill savings simply by switching rates, without making any additional effort to shift or conserve load.

FIGURE 4: RECRUITMENT SUMMARY AS OF JULY 26, 2019

	Target	BGE	Pepco	DPL
Enrollment Summary				
Targeted customers		95,012	266,707	86,035
Enrolled customers	1,400	1,772	1,380	674
Enrollment rate		1.9%	0.5%	0.8%
Enrollment Rate Detail				
Structural winners without load shift		2.0%	0.8%	1.0%
Non-savers without load shift		1.5%	0.3%	0.6%
LMI/Non-LMI Breakdown				
LMI enrollees	700	925	617	416
(as share of total)		52%	45%	62%
Share of LMI enrollees who are structural winners without load shift		67%	67%	65%
Non-LMI enrollees	700	847	763	258
(as share of total)		48%	55%	38%
Share of non-LMI enrollees who are structural winners without load shift		66%	68%	64%

Note: Includes all enrolled customers, some of whom are subsequently excluded from the impact analysis due to incomplete data. The last enrollment occurred on July 26, 2019 (Pepco).

Figure 4 summarizes enrollment status by utility at the end of the recruitment window. BGE enjoyed the highest enrollment rate, with 1.9% of the targeted customers opting to enroll. Unsurprisingly, structural winners were more likely to enroll (at around 65-68%) than non-savers without load shift. This is true for all three utilities.

Both BGE and Pepco attained the target number of non-LMI enrollees; BGE also attained the target for LMI customers. The share of both LMI and Non-LMI enrollees that are structural winners is similar across all three utilities. Based on their 2018 load usage patterns, roughly two-thirds of the enrollees in all six customer groups could expect to save when moved to the pilot rate, even before shifting any load.

Excluding enrollees for whom we do not have sufficient pre-period data to be included in the impact assessment, 1,614 treatment customers from BGE, 1,342 from Pepco, and 653 from DPL remain in the study, as discussed in Section III.A below.

B. Summary of Matching Process

Based on observable pre-treatment data for all targeted customers (i.e., all customers to whom recruitment materials were sent), we identify the variables (such as electricity consumption at particular times of the day, or participation in other utility programs) that are most highly correlated with the decision to participate in the pilot.[12] Then, using the identified variables, we estimate a "propensity score" for each customer who was targeted for enrollment (regardless of their acceptance or refusal to participate). Conceptually, this propensity score represents the probability that a targeted customer with that set of observable characteristics would choose to enroll in the pilot. We then use the parameters from this regression analysis to estimate the propensity score for each customer in the pool that was set aside for control group selection. Then, for each enrolled treatment customer, we identify the single set-aside control customer whose propensity score is most similar and place this matched customer in the control group.[13]

After the matched control group was formed, we undertook several diagnostics and confirmed that the resulting match was satisfactory and the matched control group would accurately represent the "but-for" usage of the treatment customers. Information on the results of this matching process, as well as the diagnostics we performed to assess the resulting balance between the treatment group and the matched control group, are discussed later in this report.

As described below, the difference-in-difference approach we use in our impact analysis controls for persistent customer differences between the "treatment" group and the control group. As long as the trends of the control group and the treatment group would have been the same in the absence of the pilot, then the resulting estimates are valid even without matching. This condition is known as the "parallel trend assumption." The primary benefit of matching is that by accounting for observable pre-

[12] We identify the included variables based on an algorithm that is similar to that developed by Imbens and Rubin. *See* Imbens, Guido W. and Donald B. Rubin. 2015. Causal Inference in Statistics, Social, and Biomedical Sciences. New York: Cambridge University Press ("Imbens and Rubin"). Provided with a set of *k* candidate variables, the algorithm first estimates *k* univariate logit regressions and identifies the variable that is the single best predictor of enrollment. Then, it keeps that variable, and estimates *k-1* logit regressions with both the selected variable and one of the remaining *k-1* variables, ultimately identifying the variable that provides the greatest improvement (in terms of predicting enrollment) over the single-variable logit regression. This process is iterated until the improvement from adding an additional variable falls below a threshold we specified.

For each of the three utilities, the algorithm selects more than 35 variables, including a mix of seasonal hourly load variables (*e.g.*, average load on hour 18 of summer weekdays) and other non-load variables, such as participation in direct load control programs and median household income in the customer zip code. Additional details are available in Section III.C.

[13] We impose minimal restrictions on the match. One such restriction is to separate both the set of enrolled customers and the pool of potential control customers according to whether those customers have net metering. We identify such customers using a combination of information from the utility and by observing load patterns displaying negative net load.

We also experimented with a geographic restriction, whereby we limited each enrolled customer's match based on zip code of the respective premises. However, the control group balance was not as strong, and furthermore we found for each utility that the unrestricted match yielded geographic distributions of matched customers that were similar to the geographic distribution of enrolled customers. Maps demonstrating these distributions are provided in the Appendix A.3.

pilot differences in constructing the control group, we increase the likelihood that the parallel trend assumption holds.

C. Methodological Approach to Impact Evaluation

We have employed a dual approach to evaluating the impacts of the PC44 TOU pilots. The first set of analyses involves models to estimate load impacts resulting from exposure to the TOU rates. The second set of analyses uses models to estimate substitution and daily price elasticities representing customers' sensitivity to prices. These estimated elasticities can subsequently be used to model the impact of prices that are different from those tested in the pilots. This is important because the prices in a future full-scale roll-out might differ from those tested in the pilot.

Below, we describe each of these approaches in more detail.

1. Load Impact Analysis

We employ panel data analysis as the load impact evaluation method for the PC44 TOU pilots. There are several reasons for this decision. First, the TOU pilots run over multiple years and yield repeated measurements for the treatment and control groups. Furthermore, several months' worth of pre-treatment data are available for both treatment and control group customers. Given that the repeated measurements are available for both groups before and during the treatment period, a panel data regression can utilize the variations in the data across individuals, as well as across time, to fit a relationship between dependent and independent variables and as a result yield the most precise impact estimate. Second, this panel data approach provides flexibility in how we control for differences in weather, seasonality and other factors. Third, through the use of customer-level "fixed effects," panel data analysis allows us to control for time-invariant but unobservable characteristics of individuals that could otherwise introduce bias into the estimation results.[14]

The general form of the preferred regression models we estimated, which are also known as *difference-in-differences regressions* is as follows:

[14] These factors could be certain socio-demographic characteristics such as the education level of the head of household, housing characteristics, or whether the home has electric heating. If a researcher does not observe, or have reliable data on these characteristics, it is not possible to employ these variables as independent variables even though they have the potential to explain the variation in the dependent variable. Omission of these variables from the regression model leads to an "omitted variable" problem, which may result in biased parameter estimates.

Fixed-effects (FE) estimation assumes that the unobservable factor (in the error term) is related to one or more of the model's independent variables. Therefore, it removes the unobserved effect from the error term prior to model estimation using a data transformation process. During this process, other independent variables that are constant over time are also removed. This drawback of the FE estimation implies that it is not possible to estimate the impact of variables that remain constant over time, such as ownership of a single-family house.

For additional discussion of the methodological approaches considered, please refer to Section III of the EM&V Plan.

$$Load_{it} = \kappa_i + \pi PilotPeriod_t + \gamma PilotPeriod * Treatment_{it} + \theta_t + \delta Z_i + \varepsilon_{it} \quad (1)$$

where:

- $Load_{it}$ is the natural log of the electricity consumed by customer *i* in hour t;
- κ_i is a time-invariant customer-specific effect or intercept, which we model as a fixed effect;
- $PilotPeriod_t$ is an indicator (dummy) variable equal to 1 during the pilot period and 0 otherwise;
- π measures the difference in consumption between the pre-treatment period and the pilot period that is common to both control and treatment customers;
- $PilotPeriod * Treatment_{it}$ is the treatment indicator, which will be 0 for all control group customers at all time, and will be equal to 0 for treated customers prior to the treatment and will equal 1 once those customers are on the TOU rates;[15]
- γ is the primary parameter of interest, as it measures the average impact of the TOU pilot treatment on load;
- θ_t is a vector of variables which measures a shift in consumption (possibly due to weather or other seasonal effects) that affects all customers similarly;[16]
- Z_i is a vector of time-invariant customer characteristics of interest, such as self-reported LMI status;[17]
- δ measures the effect on load associated with the Z_i vector; and
- ε_{it} is the residual or error term.

In the course of our analysis, we have estimated separate impacts for the summer period and the non-summer period. We do this within the framework laid out here by estimating this regression on the corresponding subsets of the data. Specifically, we estimated equation (1) on a summer-only dataset (covering June through September, including both pre-treatment data from 2018 and pilot period data from 2019) in order to estimate the average summer impact. We have estimated analogous regressions on non-summer data in order to estimate the average non-summer impact. Similarly, another

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15 If a customer opts to leave the PC 44 pilot, either because they switch to a different rate, switch to a third-party supplier, or move, we exclude all post-unenrollment data for that customer from the analysis.

16 In our primary specification, we include in θ_t a variety of terms, including calendar month dummies, the temperature heat index ("THI") which should capture the effects of weather, as well as month-THI interaction terms, which allow the effect of THI to vary. For example, we do not generally expect the impact of a 10-degree increase in temperature to have the same effect on customer load in May that it does in January. In sensitivity checks, we instead model θ_t using daily fixed effects, which do not impose any functional form assumptions regarding the effects of weather on load. As discussed further in other sections of this report, the coefficients and standard errors of the main parameters of interest (namely γ) are nearly identical under these two approaches.

17 Note that because we include customer-specific fixed effects, the Z_i term is no longer identifiable and is omitted from the regression, due to multi-collinearity. However, when interacted with $PilotPeriod * Treatment_{it}$, the resulting interaction term allows us to measure differential impacts of the TOU treatment on subsets of customers.

requirement of the TOU pilot is the estimation of impacts for LMI customers. Thus, to estimate impacts for LMI customers, we limited the data to the set of LMI treated customers and their matched control customers.[18]

Equation (1) can also be augmented with various interaction terms in order to estimate the impact on specific groups of customers, or during specific time periods. For example, customer response to the pilot rates during the summer period might differ depending on the weather. Thus, we also perform estimation of the following variation on equation (1):

$$Load_{it} = \kappa_i + \pi PilotPeriod_t + \gamma PilotPeriod * Treatment_{it} + \gamma_2 PilotPeriod * Treatment_{it} * THI_t + \delta Z_i + \theta_t + \varepsilon_{it} \quad (1')$$

where:

- THI_t is a vector of indicator variables categorizing days as high-, or low-THI days;[19] and
- γ_2 measures the additional impact of the treatment on days with a given THI classification.

The other variables are as described above, but the interpretation of γ changes in equation (1'), relative to equation (1), as it now measures the average impact on medium-THI days. This is just one example of how, in the course of our subgroup analysis, we use interaction terms to estimate differential impacts on different subsets of the data; another possible example would be measuring a differential impact for structural winners relative to other customers.

In order to minimize the influence of confounding factors, we conduct the impact evaluation of the PC44 pilot after excluding Peak Time Rewards event days from the data.[20]

2. Price Response

After estimating the load impacts using the difference-in-differences approach described above, we next estimated electricity demand models that represent the electricity consumption behavior of the PC44 TOU customers. These models yield estimates of substitution and own-price elasticities, along with the demand curve of the average customer, which are vital to being able to estimate the impact of rates other than those used in the pilot.

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18 In order to test for differences between the impacts on LMI and non-LMI customers, we have also estimated these regressions using data from all customers and employing interaction terms that measure the differential impacts of the pilot on LMI customers.

19 In this example, the THI_t vector does not include an indicator for medium-THI days, in order to avoid multi-collinearity issues.

20 In our extended analyses, we also run one interaction specification where we include these days and test whether the impact of TOU prices varies on PTR event days.

Consistent with common practice in the literature on demand models, we use a constant elasticity of substitution (CES) model to estimate peak/off-peak substitution and own price elasticities. The CES model allows the elasticity of substitution to take on any value and it has been found to be well-suited to TOU pricing studies involving electricity since there is strong prior evidence that these substitution and own-price elasticities are generally small.

For a two-period rate structure, the CES model consists of two equations. The first equation models the ratio of the log of peak to off-peak quantities as a function of the ratio of the log of peak to off-peak prices and yields the "elasticity of substitution". The second equation models average daily electricity consumption as a function of the daily price of electricity and yields the "own price elasticity of demand". The two equations constitute a system for predicting electricity consumption by time period where the first equation essentially predicts the changes in the load shape caused by changing peak to off-peak price ratios and the second equation predicts the changes in the level of daily electricity consumption caused by changing average daily electricity price.

i. Substitution Demand Equation:

The final specification of the substitution demand model will be determined during the estimation process, but the functional form below represents a starting point for the model to be tested and estimated:

$$\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it} = \alpha_0 + \alpha_1 THI\_DIFF_t + \alpha_2 ln(\frac{Peak\_Price}{OffPeak\_Price})_{it} + \sum_{k=1}^{K} \delta_k (THI\_DIFF_t xD\_Month_k) + \alpha_3 D\_TreatPeriod_t + \sum_{k=1}^{K} \beta_k D\_Month_k + v_i + u_{it}$$

Where:

$\ln(\frac{Peak\_kWh}{OffPeak\_kWh})_{it}$	Logarithm of the ratio of peak to off-peak load for a given day
THI_DIFF_t	The difference between average peak and average off-peak temperature-humidity index ("THI"). THI= 0.55 x Drybulb Temperature + 0.20 x Dewpoint + 17.5
$\ln(\frac{Peak\_Price}{OffPeak\_Price})_{it}$	Logarithm of the ratio of peak to off-peak load for a given day
$\ln(\frac{Peak\_Price}{OffPeak\_Price})_{it} xTHI\_DIFF_t$	Interaction of ratio of peak to off-peak prices and *THI_DIFF* for a given day
$THI\_DIFF_t xD\_Month_k$	Interaction of THI_DIFF variable with monthly dummies.
$D\_TreatPeriod_t$	Dummy variable is equal to 1 if treatment period
D_Month_k	Dummy variable that is equal to 1 when the month is k.
v_i	Time invariant fixed effects for customers.
u_{it}	Normally distributed error term.

In the estimated model, α_2 represents the substitution elasticity.

ii. Daily Demand Equation:

The daily demand equation captures the change in the level of overall consumption due to the changes in the average daily price. Similar to the substitution equation, the final specification of the daily demand equation will be specified in the estimation stage, but below we present a starting point for the model to be tested and estimated:

$$\ln(kWh)_{it} = \alpha_0 + \alpha_1 \ln(THI)_t + \alpha_2 ln(Price)_{it} + \sum_{k=1}^{K} \delta_k (\ln(THI)_t xD\_Month_k) + \alpha_3 D\_TreatPeriod_t + \sum_{k=1}^{K} \beta_k D\_Month_k + \nu_i + u_{it}$$

where:

$\ln(kWh)_{it}$	Logarithm of the daily average of the hourly load.
$\ln(THI)_{it}$	Logarithm of the daily average of the hourly THI.
$\ln(Price)_{it}$	Logarithm of the daily average of the hourly Price.
$\ln(THI)_t xD\_Month_k$	Interaction of ln(*THI)* variable with monthly dummies.
$D\_TreatPeriod_t$	Dummy variable is equal to 1 if treatment period.
D_Month_k	Dummy variable that is equal to 1 when the month is k.
v_i	Time invariant fixed effects for customers.
u_{it}	Normally distributed error term.

In the estimated model, α_2 represents the daily price elasticity.

III. Description of Data

A. Enrollment and Attrition Summary

Our ability to quantify the impact of the pilot rates depends on having a large enough sample size to detect an average impact that stands out from inevitable variation or statistical "noise." During the pilot design stage, we undertook statistical power calculations to determine the sample sizes required to estimate a minimum detectable peak impact of 6% at the 5% statistical significance and 80% power.[21] The resulting sample size target is 700 customers for each of the LMI and non-LMI treatments, and for each of the JUs. While JUs were able to meet this target to a large extent (with the exception of DPL), it is natural to observe some attrition during the pilot. Figure 5 below presents the attrition statistics over the course of the first year of the pilot. As of May 2020, 21% of BGE, 15% of Pepco and 14% of DPL treatment customers have left the pilot. It is important to note that most of the attrition was due to customers moving or switching to other suppliers, rather than opting-out of the pilot.[22] Figure 6 through Figure 8 present the pilot sample evolution for each of the JUs.

[21] Note that these sample size assumptions are different from those filed in the EM&V report and have been revised following lower than expected initial recruitment statistics, by relaxing some of the earlier highly conservative assumptions.

[22] 49% of BGE attrition is due to customers moving or closing their account, 28% is due to the customer switching to a third-party supplier, and the remaining 23% indicated "work," "savings," or "other" as unenrollment reasons. Of the 90 DPL customers for whom the reason for attrition is known, 40% moved out of their homes, 22% opted out of the pilot, and 38% moved their service to a third-party supplier. Among 194 Pepco customers who unenrolled, 32% moved out, 26% opted out of the pilot, and 42% moved to a third-party supplier. There are 13 Pepco customers and 1 DPL customer for whom the reason for unenrollment is not known.

FIGURE 5: ENROLLMENT AND ATTRITION AS OF MAY 31, 2020

# of customers	BGE		Pepco		DPL	
Enrolled	1,772		1,380		674	
Attrition						
By 6/1/2019	97	5%	57	4%	22	3%
By 10/1/2019	232	13%	127	9%	55	8%
By 5/31/2020	367	21%	207	15%	91	14%
Potential Sample Size						
For summer analysis	1,675	95%	1,323	96%	652	97%
For non-summer analysis	1,540	87%	1,253	91%	619	92%
Eligible						
For summer analysis	1,614	91%	1,247	90%	620	92%
For non-summer analysis	1,487	84%	1,177	85%	571	85%

Notes: The reported "Enrolled" total includes all customers who ever enrolled in the pilot, regardless of the date or duration of their enrollment. The difference between the "Potential Sample Size" and the "Eligible" totals reflects the removal of customers due to high amounts of missing or incomplete data.

The remaining number of customers eligible for analysis is sufficient for the summer analysis. However, we occasionally run into some issues with statistical significance in the non-summer analysis, as the realized impacts (and hence impacts to be detected) tend to be lower. As the pilot proceeds into the second year, we may observe further attrition.

FIGURE 6: BGE PILOT SAMPLE EVOLUTION, AS OF 5/31/2020

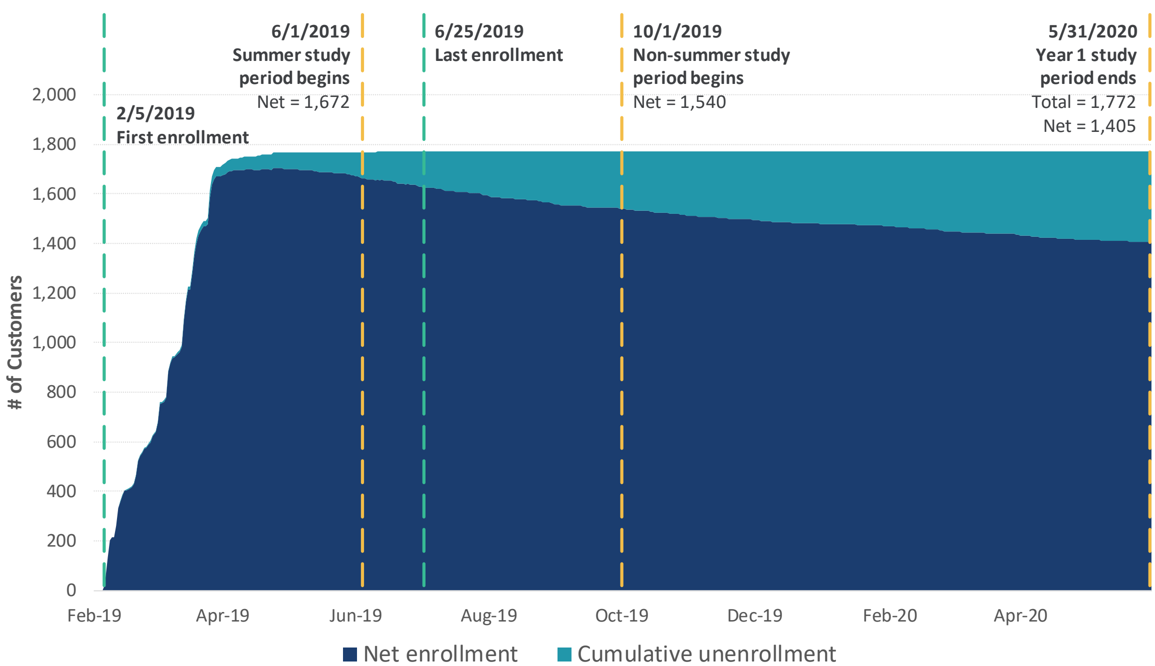


FIGURE 7: PEPCO PILOT SAMPLE EVOLUTION, AS OF 5/31/2020

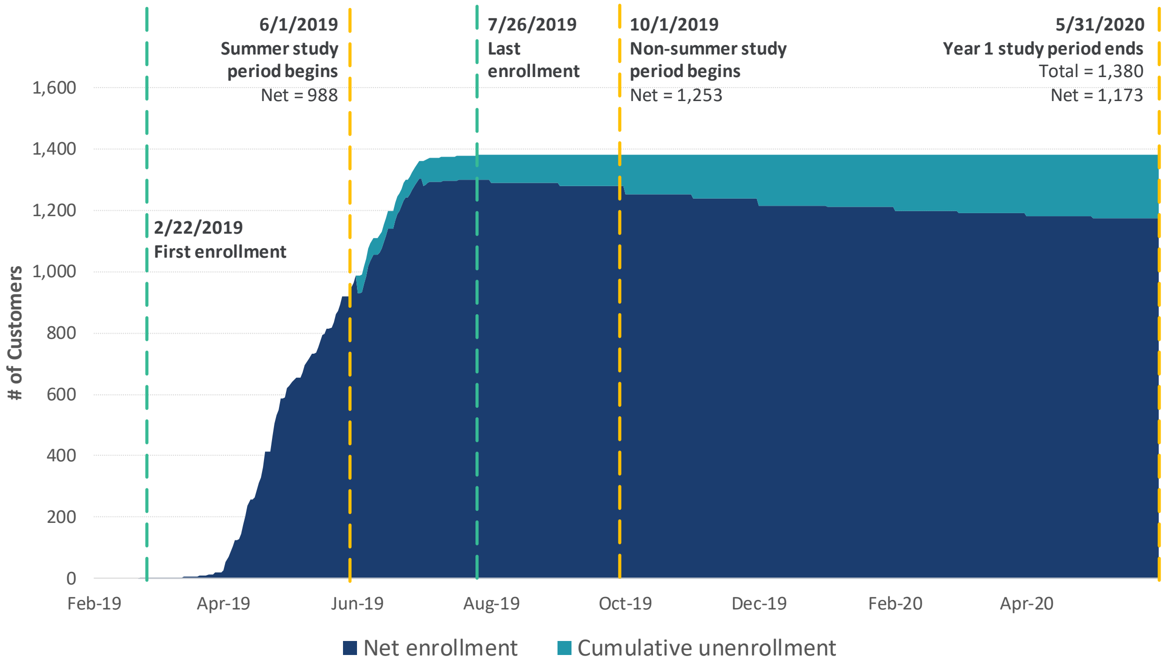
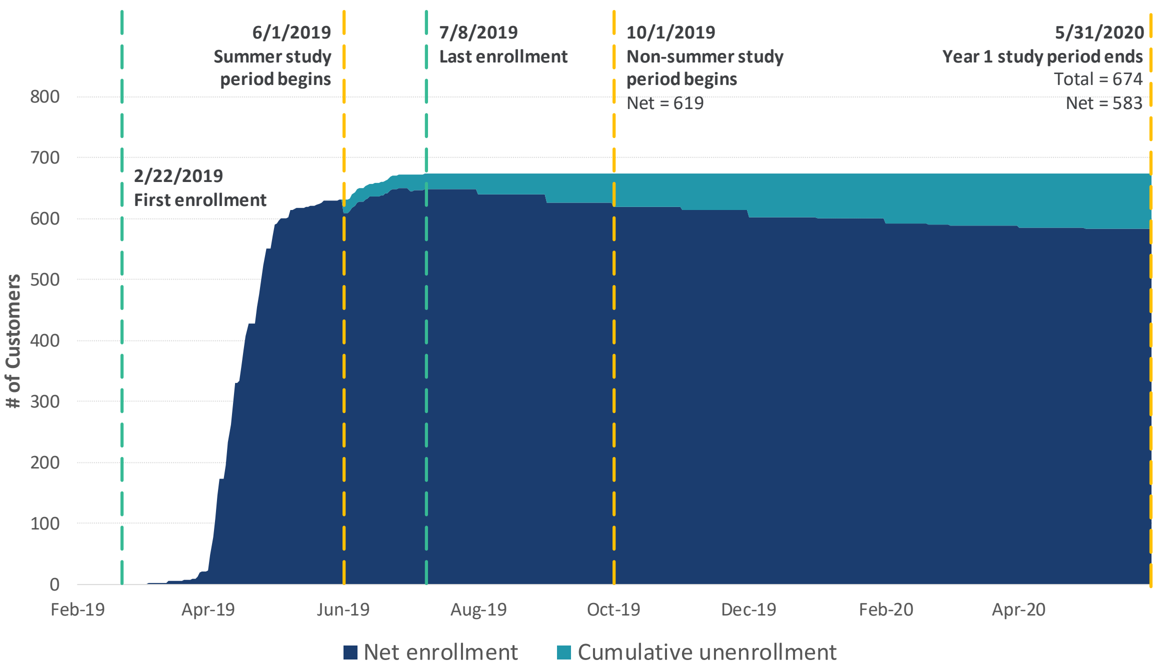


FIGURE 8: DPL PILOT SAMPLE EVOLUTION, AS OF 5/31/2020



B. Summary of Datasets

In addition to regular enrollment and attrition updates, the JUs also provided the following datasets that we subsequently used in our Year 1 analysis:

- hourly load data covering all residential customers from January 2018 through the end of May 2020;
- zip codes for each masked customer ID;
- information, for each masked customer ID, on enrollment in various energy efficiency and other utility programs at various points over the relevant time period;
- hourly weather data used by each of the utilities;[23]
- information, for each masked customer ID, on move-outs, switches to third-party suppliers, and tariff code changes; and
- detailed monthly rates data for the relevant tariff classes, covering the 2018 through 2020 period.

Using these input data, we eventually construct three main datasets for analysis for each utility, as described below.[24]

1. We use the first dataset to **analyze the participation decision** – which factors made target customers more likely to opt in to the TOU pilot? This dataset is limited to recruitment target customers, including both those who ended up enrolling in the pilot and those who did not. This dataset includes:
   - average load data for 2018, by season and hour of day;
   - other utility data about the customer, including their tariff code and data on the customer's participation status in various utility programs as of the end of 2018;
   - estimates of household income, whether at the zip code level or, for most BGE customers, an estimate provided by a third-party data provider; and
   - the outcome of the enrollment decision – did the target customer decide to enroll or not?
2. We use the second dataset to **construct the matched control group**. Specifically, we apply the results of the participation decision analysis to enrolled customers and to eligible potential control group customers in order to identify a control group that is as similar as possible to the treatment group. This dataset contains the same variables as is described above, but for a different set of customers.

[23] For BGE, the weather data is from the Baltimore-Washington International airport, Pepco provided weather data from Washington National Airport, and DPL provided weather data from New Castle Airport

[24] We take various steps to clean and process the data in order to deal with missing or incomplete data and changes in customer status. Those processing steps are described in detail in the Appendix A.2.

3. Finally, we construct, for each season, a dataset that we use to **analyze the impacts of the pilot**. This dataset contains daily observations from the pre-pilot and pilot periods, for enrolled and matched control customers, with the following variables:[25]
   - average hourly load in peak hours, off-peak hours, and all hours;
   - the average THI in peak hours, off-peak hours, and all hours;
   - indicators for whether the customer is a treatment customer or control customer, and whether the treatment customer remains enrolled on a given day;
   - time indicators, including month dummies, weekday and weekend indicators, and a pilot period indicator; and
   - the effective rates (in cents/kWh) at any given point in time, for that customer (for use in the elasticity analysis).

C. Control Group Balance

The matching analysis as described in Section II.B above yielded a number of key insights. Generally speaking, the results validated the decision to consider non-load variables when identifying a control group. Load variables are certainly correlated with targeted customers' participation decisions, with the results generally comporting with expectations. All things equal, higher off-peak loads made customers more willing to enroll, while higher peak loads made targeted customers less likely to enroll. However, several non-load variables were among the variables most highly correlated with the participation decision.

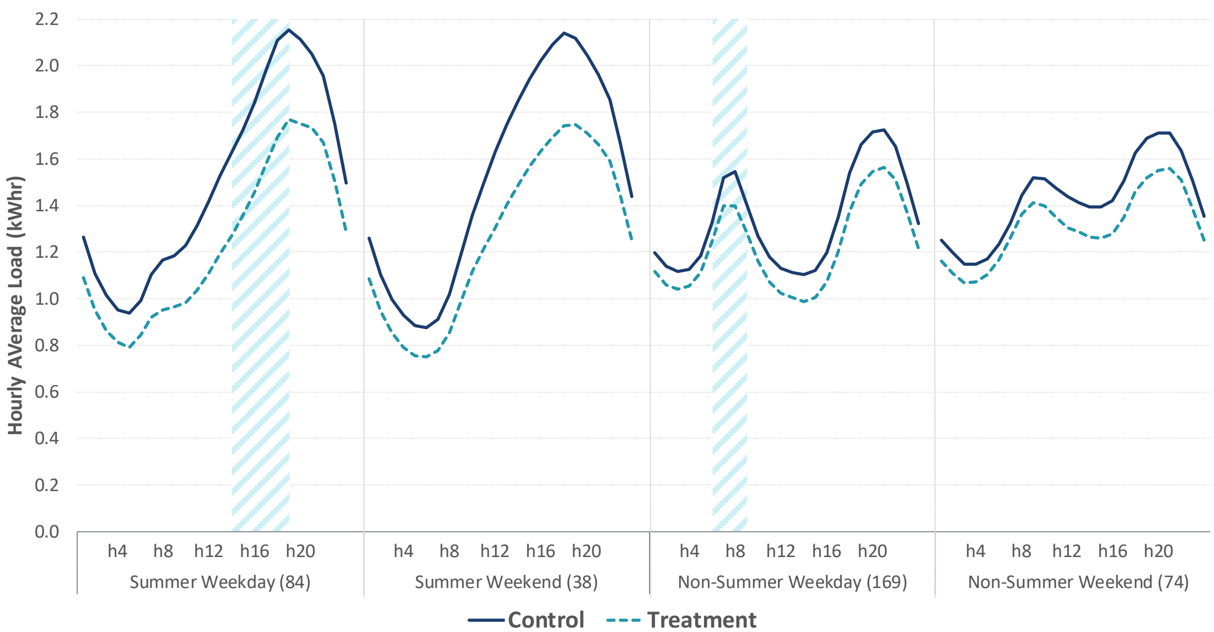
For example, BGE provided information indicating whether the customer's air conditioning unit (or multiple air conditioning units) is connected to a programmable thermostat that allows for cycling on event days. This variable was the single best predictor of enrollment in BGE's TOU pilot. Similarly, for Pepco and DPL, participation in the direct load control program, which is very similar to BGE's Peak Rewards program, was the single best predictor of participation in the TOU pilots. Other non-load variables that were highly correlated with the participation decision for one or more utility's customers included income measures, previous participation in home energy audits, and enrollment in net metering.[26] Many of these variables indicate a level of engagement with the utility or a willingness to be a more active utility customer. Including these variables in our matching analysis means that our control group is more similar to the treatment group than if we relied on load data alone.

25 Note that the original datasets are hourly; we collapse them into daily period granularity after standard data cleaning procedures.

26 Six of the first seven variables selected by our algorithm when applied to BGE were non-load variables. In addition to the Peak Rewards Air Conditioning variable, these included an analogous Peak Rewards Water Heater variable, the natural log of household income, the Quick Home Energy Check variable, a Home Energy Audit indicator, and the legacy TOU rate tariff.

After completing the matching analysis, we next undertake various diagnostics to assess our success in identifying comparable control groups. The following charts and tables indicate that we were generally successful in achieving the objective of the matching analysis. First, for each utility, we present two graphs. Beginning with BGE, Figure 9 compares the average load profiles of the "treatment" customers in dark blue with the average load profiles of all potential control customers (residential customers who the utility did not approach about the pilot) in light blue. The figure depicts four such average load profiles, one for each combination of season (summer or non-summer) and day type (weekdays and weekends). While the shape of the load profiles of the potential control group is similar to that of the treatment group, the average load is uniformly higher than the treatment group, indicating that there are some substantial differences between the two groups.

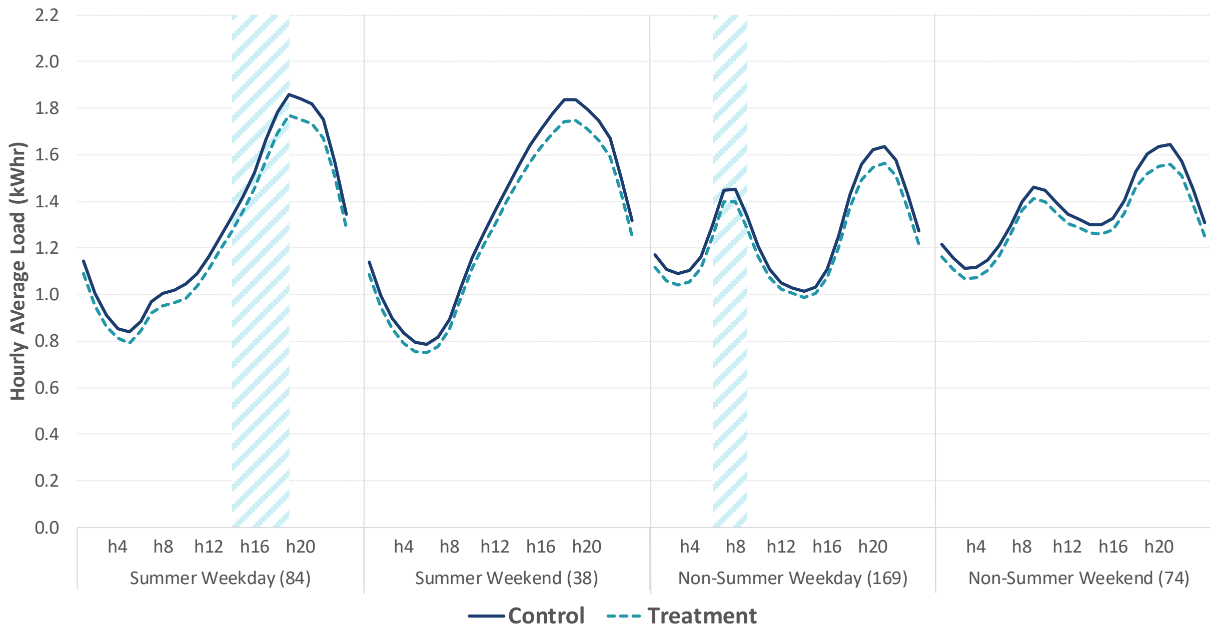
FIGURE 9: BGE AVERAGE LOAD PROFILE, 2018 – UNMATCHED (# OF CONTROL = 398,222)



Note: Numbers in parenthesis indicate the number of days in the period. Only includes customers eligible for the matching process and regression analysis.

Figure 10 instead compares the same treatment customer load profiles (in dark blue) with the average load profiles from matched control customers. While the load profiles are not identical, shifting to the matched control group eliminates the majority of the difference between the treatment group's average load profile and that of the control group.

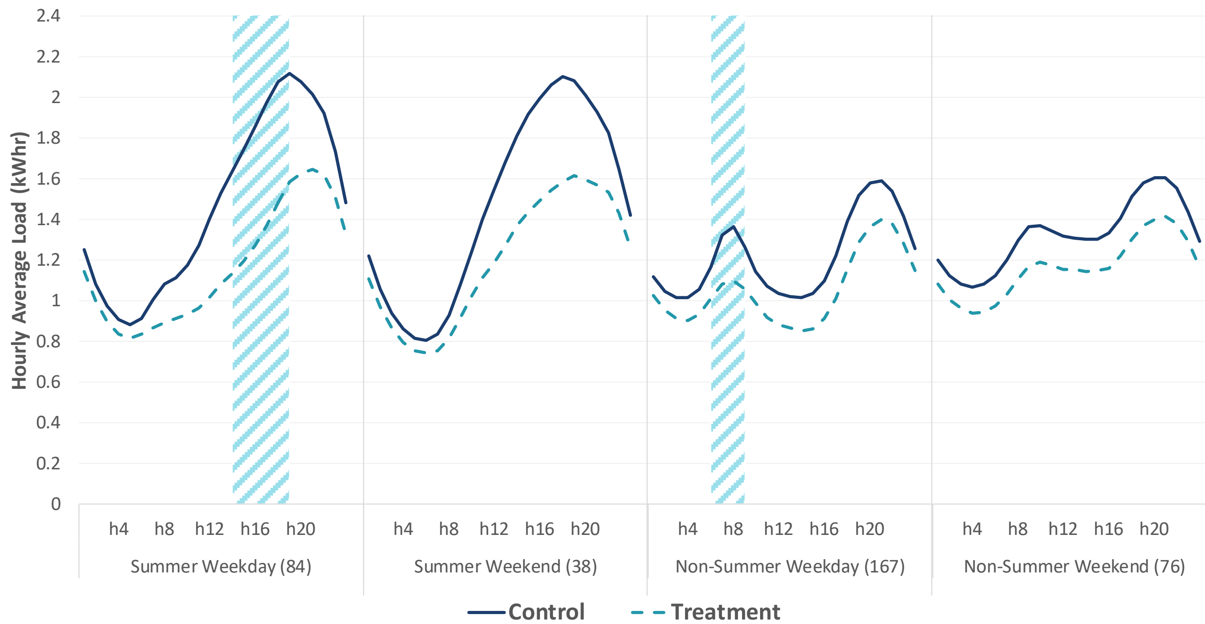
FIGURE 10: BGE AVERAGE LOAD PROFILE, 2018 – MATCHED (# OF CONTROL = 1,614)



Note: Numbers in parenthesis indicate the number of days in the period. Only includes customers eligible for the matching process and regression analysis.

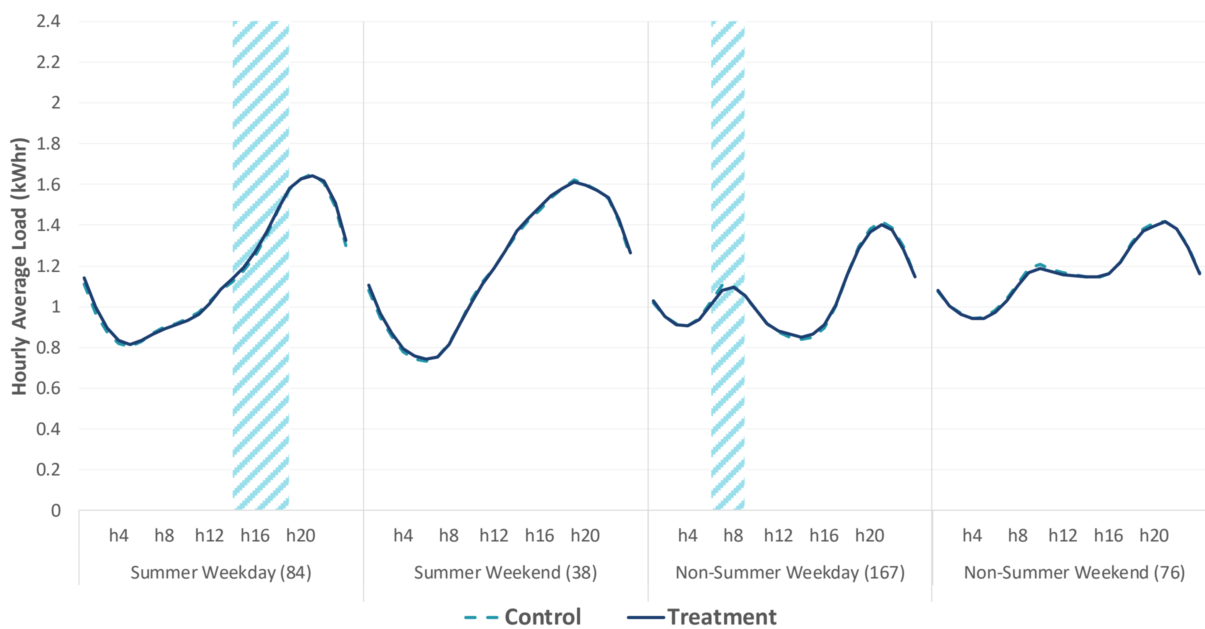
In Figure 11 through Figure 14, we perform the same diagnostic exercise for the Pepco and DPL treatment and control groups. Again, the load profiles of the matched control group are much more similar to those of the treatment group than are the load profiles of the potential control group. In the case of both Pepco and DPL, the average load profiles of the matched control group are almost identical to those of the treatment group, as indicated by the high degree of overlap between the dark blue and light blue lines in Figure 12 and Figure 14.

FIGURE 11: PEPCO AVERAGE LOAD PROFILE, 2018 – UNMATCHED (# OF CONTROL = 14,803)



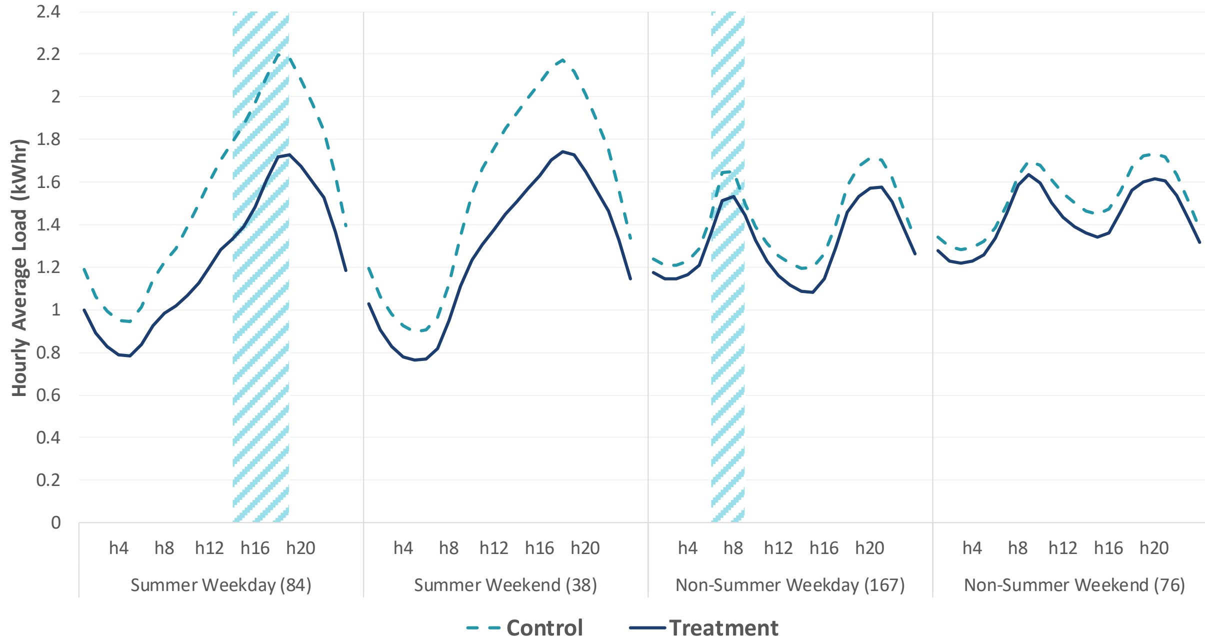
Note: Numbers in parenthesis indicate the number of days in the period. Only includes customers eligible for the matching process and regression analysis.

FIGURE 12: PEPCO AVERAGE LOAD PROFILE, 2018 – MATCHED (# OF CONTROL = 1,716)



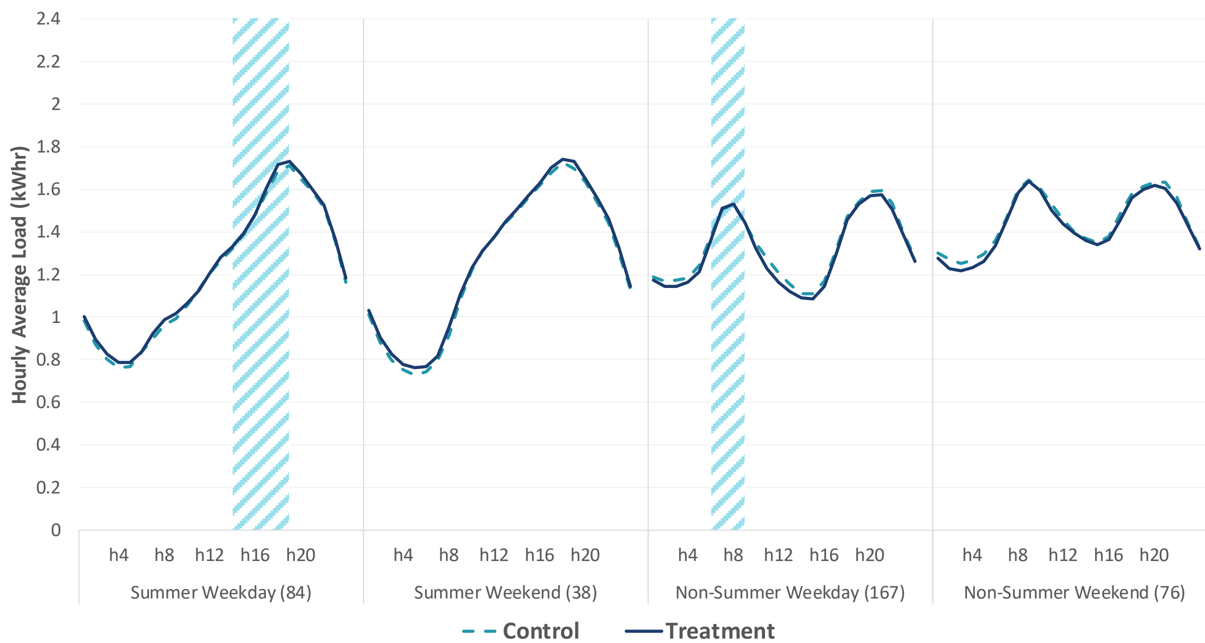
Note: Numbers in parenthesis indicate the number of days in the period. Only includes customers eligible for the matching process and regression analysis.

FIGURE 13: DPL AVERAGE LOAD PROFILE, 2018 – UNMATCHED (# OF CONTROL = 8,050)



Note: Numbers in parenthesis indicate the number of days in the period. Only includes customers eligible for the matching process and regression analysis.

FIGURE 14: DPL AVERAGE LOAD PROFILE, 2018 – MATCHED (# OF CONTROL = 595)



Note: Numbers in parenthesis indicate the number of days in the period. Only includes customers eligible for the matching process and regression analysis.

The inclusion of non-load variables in the matching analysis also has implications for covariate balance with respect to these customer characteristics. The control group that resulted from the matching process is much more similar to the treatment group on these non-load dimensions than is the unmatched control group. The following three figures demonstrate these results for selected non-load variables. For example, in Figure 15, we see that the average number of Peak Rewards Air Conditioner devices was 0.59 per customer for the treatment group, compared with 0.32 for the unmatched control group. In other words, treatment customers were about twice as likely to have a Peak Rewards-enabled Air Conditioner as was a randomly-selected control customer. However, in the matched sample, this difference between treatment and control group is largely eliminated. Figure 15 through Figure 17 present selected control variables for each respective utility, demonstrating significant improvements in the control group balance due to matching. The Appendix A.3 includes extended versions of these tables, with the full set of non-load variables used for each utility's control matching procedure.

FIGURE 15: BGE COVARIATE BALANCE OF SELECTED NON-LOAD VARIABLES

	LMI	Non-LMI	All Treatment	Unmatched Control	Matched Control
Energy Efficiency Measures					
Quick Home Energy Check (QHEC)	18.7%	15.8%	17.3%	9.1%	15.1%
Home Energy Audit	2.4%	5.9%	4.2%	2.0%	4.2%
Net Metering	2.3%	5.1%	3.7%	2.9%	3.8%
# of Peak Rebate Devices					
Air Conditioner	0.51	0.68	0.59	0.32	0.62
Water Heater	0.08	0.09	0.09	0.02	0.08

Note: An extended version of this table, with additional variables, is provided in Appendix A.3.

FIGURE 16: PEPCO COVARIATE BALANCE OF SELECTED NON-LOAD VARIABLES

	LMI	Non-LMI	All Treatment	Unmatched Control	Matched Control
Energy Efficiency Measures					
Net Metering	2.3%	4.5%	3.5%	2.5%	3.9%
Direct Load Control (DLC)	54.0%	54.9%	54.4%	38.6%	53.2%
HVAC Efficiency Program	0.8%	2.7%	1.9%	1.1%	2.0%

Note: An extended version of this table, with additional variables, is provided in Appendix A.3.

FIGURE 17: DPL COVARIATE BALANCE OF SELECTED NON-LOAD VARIABLES

	LMI	Non-LMI	All Treatment	Unmatched Control	Matched Control
Energy Efficiency Measures					
Net Metering	2.7%	4.8%	3.5%	1.6%	4.4%
Direct Load Control (DLC)	36.8%	47.6%	40.9%	19.0%	39.4%
Quick Home Energy Check (QHEC)	2.2%	0.8%	1.7%	1.0%	1.5%

Note: An extended version of this table, with additional variables, is provided in Appendix A.3.

In addition to the balance diagnostics presented here, we also calculate for each pre-treatment variable analyzed here a variety of metrics that measure the balance between the control group and the treatment group.[27] The variables assessed include the non-load variables discussed here as well as 96 load variables, corresponding to average load values for each of 24 hours in each of two seasons and for each of two day types (non-holiday weekdays and weekends/holidays). For all three utilities and for all variables analyzed, the matched control sample performs well on these balancing diagnostics, providing further reassurance that the matched control samples are sufficiently comparable on all observable characteristics, supporting the validity of the results that we describe in the following section.

27 Specifically, we calculate the standardized difference in averages, the logarithm of the ratio of standard deviations, and assessments of the frequency with which an observed value for a given variable in one group (*i.e.*, the treatment group) would be a statistical outlier had it been observed in the control group (and vice versa). The construction of and rationale for these diagnostics are described in detail in Chapter 14 of Imbens and Rubin. The details of the results of these diagnostics as applied to our data are available upon request.

IV. Year 1 Impact Evaluation Results

A. Introduction

In this section, we present the results of our impact evaluation. This section is primarily organized by utility, and by season within each utility subsection. For each utility, we focus on the impact results from our preferred econometric specification and dataset. To test the sensitivity of our main impact results, we also estimate several alternative specifications. While the results of these sensitivity specifications differ somewhat from our primary results, any differences are modest; the sensitivity results are broadly supportive of the same fundamental conclusions from the results presented here. These sensitivity results are presented in the Appendix A.7. In each utility sub-section, we also present a series of "subgroup analyses" that investigate how the peak weekday impact results differ across various periods and customer groups.

After discussing the impact results for each utility, we also investigate whether the main results of the pilot changed after the onset of the COVID-19 pandemic, which undoubtedly had effects on electricity consumption by Maryland customers, as we will demonstrate. Finally, we will discuss the results of our price elasticity analysis.

Before discussing the results, a brief reminder of the expected impacts of TOU rates is appropriate. Broadly speaking, we expect the significant changes in price experienced by TOU customers to induce them to lower their consumption in peak hours, relative to what they would have consumed on a flat rate. At the same time, we generally expect the lower prices faced by TOU customers in the off-peak period to induce additional consumption, again relative to what they would have consumed on a flat rate. The extent to which these predictions are borne out depends on the relative magnitude of the peak to off-peak differential, but also on the price responsiveness of electricity customers. Total consumption can decrease, increase, or remain more or less unchanged, depending on factors including relative prices, the length of the peak windows, and other factors already discussed. In the PC44 TOU pilots, the presence of the behavioral load shaping tool and information provision to the customers add an additional factor that is of particular interest.

For simplicity and clarity, in the exposition that follows, we illustrate the key impacts of our econometric analysis in a graphical format. *In the graphs that follow, the error bars denote the 95% confidence interval of the estimated impact. This provides a sense of the precision of each of our estimates; roughly speaking we can be 95% confident that the true effect lies within the range depicted by the error bar. Relatedly, when the column depicting a point estimate is shaded gray, the 95% confidence interval includes 0, indicating a lack of statistical significance for that impact estimate. In other words, for impact estimates that are "grayed out," we are less than 95% confident that there is a measurable effect of the pilot for that customer group and time period.*

For those readers who are interested in the econometric details, the underlying regression tables are available in the Appendix A.4.

B. Baltimore Gas & Electric

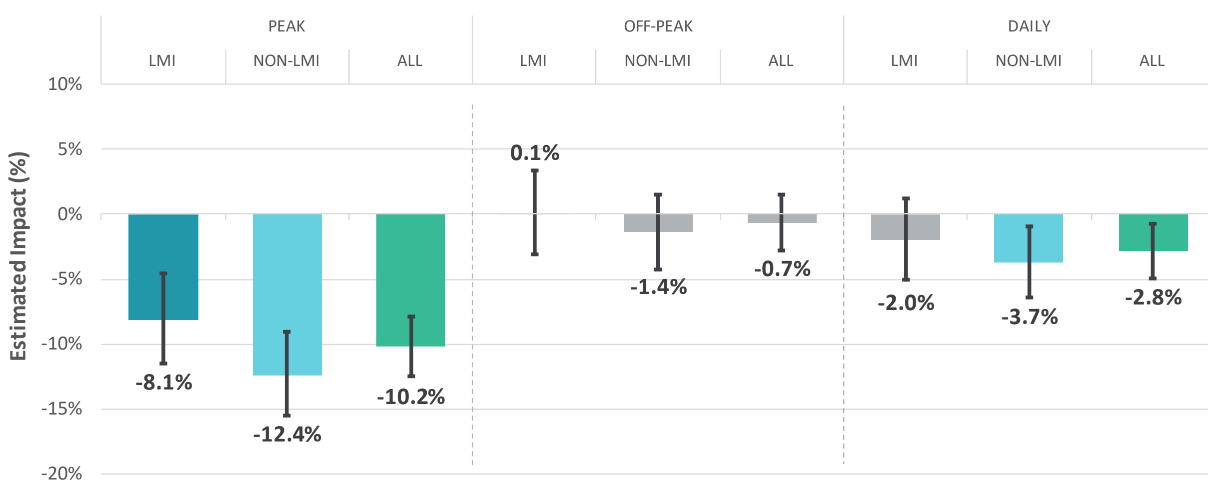
1. Main Impact Results

i. Summer Analysis

We begin our discussion of the primary impact results by presenting the summer results for BGE, which are summarized in Figure 18. Weekday peak impacts across all pilot customers average a 10.2% reduction. This is in effect a weighted average of the LMI peak load reduction (8.1%) and the non-LMI peak load reduction (12.4%). This is an important finding. While the difference between the LMI and non-LMI groups is *weakly* statistically significant, the LMI impact itself is statistically different from zero.[28] These weekday peak impacts are presented in the left-most panel of Figure 18.

At the same time, as the middle panel of Figure 18 indicates, we find little evidence that BGE treatment customers (regardless of household income level) altered their weekday off-peak consumption in response to the TOU pilot. In aggregate, as depicted in the right-most panel of Figure 18, there was some conservation on weekdays. On average, the pilot reduced customers' weekday consumption by 2.8%, an effect which was statistically significant; the daily impact was also significant for non-LMI customers but not for LMI customers.

FIGURE 18: ESTIMATED BGE SUMMER WEEKDAY IMPACTS BY CUSTOMER GROUP AND PERIOD



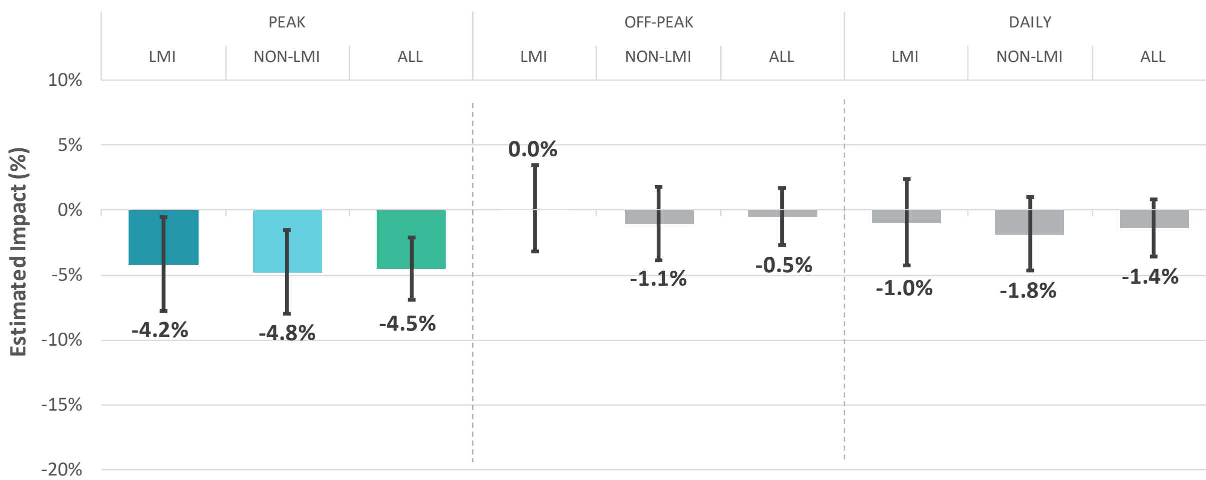
[28] Here, our use of the term weak statistical significance indicates that the null hypothesis (here, that the LMI effects are equal) can be rejected when the significance level, α, is set to 10% but not when it is set to 5% in a two-tailed test. Generally, it indicates a slightly lower degree of confidence that the estimated impacts are meaningful as opposed to the result of statistical noise.

Note: Error bars indicate the 95% confidence interval of the regression coefficients. Grey bars denote statistical insignificance at the 5% level.

Turning to weekend summer impacts for BGE, the results are somewhat surprising. On weekends (including holiday weekdays), all hours are considered off-peak, implying lower rates throughout the day. Economic theory suggests that to the extent that there is a price response, consumption should increase, relative to the counterfactual. Yet as Figure 19 shows, there are statistically significant reductions in "peak" hours (that is to say, weekend hours between 14:00 and 19:00), relative to the control group. This is true across customer groups; furthermore the LMI effect is not significantly different from the non-LMI effect in this time period.

As we will demonstrate later in this Section of the report, this pattern, of weekend load reductions during "peak" hours is repeated across Pepco and DPL as well. These weekend effects could be "spillover effects" from the BLS messaging tool, or customers may be using the same schedule for their smart thermostats during both the weekdays and weekends, resulting in a reduction in peak period usage. In any case, load reductions in "off-peak" weekend hours are either non-existent or too small to be statistically different from zero. Overall weekend daily effects also surprisingly indicate conservation, though these impacts are not statistically significant.

FIGURE 19: ESTIMATED BGE SUMMER WEEKEND IMPACTS BY CUSTOMER GROUP AND PERIOD



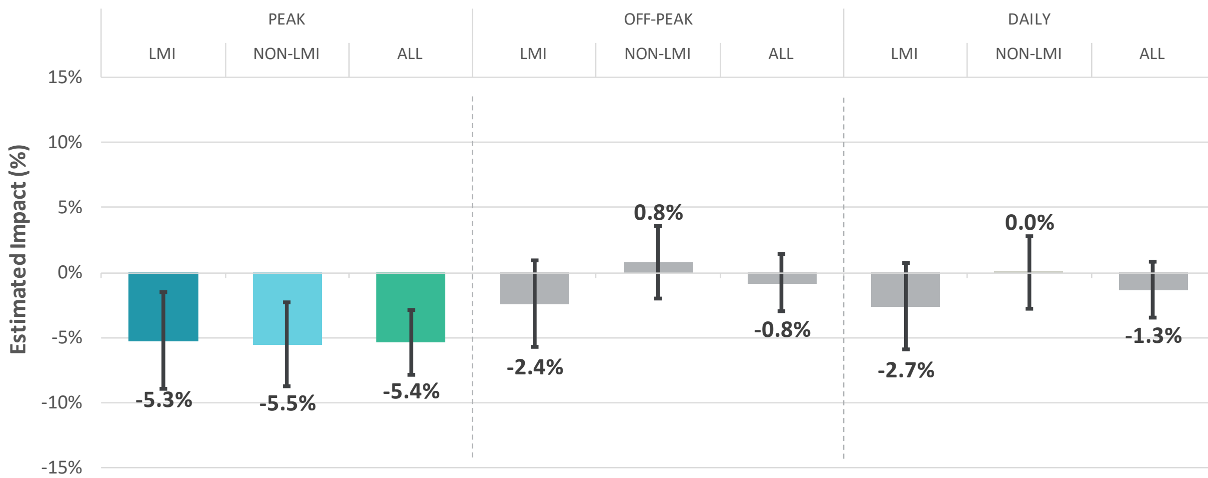
Note: Error bars indicate the 95% confidence interval of the regression coefficients. Grey bars denote statistical insignificance at the 5% level.

ii. Non-summer Analysis

On October 1, 2019, the pilot rates changed, along with the definition of the peak. The peak moved from a five-hour period covering the afternoon and early evening in the summer to a 3-hour window, again on weekdays, covering the hours 6 AM to 9 AM.

In the non-summer period, the weekday peak impacts experienced by BGE pilot customers were lower than those experienced in the summer. The average impact for pilot customers was a 5.4% reduction, as displayed in Figure 20; the small difference between LMI and non-LMI groups is not statistically significant. For both groups, as well as for pilot customers as a whole, the estimated effects are significantly different from zero. However, the off-peak and daily conservation impacts are generally not statistically significant; there are no conclusive effects with respect to either off-peak or overall impact reductions on non-summer weekdays.

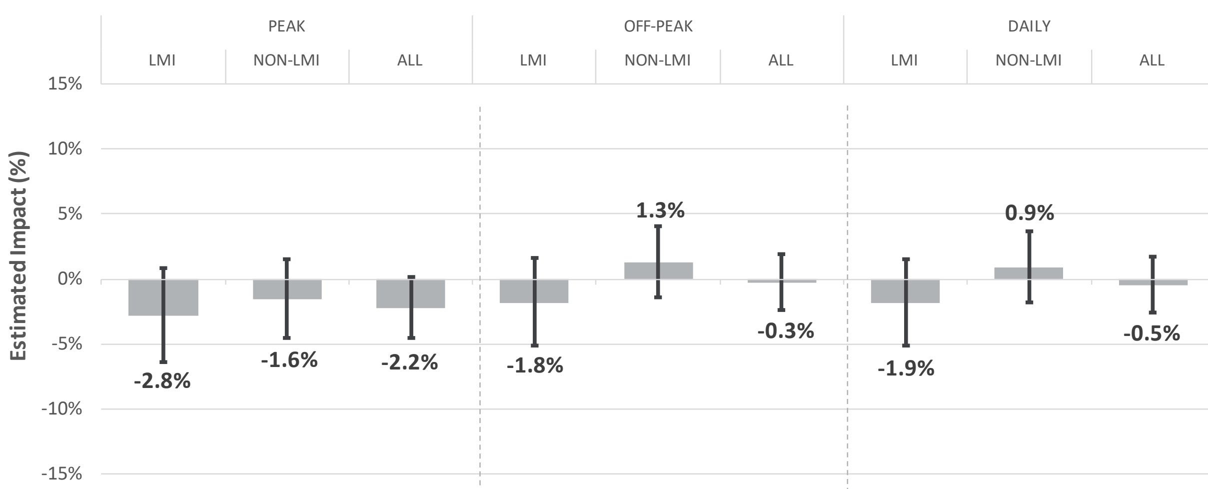
FIGURE 20: ESTIMATED BGE NON-SUMMER WEEKDAY IMPACTS BY CUSTOMER GROUP AND PERIOD



Note: Error bars indicate the 95% confidence interval of the regression coefficients. Grey bars denote statistical insignificance at the 5% level.

As depicted in Figure 21, the estimated coefficients for weekend "peak" hours are suggestive of the weekend spillover effects we identified in the summer period, but are not statistically significant for any of the customer groups. The "off-peak" and overall daily effects are similarly inconclusive on non-summer weekends for BGE customers, regardless of the customer group being analyzed.

FIGURE 21: ESTIMATED BGE NON-SUMMER WEEKEND IMPACTS BY CUSTOMER GROUP AND PERIOD



Note: Error bars indicate the 95% confidence interval of the regression coefficients. Grey bars denote statistical insignificance at the 5% level.

2. Subgroup Analysis

The impact results presented above represent average impacts for the specified period (*e.g.*, summer weekday peak hours) and customer group (*e.g.*, NEM customers). In order to understand better how these impacts vary along other observable dimensions, we estimate a series of additional regressions. In each of these extended analyses, we allow the estimated impacts to vary with some observable factor. This allows us to conduct formal statistical tests for different responses by different groups of customers or on different types of days. We conduct these analyses for weekday peak impacts, as that is the period with the largest estimated impacts and therefore is the most likely to reveal statistically significant differences among various subgroups. The following discussion refers entirely to weekday peak impacts.

The results of these extended analyses are presented in Figure 22. For reference, the top panel in Figure 22 presents the base impacts in each season. We include in the top panel the results of a base specification estimated not in natural logs but in kilowatt-hours, which allows us to include NEM customers.[29] Each of the subsequent panels of Figure 22 presents the results, in terms of estimated impacts, for each of the subgroups relevant to that analysis. In each such analysis, we use red shading to indicate the “base” group. For the base group, statistical significance is measured with respect to the null hypothesis of zero effect. For the other groups, statistical significance is measured with respect to the base group.

[29] Net-metering customers are not included in our primary regression analyses as these customers have negative net loads in some hours, and the natural log of a negative number is undefined.

FIGURE 22: BGE WEEKDAY PEAK IMPACT BY SEASON AND SUBGROUP

	Summer weekday peak	Non-summer weekday peak
Baseline Results		
% (non-NEM customers)	-10.2%***	-5.4%***
kWh (all customers)	-0.164***	-0.0919***
Group by NEM vs. non-NEM (kWh)		
Non-NEM	-0.163***	-0.0891***
NEM	-0.196	-0.160
Group by pre-treatment seasonal usage		
Medium-usage	-11.9%***	-3.3%
Lowest-usage	-3.6%***	0.7%
Highest-usage	-14.5%	-13.0%***
Group by structural winners vs. others		
Others	-9.3%***	-5.0%**
Winners	-10.7%	-5.6%
Group by daily THI		
Medium 50%	-11.1%***	-6.0%***
Coolest 25%	-8.3%**	-4.8%
Warmest 25%	-10.4%	-4.7%
Group by month		
June	-10.6%***	
July	-11.4%	
August	-9.7%	
September	-9.1%	
January		-5.5%***
February		-5.1%
March		-6.9%
April		-6.1%
May		-5.5%
October		-3.7%
November		-5.4%
December		-5.2%
Event day effects		
Non-event day	-10.2%***	
Event day	-12.3%	

Note: The red highlight indicates the base group within each analysis. ***, **, and * denote statistically significant results at the 1%, 5%, and 10% level, respectively. For the base group, statistical significance is measured with respect to zero effect. For the other groups, statistical significance is measured with respect to the base group. For the pre-treatment seasonal usage, customers were divided into three groups based on their average daily pre-pilot load during the respective seasons.

i. Net Metering Customers

As the second panel indicates, pilot customers who are net metering customers experienced larger estimated impacts than non-NEM customers. For example, in the summer, NEM customers reduced their average hourly load by 0.196 kWh while non-NEM customers' reductions were 0.163 kWh.

However, these differences are not significant in either season, perhaps due to the relatively small sample of NEM customers.[30]

ii. Pre-Pilot Customer Usage

We also test whether pilot impacts varied in conjunction with the size of the customer's pre-pilot load. To that end, for each season we divide the set of pilot customers included in the analysis into three evenly sized groups based on their average daily pre-pilot load during the respective seasons. Here, the relative effects vary by season. In the summer, the highest-usage customers saw load reductions of 14.5%, while medium- and low-usage customers saw reductions of 11.9% and 3.6%, respectively. The effect for lowest-usage customers was significantly different from that of medium-usage and high-usage customers.

In the non-summer, the order is unchanged, with the largest load reductions experienced by the highest-usage customers. In fact, the impacts for medium-usage customers are not significantly different from zero, and the estimated impact for low-usage customers is actually positive (though not significant). This suggests that the highest-usage customers, whose load impacts actually exceeded the average summer impact, are driving the overall non-summer results for the BGE pilot.

iii. Structural Winners vs. Others

As explained above, BGE provided targeted customers with information regarding their projected bill savings under the TOU pilot tariff with and without load shifting behavior, based on their 2018 usage. As indicated in Figure 4, enrollment rates were higher among these "structural winners", those who could expect savings without any change in behavior or load consumption patterns. This raised the possibility that a large share of the enrolled pilot customers would not respond to the incentives embedded in the pilot rates. We thus test whether the peak load impact for these automatic winners would differ from the impact for others, who faced potential bill increases if they didn't shift load or reduce consumption.

Our results reveal that there is not a significant difference in the load reductions realized by these two groups. In fact, automatic winners saw slightly larger load impacts in both summer (10.7% vs 9.3% for others) and non-summer (5.6% vs 5.0%), though these differences are not statistically significant.

iv. Weather-Related Variations in Impact

We also test whether pilot customers' ability to reduce their peak load varied with the weather. Specifically, we identified the 25% coolest and 25% warmest days and allowed the peak impacts to vary from those that we measure on days with more typical or average weather, which we label the medium

[30] There are 62 BGE pilot customers with NEM, each of which we matched to a control customer who also has NEM.

50% in Figure 22.[31] We rank days on the basis of THI, which has been shown to be highly correlated with electric load.[32]

In the summer period, we find that the estimated impact on the coolest days (8.3%) is significantly lower than the impact on medium days (11.1%). This may occur because the cooling load is lower on cooler days, leaving less opportunity for conservation or load shifting. On hotter days, the peak load impact (10.4%) is also slightly below that of medium days, but this difference is not statistically significant.

In the non-summer, we do not generally find a large difference in weekday peak load impacts among these groups of days. Medium-weather days saw load reductions of 6.0%, with cooler and warmer days having experienced load reductions of 4.8% and 4.7%, respectively, neither of which is statistically different from the impact on medium-weather days.

v. Impacts by Month

We also test for differences in weekday peak impacts by calendar month. In summer, we designate June as the base month, and find that while the impacts vary in the other three months, the difference between each of those months and June is never statistically significant.[33] In the non-summer months, we designate January as the base month, and fail once again to find significant differences between the January impact and the impact in any other month.[34] We also investigate whether or not the COVID-19 pandemic had an effect on the impacts in a separate analysis, discussed below.

vi. Impacts on Event Days

In conducting our primary analysis, we want to minimize the influence of other existing demand response programs already in place, which could influence our impact estimates. Thus, for example, the primary analysis, and all analysis discussed thus far, excludes peak time rebate and direct load control event days from the data. However, in an extension to our primary analysis, we restore those days to the regression sample in order to test whether the impacts differ. We find that the peak impact (12.3%) is slightly higher than the non-event day impact (10.2%). However, the difference is not statistically significant, perhaps because of the relatively few event days.

[31] We do not include Peak Time Rewards event days in our main analysis, in order to minimize the influence of other existing demand response programs already in place such as peak time rebate and direct load control programs. Thus those event days are also excluded from this and other subgroup analyses, unless specifically indicated otherwise. They are therefore not included when we rank and determine the cutoff points when constructing the interaction terms used in this analysis. There were 3 such days in the summer of 2018 and 2 in the summer of 2019.

[32] Ahmad Faruqui and Sanem Sergici (2011). Dynamic pricing of electricity in the mid-Atlantic region: econometric results from the BGE Experiment. Journal of Regulatory Economics.

[33] Even the difference between the July impact (-11.4%) and September impact (-9.1%) is only marginally significant.

[34] Again, even the difference between the highest monthly impact (March, at -6.9%) and the lowest monthly impact (October, at -3.7%) is only significant at the 10% level.

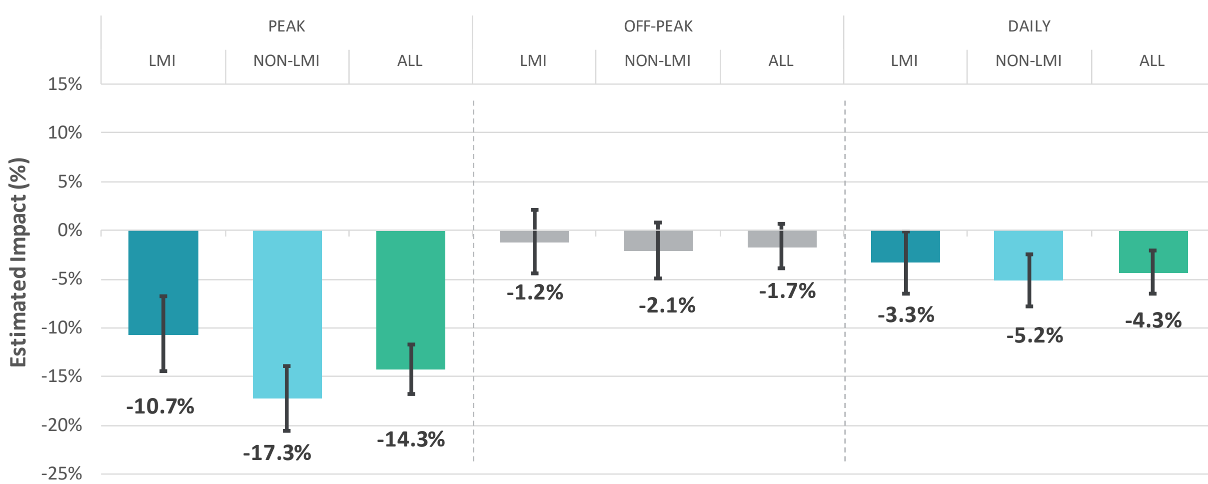
C. Pepco Maryland

1. Main Impact Results

i. Summer Analysis

The summer impact results for Pepco are broadly similar to those presented above for BGE. Beginning with weekday peak impacts, we find that the average pilot customer reduced their peak load by 14.3% relative to the control group. This is the result of a 10.7% reduction by LMI customers and a 17.3% reduction by non-LMI customers. This difference in peak load reductions is statistically significant; we can safely conclude that LMI customers' load reductions were smaller. These results are depicted in the left-hand panel of Figure 23. The center panel of that same figure illustrates that while the point estimates from the weekday off-peak analysis indicate that there were modest load reductions, there is not enough information to separate these effects from statistical noise and reach a conclusive finding. Nevertheless, the sizeable peak reductions mean that the overall impacts, presented in the rightmost panel of Figure 23, are a statistically significant load reduction. Pepco's TOU pilot customers reduced their load by 4.3% in the first year of the pilot; the differences between LMI customers (who reduced their load by 3.3%) and non-LMI customers (who reduced their load by 5.2%) are not statistically significant. However, we can conclude that both groups achieved statistically significant reductions in daily weekday load.

FIGURE 23: ESTIMATED SUMMER WEEKDAY IMPACTS BY CUSTOMER GROUP AND PERIOD

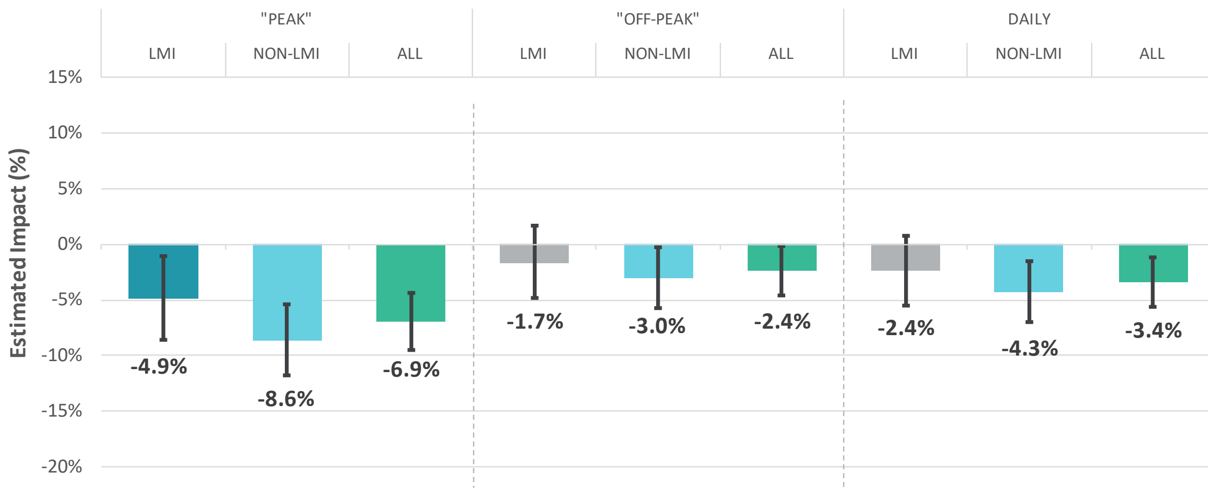


Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars denote statistical insignificance at the 5% significance level.

On weekends, we again find evidence of a "spillover effect" in that Pepco customers reduced their load in the hours that would have fallen in the peak window on weekdays. As shown in the first panel of Figure 24, weekend "peak" load reductions averaged 6.9% for Pepco's pilot customers. These "peak" window spillover effects are statistically significant for both LMI and non-LMI customers.

Interestingly, even in the "off-peak" weekend window, there were small but statistically significant load reductions for non-LMI customers and for the average pilot customer as well. As a result, Pepco pilot customers saw statistically significant weekend conservation effects of 3.4%.

FIGURE 24: ESTIMATED SUMMER WEEKEND IMPACTS BY CUSTOMER GROUP AND PERIOD

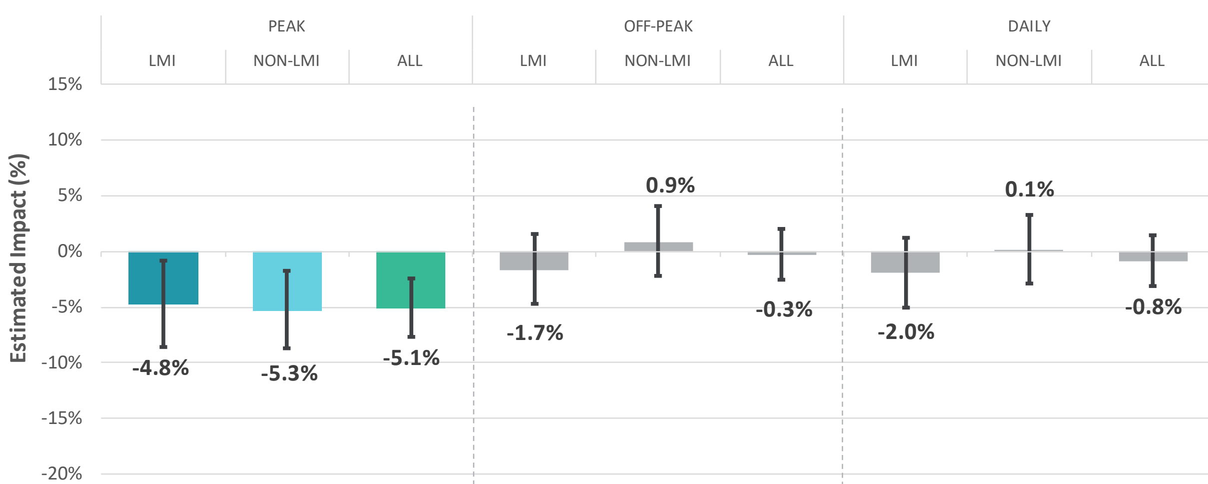


Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars denote statistical insignificance at the 5% significance level.

ii. Non-summer Analysis

In the non-summer, we again find that Pepco pilot customers reduced their load during weekday peak hours, a statistically significant finding. On average, customers reduced their load by 5.1%, which is a smaller reduction than was measured in the summer. The LMI and non-LMI groups experienced similar levels of weekday peak load reductions. In both weekday off-peak hours and for weekdays as a whole, the impacts are not statistically significant. We summarize our findings with respect to Pepco's non-summer weekday impacts in Figure 25.

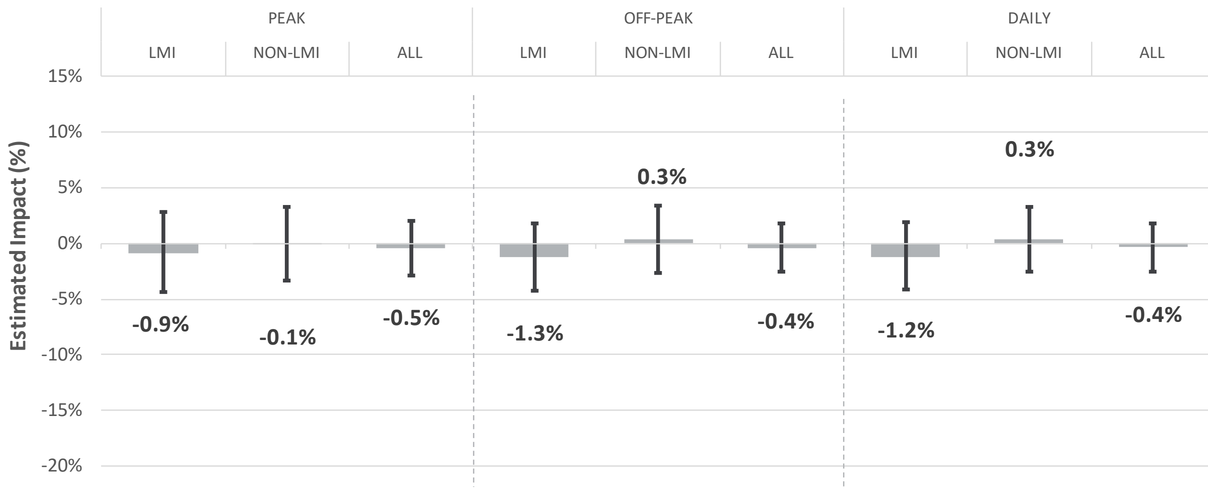
FIGURE 25: ESTIMATED NON-SUMMER WEEKDAY IMPACTS BY CUSTOMER GROUP AND PERIOD



Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars denote statistical insignificance at the 5% significance level.

On non-summer weekends, there are no statistically detectable impacts for Pepco pilot customers, regardless of which period or customer group is being considered. These findings are summarized in Figure 26.

FIGURE 26: ESTIMATED NON-SUMMER WEEKEND IMPACTS BY CUSTOMER GROUP AND PERIOD



Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars statistical insignificance at the 5% significance level.

2. Subgroup Analysis

As reported for BGE, we estimate for Pepco a series of supplementary regressions using interaction terms in order to provide some insight into the extent to which the average weekday peak impacts reported above vary along different dimensions. In what follows, we discuss those results, which we summarize in Figure 27.[35]

[35] Our discussion of the Pepco subgroup analysis is similar to that of the BGE subgroup analysis above. For reference, the top panel in Figure 27 presents the baseline impacts in each season. We include in that top panel the results of a base specification estimated not in natural logs but in kilowatt-hours, which allows us to include NEM customers. Each of the subsequent panels of Figure 27 presents the results, in terms of estimated impacts, for each of the subgroups relevant to that analysis. In each such analysis, we use red shading to indicate the "base" group. For the base group, statistical significance is measured with respect to the null hypothesis of zero effect. For the other groups, statistical significance is measured with respect to the base group.

For further details on the rationale or interpretation of various aspects of the subgroup analysis, please refer to the corresponding BGE discussion above.

FIGURE 27: PEPCO WEEKDAY PEAK IMPACT BY SEASON AND SUBGROUP

	Summer weekday peak	Non-summer weekday peak
Baseline Results		
% (non-NEM customers)	-14.3%***	-5.1%***
kWh (all customers)	-0.183***	-0.0593***
Group by NEM vs. non-NEM (kWh)		
Non-NEM	-0.174***	-0.0564***
NEM	-0.401	-0.1256
Group by pre-treatment seasonal usage		
Medium-usage	-14.8%***	-5.6%**
Lowest-usage	-12.1%	1.8%**
Highest-usage	-15.8%	-11.0%*
Group by structural winners vs. others		
Others	-13.6%***	-9.3%***
Winners	-14.6%	-2.9%**
Group by daily THI		
Medium 50%	-15.2%***	-5.0%***
Coolest 25%	-9.7%***	-7.1%*
Warmest 25%	-17.0%**	-3.0%
Group by month		
June	-13.2%***	
July	-15.8%**	
August	-15.6%*	
September	-12.0%	
January		-6.4%***
February		-6.3%
March		-5.7%
April		-4.3%
May		-2.6%
October		-2.5%
November		-5.6%
December		-7.3%
Event day effects		
Non-event day	-14.2%***	
Event day	-11.7%*	

Note: The red highlight indicates the base group within each analysis. ***, **, and * denote statistically significant results at the 1%, 5%, and 10% level, respectively. For the base group, statistical significance is measured with respect to zero effect. For the other groups, statistical significance is measured with respect to the base group. For the pre-treatment seasonal usage, customers were divided into three groups based on their average daily pre-pilot load during the respective seasons.

i. Net Metering Customers

The point estimates for net metering customers indicate that the peak load impacts associated with the pilot were much higher than for non-NEM customers. For example, our results indicate that NEM customers reduced their load by 0.401 kWh/hour in the summer weekday peak, compared to 0.174 kWh/hour for non-NEM customers. However, the difference is not statistically significant in either the summer or non-summer. This is likely an artifact of the relatively small sample size of NEM pilot customers.[36]

ii. Pre-Pilot Customer Usage

After using pre-pilot load to identify the heaviest and lightest users in each season, we also explore whether the weekday peak impacts varied in conjunction with usage by allowing for separate impact estimates for low users, medium users, and high-usage customers. In the summer, the differences were small in magnitude and not statistically significant, as the estimated impacts range from 12.1% to 15.8% across the three groups. In the non-summer, there was a wide range of impacts. While medium-usage customers saw load reductions of 5.6%, the lowest-usage customers saw load *increases* of 1.8%, a difference that is statistically significant.[37] On the other hand, the highest-usage customers saw load reductions of 11%, a difference (relative to the medium group) that is statistically significant at the 10% level.

iii. Structural Winners vs. Others

We also test whether the "structural winners" – those who could expect bill increases on the PC44 TOU rate without changing their load levels or patterns – nevertheless saw peak impacts. In the summer, we find that the load impacts of the two groups are statistically indistinguishable, as structural winners saw peak load reductions of 14.6% while other enrollees saw peak load reductions of 13.6%. In the non-summer, on the other hand, structural winners' load reductions (2.9%) were significantly smaller than those of other enrolled customers (9.3%).

iv. Weather-Related Variations in Impact

The pilot's weekday peak impacts varied with weather conditions, especially in the summer. Employing the same interaction term-based approach described above, we find that for Pepco, the weekday peak impacts in the summer increased with the temperature. On medium-THI days, the impact was a 15.2% reduction. However, on cooler days the reduction was smaller, at 9.7%, while on the warmest days, the reduction was larger, at 17.0%. Both the cool-day impact and the warm-day impact are significantly different from the medium-day impact. In the non-summer, differences were not as stark. The impact on medium-THI days was 5.0%, and the impact on cool days was 7.1%. The difference between the two is only marginally significant, and the impact on warmer non-summer days was similar to that of the medium-THI days.

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36 For example, only 53 of the 1,247 pilot customers included in the summer regression for this NEM subgroup analysis were NEM customers.

37 This 1.8% load increase is not statistically different from zero either.

v. Impacts by Month

We also identify some differences in weekday peak impacts by month, but only in the summer. June and September had slightly smaller reductions, at 13.2% and 12.0%, respectively. July and August had slightly larger reductions, at 15.8% and 15.6%, respectively. The July and August differences are significant and marginally significant, respectively, relative to the baseline effects in June.[38] In non-summer, we do not generally identify statistically significant differences between each month's impacts. The January effect was a 6.4% reduction. While reductions in the other non-summer months ranged from 2.5% to 7.3%, none are significantly different from the January effect.

vi. Impacts on Event Days

Finally, we also test whether the impact of the pilot varies on event days, which are excluded from the primary analysis. Here, when we include the event days in the estimation sample and allow their effects to differ from non-event days, we find that the reduction (11.7%) was somewhat smaller than the non-event day reduction (14.2%), and that the difference is marginally significant. This is in line with expectations, as control customers also have increased incentives to reduce their peak load on event days, relative to non-event days.

D. DPL Maryland

1. Main Impact Results

Below, we present the impact results for DPL. It is important to note that DPL sample sizes for LMI and non-LMI treatments are materially smaller than those of BGE and Pepco. Therefore, some of the impacts we estimate for individual customer groups (LMI and non-LMI) fall short of statistical significance.

i. Summer Analysis

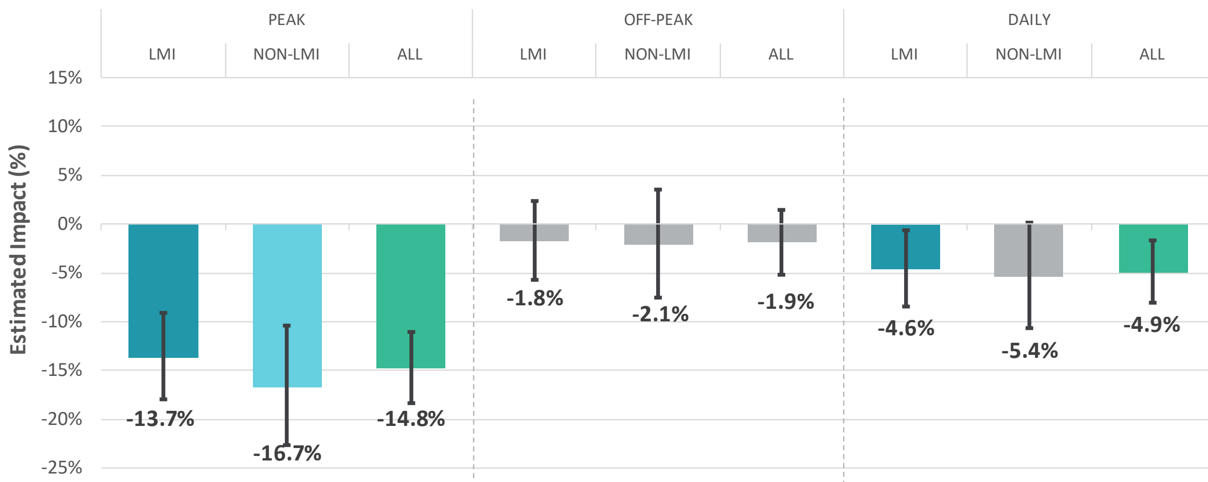
DPL pilot customers exhibit behavior that largely aligns with that of their counterparts at Pepco and BGE. The leftmost panel in Figure 28 shows that non-LMI customers reduced their usage during peak hours by 16.7%, while LMI customers showed a relatively lower impact, with a reduction of 13.7%. The difference between the impacts for the two groups, however, is statistically insignificant. In other words, peak usage behavior for the two groups of customers is statistically indistinguishable from each other. In aggregate, DPL customers reduced peak usage on weekdays by 14.8%, which is higher than the impact observed for both Pepco and BGE. Given that DPL customers were exposed to the largest price signal

[38] Note that these differences in month effects are above and beyond the weather controls we include in all regressions.

(see Figure 3), this finding is consistent with our observations in past pilots which show that higher price signals, on average, produced higher peak reductions.[39]

The point estimates for impacts during the off-peak hours on weekdays, depicted in the center panel in Figure 28, are negative for all customers, implying some reduction during low-price hours. These estimates, however, are statistically insignificant. Therefore, we cannot definitively say that customers reduced load during off-peak hours. Turning to the daily conservation impacts, the right-hand panel in the figure below shows that DPL customers, on average, reduced their load by 4.9% during the first summer of the pilot. While non-LMI customers exhibit a statistically insignificant reduction of 5.4%, it is not statistically different from the 4.6% reduction that the LMI customers observed.

FIGURE 28: ESTIMATED SUMMER WEEKDAY IMPACTS BY CUSTOMER GROUP AND PERIOD



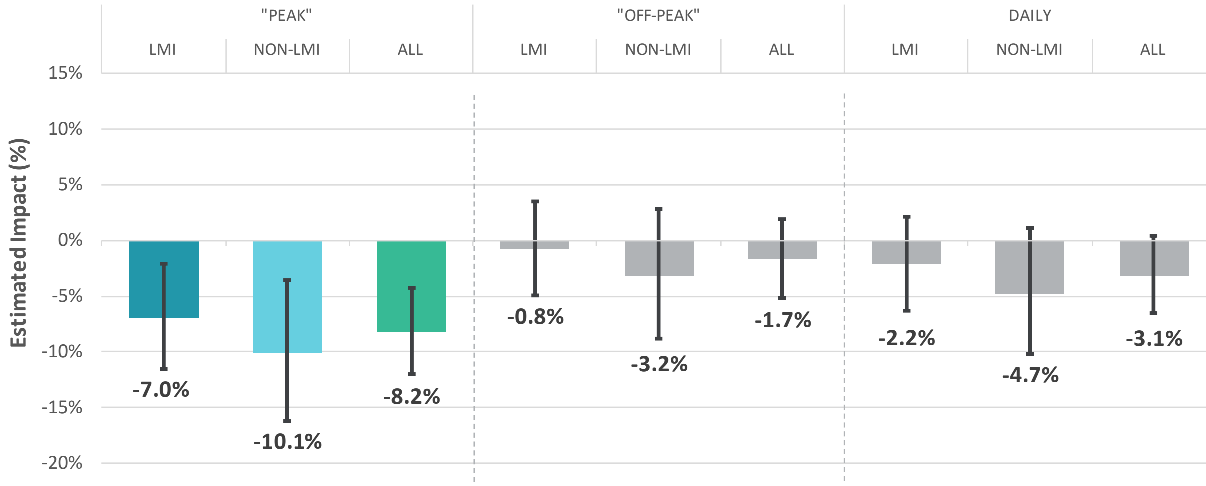
Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars statistical insignificance at the 5% significance level.

The "spillover" effect on weekends noted above for BGE and Pepco is observed for DPL customers as well. The left-hand panel in Figure 29 shows that, in aggregate, DPL's pilot customers reduced their weekend consumption during "peak" hours by 8.2%. The point estimate for non-LMI customers, at -10.1%, indicates a higher impact than for LMI customers, who reduced their usage by 7%. The difference between the impacts for the two groups, however, is statistically insignificant.

Point estimates during weekend "off-peak" hours for DPL pilot customers, LMI and non-LMI alike, are negative but statistically insignificant (center panel in Figure 29). The same is true for weekend conservation impacts, shown in the right-hand panel below. All customers exhibit a negative point estimate, albeit statistically insignificant.

[39] Faruqui, Ahmad, Sanem Sergici and Cody Warner, "Arcturus 2.0: A Meta Analysis of Time Varying Rates of Electricity", The Electricity Journal, Volume 30, Issue 10, December 2017, Pages 64-72.

FIGURE 29: ESTIMATED SUMMER WEEKEND IMPACTS BY CUSTOMER GROUP AND PERIOD



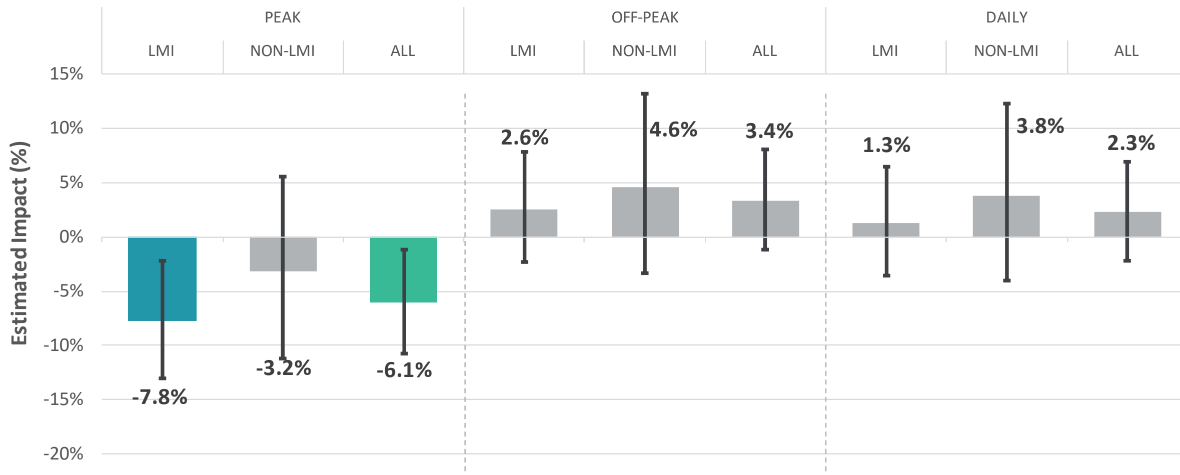
Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars statistical insignificance at the 5% significance level.

ii. Non-summer Analysis

In the non-summer, we measure statistically significant peak reductions on weekdays that are smaller than are those seen in the summer. As summarized in Figure 30, DPL pilot customers reduced their peak weekday usage by 6.1%. Once again, this impact is higher when compared to BGE and Pepco. LMI customers, with a statistically significant peak reduction of 7.8%, appear to be more responsive than non-LMI customers who show a statistically insignificant reduction. The difference between the impacts for the two groups, however, is statistically insignificant. We therefore cannot draw definite conclusions on the difference in their behavior.

DPL pilot customers differ from BGE and Pepco in that the point estimates for off-peak and conservation impacts, depicted in the center- and right-hand panels of Figure 30, respectively, are positive. This implies that pilot customers appear to have increased their usage during off-peak hours and on a daily basis. All estimates for off-peak and conservation impacts, however, are statistically insignificant.

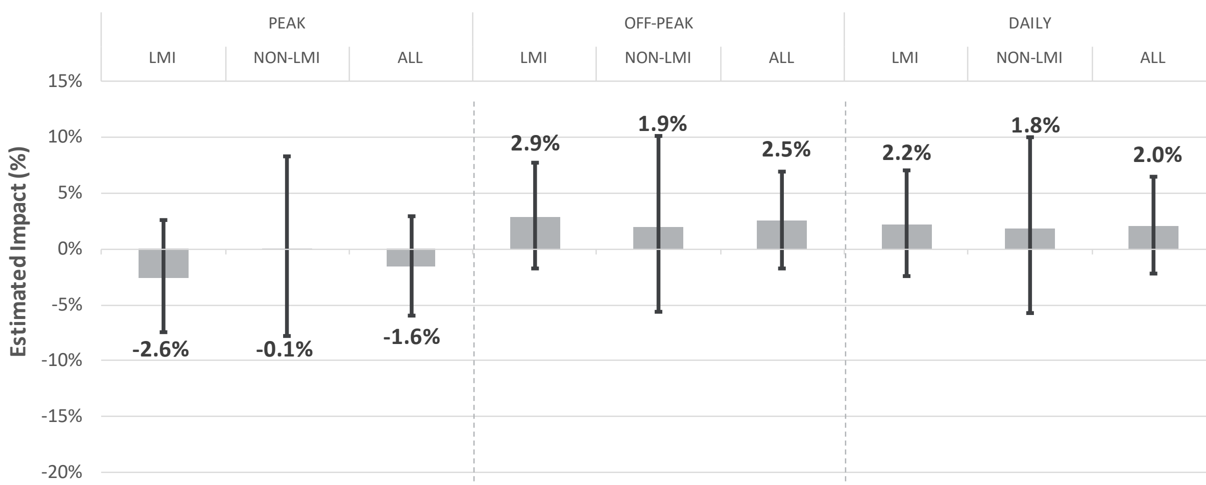
FIGURE 30: ESTIMATED NON-SUMMER WEEKDAY IMPACTS BY CUSTOMER GROUP AND PERIOD



Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars statistical insignificance at the 5% significance level.

Figure 31 shows that impacts on non-summer weekends are statistically insignificant, regardless of the pricing period and the customer group being considered.

FIGURE 31: ESTIMATED NON-SUMMER WEEKEND IMPACTS BY CUSTOMER GROUP AND PERIOD



Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars statistical insignificance at the 5% significance level.

2. Subgroup Analysis

As discussed above for BGE and Pepco, we estimate for DPL a series of supplementary regressions using interaction terms in order to provide some insight into the extent to which the average weekday peak impacts reported above vary along different dimensions. In what follows, we discuss those results, which we summarize in Figure 32.[40]

FIGURE 32: DPL WEEKDAY PEAK IMPACT BY SEASON AND SUBGROUP

	Summer weekday peak	Non-summer weekday peak
Baseline Results		
% (non-NEM customers)	-14.8%***	-6.1%**
kWh (all customers)	-0.234***	-0.0962***
Group by NEM vs. non-NEM (kWh)		
Non-NEM	-0.226***	-0.0997***
NEM	-0.402	-0.0128
Group by pre-treatment seasonal usage		
Medium-usage	-14.4%***	-9.1%**
Lowest-usage	-10.7%	2.0%**
Highest-usage	-19.0%	-10.5%
Group by structural winners vs. others		
Others	-17.6%***	-9.7%**
Winners	-13.4%	-4.0%
Group by daily THI		
Medium 50%	-15.9%***	-6.2%**
Coolest 25%	-10.5%***	-10.4%*
Warmest 25%	-17.1%	-1.0%**
Group by month		
June	-15.8%***	
July	-17.8%	
August	-14.1%	
September	-11.3%**	
January		-8.9%***
February		-11.7%
March		-6.2%
April		-1.2%**
May		1.1%**
October		-4.4%
November		-7.0%
December		-10.1%
Event day effects		
Non-event day	-14.8%***	
Event day	-12.7%	

Note: The red highlight indicates the base group within each analysis. ***, **, and * denote statistically significant results at the 1%, 5%, and 10% level, respectively. For the base group, statistical significance is measured with respect to zero effect. For the other groups, statistical significance is measured with respect to the base group. For the pre-treatment seasonal usage, customers were divided into three groups based on their average daily pre-pilot load during the respective seasons.

[40] Our discussion of the DPL subgroup analysis is similar to that of the BGE subgroup analysis above. For reference, the top panel in Figure 32 presents the baseline impacts in each season. We include in that top panel the results of a base specification estimated not in natural logs but in kilowatt-hours, which allows us to include NEM customers. Each of the subsequent panels of Figure 32 presents the results, in terms of estimated impacts, for each of the subgroups relevant to that analysis. In each such analysis, we use red shading to indicate the "base" group. For the base group, statistical significance is measured with respect to the null hypothesis of zero effect. For the other groups, statistical significance is measured with respect to the base group. For further details on the rationale or interpretation of various aspects of the subgroup analysis, please refer to the corresponding BGE discussion above.

i. Net Metering Customers

We test for differences in behavior among NEM and non-NEM customers. As NEM customers have lower pre-pilot net usage on average, and some negative net load hours, we conduct this analysis in absolute (kWh) rather than relative (%) terms. The results are depicted in the second panel in Figure 32. Point estimates for NEM customers show that they reduced more than non-NEM customers did in the summer (0.402 kWh vs. 0.226 for non-NEM), but that the reduction was lower than that of non-NEM customers in the non-summer. The difference in impacts, however, is statistically insignificant in both seasons. Therefore, we cannot make conclusory statements on any differences in behavior.

ii. Pre-Pilot Customer Usage

We also test for differences in customers' peak impacts based on their level of load consumption. We split customers into three groups based on their pre-pilot average daily load. The fourth panel in Figure 32 summarizes our findings for the three subgroups. In the summer, we do see some differences in the magnitude of reductions, with the lowest usage group having reduced peak load by 10.7% while the highest usage group reduced peak load by 19%. There is no statistical difference in the reduction between the groups, however. In the non-summer, medium usage customers, our base comparison group, reduced usage by 9.1%. The highest usage customers showed no statistical difference in reduction when compared to the medium usage cohort. The lowest usage group appear to have *increased* their usage during peak hours by 2%[41], and this result is statistically different from that exhibited by the medium usage customers.

iii. Structural Winners vs. Others

Similar to the analysis conducted for BGE and Pepco, we also test whether structural winners – customers identified prior to the pilot as beneficiaries of the PC44 pilot rates – responded differently to TOU pricing. Point estimates indicate that these customers reduced peak usage – by 13.4% in the summer and by 4% in the non-summer - less than others (reductions of 17.6% in the summer and 9.7% in the non-summer). The difference in impacts, however, is statistically insignificant for both seasons.

iv. Weather-related Variations in Impact

There is also evidence that the TOU peak impacts as measured in the DPL pilot vary with weather conditions. In the summer, the impacts on the warmest days (a 17.1% reduction) were consistent with those on more typical weather days, when the average reduction was 15.9%. However, the reductions on cooler summer days, at 10.5%, were significantly lower, perhaps because there was less discretionary peak load to reduce or shift on those days.

[41] The 2% peak non-summer weekday impact for the lowest usage customer group is not statistically different from zero.

In the non-summer months, peak impacts also varied with weather. The impact on days with more typical levels of THI was a 6.2% reduction, which is consistent with the average over the entire non-summer. However, on warmer (higher-THI) days, the load reductions were significantly smaller, at 1.0%. In fact, on these days, the load reductions were not significantly different from zero. On the other hand, on cooler days, when the electric heating load would tend to be higher, the peak reduction was higher, at 10.4%. This difference, relative to the medium-THI days, is marginally significant.

v. Impacts by Month

We also identify impacts that vary by month in both seasons. In June, the base comparison group for the summer, customers reduced peak usage by 15.8%. Peak impacts in July and August, while numerically different, were not statistically different from those in June. Peak reduction in September, however, was lower, at 11.3%, and statistically different from June.

In the non-summer months, customers reduced peak usage by 8.9% in January; most non-summer months show no statistical difference in peak reduction relative to January. Customers reduced peak usage by a considerably lower amount (1.2%[42]) in April, and appear to have *increased* their peak usage in May by 1.1%[43], both of which are statistically different from the impacts in January. These effects may be confounded by the onset of restrictions due to COVID-19, which we discuss in the section that follows.

vi. Impact on Event Days

Finally, we also estimate the summer weekday peak impacts for peak event days, which were otherwise excluded from the primary analysis. The point estimates indicate that the TOU impacts were slightly lower on event days (which saw a 12.7% reduction) than on non-event days (where the reduction measures 14.8%), which comports with expectations. However, this difference is not statistically significant.

E. Potential Implications of COVID-19 for the Analysis

1. Changes in Load Profiles

Before discussing the impact of COVID-19 on the TOU pilots, it is first helpful to provide some context for that analysis. Governor Hogan confirmed the first known cases of COVID-19 in Maryland and

42 The 1.2% estimated peak reduction in April is not statistically different from zero.

43 The 1.1% estimated increase in peak usage in May is not statistically different from zero.

declared a state of emergency on March 5, 2020.[44] Over the next week, the state gradually shut down, with school closures announced on March 12th and taking effect on March 16th.[45] As people spent more time at home during the weekday daytime hours (and perhaps to a lesser extent during weekend hours), we would expect load patterns to shift, with increases in midday consumption and some possible offsetting reductions in the early mornings and evenings.

These predictions are largely borne out in the data, as presented in the figures that follow. Figure 33 through Figure 35 display average weekday load profiles for each of the first five months of the calendar year, for each of the past three calendar years, using data from the full pool of potential control customers.[46] Beginning with January and February in Figure 33, we see that while there are differences in the levels of consumption (likely related to weather, as these charts are not weather-normalized), the load *shapes* in January and February of 2020 are consistent with those in January and February from the two preceding years. In particular, all display an early-morning peak followed by a mid-afternoon valley and then a second higher evening peak.

However, beginning in March, we start to see differences in the 2020 load shape relative to the load shapes in the corresponding months for 2018 and 2019, as the daytime load begins to flatten somewhat. This is especially apparent in April, when 2020 midday loads are substantially above the 2018 and 2019 levels, despite the evening peaks being at similar levels. In May, the pattern is less salient due to seasonal shifts in load shapes (and perhaps due to a loosening of the COVID-related restrictions), but the 2020 loads have less of a mid-day "dip" than in 2018 and 2019.[47] The same patterns described here are repeated to varying degrees in the analogous charts for Pepco and DPL.

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44 Cohn, Meredith; Wood, Pamela (March 5, 2020). "First three cases of coronavirus confirmed in Maryland, all in Montgomery County". The Baltimore Sun; State of Maryland, "Declaration of State of Emergency and Existence of Catastrophic Health Emergency – COVID-19". March 5, 2020.

45 Swanson, Ian (March 12, 2020). "Maryland confirms community spread, will close schools". TheHill

46 For this examination of general effects of COVID-19 on load profiles, we focus on this group in order to avoid having the impacts of the PC44 pilots influence this cross-year comparison.

47 Richman, Talia. "Baltimore City extends stay-at-home order; Baltimore, Anne Arundel, Howard counties announce limited reopening". baltimoresun.com.

FIGURE 33: MONTHLY AVERAGE WEEKDAY LOAD PROFILE – BGE CONTROL CUSTOMERS (N = 398,222)

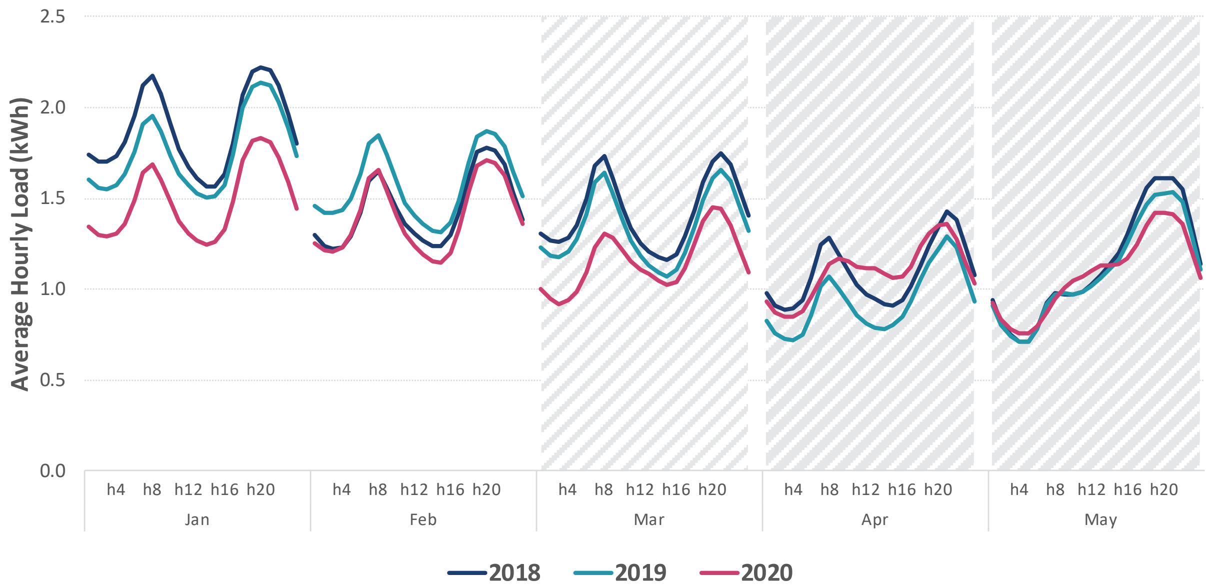


FIGURE 34: MONTHLY AVERAGE WEEKDAY LOAD PROFILE – PEPCO CONTROL CUSTOMERS (N = 14,803)

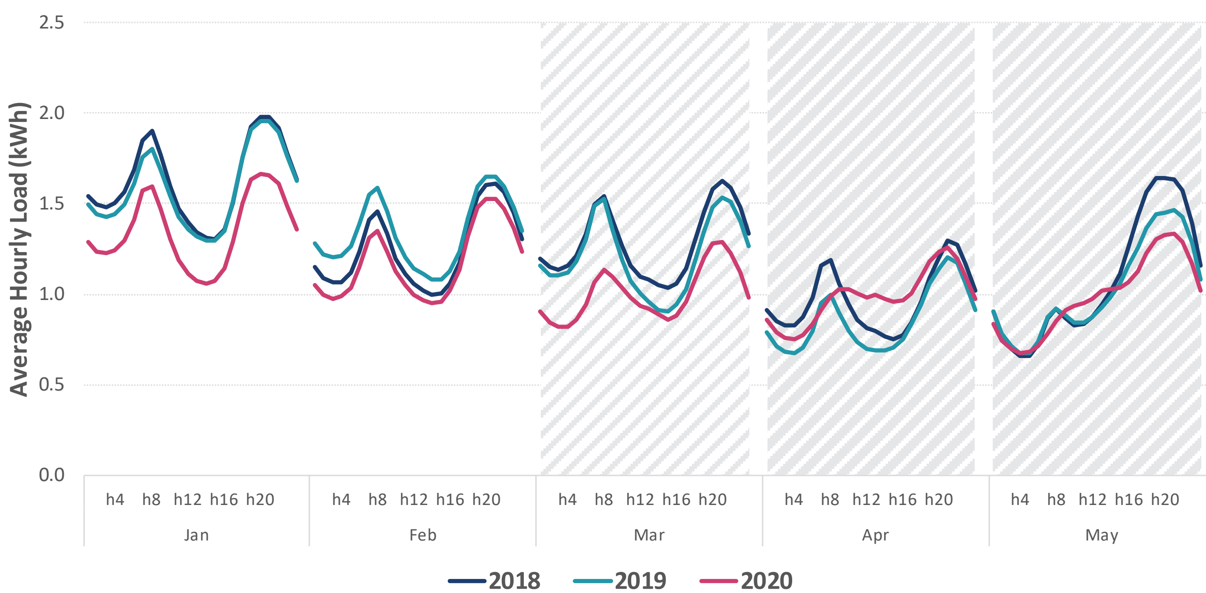
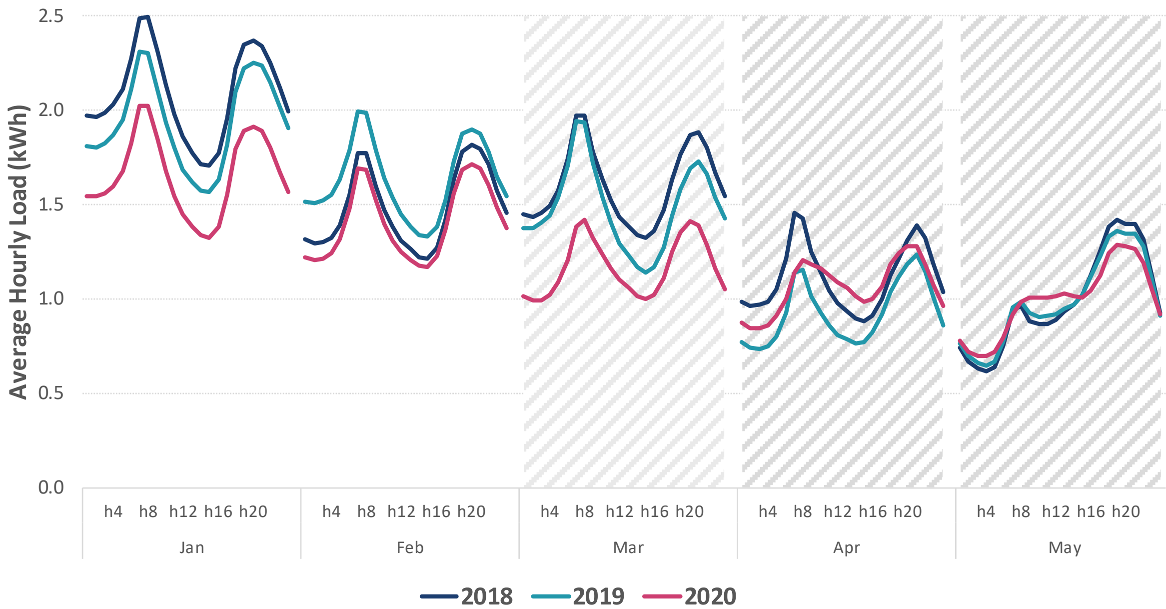


FIGURE 35: MONTHLY AVERAGE WEEKDAY LOAD PROFILE – DPL CONTROL CUSTOMERS (N = 8,050)



2. Econometric Analysis

The changes in load shapes as displayed in the figures above demonstrate clearly that residential customers' load patterns shifted substantially as part of the changes in daily life brought about by the COVID-19 pandemic. We now turn to the question of whether the TOU pilots' impacts differed during the months after the onset of the COVID-19 pandemic. This upheaval to daily life that happened to coincide with the Maryland TOU pilots provides a unique opportunity to understand further the effects of TOU pricing.

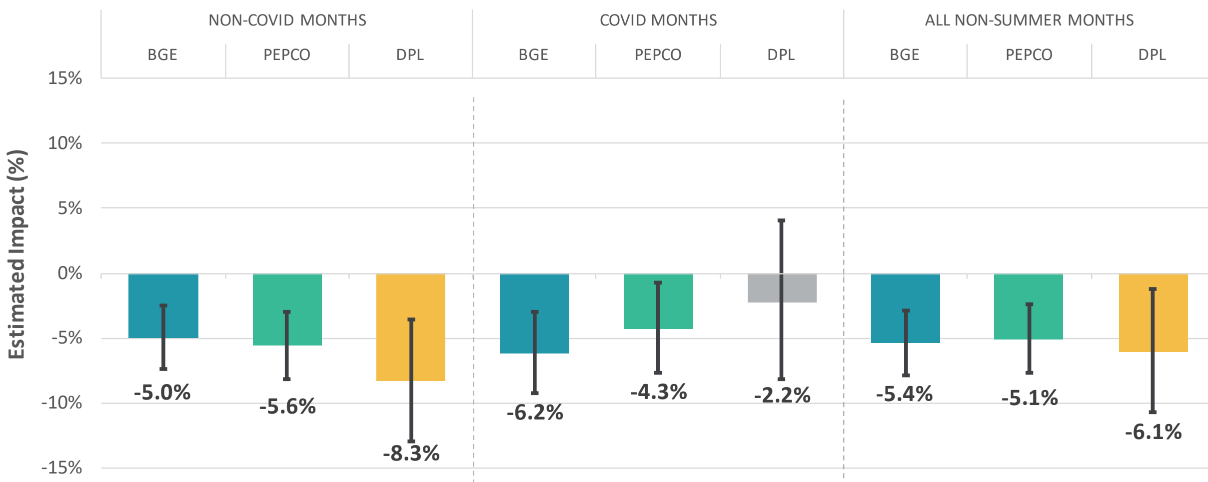
In order to assess the effects of COVID-19 on the TOU impacts, we estimate variants of our primary regression analyses, in which we allow the effect of the pilots to differ during the three months in our sample where COVID-19 had become a factor.[48] We implement this using interaction terms, as described above in Section II.C.1. As with the sub-group analysis, we focus on weekday peak impacts, which we explore for both customer groups (LMI vs. non-LMI) as well as the combined group (all customers).

Looking first at weekday peak effects for all customers, displayed in Figure 36, we find mixed results. *In the case of BGE and Pepco, while the point estimates change between COVID months and non-COVID*

[48] Note that, to the extent that seasonal factors would have caused the pilot impacts to vary in these three months relative to the earlier non-summer months (October through February), we are not able to disentangle those effects from changes brought about by COVID. That said, we do control for: systemic calendar month differences (*e.g.*, those that affect load in March, April, or May in every year) through the inclusion of month dummies; weather differences (through the use of the THI variable, whose impacts we allow to vary by month); and common COVID impacts (*i.e.*, changes to load affecting both control and treatment customers).

months, the differences are not statistically significant. For example, the weekday peak impact for Pepco customers in the first five months of the non-summer was a 5.6% reduction in load. During the COVID months, that decrease was slightly lower, at 4.3%, but the difference in impacts is not statistically significant. However, *there are significant differences in the weekday peak impacts for DPL customers, where the estimated effects shift from an 8.3% reduction in the first five months of the non-summer to a 2.2% reduction that is statistically indistinguishable from zero in the March to May period.* Furthermore, the difference itself is statistically significant.

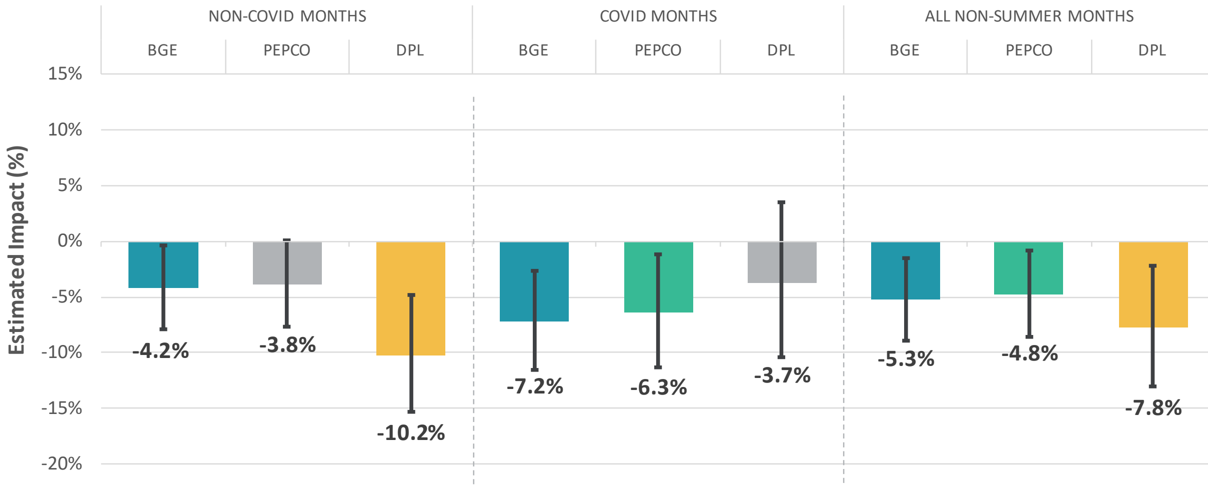
FIGURE 36: COVID-19 EFFECTS – WEEKDAY PEAK – ALL CUSTOMERS



Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars denote statistical insignificance at the 5% significance level.

Turning to LMI customers, the differences in the weekday peak impacts between the non-COVID non-summer months and the COVID months are similar to those above. In particular, while LMI customers show a higher peak impact during COVID months for BGE and Pepco, the difference is statistically insignificant. On the other hand, DPL LMI customers exhibit a reduced peak impact during COVID months that is statistically different from that observed during non-COVID months. These results are depicted in Figure 37.

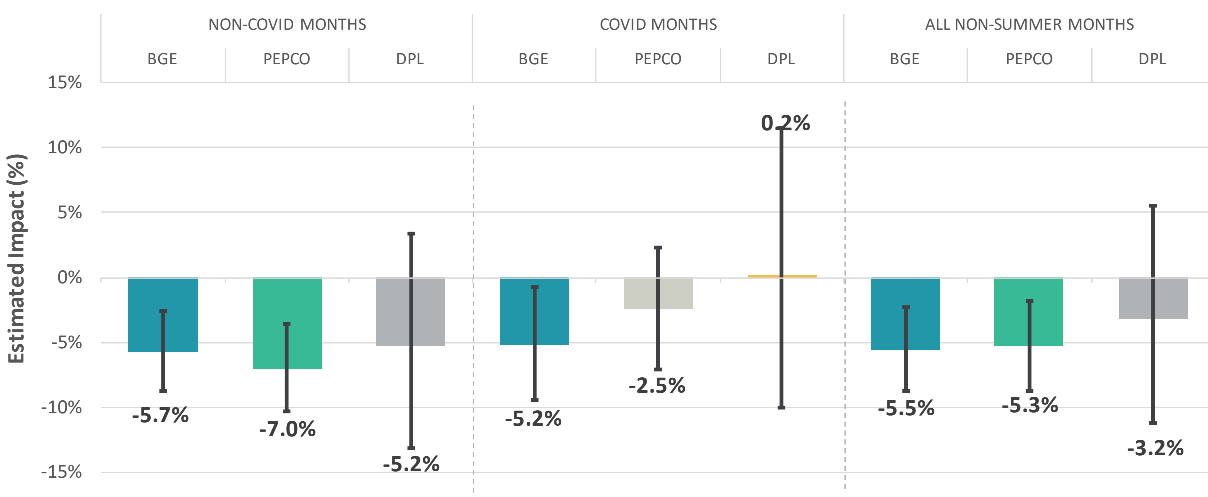
FIGURE 37: COVID-19 EFFECTS – WEEKDAY PEAK – LMI CUSTOMERS



Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars denote statistical insignificance at the 5% significance level.

Finally, we complete our discussion of pandemic-related differences in weekday peak impacts with an examination of non-LMI customers (see Figure 38). In general, non-LMI customers show a lower peak impact during COVID months for DPL and Pepco. However, that difference is only statistically significant in the case of Pepco.

FIGURE 38: COVID-19 EFFECTS – WEEKDAY PEAK – NON-LMI CUSTOMERS



Note: The error bar indicates the 95% confidence interval of the regression coefficient. Grey bars denote statistical insignificance at the 5% significance level.

To summarize, DPL's LMI customers saw significant reductions in their weekday peak impacts during the COVID period, which is also true of Pepco's non-LMI customers. At the same time, weekday peak impacts for BGE customers was largely unchanged.

F. Price Response Results

In addition to the difference-in-differences impacts that are the focus of the results presented to this point, we also estimated a series of regressions that measure the price response of the pilot participants. As discussed in the Methodology section above, for each utility, customer group, and season, we estimate the following two parameters of interest:

- **the substitution elasticity**, which measures the extent to which changes to the ratio of peak to off-peak prices results in changes in the ratio of peak to off-peak consumption on weekdays; and
- **the daily demand elasticity**, which measures the extent to which changes in the daily average price[49] result in changes to the total amount consumed in a day.

We generally expect both elasticities to be negative. This analysis is vital in order to be able to estimate the impact of rates other than those used in the pilot. The results of this analysis are summarized in Figure 39 and Figure 42.

FIGURE 39: SUMMARY OF PRICE ELASTICITY – SUMMER

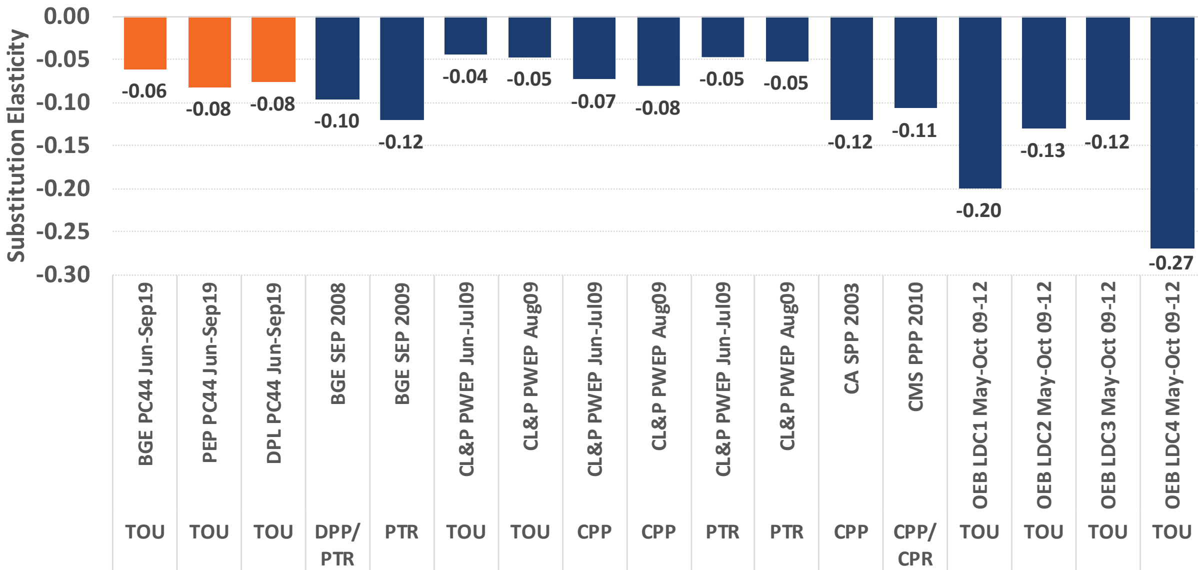
	BGE			Pepco			DPL		
	All	LMI	Non-LMI	All	LMI	Non-LMI	All	LMI	Non-LMI
Substitution elasticity									
Summer	-0.061***	-0.048***	-0.075***	-0.082***	-0.057***	-0.104***	-0.076***	-0.069***	-0.087***
Daily demand elasticity									
Summer	-0.047	-0.017	-0.076	-0.046	-0.100	-0.008	-0.092**	-0.099**	-0.075

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage.

Beginning with the summer, we find that substitution elasticities of LMI customers are in the range of -0.048 to -0.069. Non-LMI substitution elasticities range from -0.087 to -0.104, and the substitution elasticities for all customers ranges from -0.061 to -0.082. In all cases, the substitution elasticities are significant at the 1% level. In Figure 40, we compare the "all customer" summer substitution elasticities from each of the three PC44 pilots to substitution elasticities we have estimated in a variety of other summer pricing pilots with time-varying rates, and find that they are generally consistent with these benchmarks.

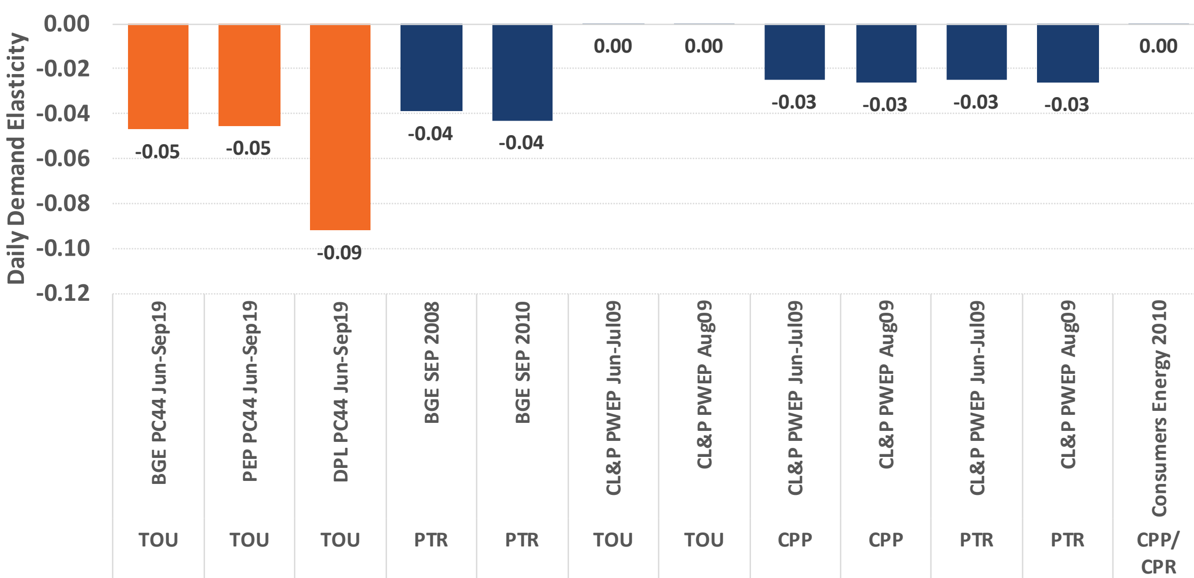
[49] In calculating the daily average price, we focus on the primary components of the bill and thus exclude various administrative charges. We need to weight peak and off-peak prices in order to calculate average daily prices for pilot customers. To do this, we exploit variation at the customer and month levels in consumption patterns; we weight the peak and off-peak price for each customer and month based on that customer's pre-pilot shares for the corresponding month in the pre-pilot period.

FIGURE 40: COMPARISON OF SUBSTITUTION ELASTICITY ACROSS SUMMER PRICING PILOTS



The daily demand elasticities we estimate for the summer period are generally negative but, with the exception of DPL, not statistically significant. In Figure 41, we compare the point estimates for the daily demand elasticities with the corresponding results, again from summer pricing pilots, and find that while the BGE and Pepco estimates are roughly in line with previous demand elasticity estimates, the DPL elasticity is somewhat larger.

FIGURE 41: COMPARISON OF DAILY DEMAND ELASTICITY ACROSS SUMMER PRICING PILOTS



Moving to the non-summer period and Figure 42, we find that substitution elasticities are again negative and for the most part significant. The "all customer" substitution elasticities range from -0.027 to -0.052. For all three utilities, the non-summer substitution elasticities are somewhat lower than those from the summer, suggesting that customers are more willing or able to shift peak load in the summer than in the non-summer. Exclusion of the COVID-19 months does not significantly change the estimated substitution elasticities.

FIGURE 42: SUMMARY OF PRICE ELASTICITY – NON-SUMMER

	BGE			Pepco			DPL		
	All	LMI	Non-LMI	All	LMI	Non-LMI	All	LMI	Non-LMI
Substitution elasticity									
Non-summer	-0.027***	-0.011	-0.043***	-0.028***	-0.018*	-0.037***	-0.052***	-0.058***	-0.042***
Pre-COVID non-summer	-0.023***	-0.006	-0.040***	-0.034***	-0.022**	-0.044***	-0.052***	-0.058***	-0.042***
Daily demand elasticity									
Non-summer	-0.312***	-0.235**	-0.395***	-0.234***	-0.377***	-0.098	-0.241***	-0.102	-0.484***
Pre-COVID non-summer	-0.023	-0.055	0.019	-0.200**	-0.311**	-0.087	-0.122	-0.031	-0.286

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage.

Surprisingly, the non-summer daily demand elasticities that we estimate are substantially higher than those we observe in the literature, which typically fall in the range of -0.01 to -0.15. Exclusion of the COVID-19 months (March-May 2020) substantially reduces these elasticities. The BGE and DPL elasticities become insignificant after the exclusion, while the Pepco elasticity is still significant but lower. One hypothesis is that a later start to the day experienced in many households during the COVID-19 months made it easier for customers to conserve or shift morning load. However, additional data from Year 2 of the pilot may allow us to improve the precision and reliability of these non-summer demand elasticity estimates.

G. Bill Impact Analysis

One key question regarding TOU rates is whether they lead to lower bills. Ideally, we would calculate bill impacts by comparing, for each enrolled customer, their bill in the first year of the pilot to the bill they would have had if they continued on the default “R” rate, also known as their “but-for” bill. Of course, the challenge is we do not observe each customer’s “but-for” consumption.

Instead, in order to calculate bill impacts for the first year of the pilot, we undertake a difference-in-differences approach that relies on the matched control groups. This approach allows us to isolate the “bill impacts” experienced by the treatment customers due to the TOU rates, by netting out the bill changes that were experienced by the control customers for reasons unrelated to the pilot (i.e., due to weather or technology-driven changes to demand). We followed the steps below:

1. Calculate the actual monthly bills for each enrolled customer and their matched control covering two 12-month periods:[50] February 2018 to January 2019 (the last 12 month period before recruitment began); and June 2019 to May 2020 (the Year 1 evaluation period).
2. Divide each customer's annual bill by twelve to calculate an average monthly bill in both the pre-period and the pilot period and calculate for each customer the average percentage change in the average monthly bills between the two periods.
3. Calculate, across customers in each group, the average percentage change in average monthly bills, where there are distinct groups for the treatment and matched control customers for each JU
4. Use a difference-in-differences approach (by subtracting the control group customers' bill impact from that of treatment customers) to calculate each pilot's average bill impact.

Figure 43 summarizes the results of this analysis.

FIGURE 43: AVERAGE MONTHLY BILL IMPACT BY UTILITY

	BGE	Pepco	DPL
Pre-Pilot Avg. Monthly Bill ($)	$116	$121	$139
Pilot Customers	-10.4%	-8.2%	-9.5%
Control Customers	-5.3%	2.0%	-4.0%
Net Impact %	-5.0%	-10.1%	-5.6%

Note: Excludes net-metering customers, customers who were on three-period rates before enrolling in the pilot, and customers who enrolled after May 31, 2019 or unenrolled before June 1, 2020. Details of calculations described in text.

As Figure 43 indicates, before introducing the control group bill impact adjustment, the average monthly and therefore annual savings are comparable across the three JUs, with bill reductions ranging from 8.2% for Pepco to 10.4% for BGE. However, it is of course important to net off the bill increases or reductions experienced by control group customers during the same period. Once we make that adjustment, we see that Pepco TOU customers have enjoyed markedly larger bill impacts (savings of 10.1%) than their counterparts at BGE and DPL (who saw savings of 5.0% and 5.6%, respectively). While Pepco's TOU customers saw bill reductions, its control customers saw modest bill increases. The latter is partly a function of higher rates for Pepco default customers during the pilot period.

Figure 44 reveals some seasonal detail underlying the net impacts presented in Figure 43. Interesting differences emerge, in that at both BGE and DPL, the summer TOU bill impacts took the form of bill increases of 7.5% and 3.6%, respectively, while the non-summer bill impacts were large bill

[50] We exclude net-metering customers, customers who were on three-period rates before enrolling in the pilot, and customers who enrolled after May 31, 2019 or unenrolled before June 1, 2020.

reductions, of 11.4% and 10.1%, respectively. On the other hand, at Pepco, pilot customers enjoyed bill savings in both seasons, with the summer bill impact of 15.5% exceeding that of the non-summer period. These differences are largely driven by differences in the underlying TOU rate structures implemented at each utility.[51]

FIGURE 44: SEASONAL DETAIL OF AVERAGE BILL IMPACTS

	BGE	Pepco	DPL
Summer	7.5%	-15.5%	3.6%
Non-summer	-11.4%	-6.6%	-10.1%
Annual	-5.0%	-10.1%	-5.6%

Note: Excludes net-metering customers, customers who were on three-period rates before enrolling in the pilot, and customers who enrolled after May 31, 2019 or unenrolled before June 1, 2020.

Finally, it is also important to understand whether these bill impacts differed for LMI customers. As summarized in Figure 45, there are some differences, though customers in all groups enjoyed bill savings stemming from the pilot. At BGE, LMI customer savings as a percentage of their bill were somewhat larger than those enjoyed by non-LMI customers. At Pepco and DPL, the converse was true as non-LMI customers saved more than LMI customers.

FIGURE 45: SUMMARY OF ANNUAL AVERAGE BILL IMPACTS BY CUSTOMER GROUP

	BGE	Pepco	DPL
All Customers	-5.0%	-10.1%	-5.6%
LMI Customers	-6.4%	-9.6%	-4.4%
Non-LMI Customers	-3.7%	-10.6%	-7.5%

Note: Excludes net-metering customers, customers who were on three-period rates before enrolling in the pilot, and customers who enrolled after May 31, 2019 or unenrolled before June 1, 2020.

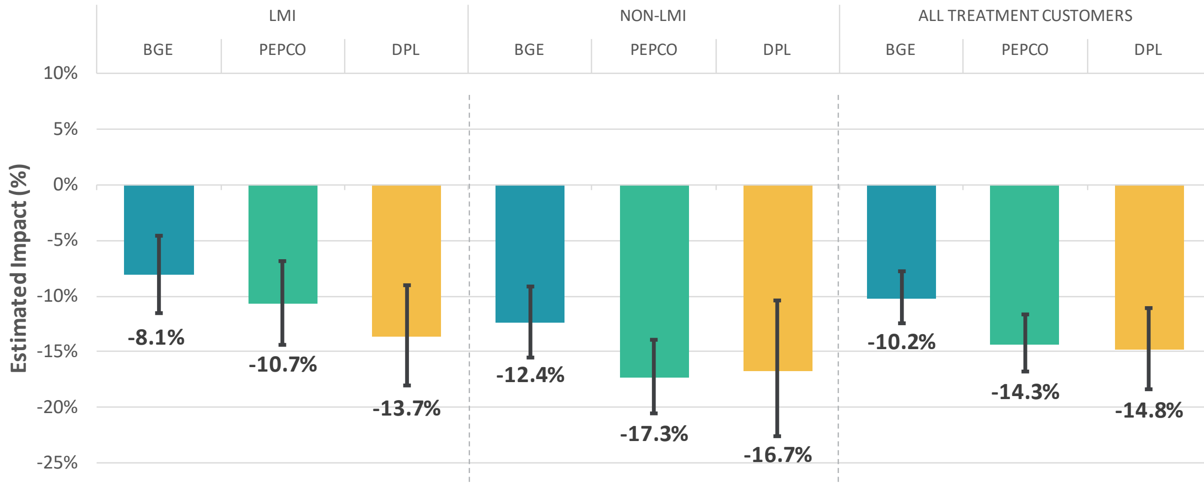
51 The pilot rates for all three JUs were set with the objective of revenue neutrality (assuming no load shifting) over the course of the full year. For both BGE and DPL, this led to rates that were generally not revenue neutral within seasons. Rather, customers moving from the standard "R" rate to the TOU tariff could expect to see dis-savings in the summer, which would then, in aggregate, be offset in the winter. This was not the case for Pepco, where the setting of rates subject to annual revenue neutrality happened to generate rates that were also roughly revenue neutral on a seasonal basis.

V. Summary

The results from the first year analysis of the PC44 TOU pilots reveal that customers respond to higher peak prices by reducing their consumption in both summer and non-summer seasons. This result holds for all three JUs and for both LMI and non-LMI groups. We identified seven key results from the 1st year analysis:

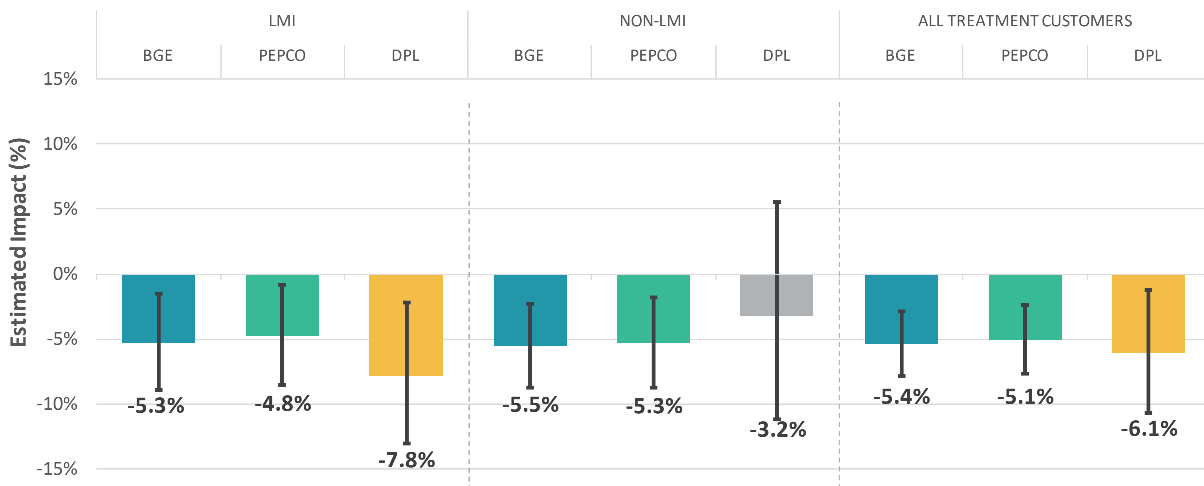
1. Summer peak impacts range from -10.2% to -14.8% and non-summer peak impacts range from -5.1% to-6.1% for all three JUs (see Figure 46 and Figure 47).
2. Daily weekday summer conservation impacts range from -2.8% to -4.9%, while the daily non-summer weekday conservation impacts are statistically insignificant.
3. Peak demand reductions and substitution and daily elasticities estimated from the 1st year analysis of the TOU pilots are consistent with those from prior pilots (see Figure 48 through Figure 50).
4. By including separate treatment cells for LMI and non-LMI customers, the PC44 pilots conclusively showed that LMI customers respond to the price signals just like the non-LMI customers, and in most cases in similar magnitudes.
5. While we expected customers to increase their usage during off-peak hours (including weekends), we find evidence of conservation during weekday off-peak hours and weekends (though impacts are usually insignificant). This result, while unexpected, may be an artifact of the behavioral load shaping tool, which encouraged customers to conserve across all hours. Another potential explanation might be customers' use of a single smart thermostat schedule for both weekdays and weekends.
6. Non-summer peak impacts remained largely similar for BGE and Pepco during months affected by the COVID-19 pandemic, while they were lower for DPL. All JUs revealed larger conservation tendency during COVID-19 months exhibited by large daily price elasticities.
7. Structural winners' peak reductions were comparable to those of others' in most cases, indicating that structural winners still respond to the incentives embedded in price signals.

FIGURE 46: SUMMER WEEKDAY PEAK IMPACTS



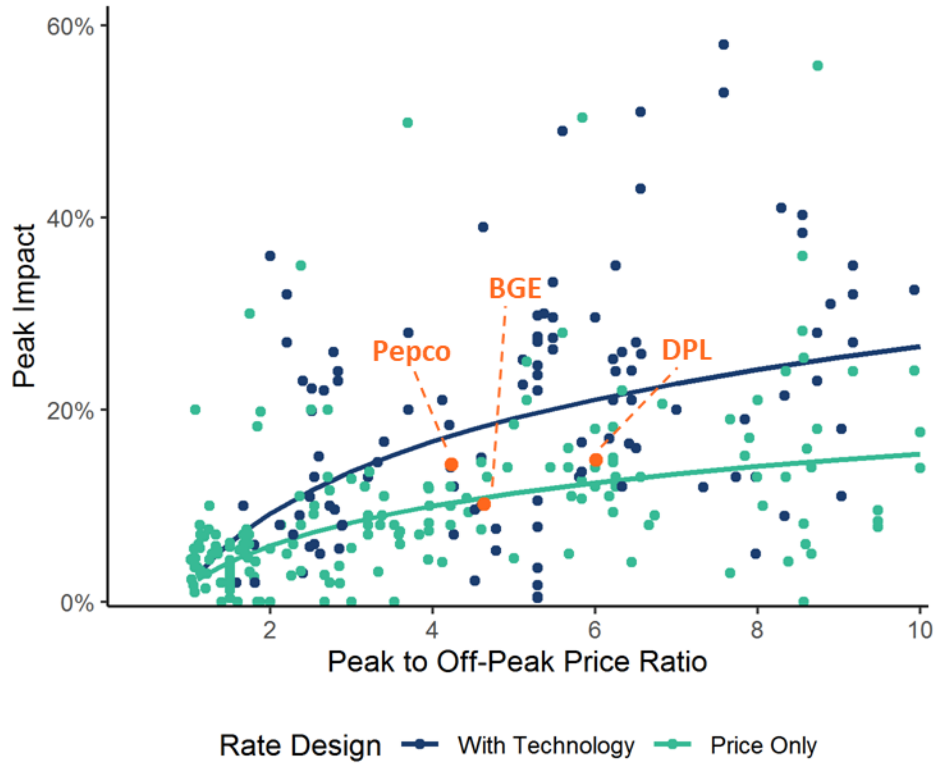
Note: Error bars indicate the 95% confidence interval of the regression coefficients. Grey bars denote statistical insignificance at the 5% level.

FIGURE 47: NON-SUMMER WEEKDAY PEAK IMPACTS



Note: Error bars indicate the 95% confidence interval of the regression coefficients. Grey bars denote statistical insignificance at the 5% level.

FIGURE 48: SUMMER PEAK IMPACTS FROM OTHER TIME VARYING PRICING PILOTS AND PC44 TOU IMPACTS



Note: The PC44 data points are based on the results for all customers (combined LMI and non-LMI effects).

FIGURE 49: PC44 TOU PILOT SUBSTITUTION ELASTICITIES AND THOSE FROM OTHER TIME VARYING PRICING PILOTS

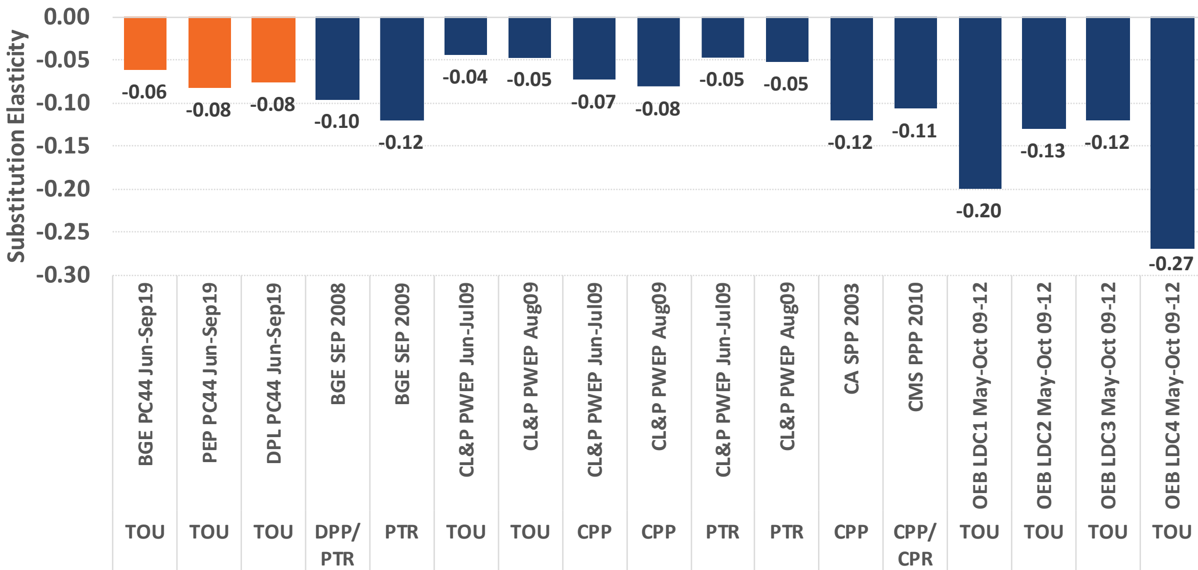
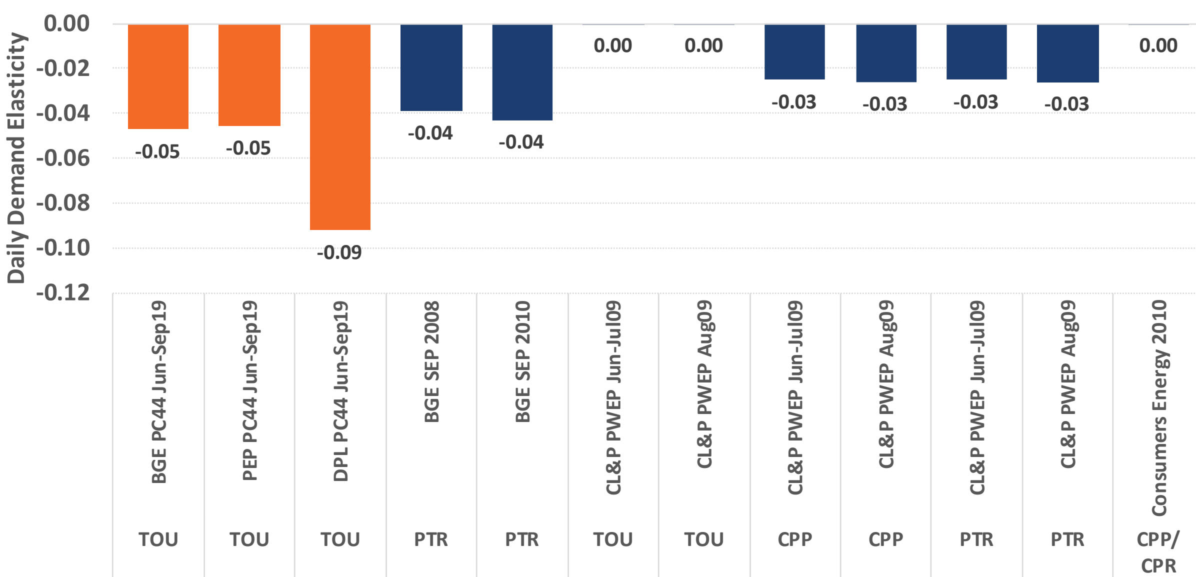


FIGURE 50: PC44 TOU PILOT DAILY PRICE ELASTICITIES AND THOSE FROM OTHER TIME VARYING PRICING PILOTS

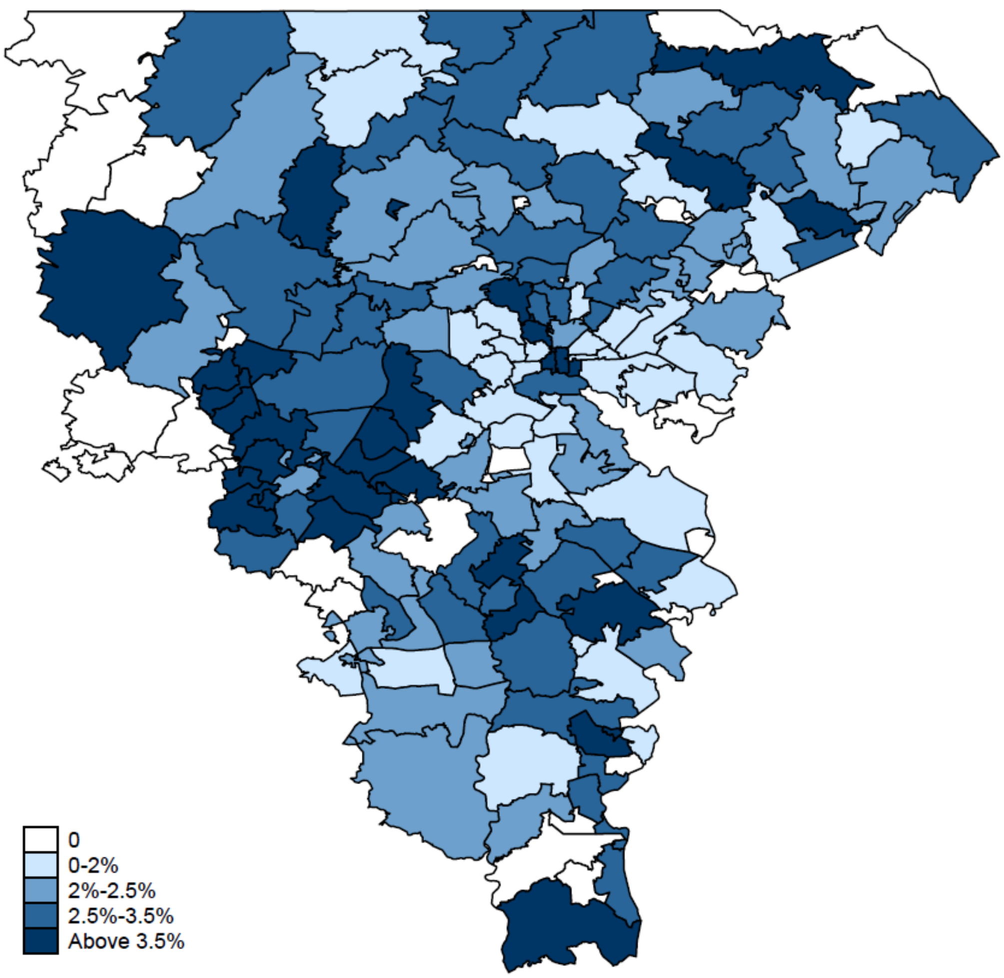


Appendix A – Supplemental Analyses

A.1 Recruitment - Geographical Details

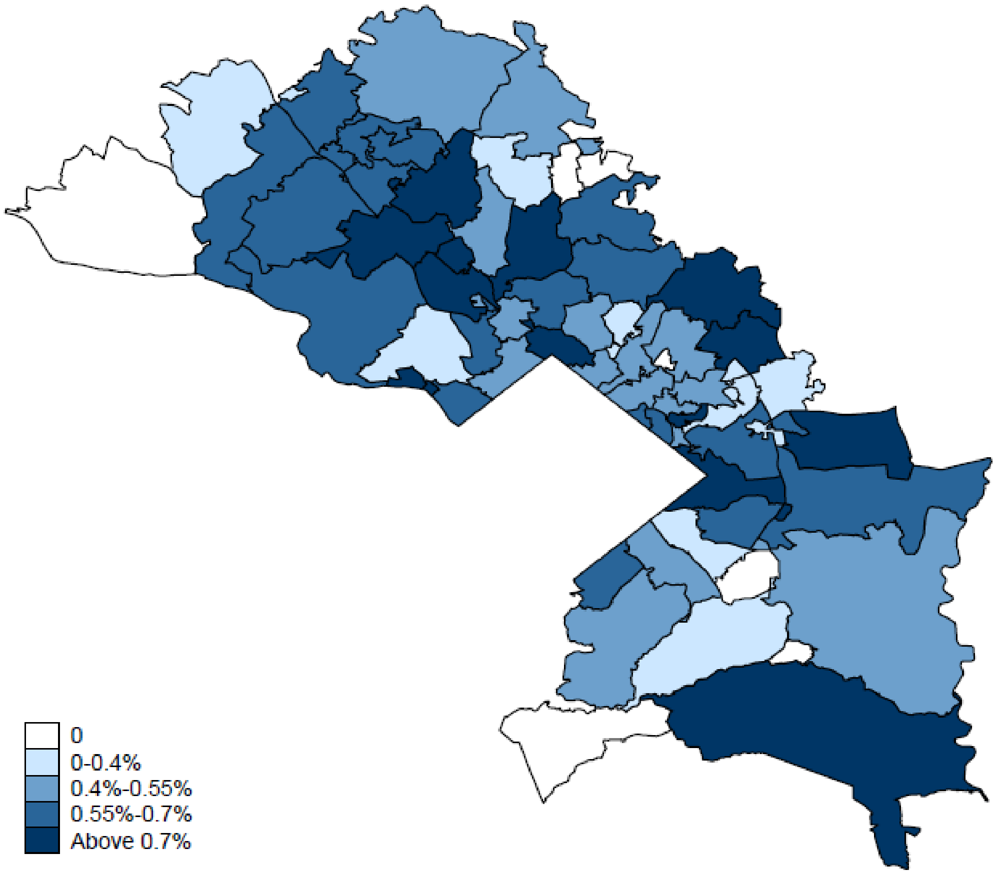
The following maps illustrate variation in the enrollment rate by zip code tabulation areas (geographically contiguous areas that are largely consistent with zip code definitions).

FIGURE 51: BGE ENROLLMENT RATE BY ZIP CODE



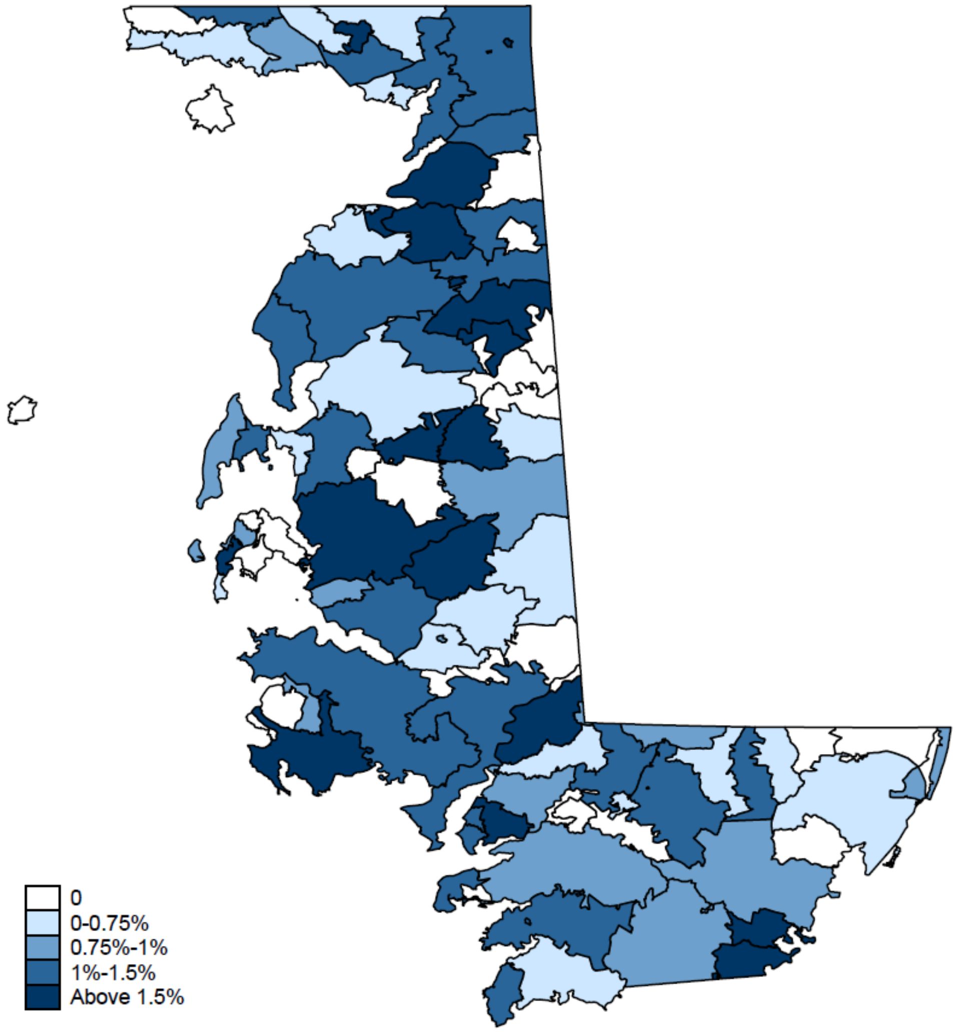
Notes: Enrollment rates by zip code tabulation area (ZCTA).

FIGURE 52: PEPCO ENROLLMENT RATE BY ZIP CODE



Notes: Enrollment rates by zip code tabulation area (ZCTA).

FIGURE 53: DPL ENROLLMENT RATE BY ZIP CODE



Notes: Enrollment rates by zip code tabulation area (ZCTA).

A.2 Data Cleaning and Processing

We applied a series of criteria to exclude customers with data issues. We first removed customers with account or tariff-related issues, as follows:

- Control customers
  - whose account with the relevant JU started after January 1, 2018;
  - who closed their account between January 1, 2018 and May 31, 2020; or
  - who switched rates between January 1, 2018 and May 31, 2020, including volunteer enrollees to the PC44 TOU tariff.
- Targeted non-enrollees
  - who closed account in 2018;
  - who switched to third-party supplier during the recruitment period (between February 1, 2019 and May 31, 2019)
- Enrollees
  - who unenrolled by June 1, 2019; and
  - who unenrolled between June 1, 2019 and September 30, 2019 (excluded from the non-summer analysis only).

Then we implemented the following steps to exclude customers with insufficient load data:

- We set all hours with exactly zero load to missing.
- If a customer's load is missing in one or more hours on a given day, we drop that customer-day.
- Enrolled and control customers are dropped from the analysis if
  - They have incomplete load data on more than 10 days in the summer control (Jun – Sept 2018, 122 days total) or treatment (Jun – Sept 2019, 122 days total) period OR
  - They have incomplete load data on more than 20 days in the non-summer control (Jan – May 2018, Oct 2018 – Jan 2019, 274 days total) or treatment (Oct 2019 – May 2020, 244 days total) period.
- Targeted non-enrollees are dropped from the logit estimate if
  - They have incomplete load data on more than 10 days in summer (Jun – Sept) 2018 (122 days total) OR
  - They have incomplete load data on more than 20 days in non-summer (Jan – May and Oct – Dec) 2018 (243 days total).

A.3 Control Group Balance

Here, we provide additional details from the balance diagnostics we conducted to ensure that the matched control group was similar to the treatment group with respect to observable pre-pilot information. In addition to the load profile comparison provided in the main body of the report, we first present a comparison of treatment customer means for non-load variables with that of both the unmatched (naïve) control group and the matched control group. We then provide maps illustrating the geographic balance between the treatment group and the matched control group. These generally indicate that zip codes with high numbers of pilot enrollees also contain high numbers of matched control customers.

FIGURE 54: FULL COVARIATE BALANCE OF NON-LOAD VARIABLES – BGE

	LMI	Non-LMI	All Treatment	Unmatched Control	Matched Control
Energy Efficiency Measures					
Quick Home Energy Check (QHEC)	18.7%	15.8%	17.3%	9.1%	15.1%
New Home	0.4%	1.8%	1.1%	1.2%	0.9%
HVAC Equipment	2.4%	7.3%	4.8%	5.3%	5.1%
Home Performance with Energy Sta	0.9%	2.8%	1.8%	0.7%	2.4%
Home Energy Audit	2.4%	5.9%	4.2%	2.0%	4.2%
Appliance Recycle	2.3%	2.9%	2.6%	1.6%	2.7%
Appliance Rebate	10.3%	16.9%	13.6%	12.8%	12.8%
Net Metering	2.3%	5.1%	3.7%	2.9%	3.8%
High Bill	8.1%	5.8%	6.9%	6.1%	5.0%
Electric Vehicle TOU	0.0%	0.5%	0.2%	0.0%	0.2%
Residential Optional TOU	7.2%	12.3%	9.7%	7.0%	9.9%
# of Peak Rebate Devices					
Air Conditioner	0.51	0.68	0.59	0.32	0.62
Water Heater	0.08	0.09	0.09	0.02	0.08
Customer Characteristics					
Average Income ($)	$75,004	$135,485	$104,870	$111,352	$122,820
Total Annual Energy (kWh)	6,760	10,543	8,910	10,855	9,269

FIGURE 55: FULL COVARIATE BALANCE OF NON-LOAD VARIABLES - PEPCO

	LMI	Non-LMI	All Treatment	Unmatched Control	Matched Control
Energy Efficiency Measures					
Net Metering	2.3%	4.5%	3.5%	2.5%	3.9%
Direct Load Control (DLC)	54.0%	54.9%	54.4%	38.6%	53.2%
Appliance Rebate	0.8%	3.0%	2.0%	1.3%	1.5%
Appliance Recycling	0.5%	0.3%	0.4%	0.4%	0.2%
Home Performance with Energy Star	0.8%	1.2%	1.1%	0.5%	1.1%
HVAC Efficiency Program	0.8%	2.7%	1.9%	1.1%	2.0%
Quick Home Energy Check (QHEC)	3.3%	1.9%	2.6%	2.2%	3.0%
Customer Characteristics					
Average Income ($)	$99,777	$119,631	$110,717	$113,752	$111,689
Total Annual Energy (kWh)	9,516	9,970	9,778	11,599	9,775

FIGURE 56: FULL COVARIATE BALANCE OF NON-LOAD VARIABLES - DPL

	LMI	Non-LMI	All Treatment	Unmatched Control	Matched Control
Energy Efficiency Measures					
Net Metering	2.7%	4.8%	3.5%	1.6%	4.4%
Direct Load Control (DLC)	36.8%	47.6%	40.9%	19.0%	39.4%
Appliance Rebate	0.5%	2.4%	1.2%	0.8%	0.5%
Appliance Recycle	0.2%	1.6%	0.8%	0.3%	0.9%
Home Performance with Energy Star	0.5%	0.0%	0.3%	0.1%	0.5%
HVAC Efficiency Program	0.5%	1.2%	0.8%	0.5%	0.3%
Quick Home Energy Check (QHEC)	2.2%	0.8%	1.7%	1.0%	1.5%
Customer Characteristics					
Average Income ($)	$72,550	$77,649	$74,487	$75,482	$75,446
Total Annual Energy (kWh)	11,763	10,997	11,472	12,919	11,540

FIGURE 57: BGE GEOGRAPHICAL DISTRIBUTION OF ENROLLED AND MATCHED CONTROL CUSTOMERS

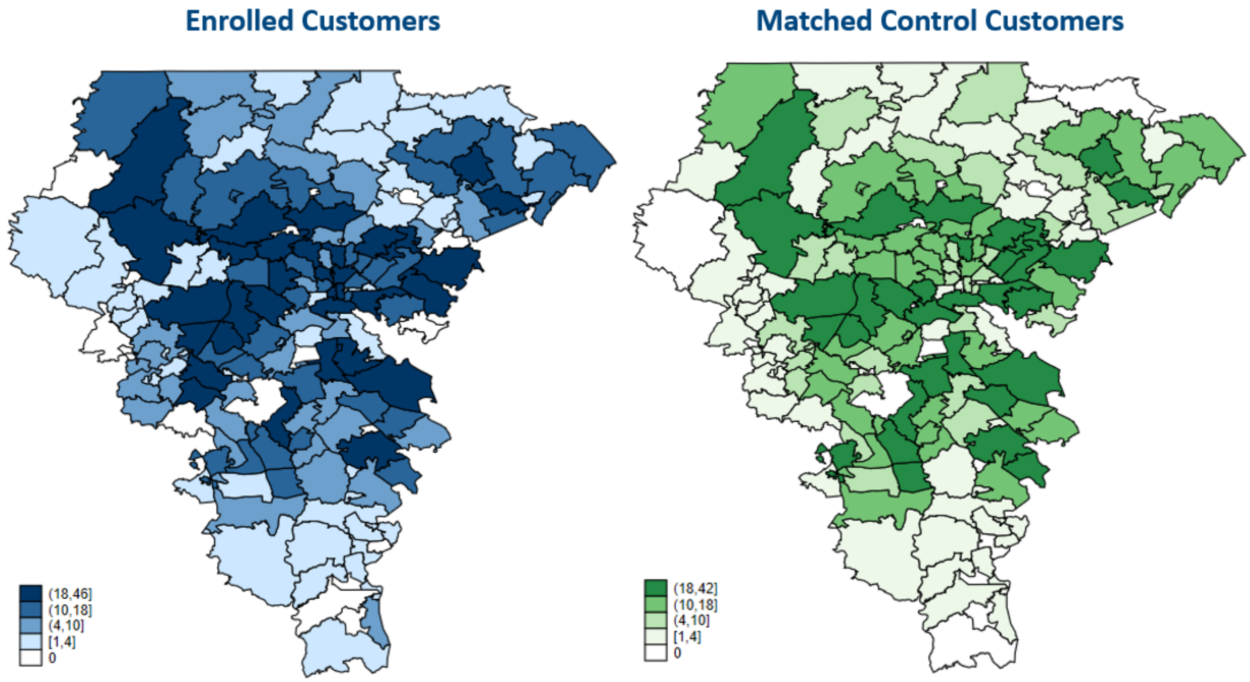


FIGURE 58: PEPCO GEOGRAPHICAL DISTRIBUTION OF ENROLLED AND MATCHED CONTROL CUSTOMERS

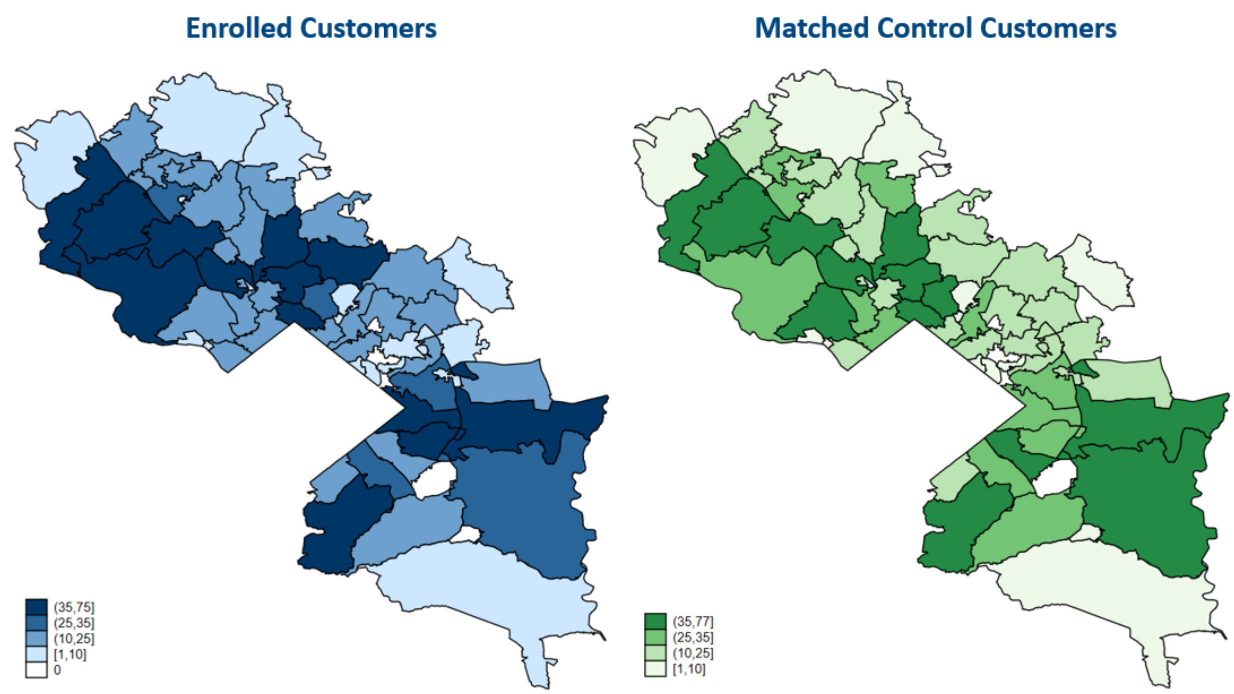
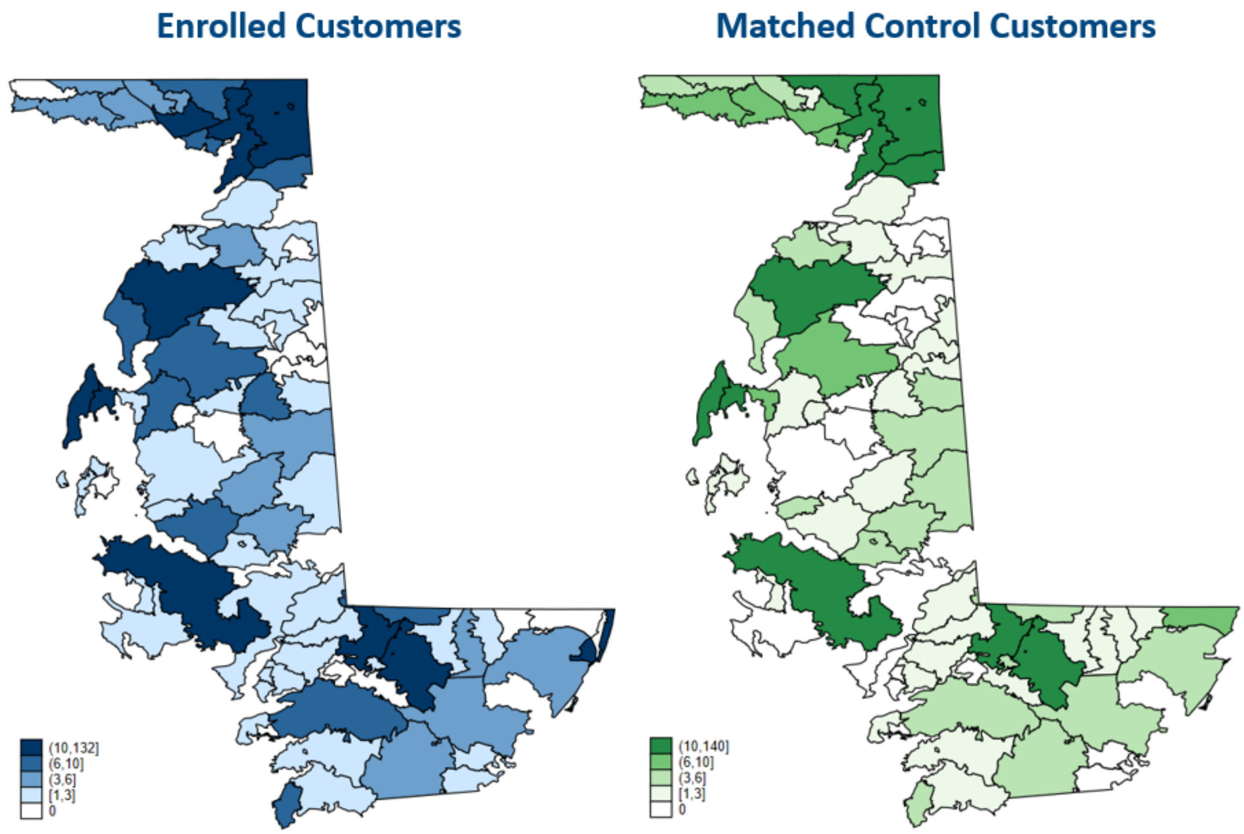


FIGURE 59: DPL GEOGRAPHICAL DISTRIBUTION OF ENROLLED AND MATCHED CONTROL CUSTOMERS



A.4 Regression Tables – Main Impact Results

This section presents detailed regression results for the main impact analyses presented in section IV for each utility and season.

FIGURE 60: BGE SUMMER WEEKDAY REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	0.00308	0.00847	0.0117*	-0.00231	0.000974	0.00548	0.00870	0.0162*	0.0181*
	(0.00807)	(0.00697)	(0.00698)	(0.0113)	(0.00986)	(0.00985)	(0.0115)	(0.00985)	(0.00989)
Pilot x Treatment	-0.108***	-0.00668	-0.0288***	-0.0844***	0.000601	-0.0200	-0.132***	-0.0142	-0.0379***
	(0.0134)	(0.0110)	(0.0110)	(0.0192)	(0.0164)	(0.0163)	(0.0187)	(0.0147)	(0.0147)
July	1.093***	-2.644***	-1.743***	0.910***	-2.878***	-1.987***	1.285***	-2.403***	-1.490***
	(0.233)	(0.185)	(0.192)	(0.333)	(0.263)	(0.275)	(0.326)	(0.259)	(0.268)
August	-1.112***	-4.007***	-3.678***	-0.909***	-3.952***	-3.567***	-1.317***	-4.064***	-3.793***
	(0.197)	(0.161)	(0.166)	(0.281)	(0.230)	(0.239)	(0.275)	(0.225)	(0.229)
September	1.003***	-1.207***	-1.169***	0.958***	-1.275***	-1.232***	1.053***	-1.142***	-1.106***
	(0.158)	(0.125)	(0.125)	(0.225)	(0.177)	(0.179)	(0.221)	(0.176)	(0.176)
ln(THI)	4.360***	2.968***	3.375***	4.290***	2.981***	3.371***	4.433***	2.953***	3.378***
	(0.0497)	(0.0358)	(0.0380)	(0.0705)	(0.0512)	(0.0543)	(0.0701)	(0.0500)	(0.0530)
July x ln(THI)	-0.228***	0.631***	0.420***	-0.184**	0.686***	0.478***	-0.274***	0.573***	0.360***
	(0.0536)	(0.0431)	(0.0447)	(0.0765)	(0.0613)	(0.0639)	(0.0750)	(0.0604)	(0.0623)
August x ln(THI)	0.270***	0.943***	0.864***	0.225***	0.931***	0.840***	0.314***	0.954***	0.889***
	(0.0454)	(0.0376)	(0.0386)	(0.0648)	(0.0538)	(0.0557)	(0.0635)	(0.0525)	(0.0535)
September x ln(THI)	-0.240***	0.274***	0.264***	-0.228***	0.290***	0.280***	-0.254***	0.258***	0.248***
	(0.0366)	(0.0294)	(0.0294)	(0.0522)	(0.0416)	(0.0418)	(0.0513)	(0.0416)	(0.0413)
Constant	-18.80***	-12.77***	-14.49***	-18.60***	-12.92***	-14.57***	-19.01***	-12.62***	-14.40***
	(0.215)	(0.153)	(0.163)	(0.305)	(0.219)	(0.233)	(0.303)	(0.213)	(0.226)
Observations	506,740	506,740	506,740	258,341	258,341	258,341	248,399	248,399	248,399
Number of Customers	3,104	3,104	3,104	1,594	1,594	1,594	1,510	1,510	1,510
Adjusted R-squared	0.222	0.222	0.256	0.212	0.219	0.250	0.235	0.225	0.263
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

FIGURE 61: BGE SUMMER WEEKEND REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0337***	-0.0141**	-0.0171**	-0.0376***	-0.0256**	-0.0266***	-0.0298**	-0.00234	-0.00741
	(0.00809)	(0.00707)	(0.00706)	(0.0113)	(0.0100)	(0.00996)	(0.0116)	(0.00997)	(0.00999)
Pilot x Treatment	-0.0463***	-0.00518	-0.0141	-0.0433**	0.000391	-0.00988	-0.0494***	-0.0109	-0.0184
	(0.0129)	(0.0113)	(0.0112)	(0.0192)	(0.0170)	(0.0170)	(0.0173)	(0.0147)	(0.0147)
July	-6.008***	-1.852***	-1.774***	-5.566***	-1.926***	-1.746***	-6.475***	-1.785***	-1.811***
	(0.255)	(0.228)	(0.227)	(0.366)	(0.320)	(0.320)	(0.353)	(0.326)	(0.321)
August	-7.424***	-0.667***	-1.200***	-7.157***	-0.693**	-1.105***	-7.702***	-0.648**	-1.306***
	(0.322)	(0.231)	(0.236)	(0.459)	(0.327)	(0.333)	(0.452)	(0.327)	(0.335)
September	-0.667***	2.254***	1.812***	-0.327	2.330***	1.991***	-1.021***	2.172***	1.623***
	(0.229)	(0.209)	(0.206)	(0.328)	(0.303)	(0.298)	(0.320)	(0.286)	(0.282)
ln(THI)	3.103***	3.377***	3.596***	3.136***	3.443***	3.658***	3.068***	3.306***	3.530***
	(0.0503)	(0.0483)	(0.0485)	(0.0721)	(0.0696)	(0.0698)	(0.0701)	(0.0667)	(0.0672)
July x ln(THI)	1.405***	0.446***	0.426***	1.306***	0.465***	0.422***	1.511***	0.429***	0.433***
	(0.0587)	(0.0533)	(0.0527)	(0.0844)	(0.0747)	(0.0744)	(0.0813)	(0.0760)	(0.0747)
August x ln(THI)	1.727***	0.163***	0.288***	1.667***	0.171**	0.267***	1.790***	0.157**	0.311***
	(0.0744)	(0.0542)	(0.0551)	(0.106)	(0.0766)	(0.0778)	(0.104)	(0.0766)	(0.0781)
September x ln(THI)	0.145***	-0.537***	-0.432***	0.0663	-0.555***	-0.474***	0.227***	-0.518***	-0.388***
	(0.0532)	(0.0492)	(0.0482)	(0.0761)	(0.0714)	(0.0700)	(0.0743)	(0.0674)	(0.0662)
Constant	-13.23***	-14.47***	-15.35***	-13.48***	-14.84***	-15.72***	-12.96***	-14.07***	-14.97***
	(0.217)	(0.206)	(0.207)	(0.311)	(0.297)	(0.299)	(0.303)	(0.284)	(0.287)
Observations	229,502	229,502	229,502	117,046	117,046	117,046	112,456	112,456	112,456
Number of Customers	3,104	3,104	3,104	1,594	1,594	1,594	1,510	1,510	1,510
Adjusted R-squared	0.162	0.192	0.209	0.158	0.193	0.209	0.167	0.191	0.211
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 62: BGE NON-SUMMER WEEKDAY REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0408***	-0.0155*	-0.0194**	-0.0373***	-0.00797	-0.0128	-0.0442***	-0.0230**	-0.0259**
	(0.00896)	(0.00800)	(0.00797)	(0.0135)	(0.0121)	(0.0121)	(0.0118)	(0.0104)	(0.0104)
Pilot x Treatment	-0.0556***	-0.00839	-0.0134	-0.0542***	-0.0246	-0.0270	-0.0569***	0.00760	3.56e-05
	(0.0133)	(0.0113)	(0.0112)	(0.0200)	(0.0175)	(0.0174)	(0.0174)	(0.0142)	(0.0141)
February	0.890***	0.440***	0.495***	0.804***	0.437***	0.483***	0.974***	0.442***	0.506***
	(0.0442)	(0.0408)	(0.0396)	(0.0618)	(0.0577)	(0.0559)	(0.0632)	(0.0576)	(0.0560)
March	1.130***	0.400***	0.469***	1.031***	0.449***	0.503***	1.226***	0.350***	0.435***
	(0.0789)	(0.0783)	(0.0767)	(0.116)	(0.119)	(0.116)	(0.106)	(0.102)	(0.101)
April	1.123***	-0.198***	-0.0119	1.245***	0.0124	0.186*	1.000***	-0.408***	-0.210**
	(0.0732)	(0.0755)	(0.0723)	(0.108)	(0.112)	(0.108)	(0.0990)	(0.101)	(0.0961)
May	-2.318***	-5.990***	-5.550***	-2.302***	-5.650***	-5.242***	-2.335***	-6.327***	-5.856***
	(0.123)	(0.132)	(0.128)	(0.182)	(0.194)	(0.188)	(0.167)	(0.178)	(0.173)
October	-2.331***	-6.727***	-6.063***	-2.379***	-6.508***	-5.883***	-2.283***	-6.945***	-6.243***
	(0.0912)	(0.107)	(0.103)	(0.133)	(0.157)	(0.150)	(0.125)	(0.146)	(0.140)
November	0.838***	0.728***	0.723***	0.902***	0.875***	0.855***	0.774***	0.582***	0.591***
	(0.0536)	(0.0526)	(0.0513)	(0.0780)	(0.0780)	(0.0761)	(0.0737)	(0.0705)	(0.0686)
December	0.566***	-0.203***	-0.0586	0.549***	-0.129**	0.00785	0.581***	-0.277***	-0.125**
	(0.0434)	(0.0426)	(0.0404)	(0.0605)	(0.0606)	(0.0570)	(0.0622)	(0.0597)	(0.0572)
ln(THI)	-0.780***	-0.898***	-0.880***	-0.740***	-0.847***	-0.830***	-0.820***	-0.948***	-0.930***
	(0.0130)	(0.0136)	(0.0134)	(0.0182)	(0.0194)	(0.0190)	(0.0186)	(0.0190)	(0.0187)
February x ln(THI)	-0.246***	-0.128***	-0.142***	-0.221***	-0.127***	-0.138***	-0.270***	-0.129***	-0.145***
	(0.0117)	(0.0107)	(0.0104)	(0.0164)	(0.0151)	(0.0146)	(0.0168)	(0.0151)	(0.0147)
March x ln(THI)	-0.318***	-0.119***	-0.137***	-0.291***	-0.132***	-0.147***	-0.344***	-0.105***	-0.128***
	(0.0143)	(0.0267)	(0.0257)	(0.0208)	(0.0392)	(0.0376)	(0.0196)	(0.0363)	(0.0350)
April x ln(THI)	-0.334***	0.0194	-0.0287	-0.365***	-0.0342	-0.0792***	-0.303***	0.0728***	0.0217
	(0.0143)	(0.0137)	(0.0257)	(0.0208)	(0.0204)	(0.0376)	(0.0196)	(0.0184)	(0.0350)
May x ln(THI)	0.509***	1.443***	1.333***	0.504***	1.356***	1.254***	0.513***	1.529***	1.412***
	(0.0143)	(0.0137)	(0.0134)	(0.0208)	(0.0204)	(0.0199)	(0.0196)	(0.0184)	(0.0179)
October x ln(THI)	0.528***	1.616***	1.455***	0.540***	1.561***	1.409***	0.516***	1.671***	1.501***
	(0.0115)	(0.0137)	(0.0134)	(0.0160)	(0.0204)	(0.0199)	(0.0165)	(0.0184)	(0.0179)
November x ln(THI)	-0.245***	-0.209***	-0.208***	-0.260***	-0.246***	-0.242***	-0.229***	-0.172***	-0.175***
	(0.0115)	(0.0112)	(0.0134)	(0.0160)	(0.0159)	(0.0199)	(0.0165)	(0.0157)	(0.0179)
December x ln(THI)	-0.153***	0.0592***	0.0205*	-0.148***	0.0390**	0.00243	-0.158***	0.0794***	0.0385**
	(0.0115)	(0.0112)	(0.0106)	(0.0160)	(0.0159)	(0.0149)	(0.0165)	(0.0157)	(0.0150)
Constant	2.947***	3.418***	3.360***	2.689***	3.135***	3.077***	3.204***	3.699***	3.642***
	(0.0510)	(0.0536)	(0.0527)	(0.0710)	(0.0760)	(0.0746)	(0.0729)	(0.0751)	(0.0741)
Observations	999,632	999,632	999,632	497,822	497,822	497,822	501,810	501,810	501,810
Number of Customers	2,854	2,854	2,854	1,426	1,426	1,426	1,428	1,428	1,428
Adjusted R-squared	0.181	0.174	0.185	0.163	0.159	0.169	0.200	0.191	0.203
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 63: BGE NON-SUMMER WEEKEND REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0278***	-0.0213***	-0.0217***	-0.0214	-0.0157	-0.0166	-0.0340***	-0.0268***	-0.0268***
	(0.00871)	(0.00795)	(0.00794)	(0.0132)	(0.0122)	(0.0122)	(0.0114)	(0.0103)	(0.0102)
Pilot x Treatment	-0.0222*	-0.00266	-0.00470	-0.0287	-0.0181	-0.0188	-0.0158	0.0126	0.00928
	(0.0123)	(0.0112)	(0.0111)	(0.0190)	(0.0176)	(0.0174)	(0.0156)	(0.0139)	(0.0138)
February	0.160***	-0.511***	-0.403***	0.186**	-0.424***	-0.321***	0.133*	-0.597***	-0.485***
	(0.0548)	(0.0515)	(0.0497)	(0.0809)	(0.0760)	(0.0734)	(0.0738)	(0.0696)	(0.0671)
March	1.375***	0.705***	0.857***	1.265***	0.706***	0.824***	1.483***	0.704***	0.889***
	(0.0689)	(0.0815)	(0.0758)	(0.0986)	(0.118)	(0.110)	(0.0963)	(0.112)	(0.105)
April	1.195***	-0.903***	-0.725***	1.082***	-0.695***	-0.551***	1.306***	-1.111***	-0.898***
	(0.0940)	(0.0839)	(0.0820)	(0.134)	(0.120)	(0.118)	(0.131)	(0.117)	(0.114)
May	-1.615***	-4.963***	-4.497***	-1.649***	-4.745***	-4.308***	-1.584***	-5.180***	-4.685***
	(0.108)	(0.105)	(0.101)	(0.157)	(0.151)	(0.146)	(0.148)	(0.145)	(0.140)
October	-2.173***	-4.211***	-4.024***	-2.249***	-3.919***	-3.769***	-2.096***	-4.503***	-4.279***
	(0.113)	(0.116)	(0.113)	(0.161)	(0.172)	(0.166)	(0.158)	(0.156)	(0.152)
November	1.204***	0.266***	0.458***	1.073***	0.411***	0.580***	1.334***	0.122	0.335***
	(0.0832)	(0.0728)	(0.0707)	(0.123)	(0.108)	(0.105)	(0.112)	(0.0975)	(0.0950)
December	0.628***	0.0818	0.177***	0.588***	0.0979	0.180**	0.668***	0.0658	0.174**
	(0.0551)	(0.0536)	(0.0512)	(0.0791)	(0.0764)	(0.0729)	(0.0767)	(0.0751)	(0.0721)
ln(THI)	-0.849***	-0.850***	-0.843***	-0.802***	-0.806***	-0.798***	-0.896***	-0.893***	-0.887***
	(0.0142)	(0.0137)	(0.0136)	(0.0201)	(0.0195)	(0.0193)	(0.0200)	(0.0192)	(0.0192)
February x ln(THI)	-0.0348**	0.126***	0.100***	-0.0427*	0.104***	0.0788***	-0.0267	0.149***	0.121***
	(0.0150)	(0.0137)	(0.0133)	(0.0222)	(0.0202)	(0.0196)	(0.0201)	(0.0184)	(0.0178)
March x ln(THI)	-0.386***	-0.212***	-0.250***	-0.357***	-0.211***	-0.241***	-0.415***	-0.212***	-0.259***
	(0.0220)	(0.0288)	(0.0280)	(0.0324)	(0.0426)	(0.0412)	(0.0297)	(0.0387)	(0.0378)
April x ln(THI)	-0.348***	0.192***	0.147***	-0.319***	0.139***	0.103***	-0.378***	0.244***	0.191***
	(0.0220)	(0.0189)	(0.0280)	(0.0324)	(0.0280)	(0.0412)	(0.0297)	(0.0253)	(0.0378)
May x ln(THI)	0.356***	1.197***	1.082***	0.364***	1.140***	1.032***	0.348***	1.253***	1.131***
	(0.0220)	(0.0189)	(0.0184)	(0.0324)	(0.0280)	(0.0272)	(0.0297)	(0.0253)	(0.0247)
October x ln(THI)	0.481***	0.993***	0.947***	0.499***	0.921***	0.883***	0.463***	1.066***	1.010***
	(0.0145)	(0.0189)	(0.0184)	(0.0208)	(0.0280)	(0.0272)	(0.0202)	(0.0253)	(0.0247)
November x ln(THI)	-0.327***	-0.0933***	-0.141***	-0.293***	-0.129***	-0.172***	-0.360***	-0.0574**	-0.111***
	(0.0145)	(0.0138)	(0.0184)	(0.0208)	(0.0197)	(0.0272)	(0.0202)	(0.0194)	(0.0247)
December x ln(THI)	-0.159***	-0.0205	-0.0448***	-0.149***	-0.0244	-0.0455**	-0.169***	-0.0166	-0.0441**
	(0.0145)	(0.0138)	(0.0132)	(0.0208)	(0.0197)	(0.0188)	(0.0202)	(0.0194)	(0.0186)
Constant	3.113***	3.312***	3.275***	2.831***	3.048***	3.006***	3.395***	3.575***	3.543***
	(0.0550)	(0.0538)	(0.0535)	(0.0779)	(0.0763)	(0.0757)	(0.0774)	(0.0756)	(0.0752)
Observations	442,042	442,042	442,042	220,193	220,193	220,193	221,849	221,849	221,849
Number of Customers	2,854	2,854	2,854	1,426	1,426	1,426	1,428	1,428	1,428
Adjusted R-squared	0.188	0.148	0.162	0.167	0.135	0.147	0.209	0.163	0.178
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 64: PEPCO SUMMER WEEKDAY REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	0.0444***	0.0227**	0.0319***	0.0349**	0.0196	0.0276**	0.0525***	0.0253**	0.0355***
	(0.0107)	(0.00898)	(0.00892)	(0.0147)	(0.0124)	(0.0123)	(0.0136)	(0.0108)	(0.0107)
Pilot x Treatment	-0.154***	-0.0169	-0.0440***	-0.113***	-0.0122	-0.0335**	-0.189***	-0.0209	-0.0530***
	(0.0153)	(0.0118)	(0.0117)	(0.0216)	(0.0170)	(0.0169)	(0.0204)	(0.0148)	(0.0146)
July	-1.198***	-1.778***	-1.260***	-0.697	-1.949***	-1.365***	-1.608***	-1.621***	-1.155***
	(0.320)	(0.227)	(0.238)	(0.445)	(0.321)	(0.338)	(0.437)	(0.302)	(0.317)
August	-1.792***	-3.598***	-3.305***	-1.270***	-3.517***	-3.169***	-2.219***	-3.655***	-3.406***
	(0.267)	(0.206)	(0.212)	(0.377)	(0.304)	(0.313)	(0.362)	(0.267)	(0.275)
September	3.239***	-0.0581	0.419***	3.404***	0.252	0.728***	3.115***	-0.310	0.171
	(0.214)	(0.151)	(0.154)	(0.297)	(0.215)	(0.219)	(0.296)	(0.204)	(0.207)
ln(THI)	4.343***	3.173***	3.548***	4.259***	3.083***	3.449***	4.419***	3.253***	3.635***
	(0.0667)	(0.0467)	(0.0497)	(0.0940)	(0.0679)	(0.0719)	(0.0903)	(0.0622)	(0.0662)
July x ln(THI)	0.289***	0.419***	0.298***	0.175*	0.459***	0.323***	0.384***	0.382***	0.274***
	(0.0734)	(0.0526)	(0.0550)	(0.102)	(0.0745)	(0.0782)	(0.100)	(0.0699)	(0.0733)
August x ln(THI)	0.417***	0.829***	0.760***	0.297***	0.812***	0.730***	0.515***	0.841***	0.782***
	(0.0615)	(0.0481)	(0.0494)	(0.0870)	(0.0708)	(0.0726)	(0.0835)	(0.0623)	(0.0641)
September x ln(THI)	-0.763***	-0.00277	-0.114***	-0.801***	-0.0755	-0.186***	-0.734***	0.0563	-0.0564
	(0.0498)	(0.0357)	(0.0361)	(0.0691)	(0.0506)	(0.0513)	(0.0687)	(0.0481)	(0.0487)
Constant	-18.96***	-13.78***	-15.38***	-18.64***	-13.45***	-15.02***	-19.24***	-14.06***	-15.70***
	(0.289)	(0.200)	(0.213)	(0.408)	(0.291)	(0.309)	(0.392)	(0.266)	(0.284)
Observations	380,427	380,427	380,427	175,687	175,687	175,687	204,740	204,740	204,740
Number of Customers	2388	2388	2388	1098	1098	1098	1290	1290	1290
Adjusted R-squared	0.182	0.230	0.257	0.175	0.225	0.248	0.190	0.235	0.264
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 65: PEPCO SUMMER WEEKEND REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0236**	-0.0109	-0.0130	-0.0268*	-0.0177	-0.0187	-0.0208	-0.00512	-0.00806
	(0.0104)	(0.00894)	(0.00891)	(0.0144)	(0.0123)	(0.0122)	(0.0131)	(0.0106)	(0.0106)
Pilot x Treatment	-0.0719***	-0.0244**	-0.0348***	-0.0506**	-0.0168	-0.0246	-0.0902***	-0.0309**	-0.0436***
	(0.0140)	(0.0116)	(0.0116)	(0.0201)	(0.0168)	(0.0166)	(0.0180)	(0.0145)	(0.0145)
July	-10.69***	-1.441***	-2.983***	-10.54***	-1.430***	-3.049***	-10.81***	-1.446***	-2.920***
	(0.348)	(0.302)	(0.297)	(0.504)	(0.425)	(0.426)	(0.463)	(0.400)	(0.388)
August	-9.733***	0.473	-1.115***	-9.339***	0.174	-1.391***	-10.06***	0.733*	-0.871**
	(0.405)	(0.298)	(0.295)	(0.586)	(0.415)	(0.416)	(0.547)	(0.409)	(0.402)
September	-2.997***	3.372***	2.022***	-2.547***	3.295***	2.010***	-3.376***	3.444***	2.041***
	(0.266)	(0.254)	(0.240)	(0.389)	(0.365)	(0.345)	(0.348)	(0.342)	(0.323)
ln(THI)	2.462***	3.650***	3.538***	2.373***	3.532***	3.409***	2.538***	3.751***	3.649***
	(0.0554)	(0.0639)	(0.0605)	(0.0819)	(0.0909)	(0.0864)	(0.0723)	(0.0863)	(0.0814)
July x ln(THI)	2.473***	0.336***	0.695***	2.440***	0.334***	0.711***	2.501***	0.337***	0.680***
	(0.0798)	(0.0702)	(0.0689)	(0.116)	(0.0989)	(0.0987)	(0.106)	(0.0931)	(0.0900)
August x ln(THI)	2.244***	-0.121*	0.251***	2.153***	-0.0489	0.317***	2.320***	-0.183*	0.193**
	(0.0933)	(0.0695)	(0.0687)	(0.135)	(0.0968)	(0.0968)	(0.126)	(0.0957)	(0.0937)
September x ln(THI)	0.675***	-0.804***	-0.487***	0.573***	-0.785***	-0.484***	0.762***	-0.822***	-0.492***
	(0.0616)	(0.0596)	(0.0562)	(0.0902)	(0.0856)	(0.0808)	(0.0806)	(0.0803)	(0.0757)
Constant	-10.58***	-15.74***	-15.22***	-10.27***	-15.30***	-14.74***	-10.85***	-16.12***	-15.65***
	(0.240)	(0.273)	(0.259)	(0.354)	(0.389)	(0.371)	(0.313)	(0.369)	(0.349)
Observations	177,272	177,272	177,272	81,861	81,861	81,861	95,411	95,411	95,411
Number of Customers	2388	2388	2388	1098	1098	1098	1290	1290	1290
Adjusted R-squared	0.136	0.203	0.212	0.129	0.198	0.206	0.142	0.207	0.217
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 66: PEPCO NON-SUMMER WEEKDAY REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0387***	-0.0175**	-0.0208**	-0.0387***	-0.0168	-0.0201*	-0.0388***	-0.0180	-0.0214*
	(0.00994)	(0.00879)	(0.00866)	(0.0144)	(0.0116)	(0.0115)	(0.0129)	(0.0120)	(0.0118)
Pilot x Treatment	-0.0521***	-0.00299	-0.00842	-0.0491**	-0.0168	-0.0199	-0.0545***	0.00865	0.00124
	(0.0141)	(0.0117)	(0.0116)	(0.0207)	(0.0163)	(0.0161)	(0.0187)	(0.0159)	(0.0157)
February	0.944***	0.569***	0.634***	1.045***	0.649***	0.720***	0.859***	0.501***	0.561***
	(0.0428)	(0.0401)	(0.0394)	(0.0616)	(0.0596)	(0.0583)	(0.0571)	(0.0518)	(0.0508)
March	1.101***	0.646***	0.686***	1.265***	0.792***	0.839***	0.962***	0.521***	0.556***
	(0.0648)	(0.0643)	(0.0627)	(0.0929)	(0.0930)	(0.0903)	(0.0865)	(0.0845)	(0.0828)
April	1.004***	0.206**	0.319***	1.098***	0.400***	0.499***	0.926***	0.0422	0.169*
	(0.0696)	(0.0815)	(0.0779)	(0.101)	(0.120)	(0.115)	(0.0939)	(0.106)	(0.101)
May	-2.303***	-5.671***	-5.284***	-2.176***	-5.209***	-4.850***	-2.412***	-6.065***	-5.653***
	(0.133)	(0.155)	(0.150)	(0.199)	(0.225)	(0.218)	(0.171)	(0.206)	(0.198)
October	-1.685***	-5.735***	-5.124***	-1.754***	-5.422***	-4.867***	-1.625***	-6.002***	-5.343***
	(0.0972)	(0.128)	(0.122)	(0.144)	(0.187)	(0.177)	(0.127)	(0.168)	(0.159)
November	0.618***	0.701***	0.676***	0.702***	0.763***	0.745***	0.546***	0.647***	0.617***
	(0.0458)	(0.0483)	(0.0464)	(0.0641)	(0.0672)	(0.0646)	(0.0635)	(0.0669)	(0.0642)
December	0.619***	0.227***	0.302***	0.685***	0.261***	0.346***	0.564***	0.199***	0.266***
	(0.0410)	(0.0448)	(0.0420)	(0.0591)	(0.0623)	(0.0585)	(0.0552)	(0.0623)	(0.0582)
ln(THI)	-0.522***	-0.658***	-0.638***	-0.539***	-0.679***	-0.658***	-0.507***	-0.640***	-0.621***
	(0.0102)	(0.0115)	(0.0112)	(0.0149)	(0.0167)	(0.0163)	(0.0135)	(0.0152)	(0.0148)
February x ln(THI)	-0.266***	-0.162***	-0.180***	-0.292***	-0.182***	-0.201***	-0.244***	-0.146***	-0.162***
	(0.0116)	(0.0106)	(0.0105)	(0.0167)	(0.0158)	(0.0155)	(0.0156)	(0.0138)	(0.0136)
March x ln(THI)	-0.314***	-0.178***	-0.190***	-0.358***	-0.216***	-0.229***	-0.276***	-0.147***	-0.157***
	(0.0174)	(0.0167)	(0.0164)	(0.0251)	(0.0243)	(0.0237)	(0.0233)	(0.0220)	(0.0216)
April x ln(THI)	-0.298***	-0.0687***	-0.0998***	-0.326***	-0.119***	-0.146***	-0.275***	-0.0267	-0.0608**
	(0.0184)	(0.0209)	(0.0201)	(0.0268)	(0.0310)	(0.0296)	(0.0248)	(0.0270)	(0.0261)
May x ln(THI)	0.524***	1.376***	1.280***	0.489***	1.258***	1.169***	0.554***	1.476***	1.374***
	(0.0332)	(0.0383)	(0.0371)	(0.0498)	(0.0557)	(0.0541)	(0.0428)	(0.0507)	(0.0489)
October x ln(THI)	0.384***	1.380***	1.232***	0.397***	1.298***	1.165***	0.373***	1.449***	1.290***
	(0.0249)	(0.0320)	(0.0305)	(0.0371)	(0.0467)	(0.0445)	(0.0325)	(0.0418)	(0.0399)
November x ln(THI)	-0.179***	-0.198***	-0.192***	-0.201***	-0.215***	-0.211***	-0.160***	-0.184***	-0.176***
	(0.0124)	(0.0127)	(0.0123)	(0.0174)	(0.0177)	(0.0171)	(0.0171)	(0.0176)	(0.0170)
December x ln(THI)	-0.171***	-0.0593***	-0.0799***	-0.188***	-0.0680***	-0.0912***	-0.157***	-0.0522***	-0.0706***
	(0.0112)	(0.0120)	(0.0112)	(0.0162)	(0.0167)	(0.0157)	(0.0151)	(0.0166)	(0.0156)
Constant	1.693***	2.310***	2.234***	1.732***	2.375***	2.296***	1.659***	2.254***	2.181***
	(0.0394)	(0.0454)	(0.0442)	(0.0573)	(0.0661)	(0.0643)	(0.0523)	(0.0602)	(0.0587)
Observations	789,442	789,442	789,442	361,505	361,505	361,505	427,937	427,937	427,937
Number of Customers	2254	2254	2254	1036	1036	1036	1218	1218	1218
Adjusted R-squared	0.144	0.148	0.157	0.155	0.166	0.176	0.135	0.135	0.143
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 67: PEPCO NON-SUMMER WEEKEND REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0527***	-0.0416***	-0.0429***	-0.0513***	-0.0407***	-0.0424***	-0.0537***	-0.0423***	-0.0433***
	(0.00955)	(0.00861)	(0.00854)	(0.0137)	(0.0117)	(0.0116)	(0.0123)	(0.0116)	(0.0115)
Pilot x Treatment	-0.00454	-0.00401	-0.00375	-0.00867	-0.0127	-0.0120	-0.00111	0.00326	0.00317
	(0.0128)	(0.0112)	(0.0111)	(0.0186)	(0.0157)	(0.0157)	(0.0169)	(0.0151)	(0.0150)
February	0.432***	0.0847*	0.148***	0.397***	0.0508	0.104*	0.463***	0.114*	0.186***
	(0.0430)	(0.0439)	(0.0416)	(0.0604)	(0.0594)	(0.0557)	(0.0584)	(0.0619)	(0.0591)
March	2.307***	0.832***	1.070***	2.494***	1.146***	1.363***	2.150***	0.567***	0.822***
	(0.0913)	(0.100)	(0.0962)	(0.132)	(0.148)	(0.142)	(0.120)	(0.129)	(0.124)
April	1.109***	-0.333***	-0.164	1.266***	-0.0420	0.132	0.976***	-0.581***	-0.416***
	(0.103)	(0.108)	(0.106)	(0.147)	(0.156)	(0.153)	(0.137)	(0.144)	(0.142)
May	-1.213***	-4.127***	-3.706***	-1.201***	-3.733***	-3.359***	-1.223***	-4.460***	-4.000***
	(0.111)	(0.120)	(0.115)	(0.164)	(0.170)	(0.164)	(0.147)	(0.160)	(0.154)
October	-1.810***	-3.794***	-3.629***	-1.830***	-3.654***	-3.505***	-1.793***	-3.913***	-3.734***
	(0.118)	(0.126)	(0.123)	(0.167)	(0.181)	(0.176)	(0.159)	(0.167)	(0.163)
November	1.184***	0.658***	0.717***	1.240***	0.722***	0.772***	1.137***	0.605***	0.670***
	(0.0733)	(0.0702)	(0.0672)	(0.102)	(0.0943)	(0.0896)	(0.101)	(0.0989)	(0.0951)
December	1.095***	0.791***	0.845***	1.211***	0.794***	0.870***	0.998***	0.789***	0.825***
	(0.0569)	(0.0561)	(0.0538)	(0.0780)	(0.0772)	(0.0741)	(0.0789)	(0.0772)	(0.0742)
ln(THI)	-0.528***	-0.572***	-0.562***	-0.540***	-0.592***	-0.581***	-0.519***	-0.554***	-0.546***
	(0.0102)	(0.0108)	(0.0105)	(0.0148)	(0.0155)	(0.0151)	(0.0136)	(0.0143)	(0.0140)
February x ln(THI)	-0.108***	-0.0252**	-0.0406***	-0.0960***	-0.0138	-0.0263*	-0.119***	-0.0350**	-0.0528***
	(0.0121)	(0.0118)	(0.0113)	(0.0171)	(0.0159)	(0.0150)	(0.0165)	(0.0167)	(0.0160)
March x ln(THI)	-0.632***	-0.229***	-0.291***	-0.683***	-0.310***	-0.367***	-0.590***	-0.161***	-0.228***
	(0.0248)	(0.0262)	(0.0252)	(0.0359)	(0.0388)	(0.0374)	(0.0326)	(0.0336)	(0.0324)
April x ln(THI)	-0.320***	0.0596**	0.0166	-0.362***	-0.0141	-0.0585	-0.285***	0.122***	0.0804**
	(0.0267)	(0.0274)	(0.0271)	(0.0384)	(0.0397)	(0.0391)	(0.0358)	(0.0365)	(0.0361)
May x ln(THI)	0.270***	1.003***	0.900***	0.265***	0.903***	0.812***	0.274***	1.087***	0.975***
	(0.0284)	(0.0299)	(0.0289)	(0.0418)	(0.0426)	(0.0412)	(0.0375)	(0.0398)	(0.0384)
October x ln(THI)	0.403***	0.897***	0.856***	0.406***	0.860***	0.823***	0.402***	0.928***	0.884***
	(0.0297)	(0.0313)	(0.0305)	(0.0420)	(0.0450)	(0.0439)	(0.0400)	(0.0414)	(0.0404)
November x ln(THI)	-0.312***	-0.186***	-0.200***	-0.327***	-0.203***	-0.215***	-0.299***	-0.171***	-0.187***
	(0.0197)	(0.0184)	(0.0176)	(0.0275)	(0.0247)	(0.0235)	(0.0272)	(0.0259)	(0.0250)
December x ln(THI)	-0.288***	-0.212***	-0.226***	-0.320***	-0.213***	-0.232***	-0.261***	-0.213***	-0.221***
	(0.0154)	(0.0148)	(0.0142)	(0.0211)	(0.0204)	(0.0196)	(0.0214)	(0.0204)	(0.0196)
Constant	1.641***	2.074***	2.021***	1.660***	2.129***	2.071***	1.625***	2.028***	1.978***
	(0.0387)	(0.0419)	(0.0409)	(0.0559)	(0.0603)	(0.0587)	(0.0515)	(0.0559)	(0.0547)
Observations	361,325	361,325	361,325	165,460	165,460	165,460	195,865	195,865	195,865
Number of Customers	2254	2254	2254	1036	1036	1036	1218	1218	1218
Adjusted R-squared	0.162	0.138	0.149	0.169	0.155	0.167	0.157	0.125	0.136
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 68: DPL SUMMER WEEKDAY REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	0.00780	0.00727	0.0126	-0.00709	-0.00285	0.00204	0.0322	0.0238	0.0297
	(0.0152)	(0.0134)	(0.0134)	(0.0178)	(0.0160)	(0.0158)	(0.0263)	(0.0214)	(0.0220)
Pilot x Treatment	-0.161***	-0.0192	-0.0506***	-0.147***	-0.0178	-0.0473**	-0.183***	-0.0211	-0.0557*
	(0.0219)	(0.0174)	(0.0174)	(0.0265)	(0.0210)	(0.0209)	(0.0374)	(0.0289)	(0.0290)
July	-3.396***	-3.535***	-3.463***	-3.218***	-3.624***	-3.468***	-3.692***	-3.386***	-3.455***
	(0.457)	(0.323)	(0.354)	(0.527)	(0.369)	(0.404)	(0.821)	(0.583)	(0.641)
August	0.205	-2.547***	-2.255***	0.123	-2.937***	-2.601***	0.344	-1.899***	-1.678***
	(0.375)	(0.284)	(0.299)	(0.446)	(0.331)	(0.348)	(0.632)	(0.508)	(0.536)
September	0.888***	0.124	-0.00431	0.745**	-0.121	-0.251	1.116**	0.524	0.396
	(0.302)	(0.220)	(0.230)	(0.374)	(0.273)	(0.285)	(0.474)	(0.352)	(0.367)
ln(THI)	3.934***	2.351***	2.715***	4.028***	2.378***	2.755***	3.778***	2.306***	2.647***
	(0.0857)	(0.0531)	(0.0585)	(0.104)	(0.0648)	(0.0717)	(0.142)	(0.0888)	(0.0971)
July x ln(THI)	0.812***	0.850***	0.832***	0.768***	0.870***	0.831***	0.884***	0.818***	0.833***
	(0.105)	(0.0755)	(0.0825)	(0.122)	(0.0864)	(0.0944)	(0.189)	(0.136)	(0.149)
August x ln(THI)	-0.0146	0.616***	0.548***	-0.000742	0.704***	0.624***	-0.0380	0.472***	0.421***
	(0.0865)	(0.0665)	(0.0698)	(0.103)	(0.0772)	(0.0809)	(0.146)	(0.119)	(0.125)
September x ln(THI)	-0.214***	-0.0370	-0.00710	-0.181**	0.0200	0.0498	-0.264**	-0.130	-0.0995
	(0.0704)	(0.0520)	(0.0543)	(0.0872)	(0.0646)	(0.0674)	(0.111)	(0.0834)	(0.0867)
Constant	-17.12***	-10.33***	-11.85***	-17.44***	-10.39***	-11.96***	-16.58***	-10.23***	-11.66***
	(0.370)	(0.226)	(0.250)	(0.449)	(0.276)	(0.306)	(0.613)	(0.378)	(0.414)
Observations	191,325	191,325	191,325	119,363	119,363	119,363	71,962	71,962	71,962
Number of Customers	1184	1184	1184	740	740	740	444	444	444
Adjusted R-squared	0.187	0.174	0.195	0.201	0.193	0.216	0.167	0.150	0.168
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 69: DPL SUMMER WEEKEND REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0640***	-0.0310**	-0.0384***	-0.0760***	-0.0392**	-0.0473***	-0.0442*	-0.0175	-0.0239
	(0.0163)	(0.0145)	(0.0144)	(0.0193)	(0.0170)	(0.0169)	(0.0267)	(0.0231)	(0.0233)
Pilot x Treatment	-0.0853***	-0.0173	-0.0319*	-0.0722***	-0.00811	-0.0219	-0.107***	-0.0322	-0.0484
	(0.0216)	(0.0184)	(0.0184)	(0.0259)	(0.0217)	(0.0218)	(0.0360)	(0.0306)	(0.0305)
July	-8.255***	-2.535***	-2.943***	-8.631***	-2.947***	-3.373***	-7.631***	-1.852***	-2.229***
	(0.470)	(0.372)	(0.377)	(0.560)	(0.435)	(0.440)	(0.804)	(0.648)	(0.664)
August	-5.434***	-0.0945	-0.860**	-5.341***	-0.349	-1.155**	-5.588***	0.326	-0.371
	(0.525)	(0.396)	(0.402)	(0.618)	(0.457)	(0.464)	(0.901)	(0.702)	(0.716)
September	-0.729**	1.408***	1.006***	-1.082**	1.515***	0.982**	-0.141	1.230*	1.045*
	(0.362)	(0.361)	(0.357)	(0.422)	(0.418)	(0.409)	(0.633)	(0.627)	(0.629)
ln(THI)	2.496***	2.753***	2.910***	2.472***	2.765***	2.906***	2.534***	2.732***	2.915***
	(0.0718)	(0.0775)	(0.0756)	(0.0861)	(0.0910)	(0.0887)	(0.120)	(0.131)	(0.128)
July x ln(THI)	1.936***	0.617***	0.710***	2.021***	0.711***	0.808***	1.796***	0.461***	0.547***
	(0.108)	(0.0867)	(0.0877)	(0.129)	(0.102)	(0.102)	(0.185)	(0.151)	(0.154)
August x ln(THI)	1.293***	0.0428	0.224**	1.267***	0.0986	0.289***	1.336***	-0.0493	0.117
	(0.121)	(0.0927)	(0.0939)	(0.142)	(0.107)	(0.108)	(0.208)	(0.164)	(0.167)
September x ln(THI)	0.160*	-0.331***	-0.237***	0.241**	-0.357***	-0.232**	0.0261	-0.288*	-0.244*
	(0.0844)	(0.0855)	(0.0842)	(0.0981)	(0.0988)	(0.0965)	(0.148)	(0.148)	(0.148)
Constant	-10.74***	-11.93***	-12.55***	-10.58***	-11.95***	-12.50***	-11.00***	-11.89***	-12.64***
	(0.309)	(0.330)	(0.323)	(0.371)	(0.388)	(0.379)	(0.517)	(0.559)	(0.547)
Observations	89,269	89,269	89,269	55,696	55,696	55,696	33,573	33,573	33,573
Number of Customers	1184	1184	1184	740	740	740	444	444	444
Adjusted R-squared	0.134	0.164	0.173	0.142	0.184	0.193	0.122	0.139	0.148
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 70: DPL NON-SUMMER WEEKDAY REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0471**	-0.0416**	-0.0425**	-0.0469**	-0.0489***	-0.0487***	-0.0473	-0.0297	-0.0325
	(0.0189)	(0.0173)	(0.0174)	(0.0206)	(0.0184)	(0.0184)	(0.0322)	(0.0302)	(0.0303)
Pilot x Treatment	-0.0625**	0.0330	0.0223	-0.0810***	0.0255	0.0131	-0.0326	0.0452	0.0374
	(0.0258)	(0.0228)	(0.0228)	(0.0299)	(0.0252)	(0.0252)	(0.0441)	(0.0403)	(0.0403)
February	1.243***	0.751***	0.853***	1.346***	0.828***	0.934***	1.075***	0.627***	0.722***
	(0.0709)	(0.0697)	(0.0692)	(0.0864)	(0.0775)	(0.0772)	(0.118)	(0.127)	(0.126)
March	2.134***	1.321***	1.430***	2.260***	1.498***	1.595***	1.928***	1.034***	1.160***
	(0.121)	(0.121)	(0.120)	(0.150)	(0.148)	(0.147)	(0.198)	(0.201)	(0.201)
April	1.159***	0.551***	0.683***	1.576***	1.148***	1.261***	0.479**	-0.421*	-0.259
	(0.126)	(0.152)	(0.147)	(0.150)	(0.179)	(0.173)	(0.211)	(0.255)	(0.249)
May	-1.226***	-4.039***	-3.681***	-0.916***	-3.686***	-3.335***	-1.735***	-4.620***	-4.251***
	(0.185)	(0.242)	(0.235)	(0.222)	(0.293)	(0.283)	(0.304)	(0.395)	(0.385)
October	-1.674***	-4.731***	-4.205***	-1.213***	-4.294***	-3.753***	-2.428***	-5.444***	-4.944***
	(0.151)	(0.188)	(0.181)	(0.185)	(0.228)	(0.219)	(0.244)	(0.314)	(0.303)
November	0.762***	0.818***	0.816***	0.958***	1.069***	1.058***	0.443***	0.407**	0.423**
	(0.0837)	(0.103)	(0.0999)	(0.0963)	(0.118)	(0.113)	(0.148)	(0.182)	(0.177)
December	0.678***	0.230***	0.328***	0.810***	0.389***	0.484***	0.464***	-0.0293	0.0759
	(0.0626)	(0.0760)	(0.0729)	(0.0755)	(0.0858)	(0.0827)	(0.104)	(0.138)	(0.132)
ln(THI)	-0.692***	-0.884***	-0.862***	-0.682***	-0.867***	-0.845***	-0.710***	-0.912***	-0.890***
	(0.0166)	(0.0209)	(0.0204)	(0.0201)	(0.0250)	(0.0245)	(0.0279)	(0.0360)	(0.0351)
February x ln(THI)	-0.371***	-0.224***	-0.251***	-0.401***	-0.246***	-0.275***	-0.322***	-0.187***	-0.213***
	(0.0200)	(0.0190)	(0.0190)	(0.0244)	(0.0212)	(0.0212)	(0.0331)	(0.0346)	(0.0344)
March x ln(THI)	-0.609***	-0.365***	-0.395***	-0.648***	-0.415***	-0.443***	-0.546***	-0.284***	-0.318***
	(0.0331)	(0.0319)	(0.0319)	(0.0410)	(0.0390)	(0.0390)	(0.0541)	(0.0534)	(0.0535)
April x ln(THI)	-0.370***	-0.184***	-0.219***	-0.487***	-0.344***	-0.375***	-0.179***	0.0761	0.0336
	(0.0341)	(0.0396)	(0.0385)	(0.0407)	(0.0468)	(0.0454)	(0.0566)	(0.0666)	(0.0651)
May x ln(THI)	0.216***	0.951***	0.861***	0.123**	0.850***	0.762***	0.369***	1.117***	1.024***
	(0.0473)	(0.0604)	(0.0588)	(0.0572)	(0.0731)	(0.0709)	(0.0771)	(0.0976)	(0.0954)
October x ln(THI)	0.337***	1.118***	0.988***	0.206***	0.998***	0.864***	0.551***	1.315***	1.192***
	(0.0393)	(0.0478)	(0.0462)	(0.0479)	(0.0577)	(0.0558)	(0.0642)	(0.0803)	(0.0777)
November x ln(THI)	-0.254***	-0.252***	-0.253***	-0.308***	-0.320***	-0.319***	-0.166***	-0.141***	-0.146***
	(0.0235)	(0.0279)	(0.0271)	(0.0273)	(0.0319)	(0.0309)	(0.0410)	(0.0488)	(0.0478)
December x ln(THI)	-0.204***	-0.0689***	-0.0967***	-0.240***	-0.111***	-0.138***	-0.146***	-5.85e-06	-0.0293
	(0.0174)	(0.0205)	(0.0198)	(0.0212)	(0.0234)	(0.0226)	(0.0288)	(0.0370)	(0.0355)
Constant	2.499***	3.226***	3.153***	2.588***	3.289***	3.218***	2.353***	3.123***	3.048***
	(0.0626)	(0.0800)	(0.0780)	(0.0766)	(0.0961)	(0.0937)	(0.105)	(0.138)	(0.134)
Observations	384,481	384,481	384,481	238,187	238,187	238,187	146,294	146,294	146,294
Number of Customers	1096	1096	1096	680	680	680	416	416	416
Adjusted R-squared	0.235	0.228	0.238	0.265	0.269	0.280	0.193	0.176	0.184
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 71: DPL NON-SUMMER WEEKEND REGRESSION RESULTS

	All Customers			LMI Customers			Non-LMI Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)	ln(avg peak load)	ln(avg off-peak load)	ln(avg daily load)
Pilot Period	-0.0414**	-0.0455***	-0.0450***	-0.0410**	-0.0554***	-0.0535***	-0.0420	-0.0294	-0.0311
	(0.0175)	(0.0166)	(0.0166)	(0.0191)	(0.0177)	(0.0176)	(0.0307)	(0.0293)	(0.0293)
Pilot x Treatment	-0.0164	0.0248	0.0202	-0.0261	0.0284	0.0217	-0.000640	0.0191	0.0178
	(0.0232)	(0.0217)	(0.0216)	(0.0262)	(0.0236)	(0.0235)	(0.0410)	(0.0395)	(0.0394)
February	0.800***	0.491***	0.529***	0.849***	0.395***	0.452***	0.720***	0.648***	0.655***
	(0.0601)	(0.0727)	(0.0696)	(0.0736)	(0.0852)	(0.0819)	(0.0981)	(0.128)	(0.122)
March	3.220***	3.463***	3.474***	3.356***	3.750***	3.722***	2.998***	2.994***	3.071***
	(0.132)	(0.201)	(0.187)	(0.158)	(0.232)	(0.215)	(0.222)	(0.362)	(0.337)
April	2.024***	0.506***	0.759***	2.566***	0.988***	1.259***	1.144***	-0.278	-0.0534
	(0.153)	(0.173)	(0.172)	(0.180)	(0.196)	(0.192)	(0.258)	(0.300)	(0.301)
May	-1.043***	-3.883***	-3.499***	-0.797***	-3.488***	-3.123***	-1.447***	-4.526***	-4.114***
	(0.175)	(0.192)	(0.188)	(0.217)	(0.236)	(0.231)	(0.281)	(0.309)	(0.304)
October	-1.673***	-3.557***	-3.355***	-1.394***	-3.053***	-2.852***	-2.128***	-4.380***	-4.178***
	(0.171)	(0.206)	(0.201)	(0.211)	(0.242)	(0.237)	(0.273)	(0.356)	(0.345)
November	1.203***	0.584***	0.639***	1.389***	0.847***	0.884***	0.899***	0.155	0.239
	(0.103)	(0.102)	(0.100)	(0.117)	(0.114)	(0.111)	(0.178)	(0.186)	(0.184)
December	1.183***	0.970***	1.000***	1.266***	1.092***	1.115***	1.048***	0.772***	0.813***
	(0.0725)	(0.0962)	(0.0921)	(0.0870)	(0.114)	(0.108)	(0.120)	(0.165)	(0.158)
ln(THI)	-0.553***	-0.770***	-0.746***	-0.548***	-0.765***	-0.741***	-0.561***	-0.778***	-0.755***
	(0.0129)	(0.0183)	(0.0176)	(0.0158)	(0.0224)	(0.0215)	(0.0217)	(0.0307)	(0.0298)
February x ln(THI)	-0.219***	-0.140***	-0.149***	-0.233***	-0.114***	-0.128***	-0.195***	-0.182***	-0.183***
	(0.0174)	(0.0200)	(0.0192)	(0.0216)	(0.0237)	(0.0229)	(0.0279)	(0.0347)	(0.0332)
March x ln(THI)	-0.899***	-0.927***	-0.934***	-0.940***	-1.004***	-1.001***	-0.834***	-0.800***	-0.824***
	(0.0366)	(0.0533)	(0.0498)	(0.0440)	(0.0615)	(0.0575)	(0.0616)	(0.0965)	(0.0902)
April x ln(THI)	-0.600***	-0.172***	-0.239***	-0.751***	-0.300***	-0.372***	-0.355***	0.0360	-0.0221
	(0.0408)	(0.0447)	(0.0446)	(0.0481)	(0.0504)	(0.0495)	(0.0685)	(0.0774)	(0.0780)
May x ln(THI)	0.181***	0.924***	0.827***	0.103*	0.813***	0.720***	0.309***	1.104***	1.001***
	(0.0456)	(0.0490)	(0.0482)	(0.0565)	(0.0603)	(0.0591)	(0.0725)	(0.0785)	(0.0775)
October x ln(THI)	0.331***	0.827***	0.776***	0.245***	0.690***	0.638***	0.470***	1.051***	1.000***
	(0.0439)	(0.0523)	(0.0511)	(0.0538)	(0.0612)	(0.0599)	(0.0709)	(0.0905)	(0.0879)
November x ln(THI)	-0.351***	-0.186***	-0.199***	-0.400***	-0.255***	-0.264***	-0.272***	-0.0731	-0.0942*
	(0.0285)	(0.0274)	(0.0270)	(0.0323)	(0.0305)	(0.0300)	(0.0493)	(0.0500)	(0.0496)
December x ln(THI)	-0.333***	-0.272***	-0.280***	-0.354***	-0.303***	-0.310***	-0.299***	-0.221***	-0.232***
	(0.0203)	(0.0261)	(0.0251)	(0.0244)	(0.0308)	(0.0295)	(0.0336)	(0.0447)	(0.0431)
Constant	1.928***	2.837***	2.751***	2.019***	2.930***	2.841***	1.781***	2.687***	2.602***
	(0.0478)	(0.0691)	(0.0665)	(0.0588)	(0.0850)	(0.0817)	(0.0797)	(0.116)	(0.112)
Observations	175,999	175,999	175,999	109,027	109,027	109,027	66,972	66,972	66,972
Number of Customers	1096	1096	1096	680	680	680	416	416	416
Adjusted R-squared	0.219	0.201	0.210	0.251	0.243	0.254	0.176	0.150	0.157
Customer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: The unit of observation is a customer-day. Control customers were matched to treatment customers using a propensity score approach. As the dependent variable is expressed in natural logs, matched pairs in which one or both customers experienced negative load in one or more hours and net metering customers have been dropped from the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.5 Estimated Impacts, Including Confidence Intervals

Here we present a comprehensive summary of impacts during the different pricing windows on weekdays and weekends. Presented within the tables are also the confidence interval, which provide an approximate estimate of the range of possible impacts.

FIGURE 72: BGE SUMMER IMPACT

	LMI Customers	Non-LMI Customers	All Customers
Weekday			
Peak Impact	-8.1%*** [-11.5%, -4.6%]	-12.4%*** [-15.5%, -9.1%]	-10.2%*** [-12.5%, -7.8%]
Off-Peak Impact	0.1% [-3.1%, 3.3%]	-1.4% [-4.2%, 1.5%]	-0.7% [-2.8%, 1.5%]
Overall Impact	-2.0% [-5.1%, 1.2%]	-3.7%*** [-6.4%, -0.9%]	-2.8%*** [-4.9%, -0.7%]
Weekend			
"Peak" Impact	-4.2%** [-7.8%, -0.6%]	-4.8%*** [-8.0%, -1.5%]	-4.5%*** [-6.9%, -2.1%]
"Off-Peak" Impact	0.0% [-3.2%, 3.4%]	-1.1% [-3.9%, 1.8%]	-0.5% [-2.7%, 1.7%]
Overall Impact	-1.0% [-4.2%, 2.4%]	-1.8% [-4.6%, 1.0%]	-1.4% [-3.6%, 0.8%]

FIGURE 73: BGE NON-SUMMER IMPACT

	LMI Customers	Non-LMI Customers	All Customers
Weekday			
Peak Impact	-5.3%*** [-8.9%, -1.5%]	-5.5%*** [-8.7%, -2.3%]	-5.4%*** [-7.8%, -2.9%]
Off-Peak Impact	-2.4% [-5.7%, 1.0%]	0.8% [-2.0%, 3.6%]	-0.8% [-3.0%, 1.4%]
Overall Impact	-2.7% [-5.9%, 0.7%]	0.0% [-2.7%, 2.8%]	-1.3% [-3.5%, 0.9%]
Weekend			
"Peak" Impact	-2.8% [-6.4%, 0.9%]	-1.6% [-4.5%, 1.5%]	-2.2%* [-4.5%, 0.2%]
"Off-Peak" Impact	-1.8% [-5.1%, 1.6%]	1.3% [-1.5%, 4.1%]	-0.3% [-2.4%, 1.9%]
Overall Impact	-1.9% [-5.2%, 1.6%]	0.9% [-1.8%, 3.7%]	-0.5% [-2.6%, 1.7%]

Note: The value on the top row of each cell provides the estimated impact. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The bracketed values on the second row of each cell provide the 95% confidence interval for the estimated impact.

FIGURE 74: PEPCO SUMMER IMPACT SUMMARY

	LMI Customers	Non-LMI Customers	All Customers
Weekday			
Peak Impact	-10.7%***	-17.3%***	-14.3%***
	[-14.4%, -6.8%]	[-20.5%, -13.9%]	[-16.8%, -11.7%]
Off-Peak Impact	-1.2%	-2.1%	-1.7%
	[-4.4%, 2.1%]	[-4.9%, 0.8%]	[-3.9%, 0.6%]
Overall Impact	-3.3%**	-5.2%***	-4.3%***
	[-6.5%, 0.0%]	[-7.8%, -2.4%]	[-6.5%, -2.1%]
Weekend			
"Peak" Impact	-4.9%**	-8.6%***	-6.9%***
	[-8.6%, -1.1%]	[-11.8%, -5.4%]	[-9.5%, -4.4%]
"Off-Peak" Impact	-1.7%	-3.0%**	-2.4%**
	[-4.9%, 1.6%]	[-5.8%, -0.3%]	[-4.6%, -0.2%]
Overall Impact	-2.4%	-4.3%***	-3.4%***
	[-5.6%, 0.8%]	[-7.0%, -1.5%]	[-5.6%, -1.2%]

FIGURE 75: PEPCO NON-SUMMER IMPACT SUMMARY

	LMI Customers	Non-LMI Customers	All Customers
weekend			
Peak Impact	-4.8%**	-5.3%***	-5.1%***
	[-8.6%, -0.9%]	[-8.7%, -1.8%]	[-7.7%, -2.4%]
Off-Peak Impact	-1.7%	0.9%	-0.3%
	[-4.8%, 1.5%]	[-2.2%, 4.1%]	[-2.6%, 2.0%]
Overall Impact	-2.0%	0.1%	-0.8%
	[-5.0%, 1.2%]	[-2.9%, 3.3%]	[-3.1%, 1.4%]
Weekend			
"Peak" Impact	-0.9%	-0.1%	-0.5%
	[-4.4%, 2.8%]	[-3.4%, 3.3%]	[-2.9%, 2.1%]
"Off-Peak" Impact	-1.3%	0.3%	-0.4%
	[-4.3%, 1.8%]	[-2.6%, 3.4%]	[-2.6%, 1.8%]
Overall Impact	-1.2%	0.3%	-0.4%
	[-4.2%, 1.9%]	[-2.6%, 3.3%]	[-2.5%, 1.8%]

Note: The value on the top row of each cell provides the estimated impact. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The bracketed values on the second row of each cell provide the 95% confidence interval for the estimated impact.

FIGURE 76: DPL SUMMER IMPACT SUMMARY

	LMI Customers	Non-LMI Customers	All Customers
Weekday			
Peak Impact	-13.7%*** [-18.0%, -9.1%]	-16.7%*** [-22.6%, -10.4%]	-14.8%*** [-18.4%, -11.1%]
Off-Peak Impact	-1.8% [-5.7%, 2.4%]	-2.1% [-7.5%, 3.6%]	-1.9% [-5.2%, 1.5%]
Overall Impact	-4.6%** [-8.5%, -0.6%]	-5.4%* [-10.6%, 0.1%]	-4.9%*** [-8.1%, -1.6%]
Weekend			
"Peak" Impact	-7.0%*** [-11.6%, -2.1%]	-10.1%*** [-16.2%, -3.6%]	-8.2%*** [-12.0%, -4.2%]
"Off-Peak" Impact	-0.8% [-4.9%, 3.5%]	-3.2% [-8.8%, 2.8%]	-1.7% [-5.2%, 1.9%]
Overall Impact	-2.2% [-6.3%, 2.1%]	-4.7% [-10.2%, 1.1%]	-3.1%* [-6.6%, 0.4%]

FIGURE 77: DPL NON-SUMMER IMPACT SUMMARY

	LMI Customers	Non-LMI Customers	All Customers
Weekday			
Peak Impact	-7.8%*** [-13.0%, -2.2%]	-3.2% [-11.2%, 5.5%]	-6.1%** [-10.7%, -1.2%]
Off-Peak Impact	2.6% [-2.4%, 7.8%]	4.6% [-3.3%, 13.2%]	3.4% [-1.2%, 8.1%]
Overall Impact	1.3% [-3.6%, 6.5%]	3.8% [-4.1%, 12.3%]	2.3% [-2.2%, 6.9%]
Weekend			
"Peak" Impact	-2.6% [-7.4%, 2.6%]	-0.1% [-7.8%, 8.3%]	-1.6% [-6.0%, 2.9%]
"Off-Peak" Impact	2.9% [-1.8%, 7.8%]	1.9% [-5.7%, 10.1%]	2.5% [-1.8%, 7.0%]
Overall Impact	2.2% [-2.4%, 7.0%]	1.8% [-5.8%, 10.0%]	2.0% [-2.2%, 6.5%]

Note: The value on the top row of each cell provides the estimated impact. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The bracketed values on the second row of each cell provide the 95% confidence interval for the estimated impact.

A.6 Regression Tables – Elasticity Results

This section details regression results for the price response analyses presented in section IV. For each utility, we include tables for substitution elasticity and daily demand elasticity regressions for summer and non-summer weekdays.

FIGURE 78: SUMMER WEEKDAY SUBSTITUTION ELASTICITY – BGE

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(peak to off-peak load)	ln(peak to off-peak load)	ln(peak to off-peak load)
Pilot Period	0.0136***	0.0162**	0.0109
	(0.00496)	(0.00691)	(0.00712)
Peak to off-Peak Price Ratio	-0.0613***	-0.0482***	-0.0753***
	(0.00582)	(0.00773)	(0.00871)
July	0.0377***	0.0367***	0.0389***
	(0.00517)	(0.00723)	(0.00738)
August	-0.00780	-0.00138	-0.0144**
	(0.00520)	(0.00747)	(0.00722)
September	-0.0591***	-0.0490***	-0.0696***
	(0.00531)	(0.00766)	(0.00732)
Peak/Off-Peak THI Differential	0.0225***	0.0219***	0.0231***
	(0.000702)	(0.00101)	(0.000972)
July x THI_Diff	0.0114***	0.0112***	0.0116***
	(0.000911)	(0.00131)	(0.00126)
August x THI_Diff	0.0181***	0.0170***	0.0192***
	(0.000932)	(0.00135)	(0.00127)
September x THI_Diff	0.0133***	0.0126***	0.0141***
	(0.000872)	(0.00128)	(0.00117)
Constant	0.0519***	0.0390***	0.0658***
	(0.00488)	(0.00681)	(0.00700)
Observations	410,020	212,508	197,512
Number of Customers	2,520	1,316	1,204
Adjusted R-squared	0.041	0.036	0.048
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 79: NON-SUMMER WEEKDAY SUBSTITUTION ELASTICITY – BGE

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(peak to off-peak load)	ln(peak to off-peak load)	ln(peak to off-peak load)
Pilot Period	-0.0203***	-0.0249***	-0.0155*
	(0.00576)	(0.00823)	(0.00807)
Peak to off-Peak Price Ratio	-0.0269***	-0.0108	-0.0432***
	(0.00573)	(0.00790)	(0.00828)
February	0.00665**	0.0114***	0.00175
	(0.00304)	(0.00430)	(0.00428)
March	-0.0323***	-0.0247***	-0.0400***
	(0.00424)	(0.00600)	(0.00599)
April	-0.0700***	-0.0719***	-0.0680***
	(0.00486)	(0.00688)	(0.00686)
May	-0.175***	-0.165***	-0.185***
	(0.00602)	(0.00841)	(0.00863)
October	-0.0892***	-0.0839***	-0.0947***
	(0.00543)	(0.00739)	(0.00797)
November	-0.0174***	-0.0179***	-0.0169***
	(0.00335)	(0.00491)	(0.00456)
December	-0.0209***	-0.0150***	-0.0271***
	(0.00310)	(0.00445)	(0.00430)
Peak/Off-Peak THI Differential	-0.0169***	-0.0162***	-0.0176***
	(0.000445)	(0.000629)	(0.000628)
February x THI_Diff	-0.00166***	-0.00160**	-0.00171***
	(0.000465)	(0.000676)	(0.000639)
March x THI_Diff	-0.00378***	-0.00323***	-0.00434***
	(0.000641)	(0.000934)	(0.000877)
April x THI_Diff	-0.00372***	-0.00443***	-0.00299***
	(0.000605)	(0.000867)	(0.000845)
May x THI_Diff	0.0158***	0.0143***	0.0174***
	(0.000760)	(0.00109)	(0.00106)
October x THI_Diff	0.00506***	0.00516***	0.00494***
	(0.000646)	(0.000917)	(0.000910)
November x THI_Diff	-0.00323***	-0.00338***	-0.00306***
	(0.000527)	(0.000748)	(0.000743)
December x THI_Diff	0.00224***	0.00234***	0.00214**
	(0.000645)	(0.000896)	(0.000930)
Constant	-0.0273***	-0.0415***	-0.0129***
	(0.00286)	(0.00392)	(0.00416)
Observations	801,564	405,218	396,346
Number of Customers	2,294	1,164	1,130
Adjusted R-squared	0.038	0.032	0.045
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 80: SUMMER WEEKDAY DAILY DEMAND ELASTICITY – BGE

	All Customers	**LMI Customers**	**Non-LMI Customers**
	(1)	(2)	(3)
VARIABLES	ln(peak to off-peak load)	ln(peak to off-peak load)	ln(peak to off-peak load)
Pilot Period	0.00405	0.00476	0.00343
	(0.00633)	(0.00945)	(0.00833)
Average Daily Rate	-0.0471	-0.0168	-0.0763
	(0.0343)	(0.0483)	(0.0487)
July	-0.0170	-0.0677	0.0377
	(0.0506)	(0.0719)	(0.0711)
August	-0.637***	-0.592***	-0.684***
	(0.0443)	(0.0636)	(0.0614)
September	-0.289***	-0.315***	-0.262***
	(0.0343)	(0.0490)	(0.0479)
Daily THI	0.0495***	0.0491***	0.0500***
	(0.000620)	(0.000878)	(0.000872)
July x Daily THI	0.00107	0.00181*	0.000277
	(0.000684)	(0.000968)	(0.000964)
August x Daily THI	0.00907***	0.00855***	0.00962***
	(0.000605)	(0.000869)	(0.000838)
September x Daily THI	0.00347***	0.00386***	0.00304***
	(0.000477)	(0.000677)	(0.000673)
Constant	-3.749***	-3.740***	-3.750***
	(0.0894)	(0.125)	(0.127)
Observations	410,020	212,508	197,512
Number of Customers	2,520	1,316	1,204
Adjusted R-squared	0.254	0.243	0.266
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 81: NON-SUMMER WEEKDAY DAILY DEMAND ELASTICITY – BGE

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(peak to off-peak load)	ln(peak to off-peak load)	ln(peak to off-peak load)
Pilot Period	-0.0450***	-0.0377***	-0.0526***
	(0.00716)	(0.0106)	(0.00966)
Average Daily Rate	-0.312***	-0.235**	-0.395***
	(0.0694)	(0.0981)	(0.0975)
February	-0.104***	-0.0946***	-0.113***
	(0.0120)	(0.0173)	(0.0164)
March	-0.175***	-0.151***	-0.200***
	(0.0225)	(0.0342)	(0.0292)
April	-0.405***	-0.343***	-0.469***
	(0.0205)	(0.0304)	(0.0274)
May	-1.913***	-1.815***	-2.014***
	(0.0351)	(0.0502)	(0.0489)
October	-2.043***	-1.974***	-2.114***
	(0.0289)	(0.0413)	(0.0402)
November	-0.0745***	-0.0143	-0.136***
	(0.0151)	(0.0221)	(0.0203)
December	-0.167***	-0.136***	-0.198***
	(0.0122)	(0.0171)	(0.0174)
Daily THI	-0.0221***	-0.0210***	-0.0233***
	(0.000380)	(0.000534)	(0.000538)
February x Daily THI	0.00134***	0.00117***	0.00151***
	(0.000251)	(0.000361)	(0.000348)
March x Daily THI	0.00260***	0.00206***	0.00319***
	(0.000459)	(0.000703)	(0.000586)
April x Daily THI	0.00591***	0.00467***	0.00718***
	(0.000402)	(0.000598)	(0.000533)
May x Daily THI	0.0315***	0.0295***	0.0335***
	(0.000605)	(0.000873)	(0.000833)
October x Daily THI	0.0334***	0.0320***	0.0347***
	(0.000511)	(0.000735)	(0.000707)
November x Daily THI	-6.16e-05	-0.00125***	0.00116***
	(0.000317)	(0.000473)	(0.000418)
December x Daily THI	0.00387***	0.00317***	0.00458***
	(0.000260)	(0.000366)	(0.000367)
Constant	0.292*	0.328	0.246
	(0.155)	(0.218)	(0.218)
Observations	801,564	405,218	396,346
Number of Customers	2,294	1,164	1,130
Adjusted R-squared	0.176	0.163	0.191
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

FIGURE 82: SUMMER WEEKDAY SUBSTITUTION ELASTICITY – PEPCO

	All Customers	**LMI Customers**	**Non-LMI Customers**
	(1)	(2)	(3)
VARIABLES	ln(peak to off-peak load)	ln(peak to off-peak load)	ln(peak to off-peak load)
Pilot Period	0.0385***	0.0313***	0.0450***
	(0.00756)	(0.0100)	(0.0106)
Peak to off-Peak Price Ratio	-0.0822***	-0.0574***	-0.104***
	(0.00738)	(0.00956)	(0.0108)
July	-0.0368***	-0.0351***	-0.0380***
	(0.00636)	(0.00915)	(0.00857)
August	-0.0314***	-0.0315***	-0.0310***
	(0.00605)	(0.00807)	(0.00861)
September	-0.0548***	-0.0550***	-0.0543***
	(0.00644)	(0.00856)	(0.00916)
Peak/Off-Peak THI Differential	0.0126***	0.0117***	0.0134***
	(0.000869)	(0.00124)	(0.00117)
July x THI_Diff	0.0260***	0.0250***	0.0268***
	(0.00147)	(0.00202)	(0.00206)
August x THI_Diff	0.0260***	0.0244***	0.0274***
	(0.00125)	(0.00170)	(0.00174)
September x THI_Diff	0.0120***	0.0124***	0.0116***
	(0.00108)	(0.00152)	(0.00149)
Constant	-0.00849	-0.00169	-0.0148*
	(0.00554)	(0.00759)	(0.00771)
Observations	326,006	154,434	171,572
Number of Customers	2048	966	1082
R-squared	0.023	0.019	0.027
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 83: NON-SUMMER WEEKDAY SUBSTITUTION ELASTICITY – PEPCO

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(peak to off-peak load)	ln(peak to off-peak load)	ln(peak to off-peak load)
Pilot Period	-0.0180**	-0.0190*	-0.0173*
	(0.00733)	(0.0105)	(0.00984)
Peak to off-Peak Price Ratio	-0.0279***	-0.0175*	-0.0368***
	(0.00691)	(0.0103)	(0.00914)
February	0.00790**	0.00640	0.00917*
	(0.00389)	(0.00550)	(0.00541)
March	-0.0555***	-0.0506***	-0.0599***
	(0.00553)	(0.00797)	(0.00740)
April	-0.0744***	-0.0811***	-0.0685***
	(0.00625)	(0.00881)	(0.00857)
May	-0.166***	-0.144***	-0.186***
	(0.00808)	(0.0115)	(0.0108)
October	-0.0561***	-0.0425***	-0.0682***
	(0.00702)	(0.00998)	(0.00966)
November	0.0106**	0.0154**	0.00631
	(0.00443)	(0.00602)	(0.00626)
December	-0.00316	0.00340	-0.00892*
	(0.00413)	(0.00610)	(0.00539)
Peak/Off-Peak THI Differential	-0.0147***	-0.0154***	-0.0141***
	(0.000455)	(0.000651)	(0.000611)
February x THI_Diff	-1.32e-05	0.000198	-0.000204
	(0.000506)	(0.000746)	(0.000670)
March x THI_Diff	-0.00574***	-0.00411***	-0.00718***
	(0.000680)	(0.00100)	(0.000877)
April x THI_Diff	-0.000655	-0.000657	-0.000658
	(0.000558)	(0.000832)	(0.000728)
May x THI_Diff	0.00784***	0.00881***	0.00699***
	(0.000807)	(0.00115)	(0.00109)
October x THI_Diff	0.00105	0.00204*	0.000168
	(0.000749)	(0.00111)	(0.000972)
November x THI_Diff	-0.00223***	-0.00178**	-0.00262***
	(0.000582)	(0.000867)	(0.000761)
December x THI_Diff	0.00101	0.00141	0.000665
	(0.000643)	(0.000961)	(0.000840)
Constant	-0.117***	-0.129***	-0.105***
	(0.00394)	(0.00549)	(0.00551)
Observations	678,083	316,662	361,421
Number of Customers	1934	908	1026
Adjusted R-squared	0.031	0.027	0.036
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 84: SUMMER WEEKDAY DAILY DEMAND ELASTICITY – PEPCO

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(avg daily load)	ln(avg daily load)	ln(avg daily load)
Pilot Period	0.0112*	0.0163*	0.00715
	(0.00682)	(0.00971)	(0.00858)
Average Daily Rate	-0.0455	-0.0999	-0.00791
_month	(0.0493)	(0.0811)	(0.0610)
July	-0.0264	-0.0200	-0.0282
	(0.0612)	(0.0871)	(0.0816)
August	-0.605***	-0.564***	-0.638***
	(0.0551)	(0.0799)	(0.0720)
September	0.0422	0.130**	-0.0316
	(0.0390)	(0.0566)	(0.0517)
Daily THI	0.0499***	0.0484***	0.0513***
	(0.000764)	(0.00109)	(0.00102)
July x Daily THI	0.000657	0.000606	0.000650
	(0.000812)	(0.00115)	(0.00108)
August x Daily THI	0.00769***	0.00718***	0.00808***
	(0.000745)	(0.00107)	(0.000981)
September x Daily THI	-0.00158***	-0.00280***	-0.000555
	(0.000546)	(0.000789)	(0.000728)
Constant	-3.925***	-3.985***	-3.898***
	(0.113)	(0.179)	(0.144)
Observations	326,006	154,434	171,572
Number of Customers	2048	966	1082
R-squared	0.251	0.240	0.261
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 85: NON-SUMMER WEEKDAY DAILY DEMAND ELASTICITY – PEPCO

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(avg daily load)	ln(avg daily load)	ln(avg daily load)
Pilot Period	-0.00675	0.00407	-0.0175
	(0.00942)	(0.0143)	(0.0116)
Average Daily Rate	-0.234***	-0.377***	-0.0984
_month	(0.0762)	(0.131)	(0.0802)
February	-0.0541***	-0.0287*	-0.0764***
	(0.0111)	(0.0166)	(0.0143)
March	-0.105***	-0.0663***	-0.139***
	(0.0166)	(0.0243)	(0.0218)
April	-0.301***	-0.268***	-0.330***
	(0.0204)	(0.0297)	(0.0268)
May	-1.739***	-1.673***	-1.794***
	(0.0380)	(0.0557)	(0.0500)
October	-1.753***	-1.725***	-1.778***
	(0.0302)	(0.0437)	(0.0401)
November	-0.0718***	-0.0619***	-0.0803***
	(0.0137)	(0.0190)	(0.0191)
December	-0.0779***	-0.0730***	-0.0815***
	(0.0123)	(0.0172)	(0.0169)
Daily THI	-0.0191***	-0.0198***	-0.0185***
	(0.000358)	(0.000519)	(0.000476)
February x Daily THI	0.000476**	8.65e-05	0.000814**
	(0.000242)	(0.000362)	(0.000318)
March x Daily THI	0.00180***	0.00106**	0.00244***
	(0.000347)	(0.000519)	(0.000452)
April x Daily THI	0.00527***	0.00455***	0.00587***
	(0.000399)	(0.000592)	(0.000519)
May x Daily THI	0.0298***	0.0284***	0.0310***
	(0.000644)	(0.000955)	(0.000838)
October x Daily THI	0.0295***	0.0287***	0.0301***
	(0.000540)	(0.000791)	(0.000707)
November x Daily THI	0.000691**	0.000430	0.000920**
	(0.000287)	(0.000400)	(0.000400)
December x Daily THI	0.00191***	0.00178***	0.00201***
	(0.000277)	(0.000386)	(0.000386)
Constant	0.123	-0.173	0.402**
	(0.168)	(0.288)	(0.178)
Observations	678,083	316,662	361,421
Number of Customers	1934	908	1026
R-squared	0.163	0.184	0.147
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 86: SUMMER WEEKDAY SUBSTITUTION ELASTICITY – DPL

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(peak to off-peak load)	ln(peak to off-peak load)	ln(peak to off-peak load)
Pilot Period	0.0166**	0.0124	0.0237**
	(0.00748)	(0.00884)	(0.0117)
Peak to off-Peak Price Ratio	-0.0759***	-0.0692***	-0.0869***
	(0.00787)	(0.00930)	(0.0136)
July	-0.0531***	-0.0634***	-0.0359***
	(0.00848)	(0.0105)	(0.0134)
August	-0.0352***	-0.0417***	-0.0244*
	(0.00851)	(0.0104)	(0.0138)
September	-0.0889***	-0.0957***	-0.0776***
	(0.00888)	(0.0109)	(0.0144)
Peak/Off-Peak THI Differential	0.000174	-0.000151	0.000714
	(0.00128)	(0.00157)	(0.00203)
July x THI_Diff	0.0301***	0.0316***	0.0277***
	(0.00175)	(0.00217)	(0.00272)
August x THI_Diff	0.0270***	0.0277***	0.0260***
	(0.00171)	(0.00211)	(0.00270)
September x THI_Diff	0.0163***	0.0173***	0.0146***
	(0.00154)	(0.00191)	(0.00245)
Constant	0.193***	0.225***	0.140***
	(0.00762)	(0.00901)	(0.0130)
Observations	191,325	119,363	71,962
Number of Customers	1184	740	444
Adjusted R-squared	0.028	0.028	0.028
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 87: NON-SUMMER WEEKDAY SUBSTITUTION ELASTICITY – DPL

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(peak to off-peak load)	ln(peak to off-peak load)	ln(peak to off-peak load)
Pilot Period	-0.00433	0.00200	-0.0145
	(0.00720)	(0.00902)	(0.00991)
Peak to off-Peak Price Ratio	-0.0518***	-0.0578***	-0.0422***
	(0.00737)	(0.00935)	(0.0114)
February	-0.0139***	-0.0125**	-0.0161**
	(0.00449)	(0.00565)	(0.00720)
March	-0.0224***	-0.0344***	-0.00286
	(0.00594)	(0.00751)	(0.00915)
April	-0.0361***	-0.0442***	-0.0229**
	(0.00710)	(0.00910)	(0.0106)
May	-0.163***	-0.175***	-0.143***
	(0.00894)	(0.0114)	(0.0138)
October	-0.0910***	-0.102***	-0.0732***
	(0.00860)	(0.0108)	(0.0133)
November	-0.0123**	-0.0152**	-0.00770
	(0.00562)	(0.00718)	(0.00841)
December	-0.00250	-0.00311	-0.00151
	(0.00485)	(0.00605)	(0.00769)
Peak/Off-Peak THI Differential	-0.0205***	-0.0211***	-0.0195***
	(0.000579)	(0.000722)	(0.000934)
February x THI_Diff	0.000501	0.000641	0.000274
	(0.000646)	(0.000773)	(0.00110)
March x THI_Diff	0.000937	-0.000537	0.00334***
	(0.000794)	(0.000983)	(0.00127)
April x THI_Diff	0.00371***	0.00245**	0.00577***
	(0.000821)	(0.000990)	(0.00135)
May x THI_Diff	0.00829***	0.00727***	0.00994***
	(0.000949)	(0.00119)	(0.00152)
October x THI_Diff	0.00734***	0.00655***	0.00864***
	(0.000946)	(0.00116)	(0.00155)
November x THI_Diff	0.00274***	0.00144	0.00488***
	(0.000757)	(0.000920)	(0.00126)
December x THI_Diff	0.00324***	0.00283***	0.00391***
	(0.000709)	(0.000902)	(0.00106)
Constant	-0.0246***	-0.0266***	-0.0215***
	(0.00409)	(0.00531)	(0.00604)
Observations	384,481	238,187	146,294
Number of Customers	1096	680	416
Adjusted R-squared	0.044	0.047	0.038
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 88: SUMMER WEEKDAY DAILY DEMAND ELASTICITY – DPL

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(avg daily load)	ln(avg daily load)	ln(avg daily load)
Pilot Period	-0.00166	-0.00926	0.0102
	(0.0108)	(0.0129)	(0.0177)
Average Daily Rate	-0.0921**	-0.0986**	-0.0749
_month	(0.0429)	(0.0488)	(0.0801)
July	-0.476***	-0.479***	-0.471***
	(0.0830)	(0.0947)	(0.151)
August	-0.271***	-0.366***	-0.114
	(0.0715)	(0.0839)	(0.127)
September	-0.0109	-0.0720	0.0886
	(0.0548)	(0.0681)	(0.0873)
Daily THI	0.0395***	0.0401***	0.0386***
	(0.000851)	(0.00104)	(0.00141)
July x Daily THI	0.00797***	0.00791***	0.00807***
	(0.00113)	(0.00130)	(0.00205)
August x Daily THI	0.00503***	0.00607***	0.00332*
	(0.000974)	(0.00113)	(0.00174)
September x Daily THI	-0.000337	0.000463	-0.00164
	(0.000787)	(0.000976)	(0.00126)
Constant	-3.271***	-3.265***	-3.269***
	(0.107)	(0.123)	(0.193)
Observations	191,325	119,363	71,962
Number of Customers	1184	740	444
R-squared	0.195	0.216	0.168
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 89: NON-SUMMER WEEKDAY DAILY DEMAND ELASTICITY – DPL

	All Customers	LMI Customers	Non-LMI Customers
	(1)	(2)	(3)
VARIABLES	ln(avg daily load)	ln(avg daily load)	ln(avg daily load)
Pilot Period	-0.0420***	-0.0506***	-0.0290
	(0.0109)	(0.0122)	(0.0189)
Average Daily Rate	-0.241***	-0.102	-0.484***
_month	(0.0891)	(0.100)	(0.168)
February	-0.151***	-0.126***	-0.191***
	(0.0195)	(0.0216)	(0.0360)
March	-0.0998***	-0.0542	-0.176***
	(0.0325)	(0.0398)	(0.0544)
April	-0.495***	-0.362***	-0.712***
	(0.0412)	(0.0479)	(0.0713)
May	-1.728***	-1.674***	-1.818***
	(0.0608)	(0.0727)	(0.103)
October	-1.892***	-1.820***	-2.008***
	(0.0498)	(0.0614)	(0.0827)
November	-0.248***	-0.180***	-0.359***
	(0.0310)	(0.0351)	(0.0557)
December	-0.208***	-0.157***	-0.290***
	(0.0229)	(0.0253)	(0.0428)
Daily THI	-0.0299***	-0.0294***	-0.0306***
	(0.000709)	(0.000856)	(0.00121)
February x Daily THI	0.00256***	0.00184***	0.00373***
	(0.000474)	(0.000520)	(0.000872)
March x Daily THI	0.00218***	0.000863	0.00435***
	(0.000733)	(0.000893)	(0.00123)
April x Daily THI	0.00880***	0.00557***	0.0140***
	(0.000885)	(0.00104)	(0.00151)
May x Daily THI	0.0303***	0.0284***	0.0334***
	(0.00113)	(0.00136)	(0.00185)
October x Daily THI	0.0331***	0.0309***	0.0366***
	(0.000982)	(0.00119)	(0.00166)
November x Daily THI	0.00388***	0.00219***	0.00663***
	(0.000724)	(0.000825)	(0.00128)
December x Daily THI	0.00499***	0.00378***	0.00692***
	(0.000532)	(0.000597)	(0.000976)
Constant	0.684***	1.070***	0.0189
	(0.181)	(0.202)	(0.346)
Observations	384,481	238,187	146,294
Number of Customers	1096	680	416
R-squared	0.240	0.282	0.186
Customer FE	Y	Y	Y

Note: Excludes net-metering customers and treatment-control pairs who have ever been on three-period rates other than PC44 TOU. Prices only include major components of the bill (supply, transmission, and distribution). Average daily price is weighted by pre-treatment monthly peak/off-peak share of usage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.7 Sensitivity Analyses

This section provides results for alternate regression approaches that test the robustness of our primary results. The date fixed effects approach replaces the various controls we include in the primary specification with a dummy variable for each date in the relevant regression. The level regression approach uses the absolute level of peak, off-peak, and daily load as the dependent variable instead of the natural logarithm. This allows us to include net metering customers in the regression. "Full-time enrollees" refers to regressions that include only those customers who were enrolled for the entirety of the season. The "naïve" control group regressions consider the entire pool of eligible control customers instead of restricting to only those matched to pilot customers. In the tables for the non-summer season, we also present the impacts for pre-COVID months and the incremental impact observed during COVID months.

FIGURE 90: BGE SUMMER WEEKDAY SENSITIVITY RESULTS

	Primary Results	Date-Fixed Effects	Level Regression	Full-time enrollees	Naive Control Group
LMI Customers					
On-Peak	-8.1%***	-8.1%***	-9.4%***	-8.2%***	-7.4%***
Off-Peak	0.1%	0.1%	-1.5%	-0.1%	0.4%
Daily	-2.0%	-2.0%	-3.6%***	-2.1%	-1.5%
Non-LMI Customers					
On-Peak	-12.4%***	-12.4%***	-10.7%***	-12.5%***	-10.0%***
Off-Peak	-1.4%	-1.4%	-2.3%**	-1.4%	1.4%
Daily	-3.7%***	-3.7%***	-4.6%***	-3.8%***	-1.2%
All Customers					
On-Peak	-10.2%***	-10.2%***	-10.2%***	-10.4%***	-8.6%***
Off-Peak	-0.7%	-0.7%	-2.0%**	-0.8%	1.0%
Daily	-2.8%***	-2.9%***	-4.2%***	-2.9%***	-1.3%

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the "Level Regression," the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded.

FIGURE 91: BGE SUMMER WEEKEND SENSITIVITY RESULTS

	Primary Results	Date-Fixed Effects	Level Regression	Full-time enrollees	Naive Control Group
LMI Customers					
On-Peak	-4.2%**	-4.2%**	-7.7%***	-4.3%**	-3.9%**
Off-Peak	0.0%	0.0%	-3.1%**	-0.1%	0.8%
Daily	-1.0%	-1.0%	-4.3%***	-1.1%	-0.2%
Non-LMI Customers					
On-Peak	-4.8%***	-4.8%***	-4.7%***	-4.8%***	-3.0%*
Off-Peak	-1.1%	-1.1%	-1.9%*	-1.3%	0.8%
Daily	-1.8%	-1.8%	-2.7%**	-2.0%	-0.1%
All Customers					
On-Peak	-4.5%***	-4.5%***	-5.9%***	-4.5%***	-3.4%***
Off-Peak	-0.5%	-0.5%	-2.4%***	-0.7%	0.7%
Daily	-1.4%	-1.4%	-3.4%***	-1.5%	-0.3%

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the “Level Regression,” the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded.

FIGURE 92: BGE NON-SUMMER WEEKDAY SENSITIVITY RESULTS

	Primary Results	Date-Fixed Effects	Level Regression	Full-time enrollees	Non-COVID months	COVID differential coef.	Naive Control Group
LMI Customers							
On-Peak	-5.3%***	-5.3%***	-4.7%**	-5.3%***	-4.2%**	-3.2%*	-5.1%***
Off-Peak	-2.4%	-2.4%	-2.6%	-2.4%	-1.9%	-1.6%	-0.7%
Daily	-2.7%	-2.7%	-2.9%*	-2.7%	-2.1%	-1.8%	-1.2%
Non-LMI Customers							
On-Peak	-5.5%***	-5.5%***	-7.5%***	-5.3%***	-5.7%***	0.6%	-7.4%***
Off-Peak	0.8%	0.8%	-2.2%	1.4%	-0.2%	2.6%*	-1.3%
Daily	0.0%	0.0%	-2.9%**	0.5%	-0.8%	2.2%	-2.0%
All Customers							
On-Peak	-5.4%***	-5.4%***	-6.4%***	-5.3%***	-5.0%***	-1.3%	-6.3%***
Off-Peak	-0.8%	-0.8%	-2.4%**	-0.5%	-1.0%	0.5%	-1.2%
Daily	-1.3%	-1.3%	-2.9%***	-1.1%	-1.4%	0.2%	-1.8%*

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the “Level Regression,” the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. “Full-time Enrollees” include only those customers enrolled for the entirety of the non-summer season. The COVID differential effect presents the incremental impact over that observed during the non-COVID months. The “*” indicates an impact that is statistically different from the non-COVID months.

FIGURE 93: BGE NON-SUMMER WEEKEND SENSITIVITY RESULTS

	Primary Results	Date-Fixed Effects	Level Regression	Full-time enrollees	Non-COVID months	COVID differential coef.	Naive Control Group
LMI Customers							
On-Peak	-2.8%	-2.8%	-3.4%*	-2.7%	-2.1%	-1.9%	-1.3%
Off-Peak	-1.8%	-1.8%	-2.2%	-1.8%	-1.2%	-1.7%	-1.0%
Daily	-1.9%	-1.9%	-2.3%	-1.9%	-1.3%	-1.7%	-1.0%
Non-LMI Customers							
On-Peak	-1.6%	-1.5%	-5.2%***	-1.3%	-1.9%	1.0%	-4.3%***
Off-Peak	1.3%	1.3%	-2.0%	1.8%	0.0%	3.3%**	-0.7%
Daily	0.9%	0.9%	-2.4%*	1.4%	-0.2%	3.1%*	-1.2%
All Customers							
On-Peak	-2.2%*	-2.2%*	-4.5%***	-2.0%	-2.0%*	-0.5%	-3.1%***
Off-Peak	-0.3%	-0.3%	-2.1%**	0.0%	-0.6%	0.8%	-1.0%
Daily	-0.5%	-0.5%	-2.4%**	-0.2%	-0.7%	0.7%	-1.3%

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the "Level Regression," the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. "Full-time Enrollees" include only those customers enrolled for the entirety of the non-summer season. The COVID differential effect presents the incremental impact over that observed during the non-COVID months. The "*" indicates an impact that is statistically different from the non-COVID months.

FIGURE 94: PEPCO SUMMER WEEKDAY SENSITIVITY RESULTS

	Primary Result	Date Fixed Effects	Level Regression	Full-time Enrollees	Naïve Control Group
LMI Customers					
On-Peak	-10.7%***	-10.7%***	-9.4%***	-11.7%***	-10.4%***
Off-Peak	-1.2%	-1.2%	-1.5%	-2.2%	-1.4%
Daily	-3.3%**	-3.3%**	-3.5%**	-4.3%**	-3.5%***
Non-LMI Customers					
On-Peak	-17.3%***	-17.3%***	-16.0%***	-17.7%***	-15.0%***
Off-Peak	-2.1%	-2.1%	-1.6%	-2.7%	-1.4%
Daily	-5.2%***	-5.2%***	-5.2%***	-5.8%***	-4.2%***
All Customers					
On-Peak	-14.3%***	-14.3%***	-13.2%***	-14.8%***	-12.8%***
Off-Peak	-1.7%	-1.7%	-1.6%	-2.5%*	-1.3%*
Daily	-4.3%***	-4.3%***	-4.5%***	-5.1%***	-3.8%***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the "Level Regression," the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. "Full-time Enrollees" include only those customers enrolled for the entirety of the summer season.

FIGURE 95: PEPCO SUMMER WEEKEND SENSITIVITY RESULTS

	Primary Result	Date Fixed Effects	Level Regression	Full-time Enrollees	Naïve Control Group
LMI Customers					
On-Peak	-4.9%**	-4.9%**	-5.6%***	-5.6%**	-7.4%***
Off-Peak	-1.7%	-1.7%	-2.3%	-2.3%	-3.6%***
Daily	-2.4%	-2.4%	-3.2%**	-3.1%	-4.6%***
Non-LMI Customers					
On-Peak	-8.6%***	-8.6%***	-6.5%***	-10.8%***	-9.9%***
Off-Peak	-3.0%**	-3.0%**	-2.2%	-4.8%***	-3.4%***
Daily	-4.3%***	-4.3%***	-3.4%**	-6.1%***	-5.1%***
All Customers					
On-Peak	-6.9%***	-6.9%***	-6.1%***	-8.3%***	-8.8%***
Off-Peak	-2.4%**	-2.4%**	-2.2%**	-3.5%***	-3.5%***
Daily	-3.4%***	-3.4%***	-3.3%***	-4.6%***	-4.9%***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the "Level Regression," the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. "Full-time Enrollees" include only those customers enrolled for the entirety of the summer season.

FIGURE 96: PEPCO NON-SUMMER WEEKDAY SENSITIVITY RESULTS

	Primary Result	Date Fixed Effects	Level Regression	Full-time Enrollees	Non-COVID Months	COVID (Differential Coefficient)	Naïve Control Group
LMI Customers							
On-Peak	-4.8%**	-4.8%**	-5.1%**	-4.9%**	-3.8%*	-2.6%	-4.3%***
Off-Peak	-1.7%	-1.7%	-3.2%*	-1.7%	-0.1%	-4.3%**	-1.9%
Daily	-2.0%	-2.0%	-3.5%*	-2.0%	-0.4%	-4.1%**	-2.1%*
Non-LMI Customers							
On-Peak	-5.3%***	-5.3%***	-5.5%**	-5.5%***	-7.0%***	4.7%**	-3.2%**
Off-Peak	0.9%	0.9%	-0.4%	0.7%	0.2%	1.7%	1.4%
Daily	0.1%	0.1%	-1.1%	-0.1%	-0.6%	1.9%	0.8%
All Customers							
On-Peak	-5.1%***	-5.1%***	-5.3%***	-5.2%***	-5.6%***	1.4%	-3.6%***
Off-Peak	-0.3%	-0.3%	-1.7%	-0.4%	0.1%	-1.0%	-0.1%
Daily	-0.8%	-0.8%	-2.2%	-1.0%	-0.5%	-0.8%	-0.5%

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the "Level Regression," the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. "Full-time Enrollees" include only those customers enrolled for the entirety of the non-summer season. The COVID differential effect presents the incremental impact over that observed during the non-COVID months. The "*" indicates an impact that is statistically different from the non-COVID months.

FIGURE 97: PEPCO NON-SUMMER WEEKEND SENSITIVITY RESULTS

	Primary Result	Date Fixed Effects	Level Regression	Full-time Enrollees	Non-COVID Months	COVID (Differential Coefficient)	Naïve Control Group
LMI Customers							
On-Peak	-0.9%	-0.9%	-2.6%	-1.1%	-0.1%	-2.3%	-1.9%
Off-Peak	-1.3%	-1.3%	-2.8%	-1.4%	0.1%	-4.0%**	-1.8%
Daily	-1.2%	-1.2%	-2.7%	-1.4%	0.1%	-3.8%**	-1.8%
Non-LMI Customers							
On-Peak	-0.1%	-0.1%	-0.9%	-0.3%	-1.0%	2.6%	-0.8%
Off-Peak	0.3%	0.3%	-0.4%	0.2%	0.1%	0.8%	0.4%
Daily	0.3%	0.3%	-0.5%	0.2%	0.0%	0.8%	0.3%
All Customers							
On-Peak	-0.5%	-0.4%	-1.6%	-0.7%	-0.6%	0.4%	-1.2%
Off-Peak	-0.4%	-0.4%	-1.5%	-0.5%	0.1%	-1.4%	-0.6%
Daily	-0.4%	-0.4%	-1.5%	-0.5%	0.1%	-1.3%	-0.6%

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the “Level Regression,” the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. “Full-time Enrollees” include only those customers enrolled for the entirety of the non-summer season. The COVID differential effect presents the incremental impact over that observed during the non-COVID months. The “*” indicates an impact that is statistically different from the non-COVID months.

FIGURE 98: DPL SUMMER WEEKDAY SENSITIVITY RESULTS

	Primary Result	Date Fixed Effects	Level Regression	Full-time Enrollees	Naïve Control Group
LMI Customers					
On-Peak	-13.7%***	-13.7%***	-13.7%***	-13.5%***	-15.1%***
Off-Peak	-1.8%	-1.8%	-0.4%	-1.8%	-3.4%**
Daily	-4.6%**	-4.6%**	-4.1%**	-4.6%**	-6.1%***
Non-LMI Customers					
On-Peak	-16.7%***	-16.7%***	-15.7%***	-17.5%***	-15.3%***
Off-Peak	-2.1%	-2.1%	-0.9%	-2.9%	-0.9%
Daily	-5.4%*	-5.4%*	-4.9%**	-6.1%**	-4.3%**
All Customers					
On-Peak	-14.8%***	-14.8%***	-14.5%***	-15.0%***	-15.0%***
Off-Peak	-1.9%	-1.9%	-0.6%	-2.2%	-2.4%**
Daily	-4.9%***	-4.9%***	-4.4%***	-5.2%***	-5.3%***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the “Level Regression,” the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. “Full-time Enrollees” include only those customers enrolled for the entirety of the summer season.

FIGURE 99: DPL SUMMER WEEKEND SENSITIVITY RESULTS

	Primary Result	Date Fixed Effects	Level Regression	Full-time Enrollees	Naïve Control Group
LMI Customers					
On-Peak	-7.0%***	-7.0%***	-8.3%***	-6.4%**	-9.8%***
Off-Peak	-0.8%	-0.8%	-0.6%	-0.8%	-2.9%**
Daily	-2.2%	-2.2%	-2.8%	-2.0%	-4.6%***
Non-LMI Customers					
On-Peak	-10.1%***	-10.1%***	-7.1%***	-10.6%***	-10.9%***
Off-Peak	-3.2%	-3.2%	-1.8%	-3.4%	-4.1%*
Daily	-4.7%	-4.7%	-3.2%	-5.0%	-5.7%***
All Customers					
On-Peak	-8.2%***	-8.2%***	-7.8%***	-8.0%***	-10.1%***
Off-Peak	-1.7%	-1.7%	-1.1%	-1.8%	-3.2%***
Daily	-3.1%*	-3.2%*	-3.0%*	-3.2%*	-4.8%***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the "Level Regression," the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. "Full-time Enrollees" include only those customers enrolled for the entirety of the summer season.

FIGURE 100: DPL NON-SUMMER WEEKDAY SENSITIVITY RESULTS

	Primary Result	Date Fixed Effects	Level Regression	Full-time Enrollees	Non-COVID Months	COVID (Differential Coefficient)	Naïve Control Group
LMI Customers							
On-Peak	-7.8%***	-7.8%***	-5.3%**	-7.9%***	-10.2%***	7.0%***	-10.4%***
Off-Peak	2.6%	2.6%	2.6%	2.3%	0.0%	6.7%***	-2.6%
Daily	1.3%	1.3%	1.5%	1.0%	-1.2%	6.7%***	-3.5%**
Non-LMI Customers							
On-Peak	-3.2%	-3.2%	-7.9%**	-3.6%	-5.2%	5.6%	-7.7%**
Off-Peak	4.6%	4.6%	1.2%	4.4%	2.4%	5.5%	0.2%
Daily	3.8%	3.8%	-0.1%	3.6%	1.7%	5.4%	-0.7%
All Customers							
On-Peak	-6.1%**	-6.1%**	-6.2%***	-6.3%**	-8.3%***	6.4%***	-8.7%***
Off-Peak	3.4%	3.4%	2.1%	3.1%	0.9%	6.3%***	-1.1%
Daily	2.3%	2.3%	0.9%	2.0%	-0.1%	6.2%***	-1.9%

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the "Level Regression," the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. "Full-time Enrollees" include only those customers enrolled for the entirety of the non-summer season. The COVID differential effect presents the incremental impact over that observed during the non-COVID months. The "*" indicates an impact that is statistically different from the non-COVID months.

FIGURE 101: DPL NON-SUMMER WEEKEND SENSITIVITY RESULTS

	Primary Result	Date Fixed Effects	Level Regression	Full-time Enrollees	Non-COVID Months	COVID (Differential Coefficient)	Naïve Control Group
LMI Customers							
On-Peak	-2.6%	-2.6%	-1.5%	-2.8%	-4.2%	5.0%*	-5.6%***
Off-Peak	2.9%	2.9%	3.2%	2.6%	1.4%	4.3%*	-2.3%
Daily	2.2%	2.2%	2.6%	1.9%	0.7%	4.3%*	-2.7%*
Non-LMI Customers							
On-Peak	-0.1%	-0.1%	-4.5%	-0.4%	-1.4%	4.0%	-4.3%
Off-Peak	1.9%	2.0%	-2.2%	1.6%	-0.2%	5.9%	-0.1%
Daily	1.8%	1.8%	-2.5%	1.5%	-0.1%	5.5%	-0.7%
All Customers							
On-Peak	-1.6%	-1.6%	-2.6%	-1.9%	-3.2%	4.6%*	-4.8%***
Off-Peak	2.5%	2.5%	1.2%	2.2%	0.8%	4.9%**	-1.3%
Daily	2.0%	2.1%	0.7%	1.8%	0.4%	4.8%**	-1.8%

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. In the “Level Regression,” the set of customers included in the estimation is larger than in the other sets of results, as net metering customers are not excluded. “Full-time Enrollees” include only those customers enrolled for the entirety of the non-summer season. The COVID differential effect presents the incremental impact over that observed during the non-COVID months. The “*” indicates an impact that is statistically different from the non-COVID months.