

# Regulated Price Plan Roadmap Pilot Program Final Impact Evaluation

Evaluation Report  
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Prepared for:



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1. **Appendix B: OEB Required Pilot Metrics.** A spreadsheet file containing the data required by the OEB as an output from this analysis.
2. **Appendix C: General Outputs.** A spreadsheet file containing the data associated with the figures presented in Chapter 3.
3. **Appendix D: Energy Impact Outputs.** A spreadsheet file containing the data associated with the figures (excluding load profiles) presented in Section 4.1
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6. **Appendix G: CPP Event Load Profiles.** A PDF file containing the full set of average event load profiles referenced in Section 4.2
7. **Appendix H: RCT Validation and Alternative Control Group Approach.** An MS Word document outlining the alternative control group developed, but not, in the end, used, for this

evaluation. This appendix also includes a summary of Navigant's validation of the experimental assignment to participant and control groups.

8. **Appendix I: Participant Engagement Tools and Strategy.** An MS Word document providing additional detail about the Trickl app, the customer engagement strategy used by London Hydro, and customer disconnections.
9. **Appendix J: Extended Analysis – Impact of Customer Engagement.** An MS Word document describing the context, approach, and findings of Navigant's additional analysis of participant response to London Hydro's customer engagement strategy.
10. **Appendix K: Extended Analysis – Impact of Customer Engagement (Quantitative Outputs).** A spreadsheet file containing the data outputs (used in graphics and tables, etc.) associated with the analysis undertaken in Appendix J.

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## 1. EXECUTIVE SUMMARY

This executive summary provides a high-level overview of the London Hydro Regulated Price Plan (RPP) pilot program, a brief summary of the data and methods used for quantifying impacts, the key evaluation findings, and the conclusions about the program based on those findings.

### 1.1 Introduction & Program Description

London Hydro's RPP pilot is an experiment approved by the Ontario Energy Board (OEB) as part of its ongoing RPP Roadmap, and is a test of two experimental treatments, and of their interaction.

This pilot is an experiment designed to test the impacts of these two treatments across three distinct groups of participants, specifically:

- Real-Time Information (RT).** The impact on participant consumption patterns of the provision of real-time information (the RT treatment) via the mobile application "Trickl"<sup>1</sup> which provides real-time consumption data and notifications when overall energy consumption exceeds that of peer households.

London Hydro provided Navigant with cross-sectional data for 1,135 customers enrolled into this stream.

- Critical Peak Pricing (CPP).** The impact on participant consumption patterns (and demand during critical peak events) of providing customers with a slightly discounted Off-Peak time-of-use (TOU) and subjecting them to 36 one-hour critical peak pricing periods over the course of the 12-month pilot period (18 summer<sup>2</sup> events, 18 winter events). The critical peak price was set at 59.5 cents per kWh by the OEB.

All CPP participants are provided with a smart plug and a load control switch installed (by London Hydro's contractor) at the participant's electrical panel. Each switch can control up to three 30-amp circuits. These enabling technologies respond to a control signal dispatched by London Hydro and are intended to automate some CPP event demand reductions. CPP participants were also equipped with the Trickl app. This group did not have access to the real-time consumption data or energy consumption alert functionality enjoyed by the RT group. For this group, the app was used to communicate notification for CPP events and to provide participants with the ability to remotely control the technologies provided by London Hydro.

London Hydro provided Navigant with cross-sectional data for 340 customers enrolled in this stream.

- Combined Effects (CPP/RT).** The impact on participant consumption patterns (and demand during critical peak events) of combining both treatments (CPP and RT together).

London Hydro provided Navigant with cross-sectional data for 318 customers enrolled in this stream.

<sup>1</sup> Details on the functionality of this mobile application may be found in Appendix I (under a separate cover).

<sup>2</sup> Unless otherwise explicitly noted, "summer" and "winter" in this report reflect the OEB's RPP seasons: summer being May through October, winter being November through April.

In addition to the 1,793 participants in the three participant groups, London Hydro also provided cross-sectional data for 474 customers that were enrolled as control customers. These customers applied to participate in the pilot program but were not enrolled by London Hydro. This “recruit-and-deny” strategy enabled the pilot to be a randomized control trial (RCT). For the purposes of the impact analysis, these RCT control customers act in a manner analogous to that of the placebo group in a pharmaceutical trial. RCTs are generally considered the “gold standard” for program evaluation as they control for selection bias.

Enabling technology (see below) deployment and participant enrollment took place over the course of the period beginning in July of 2017 through until May 1 of 2018, at which time the pilot became live. From this point on, the participants subject to the CPP rate were liable for the all charges they incurred under the new rate. Note that all participants subject to the CPP rate did receive a \$100 incentive as a reward for participation, with \$25 provided at enrollment and the final \$75 provided at the end of the pilot.

As part of its efforts to support the success of the pilot, and to provide participants with the knowledge and ability to take advantage of the tools offered by the pilot (both informational and price-related), London Hydro maintained an active customer engagement strategy over the pilot period (May 1, 2018 through April 30, 2019). A summary of this is presented in Section 2.1, and a detailed timeline and description of this strategy may be found in Appendix I, under a separate cover.

## 1.2 Approach, Data, and Sampling for Impact Evaluation

London Hydro provided Navigant with hourly electricity consumption data for all participants and control customers, from May 1, 2016 through to the end of April 2019. As noted above, this evaluation is a randomized control trial (RCT), with control customers generated through a recruit-and-deny approach to control selection. The validity of the experimental design was verified by Navigant through the application of regression analysis to pre-period participant and control demand data.

When estimating impacts, only the program period (May, 2018 through April 2019) data were used. Consumption in pre-program periods was used to develop regression variables for the impact estimation intended to improve the precision<sup>3</sup> and accuracy<sup>4</sup> of the estimation, and Navigant used consumption in these prior periods as a contrast to consumption in the program period to better understand the program impacts.

Both energy impacts and CPP event day impacts were estimated using regression analysis. Summer impacts were estimated separately from winter impacts. The daily average energy impacts were estimated using all consumption data for the season in question, aggregated to a daily series, by TOU period (or IESO EM&V Protocols determined “coincident peak” period). CPP event impacts were estimated using only the days on which CPP events occurred.

In addition to participant consumption data, Navigant leveraged connectivity data collected by London Hydro as part of the CPP event demand analysis. These data track which CPP participants’ enabling technologies were connected and able to receive the curtailment signal during CPP events. These data

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<sup>3</sup> In econometric analysis, “precision” refers to the measure of uncertainty around estimated values, quantified in regression analysis by the estimated parameter’s standard error.

<sup>4</sup> In econometric analysis, “accuracy” commonly refers to unbiasedness of an estimate – the closer the estimate is to the true (typically unknown) value, the more accurate it is.

enabled Navigant to differentiate between purely behavioural CPP event impacts (i.e., impacts from the group whose enabling technologies were not connected) and impacts that were a combination of behaviour and automation.

### 1.3 Energy Literacy Goals and Approach

Navigant’s sub-contractor, Ipsos Public Affairs, conducted a mixed methodology survey including both telephone and online surveys among pilot participants and non-participants (the RCT group) in order to effectively evaluate the effects of the three treatments on energy literacy. Both the telephone and online survey were completed following the conclusion of the pilot in order to achieve a high response rate among participants.

The key objectives of the energy literacy analysis were to measure:

- **Participant Energy Literacy:** How well do participants understand their real-time usage data? How do they use this information to inform or adjust their behaviour?
- **Differences Between Participant and Non-Participant Energy Literacy:** How does participant energy literacy differ from that of non-participants? Approximately how much of this difference is attributable to the program, and how much is attributable to differing base levels of energy literacy?
- **Differences Between Participant and Non-Participant Consumption Behaviour:** To what degree do key self-reported electricity consumption habits of interest differ between participants and non-participants? How much of this difference may be attributed to the program?

The sample for participants and non-participants (the randomized control group of customers that had applied to, but not been enrolled in, the pilot) was provided by London Hydro. Participants included anyone who participated in each of the three streams of the pilot program (CPP/RT, RT, CPP). Non-participants were those London Hydro customers who expressed interest in the RPP pilot program but were not selected to participate. The following number of participants and non-participants were offered the opportunity to respond to the survey.

**Figure 1-1: Available Sample (Number of Potential Respondents)**

Participants	1714
RT	1105
CPP	311
CPP + RT	298
Non-Participants	1158

In total, n=1,173 interviews were completed overall across both Participant (n=821) and Non-Participant (n=352) groups. A sample of this size has a margin of error of +/- 2.2%, nineteen times out of twenty). The figure below details the number of completed interviews by program stream and the corresponding margin of error. Completed interviews by methodology include n=775 online and n=398 by telephone.

**Figure 1-2: Attained Sample (Number of Achieved Survey Respondents)**

Participants	821	(+/-2.9%)
RT	436	(+/-4.3%)
CPP	198	(+/-6.7%)
CPP + RT	187	(+/-6.9%)
Non-Participants	352	(+/-4.9%)

Fieldwork took place between May 23rd to June 24th of 2019. The telephone survey launched June 4th, 2019.

The survey yielded a response rate of 41% overall which is considered high when compared to typical response rates to consumer surveys.

## 1.4 Key Findings

There are three key components of this evaluation: the energy impact analysis, the CPP event demand impact analysis, and the energy literacy analysis.

### 1.4.1 Energy Impact Key Findings

The key findings below are high-level summaries of detailed estimated outputs. The detail underlying each of these may be found in Section 4.1 of the report, as well as in the spreadsheet Appendix D. Navigant’s key findings from the energy impact analysis include:

- **The pilot treatments deliver energy savings only in the summer.** Navigant did not estimate any statistically significant energy savings during the winter months for any of the treatment groups.
- **CPP participants delivered summer On-Peak and Mid-Peak energy savings that are statistically significant at the 90% confidence level.** CPP and CPP/RT participants reduced their daily summer (see section 4.1.2):
  - On-Peak consumption by approximately 5% on average
  - Mid-Peak consumption by approximately 3% on average

- **RT participants delivered modest On-Peak energy savings, although these results are less certain.** RT participants reduced their On-Peak consumption by approximately 2%, although these results are less certain than those of the CPP group – being just barely statistically non-significant, with a relative precision of +/- 101%. Navigant presents evidence in Section 4.1.4 that although these impacts are not statistically significant at the 90% level, it seems probable that these estimates reflect actual conservation, and not just random variation in the underlying data. That is that there is a real, though highly uncertain, impact during the On-Peak period.
- **CPP participants also equipped with the RT technology are saving the same as CPP-only participants in the summer months.** Navigant found no statistically significant difference between the energy savings achieved by CPP and CPP/RT participants in the summer months. Based on this, Navigant has concluded that it is likely that the RT treatment is not delivering any incremental savings to participants also subject to the CPP price plan (see section 3.4).
- **Statistically significant energy savings have been estimated only in summer months and are, in those months, correlated with temperature.** Although Navigant cannot categorically state what behaviour is driving energy savings, the fact that the CPP groups' estimated energy savings are statistically significantly correlated with temperature and are statistically significant only in summer months, suggests that response is driven in large part by changes in A/C use.
- **Participants that attend open-house events deliver statistically significantly more energy savings during the On-Peak and Mid-Peak periods.** In an ancillary analysis undertaken on behalf of the OEB (see Appendix J under a separate cover), Navigant found that open-house attending participants' On-Peak summer energy impact was approximately twice the average participant's On-Peak summer energy impact, and that Mid-Peak impacts were approximately three times higher than the average. While Navigant has noted that some of this difference in impacts could be a result of some selection bias (the kind of people likely to attend in-person help sessions are also likely to put more effort than average into price response), Navigant also noted that a very high proportion (26%) of open-house attendees did so help remedy basic technical issues (e.g., logging into Trickle, etc.) which could have prevented them from delivering any impacts, had these issues not been remedied.

### 1.4.2 CPP Event Demand Impact Key Findings

Figure 1-1 and Figure 1-2, below, show scatterplots of CPP event impact and temperature pairs in summer and winter (respectively). This plot contains three series of CPP event impact/temperature pairs:

- The **yellow triangles** indicate average program impact, per participant for each event.
- The **green diamonds** indicate the average program impact when only including participants whose enabling technologies were *connected* at the time of the CPP event, per participant for each event.
- The **blue squares** indicate the average program impact when only including participants whose enabling technologies were *disconnected* at the time of the CPP event, per participant for each event. Note that since all these participants are not connected, all impacts shown below are behavioural, rather than automated via signal from London Hydro.

The impacts presented in these figures are the estimated demand response impacts – a positive value indicates a savings, a negative value indicates an estimated *increase* in demand.

The whiskers surrounding each marker provide the 90% confidence interval in the impact. Note that where the whisker falls on both sides of the zero line in the y-axis, the estimated impact is not statistically significant at the 90% level, and the hypothesis that the true impact is zero cannot be rejected.

The solid lines that run through the markers indicate (in the summer figure) the average relationship between CPP event program impacts and contemporaneous outdoor temperature or the average seasonal impact (winter). These are the ex-ante estimates of program capability under a range of different temperatures. Statistically non-significant impact estimates are not shown. All summer impacts are statistically significant. In the winter, the average impact across all events of disconnected participants is not statistically significant (hence why there is no blue line), although the estimated impacts of two of the events *are* statistically significant.

These figures illustrate the estimated positive relationship between outdoor temperature and the average demand response impacts in the summer (Figure 1.1), and the lack of any such relationship in the winter (Figure 1.2). This a key finding of this study.

Figure 1-3: Ex-Ante and Ex-Post Impact Scatter Plot – Summer CPP Event Impacts

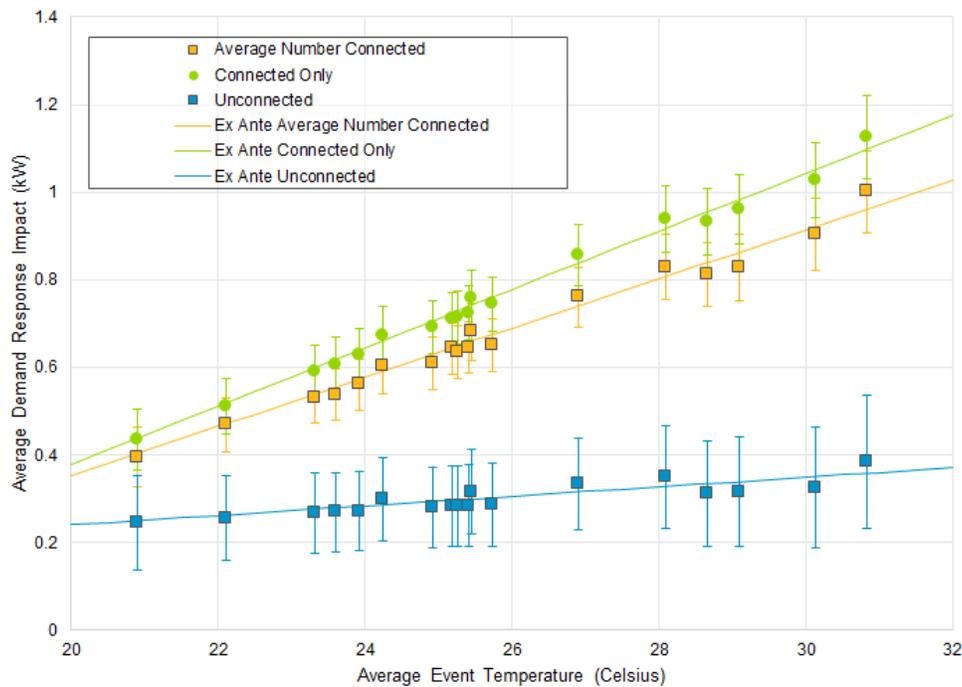
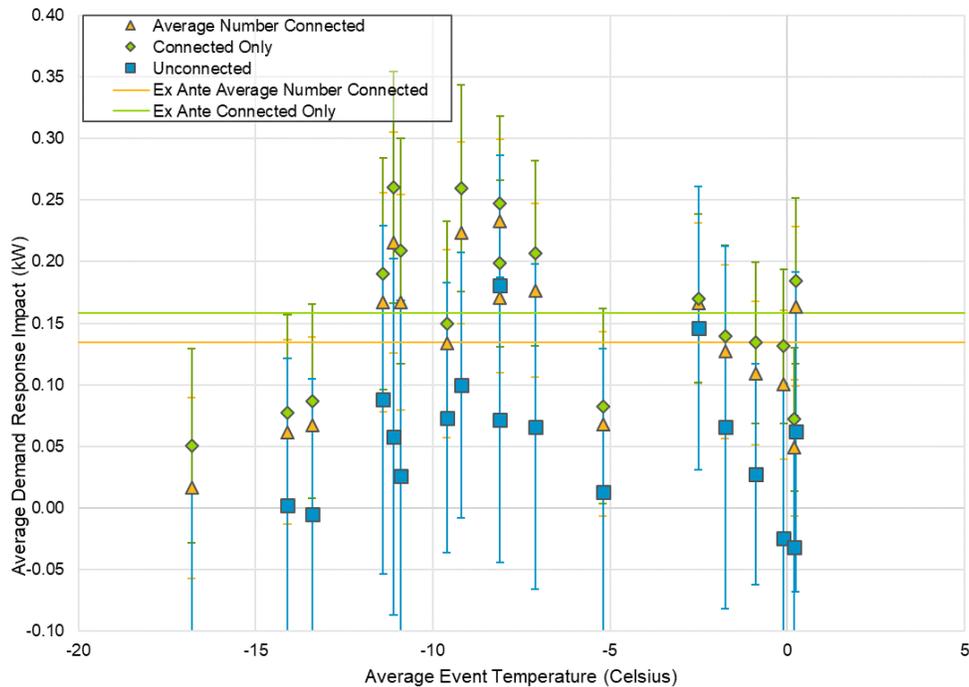


Figure 1-4: Ex-Ante and Ex-Post Impact Scatter Plot – Winter CPP Event Impacts



Navigant’s other key findings from the demand impact analysis include:

- **CPP response is very different in summer and in winter.**
  - *Summer CPP response is substantial and correlated with temperature.* In the summer months (see section 4.2.1), CPP demand response impacts were on average 0.67 kW (34%) and were positively correlated with temperature: the hotter the day, the higher the CPP impacts. During the hottest event of the summer, participants delivered an average of 1 kW each of demand response. This aligns with the finding above (in Section 1.4.1) that summer energy impacts are highly correlated with temperature.
  - *Winter CPP response is small and does not appear to be meaningfully correlated with temperature.* Winter impacts (see section 4.2.2), in contrast with those estimated in the summer, are much lower, on average, 0.13 kW per event. Winter impacts do not appear to be correlated with weather, with the highest event impact being estimated to have occurred on only a moderately cold day (0.23 kW, at -8 degrees Celsius).
- **There is a behavioural element to CPP event impacts in the summer months.** CPP participants are equipped with enabling technologies (a switch at the panel, and one smart plug) that respond automatically to London Hydro’s price signal. Even though participants receive 15 minutes’ notification of an event, there are clear behavioural elements to their response over and above the automated response delivered by the switches and smart plugs.

- *Participants reduced consumption during hours in which CPP events were likely to occur.* CPP participants reduce their exposure to the CPP rate by making changes to their consumption habits in anticipation of CPP events – substantial savings are achieved in hours of the CPP event day leading up to the CPP event, despite participants not having any knowledge of when the event will occur until 15 minutes before it does (see section 4.1.2).
- *Disconnected participants still delivered demand response.* For any given event, approximately 20% of participants’ devices could not receive, or respond to, London Hydro’s curtailment signal (see section 3.1.4). These participants were still able to (in the summer months), on average, with only 15 minutes’ notice, to reduce demand by 0.3 kW (15%) each (see section 4.2.3) without the program-deployed enabling technologies.<sup>5</sup>
- **Real-time information on consumption did not affect demand reductions.** The impacts of the CPP and CPP/RT group were not statistically significantly different from one another in either season – the availability of the online portal and energy tracking app did not impact participants’ ability to deliver demand reductions.
- **Open house attendance improved CPP event demand response by reducing the participant disconnection rate.** Navigant found that while the average participant was disconnected for 3.5 summer events, the average participant that attended an open house was disconnected only for 1.8 summer events. Indeed, approximately half of open-house attendance was motivated by disconnection issues. The lower disconnection rate for open-house attendees results in estimated higher impacts, although once this effect is controlled for, there is no statistically significant effect on demand response – i.e., after accounting for the daily shifts in energy use correlated with event attendance, and the incremental impact associated with a lower disconnection rate, there is no statistically significant incremental behaviourally-driven demand response.

### 1.4.3 Energy Literacy Analysis Key Findings

- **Energy literacy as it relates to managing electricity consumption is high amongst all applicants to the RPP pilot program.** Approximately three quarters of all pilot participants and non-participants score in the top two (of five) categories for knowledge of how to manage electricity consumption. Eighty percent of survey respondents answered five or six (out of six) questions proving their energy knowledge correctly.
- **Despite starting from a high base of knowledge, the pilot appears to have built knowledge in specific areas related to energy consumption amongst participants.** Program participants have a higher proven knowledge about how time-of-use rates work, and better understand the concept of appliance phantom power, than non-participants. For example, 79% of RT and CPP, and 82% of CPP/RT, participants could identify as “True” the statement that reducing consumption during the day will reduce bills more than reducing consumption overnight, whereas just under three-quarters of non-participants could also correctly identify that reducing consumption during the days will reduce bills more than reducing consumption overnight. This difference is statistically significant at the 90% level for the RT and CPP/RT groups.

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<sup>5</sup> Participants’ whose enabling technologies were not connected to London Hydro’s dispatch system continued to receive event notification via the Trickl app.

- **Despite the impact analysis finding no statistically significant difference between CPP/RT and CPP participants' impacts, the literacy analysis indicates that CPP/RT participants are most likely to feel that the pilot improved their knowledge.** A quarter of CPP/RT participants indicated that the Trickl app provided them with a much better understanding of their energy consumption, in contrast to 14% of RT participants and 9% of CPP-only participants.
- **Energy literacy is consistently highest amongst men of 55 years or more.** Forty-five percent of respondents in this demographic answered five or six of the proven energy knowledge questions correctly, in contrast to 42% of those 35 – 54 and only 13% of those 18 – 34 (this difference is statistically significant at the 90% confidence level).

## 1.5 Conclusions

Navigant has drawn four main conclusions from this final evaluation of the London Hydro RPP Pilot:

- **London Hydro's residential customers are able to reduce more consumption and event-period demand in the summer months than in the winter months.** This is likely because summer discretionary loads are much larger than winter discretionary loads.

The largest residential end-uses in Ontario, as a proportion of average provincial annual consumption, are (in order): space-heating, plug loads, refrigeration, lighting, miscellaneous, water heating, space cooling, washing and drying appliances, ventilation and circulation, and cooking.<sup>6</sup>

Most of London Hydro's customers use natural gas as their primary space-heating fuel, eliminating this as a discretionary (electric) load. In examining the other residential loads, the only one where loads are: concentrated in a single piece of equipment (and so are convenient to control), significant in size, occur at times of system peak and is sometimes non-essential is the space-cooling end-use.

It should come as no surprise that shorter-run behavioural impacts will be dominated by changes in how consumers use space-cooling, and thus are much smaller in the winter months.

- **The available evidence suggests that education and customer engagement are key factors in enabling participant response.** Education and engagement are key elements of *all* programs and pilots that seek to motivate a behavioural response from participants. The question may be asked, why does Navigant single this as a key factor rather than attributing impacts *only* to the pricing and informational/technological treatment? This hypothesis is driven by two findings:

- *The RT treatment motivates no incremental energy or demand impact from CPP/RT participants, but delivers summer energy savings for RT participants.* For both energy impacts and CPP event demand impacts, Navigant found that the combined CPP/RT treatment did not deliver any incremental statistically significant impacts, which Navigant has interpreted to mean that the RT treatment provided no additional benefit to participants already subject to CPP.

Yet, the RT treatment *did* deliver material summer energy savings. These two findings seem at odds – if the RT treatment on its own delivers summer savings, and the CPP

<sup>6</sup> Navigant on behalf of the IESO and OEB, *2019 Conservation Achievable Potential Study*, 2019  
See Chapter 3: Reference Forecast.

treatment on its own delivers summer savings, why would the two treatments combined not deliver more savings than one of the treatments alone?

Navigant believes that the most likely explanation is that in fact the RT technology – the app – isn't what's responsible for the energy savings.<sup>7</sup> Rather, these offerings are an incentive that entices customers to participate in the program, and savings are delivered through the concerted effort of the utility to educate participants – or to motivate participants to educate themselves – as part of the program, in effective, practical strategies that deliver energy savings.

- *The price-only treatment (CPP) motivates a change in summer consumption behaviour even when there is no direct price signal to do so.* Most of the energy savings achieved by the CPP-only group were achieved in summer non-event periods.<sup>8</sup>

Certainly, this behaviour may be explained through the lens of expected value – participants assessing when peak prices will occur and making behavioural adjustments on this basis. The problem with this hypothesis is that it cannot explain why impacts were greatest in the On-Peak period, and yet, *by design*, the CPP price can only occur in the final hour of that period (from 4pm to 5pm).

A rational economic actor responding purely to price might adjust their behaviour in the window from 4pm to 5pm, but otherwise is not motivated to adjust their behaviour in the On-Peak period.

- *Attending open houses yielded substantial – and consistent across treatments and TOU periods – incremental estimated impacts.* Navigant conducted an ancillary analysis of the incremental effect of London Hydro's customer engagement on estimated impacts at the request of the OEB. This analysis is described in detail in Appendix J (under a separate cover). One of the key findings of this analysis was that participants that attended the London Hydro Open House sessions delivered significantly higher energy savings than those that did not; the average On-Peak reduction delivered by CPP and CPP/RT participants was 0.3 kW (5%), the average On-Peak reduction delivered by CPP and CPP/RT participants that attended an open house was twice that: 0.6 kWh (see Figure 3-1 in Appendix J).

It is based on these three observations regarding the estimated impacts that Navigant infers that the customer engagement strategy used by London Hydro to support the deployment of the pilot design was a critical factor in empowering customer decision-making, and, ultimately, delivering the final reported results.

- **Critical peak pricing can be a tool for summer energy conservation as well as demand reduction.** CPP participants are provided with 15 minutes' notice when a CPP event occurs. This

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<sup>7</sup> Evaluations of real-time information pilots often yield savings estimates that are very low, or are statistically insignificant, suggesting that simply providing customers with data is insufficient for motivating real savings. Participants require an intermediary, such as the utility or some third-party home energy report provider to translate those data into *information*.

For a summary of real-time information studies and the associated impacts, see for example Table 13 on PDF page 41/95 of:

Navigant, prepared for Newfoundland Labrador Hydro, *Real Time Monitor Pilot Program: Impact and Process Evaluation*, March 2016

[https://www.exec.gov.nl.ca/exec/occ/publications/RTM\\_Complete\\_Rpt\\_F\\_Mar31\\_2016.pdf](https://www.exec.gov.nl.ca/exec/occ/publications/RTM_Complete_Rpt_F_Mar31_2016.pdf)

<sup>8</sup> CPP events only account for 18 hours of the summer.

limits the scope of what actions participants can take in the short term when they receive event notification. In response to this challenge, it appears that participants have worked to limit their exposure to the critical peak rate by reducing consumption in hours in which events are likely to occur.

Participants have been educated to understand that CPP events are driven by system needs, and that system needs are driven (in the summer) by weather, and so they understand that daily energy impacts (even when no event takes place) are correlated with temperature. Participants undertake actions that reduce their risk exposure even as the risk of a CPP event climbs (i.e., temperature increases). Put another way, participants are provided with a qualitative understanding of the factors that drive the prices they will face and develop rules of thumb for responding to those prices.<sup>9</sup>

It should be noted that Navigant has only had a single summer to quantify impacts. It may be that these changes in behaviour are short-lived. If bill savings achieved by participants don't match what they perceive to be the efforts they have made to achieve them, such savings may not be sustainable over the longer term.

- **Participants can in the summer be remarkably nimble in responding to very short-term changes in price.** Participants whose load switches were not connected, and thus whose load switches could not automatically reduce demand in response to London Hydro's signal were still able to deliver 0.3 kW (15%) of demand reductions during events, despite receiving only 15 minutes' notice.

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<sup>9</sup> It has previously been noted that when participants are provided with prices that change too frequently to allow a true "real-time" response (e.g., real-time pricing), they develop a set of rules for behaviour changes that reflect their average expectations of price changes. See for example:

Navigant, submitted to Ameren Illinois Utilities, *Power Smart Pricing 2009 Annual Report*, April 2010

<https://www2.illinois.gov/sites/ipa/Documents/CUB-Comments-Appendix-D-2009-Navigant-Power-Smart-Pricing-Annual-Report.pdf>

## 2. INTRODUCTION AND PILOT OVERVIEW

Navigant's final evaluation of London Hydro's (LH) Regulated Price Plan (RPP) pilot reproduces information regarding all evaluation activities for the summer (May through October) of 2018 first laid out in the interim report<sup>10</sup>, and adds to them by covering evaluation activities for the winter pilot period (November 2018 through April 2019). It is divided into four chapters.

1. **Introduction and Pilot Overview.** This chapter provides a high-level description of the key features of the pilot.
2. **Pilot Data and Evaluation Approach.** This chapter provides an overview of the data used as part of this evaluation, and of the analytic methods employed to estimate impacts. A detailed description of the methods used in this evaluation (including model specifications, etc.) may be found in Appendix A.
3. **Impact Results.** This chapter presents the findings of Navigant's analysis, and some discussion of the results.
4. **Key Findings and Conclusions.** This chapter presents Navigant's key conclusions regarding its evaluation of the LH RPP pilot as deployed for the period from May 1, 2018 through April 30, 2019.

The remainder of this introductory chapter is divided into four sections:

- **Pilot Overview.** Provides a brief overview of the pilot.
- **Pilot Participants.** Provides a more detailed description of the treatments applied to the participants.
- **Participant Commodity Prices.** Describes the rate structure applied as part of this pilot.
- **Evaluation Goals and Objectives.** Provides a summary of the key evaluation goals, as originally developed during the evaluation planning phase.

### 2.1 Pilot Overview

London Hydro's RPP pilot is an experiment funded by the Ontario Energy Board as part of its ongoing RPP Roadmap, and is a test of two independent treatments, and of their interaction. The evaluation is designed as a randomized control trial (RCT), with control customers drawn from pilot applicants denied enrollment by London Hydro (see below for more details).

This pilot is an experiment designed to test the impacts of the following treatments across three distinct groups of participants:

- **Real-Time Information (RT).** The impact on participant consumption patterns of the provision of real-time information (the RT treatment) via the mobile application "Trickl"<sup>11</sup> which provides real-

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<sup>10</sup> Navigant, on behalf of London Hydro, *Regulated Price Plan Roadmap Pilot: Program Interim Impact Evaluation: Summer 2018*, May 2019

<https://www.oeb.ca/sites/default/files/rpp-roadmap-interim-results-londonhydro-20190524.pdf>

<sup>11</sup> Details on the functionality of this mobile application may be found in Appendix I (under a separate cover).

time consumption data and notifications when overall energy consumption exceeds that of peer households.

London Hydro provided Navigant with cross-sectional data for 1,135 customers enrolled into this stream.

- **Critical Peak Pricing (CPP).** The impact on participant consumption patterns (and demand during critical peak events) of providing customers with a slightly discounted Off-Peak time-of-use (TOU) rate in exchange for being subjected to 36 one-hour critical peak pricing periods over the course of the 12-month pilot period (18 summer<sup>12</sup> events, 18 winter events). The critical peak price was set at 59.5 cents per kWh by the OEB.

All CPP participants are provided with a smart plug and a load control switch installed (by London Hydro's contractor) at the participant's electrical panel. Each switch can control up to three 30-amp circuits. These enabling technologies respond to a control signal dispatched by London Hydro and are intended to automate some CPP event demand reductions. CPP participants were also equipped with the Trickl app. This group did not have access to the real-time consumption data or energy consumption alert functionality enjoyed by the RT group. For this group, the app was used to communicate notification for CPP events and to provide participants with the ability to remotely control the technologies provided by London Hydro.

London Hydro provided Navigant with cross-sectional data for 340 customers enrolled in this stream.

- **Combined Effects (CPP/RT).** The impact on participant consumption patterns (and demand during critical peak events) of combining both treatments (CPP and RT together).

London Hydro provided Navigant with cross-sectional data for 318 customers enrolled in this stream.

Additional detail regarding the functionality and appearance of the Trickl app may be found in Appendix I, under a separate cover.

London Hydro did not specifically target any particular group of customers for recruitment for this pilot. London Hydro's marketing effort was multi-channel and physical and legacy media (e.g., bill inserts, radio advertisements) were determined by London Hydro (see Appendix I) to have been most successful in driving recruitment.

Additional details of marketing efforts and London Hydro's customer engagement strategy may be found in Appendix I, under a separate cover.

In addition to the 1,793 participants in the three participant groups, London Hydro also provided cross-sectional data for 474 customers that were enrolled as control customers. These customers applied to

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<sup>12</sup> Unless otherwise explicitly noted, "summer" and "winter" in this report reflect the OEB's RPP seasons: summer being May through October, winter being November through April.

participate in the pilot program but were not enrolled by London Hydro. This “recruit-and-deny” strategy<sup>13</sup> enabled the pilot to be evaluated as an (RCT). For the purposes of the impact analysis, these RCT control customers act in a manner analogous to that of the placebo group in a pharmaceutical trial. RCTs are generally considered the “gold standard” for program evaluation as they control for selection bias.

Enabling technology (see below) deployment and participant enrollment took place over the course of the period beginning in July of 2017 through until May 1 of 2018, at which time the pilot became live. From this point on, the participants subject to the CPP rate were liable for the all charges they incurred under the new rate. All participants subject to the CPP rate received a \$100 incentive as a reward for participation, with \$25 provided at enrollment and the final \$75 provided at the end of the pilot.

To support the success of the price, technology, and informational treatments, London Hydro also pursued an active customer engagement strategy. Over the course of the pilot, London Hydro engaged in several customer engagement activities, the most important of which are:

- **Open House Events.** London Hydro’s open house events allowed participants to drop in to London Hydro headquarters to get in-person help with pilot hardware and software. London Hydro held 28 of these events, with the first on June 11, 2018, and the final one held on March 8, 2019. Altogether 100 participants attended these events, of whom 50 were subject to a CPP rate, and 50 were not (i.e., were in the RT treatment group).
- **Breakfast events.** Attended by 262 pilot participants, these two events in March 2018 were designed to
  - build enthusiasm for participation;
  - provide participants with information about how they could maximize the value of the treatments; and,
  - proactively address connectivity issues reported by participants and schedule home visits to resolve those issues.
- **Ambassador focus groups.** These focus groups, attended by 62 participants, were intended to leverage participant enthusiasm and obtain participant feedback to be used for course-correction of app feature improvements.
- **Door to Door Engagement.** Proactive, in-person communication with program participants to help resolve connectivity issues and to ensure that participants felt that their experiences and engagement were valued by London Hydro. Proactive technical assistance is important for pilots such as this one. When devices cease to function properly, busy customers not have the inclination to contact London Hydro to resolve the problem. As a result of this door-knocking campaign, London Hydro has indicated to Navigant that it booked 125 appointments for in-home technical assistance.

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<sup>13</sup> Control customers were drawn from participants that applied to join the CPP or CPP/RT groups, but denied enrollment by London Hydro to ensure a control group. Navigant tested the validity of the control customers against the participants and concluded that there was no statistically significant difference in the relevant consumption patterns in the period preceding the pilot period. Note that although control customers applied to join CPP and CPP/RT groups, Navigant used them as controls for the RT group only after validating that, based on pre-period demand data, this group was a more suitable control group than a set of matched controls also developed by Navigant. See Appendix A for more details.

## 2.2 Pilot Participants

As noted above, pilot participants were recruited into one of three different groups. Details of the treatments applied to each group are summarized below.

- **RT.** These participants were provided with an in-home energy gateway that delivers information to participating customers via an IOS/Android app: Trickl. The information provided to customers includes:
  - Real-time electricity consumption data
  - Baseload analytics
  - “Push” notifications from the Trickl app to flag when participant energy use exceeded that of similar peers and other timely customized tips.
- **CPP.** These participants are subject to a critical peak price of 59.5 cents per kWh, set by the OEB. London Hydro did not decide when CPP events took place, but dispatched events chosen by OEB staff. All CPP participants were provided with a smart plug and a load control switch installed at the participant’s electrical panel. Each switch can control up to three 30-amp circuits.
- **CPP/RT.** These participants were provided with both the CPP enabling technology, and the real-time energy monitoring equipment and software and are subject to the CPP prices.

For more details regarding the technology deployed to participants, please see Appendix I, under a separate cover.

## 2.3 Participant Commodity Prices

All residential electricity consumers in Ontario are subject to time-of-use (TOU) commodity prices. Participants enrolled in the CPP and CPP/RT treatment groups received a discounted off-peak rate in exchange for being subject to a very high critical peak price when events are triggered by the OEB.

These rates, and the schedule by which they are applied are provided in Figure 2-1, below. A more detailed description of the CPP rate follows.<sup>14</sup>

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<sup>14</sup> A complete description of all rates applied in the OEB RPP Pilots may be found at: Ontario Energy Board, *Memorandum to All Rate Regulated Electricity Distributors [and] All Interested Parties*, April 23, 2018  
<https://www.oeb.ca/sites/default/files/letter-rpp-roadmap-pilot-price-update-20180423.pdf>

**Figure 2-1: RPP Standard and Pilot TOU Rates**

Pricing Period	Commodity Rate ( per kWh)	
	Standard RPP Consumers	CPP and CPP/RT Participants
Off-Peak 7pm to 7am, on weekdays 24 hours on weekends and holidays.	¢6.5	¢6
Mid-Peak 7am to 11am and 5pm to 9pm, summer <sup>15</sup> weekdays 11am to 5pm, winter weekdays	¢9.4	¢9.4
On-Peak 11am to 5pm, summer weekdays 7am to 11am and 5pm to 9pm, winter weekdays	¢13.2	¢13.2
Critical Peak 18 one-hour events in summer 18 one-hour events in winter Events occur only between 4pm and 8pm, prevailing time, on non-holiday weekdays	N/A	¢59.5

CPP events lasted for one hour each, and participants were provided with fifteen minutes' notification.

Each participant was subject to 36 CPP events over the course of the pilot. Eighteen in the summer months and eighteen in the winter. Altogether there were:

- Six events in each of:
  - July
  - August
  - January
  - February
- Three events in each of:
  - June
  - September
  - December
  - March

CPP events were called as directed by the OEB and were intended to fall on the peak demand hour falling between 4pm and 8pm on the top six (July, August, January, February) or top three (June, September, December, March) demand days of the month.

<sup>15</sup> Throughout this document, unless explicitly stated otherwise, all references to “summer” and “winter” are intended to convey the RPP summer (May through October) and RPP winter (November through April) periods.

In the summer of 2018, CPP events all either fell between 5pm and 6pm (13 events) or between 6pm and 7pm (five events). All events occurred within the Mid-Peak TOU period. In the winter of 2018/2019, CPP events all fell between 5pm and 6pm (3 events), 6pm and 7pm (10 events), or 7pm and 8pm (5 events). Thirteen events fell in the winter On-Peak periods, whereas five fell in the lowest-priced Off-Peak period.

The CPP rate to which participants were subject during CPP events was 59.5 cents per kWh.

CPP participants are incented to participate through three mechanisms:

1. All CPP participants pay a discounted Off-Peak TOU price, six cents per kWh, as opposed to the standard rate of 6.5 cents per kWh,
2. All CPP participants will receive a \$25 incentive for enrolling and an additional \$75 incentive payment at the end of the pilot.<sup>16</sup>
3. All CPP participants received 150 Aeroplan™ points for registering for the pilot.

It is Navigant's opinion that the offering of these incentives has not biased the findings of this evaluation. A detailed description of the reasons why may be found in Section A.2 of Appendix A..

## 2.4 Evaluation Goals and Objectives.

Per the approved evaluation plan, Navigant was tasked with estimating two types of impact as part of this evaluation: energy impacts, and demand impacts associated with the CPP events. More specifically, Navigant was tasked with estimating:

1. **Ex-Post Energy Impacts.** "Ex-post" impacts refer to the estimated impacts of occurring (i.e., historical) events. Ex-post estimated impacts estimated include:
  - o The average impact of the RT treatment on participant energy consumption by:
    - TOU period
    - RPP season<sup>17</sup>
  - o The average impact of the CPP treatment *on non-event days*<sup>18</sup> by:
    - TOU period
    - RPP season
  - o The average incremental impact of the RT treatment on CPP savings *on non-event days* by:
    - TOU period
    - RPP season

As noted in the evaluation plan, these impacts are reported only when they are found to be statistically significant.

<sup>16</sup> Navigant would note, that this incentive may be thought as a form of bill protection that does affect the price-signal provided to participants, but helps bolster participation amongst residential consumers who, in Ontario given the history of rates in this province, are anecdotally reported to be very risk averse with respect to electricity consumption.

<sup>17</sup> "RPP season" refers to the price-setting seasons used by the OEB: summer (May through October) and winter (November through April). Note that throughout this document, unless explicitly stated otherwise, all references to "summer" and "winter" are intended to convey the RPP summer and RPP winter periods.

<sup>18</sup> i.e., excluding days on which CPP events are called

2. **Ex-Post CPP Event Demand Impacts.** “Ex-post” impacts refer to the estimated impacts of actually-occurring (i.e., historical) critical peak pricing events. Ex-post estimated impacts include:
  - The average program demand impact for every hour (all events last an hour) in which CPP events are called.
  - The average incremental effect of the RT treatment on CPP event demand impacts for every hour in which CPP events are called.<sup>19</sup>
  
3. **Ex-Ante Impacts.** “Ex-ante” impacts refer to the predicted DR impact of a program or treatment. Where impacts are found to be a function of outdoor temperature, these values are estimated by applying a range of temperatures to the regression-estimated parameters. Where there is no statistically significant relationship between impacts and temperature, the average of the estimated ex-post impacts is used as the ex-ante impact.

In addition to estimates of the impacts above, this report includes estimates of the following: the program impact on system coincident peak demand<sup>20</sup>; own-price daily elasticity of demand; and the program-induced substitution elasticity between Mid-Peak and non-On-Peak periods. These values are provided in Appendix B, a spreadsheet document highlighting OEB-requested output metrics for this report. These values are also discussed below in the body of the report.

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<sup>19</sup> When this incremental effect is found to be statistically non-significant on average by event, only the fact that no statistically significant impact was estimated is reported.

<sup>20</sup> As defined by the IESO EM&V protocols. In the summer, the average impact between 1pm and 7pm, prevailing time, on non-holiday weekdays in June through August. In the winter, the average impact between 6pm and 8pm, standard time, on non-holiday weekdays in January, February, and December.

### 3. PILOT DATA AND EVALUATION APPROACH

This chapter of the final evaluation report provides a high-level description of the data used by Navigant for this analysis, and the methods employed. Technical readers, interested in more detail regarding the specifics of the approach, are encouraged to consult Appendix A, which includes a more technical description of the approach, including regression model specifications.

This chapter is divided into three sections:

- **Data.** This section provides an overview of the data used in this analysis.
- **Experimental Design.** This section provides an overview of the experimental design used for this evaluation.
- **Energy Impact Approach.** This section provides an overview of how TOU-period daily energy impacts were estimated.
- **CPP Demand Impact Approach.** This section provides an overview of how the CPP-driven DR impacts were estimated.

#### 3.1 Data

Navigant used the following types of data to estimate impacts:

- Participant and non-participant interval (hourly consumption) data.
- Hourly weather data
- CPP event schedule data
- CPP participant group connectivity data

##### *3.1.1 Participant and Non-Participant Hourly Consumption Data*

London Hydro provided Navigant with more than three years' worth of participant and non-participant data. The total number of customers for whom data were available on any given day is summarized below in Figure 3-1.<sup>21</sup> This includes three groups of customers: RT participants, CPP and CPP/RT participants, and what are referred to in this report as "randomized control trial" (RCT) non-participants (controls)<sup>22</sup>.

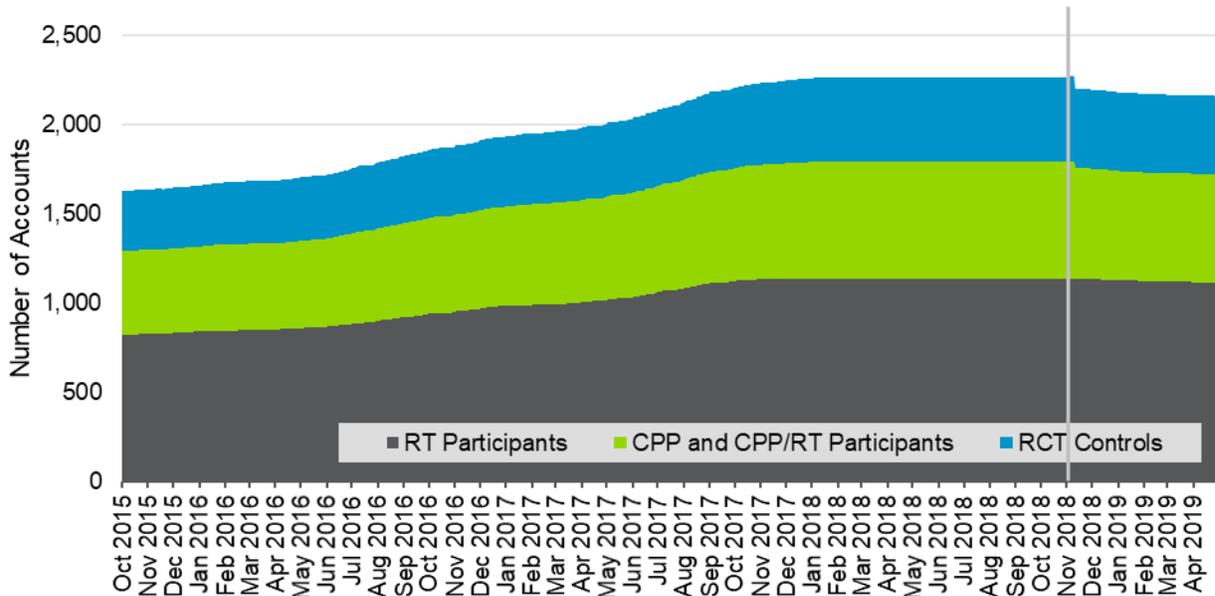
This last group is a group of customers that applied to enroll in the pilot, but were not accepted, to act as controls and provide a true experimental design for the pilot. More details regarding this feature of the evaluation may be found below.

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<sup>21</sup> Note that the drop in accounts that may be observed at the November 1, 2018 mark on the graph (flagged by the vertical light grey line) relates to participants that exited the program prior to that date. If a participant exited the program mid-summer, London Hydro provided those participant's interval data to support the interim (summer) analysis but did not do so when the data update was provided to support the final (winter) analysis.

<sup>22</sup> Controls derived from an RCT would typically just be referred to as "controls". Given that at one stage this analysis contemplated the use of matched control customers, the usage "RCT controls" was applied to reduce ambiguity. This usage has been carried through the report in order to remain as consistent as possible with previously developed materials (RCT validation memo, evaluation plan, interim report, etc.),

Figure 3-1: Summary of Interval Data Provided



Interval data used to estimate the results included in this report covered the period from May 1, 2017 through April 30, 2019. The pre-period data (from May 1, 2017 through April 30, 2018) was used to help control for non-program-related patterns in individual customer consumption (see below for more details) as independent variables in the regression. Hourly or daily consumption values used for the regression dependent variable were drawn *only* from the program period of May 1, 2018 through April 30, 2019.

The final sample size (number of customers) following the data preparation and processing are shown in Figure 3-2, below. Final sample sizes are smaller for the CPP event demand analysis than for the energy analysis due the requirements of the different regressions estimated.<sup>23</sup>

<sup>23</sup> The use of day-type determine pre-program consumption data makes the sample size sensitive to the number of summer 2018 days included in the estimation set. See Appendix A for more details.

**Figure 3-2: Final Number of Customers Included in Sample – By Analysis Type**

Group	Final Sample for Energy Analysis - Summer	Final Sample for Energy Analysis - Winter <sup>24</sup>	Final Sample for CPP Event Demand Analysis - Summer	Final Sample for CPP Event Demand Analysis - Winter
CPP	308	302	282	300
CPP/RT	334	320	308	318
RT	1,129	1133	N/A	N/A
RCT Control	454	469	446	439

Although a larger sample is always preferred, due to the additional degrees of freedom (and thus higher precision), the sample sizes available were large enough to enable a sufficiently robust analysis to support the ongoing work and analysis by the Ontario Energy Board to evolve the RPP.

Note that these sample sizes reflect a count of unique customers included in the data sets used to estimate impacts. Sample sizes change from season to season for two reasons: attrition and availability of pre-period data. Attrition during the summer results in smaller winter sample sizes as all participants that drop out in the summer are excluded from all winter periods. Where pre-period data for a given participant for the given season is missing that participant must be excluded from the estimation set for that season - as noted in Chapter, 3 impacts are estimated using a lagged dependent variable. Absence of pre-period data mean missing values for the lagged dependent variable and thus the exclusion of the participant from the estimation set.

Monthly consumption values were very similar across all four groups considered in this analysis (CPP, CPP/RT, RT, and RCT controls). The average monthly consumption values of each group during the three summers are presented in Figure 3-3 below. The whisker bars represent the 90% confidence interval around the sample mean in each year. As may be seen, not only are all monthly consumption values very close, but in every year, the confidence intervals of all groups overlap.

<sup>24</sup> Two changes affect the values in the winter and summer column: the availability of pre-pilot data, and whether a participant exited the program before it ended. Altogether 21 CPP-only (out of 318), 31 CPP/RT (out of 340), and 24 (out of 1135) participants exited the program before the end-date of April 30, 2019. The interaction of these changes over time is what yields the results above. For example: all 31 CPP/RT participants that exited the program did so in the summer, and so their data series were completely unavailable for the winter estimation, whereas in the summer six CPP/RT participants had insufficient interval data history to be included in the regression.

Figure 3-3: Participant and Control Monthly Summer Consumption<sup>25</sup>

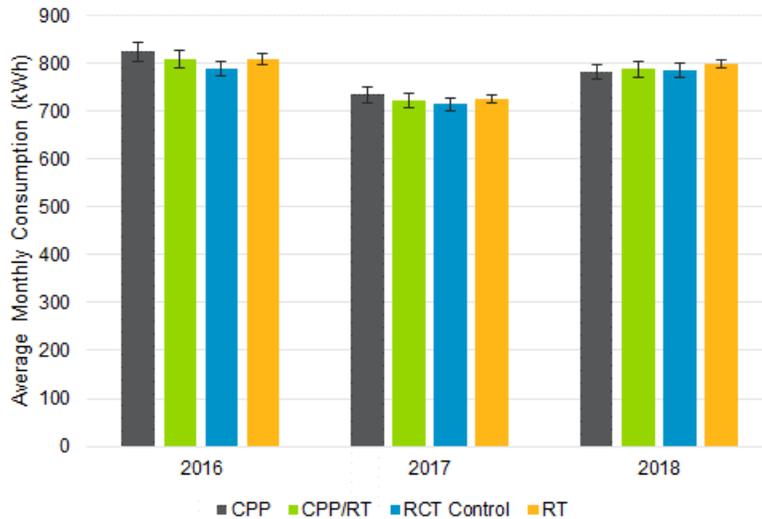


Figure 3-4: Participant and Control Monthly Winter Consumption<sup>26</sup>

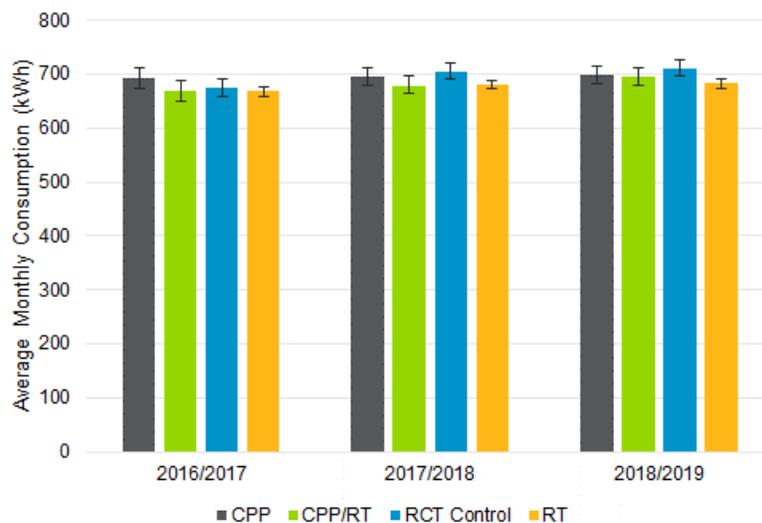


Figure 3-5 and Figure 3-6, below show, for summer and winter respectively, participants' average non-coincident peak demand.<sup>27</sup>

<sup>25</sup> Average monthly consumption values are provided only for participants and controls included in the energy analysis. The sample population of each year is somewhat larger than the previous one due to move-ins. Monthly average consumption in each summer is calculated by estimating average monthly consumption for each customer by multiplying average hourly consumption by the number of hours in the month (customer/month pairs missing more than 20% of hours in a month are excluded). Customer monthly values are then averaged across customers and the summer to deliver the values provided above.

<sup>26</sup> Derived in the same manner as summer monthly consumption.

<sup>27</sup> This is calculated as the mean (across participants), of the mean (by participant, across months) of non-coincident monthly peak demand by six-month seasonal period. Participants missing more than 20% of observations in any period are removed from the sample.

Figure 3-5: Participant and Control Average Monthly Non-Coincident Peak Demand - Summer

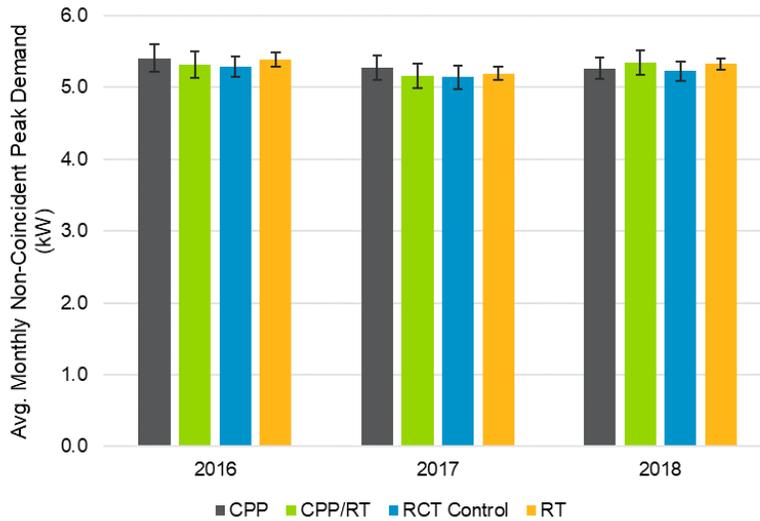
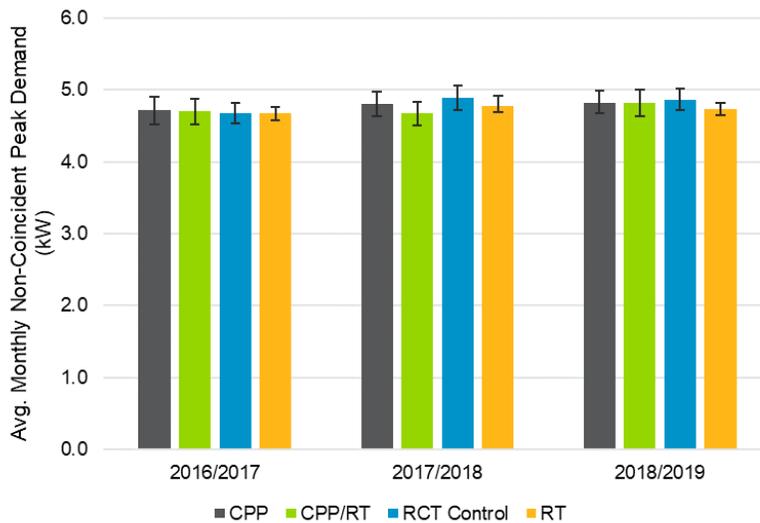


Figure 3-6: Participant and Control Average Monthly Non-Coincident Peak Demand - Winter



3.1.2 Hourly Weather Data

To support the analysis, London Hydro provided Navigant with hourly weather data from Environment Canada’s “London A” weather station (TC identifier: YXU).

Figure 3-7, below, provides a summary of the summer daily mean (grey line) and maximum (yellow line) observed temperatures during the program period. CPP event days are flagged with red diamonds.

Figure 3-7: Daily Temperatures in Program Period – Summer

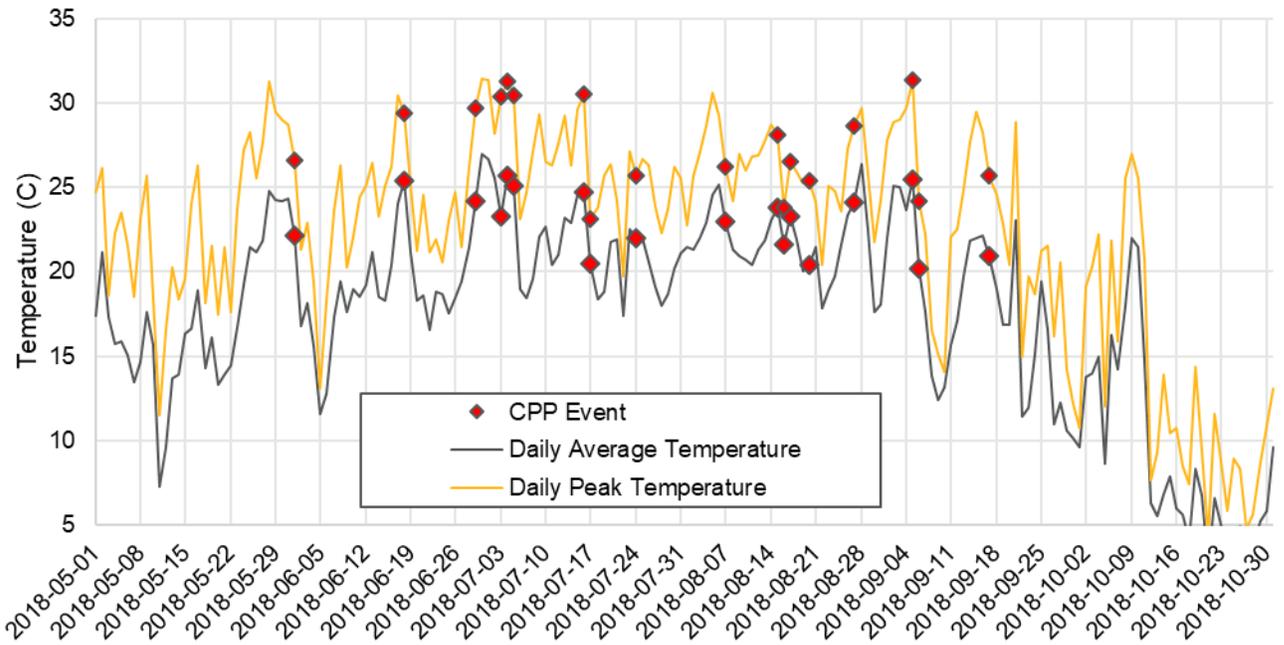
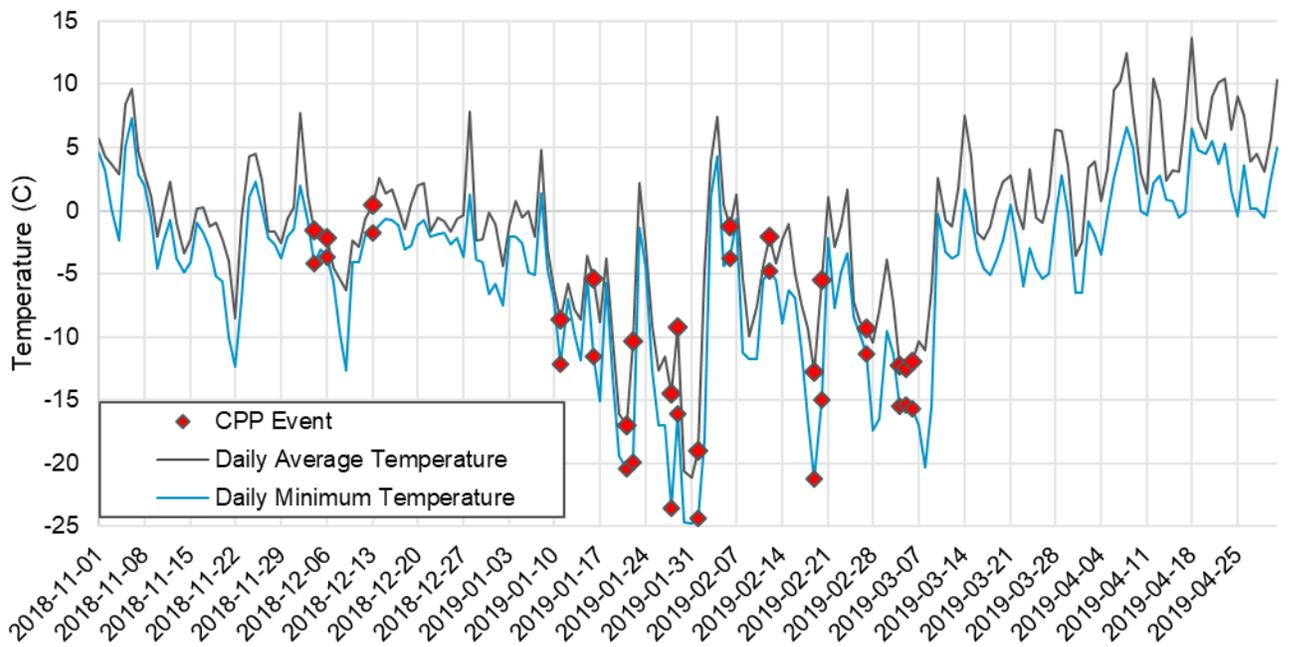


Figure 3-8, below, provides a summary of the winter daily mean (grey line) and *minimum* (blue line) observed temperatures during the winter program period.

Figure 3-8: Daily Temperatures in Program Period - Winter



### 3.1.3 CPP Event Schedule

Altogether 36 CPP events were called during the pilot program period. These dates of events are selected by the OEB to maximize the information value of pilot. Altogether 13 summer events were called for the period between 5pm and 6pm, and five events were called for the period between 6pm and 7pm. Three events were called for the period between 5pm and 6pm, 10 events were called for the period between 6pm and 7pm, and four events were called for the period between 7pm and 8pm.

**Figure 3-9: Program Period CPP Schedule**

Date	Event Start Time	Event End Time
2018-06-01	6:00 PM	7:00 PM
2018-06-18	5:00 PM	6:00 PM
2018-06-29	6:00 PM	7:00 PM
2018-07-03	5:00 PM	6:00 PM
2018-07-04	6:00 PM	7:00 PM
2018-07-05	6:00 PM	7:00 PM
2018-07-16	5:00 PM	6:00 PM
2018-07-17	5:00 PM	6:00 PM
2018-07-24	5:00 PM	6:00 PM
2018-08-07	5:00 PM	6:00 PM
2018-08-15	6:00 PM	7:00 PM
2018-08-16	5:00 PM	6:00 PM
2018-08-17	5:00 PM	6:00 PM
2018-08-20	5:00 PM	6:00 PM
2018-08-27	5:00 PM	6:00 PM
2018-09-05	5:00 PM	6:00 PM
2018-09-06	5:00 PM	6:00 PM
2018-09-17	5:00 PM	6:00 PM
2018-12-04	5:00 PM	6:00 PM
2018-12-06	5:00 PM	6:00 PM
2018-12-13	5:00 PM	6:00 PM
2019-01-11	6:00 PM	7:00 PM
2019-01-16	6:00 PM	7:00 PM
2019-01-21	6:00 PM	7:00 PM
2019-01-22	6:00 PM	7:00 PM
2019-01-28	6:00 PM	7:00 PM
2019-01-29	6:00 PM	7:00 PM
2019-02-01	6:00 PM	7:00 PM
2019-02-06	6:00 PM	7:00 PM
2019-02-12	6:00 PM	7:00 PM
2019-02-19	7:00 PM	8:00 PM
2019-02-20	6:00 PM	7:00 PM
2019-02-27	7:00 PM	8:00 PM
2019-03-04	7:00 PM	8:00 PM
2019-03-05	7:00 PM	8:00 PM

### 3.1.4 CPP Group Connectivity Data

As part of this pilot, London Hydro staff have tracked the connectivity of individual CPP and CPP/RT participants. For any given event, participants' enabling technologies (the switch at the panel and the smart plug) may or may not be connected, via a hub, to the London Hydro dispatch system. Those participants not connected to the system on event days did not benefit from the automatic control of connected appliances (e.g., central A/C).

On average approximately 80% of participants were connected for any given event. Figure 3-10, below shows the connectivity rate for each CPP event. Note that the small increase in connectivity during the December events is attributed by London Hydro staff to trouble-shooting activities undertaken during the October and November in preparation for winter CPP events.

Figure 3-10: Event-Specific Connectivity Rate

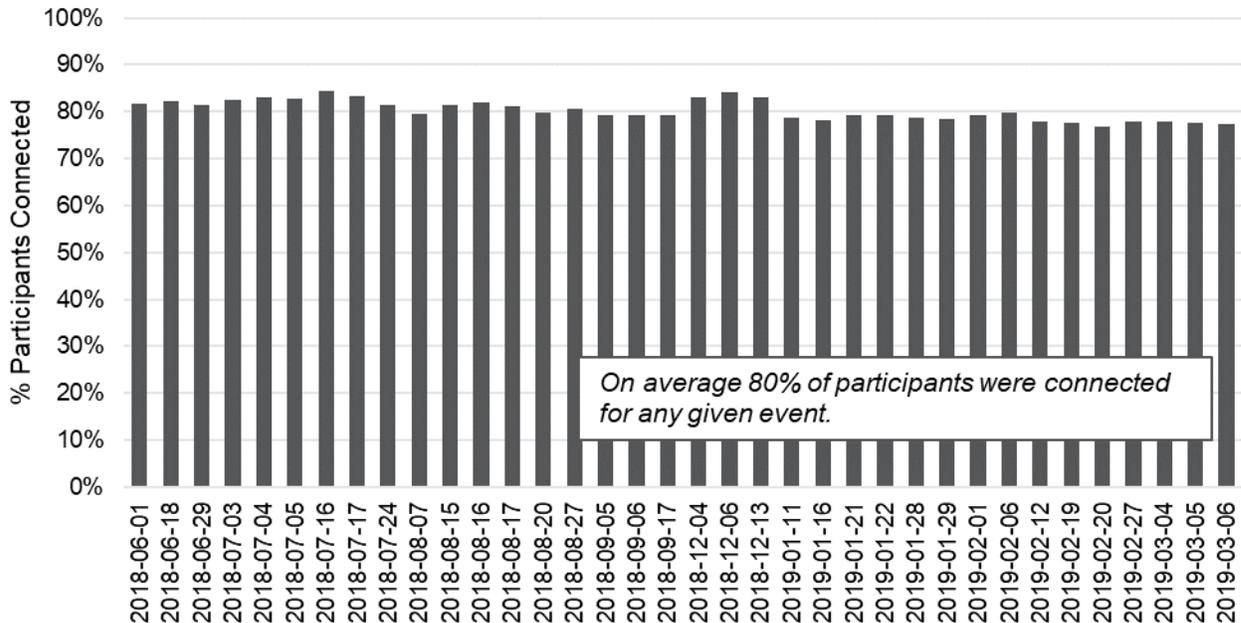


Figure 3-11, below, shows the distribution across CPP and CPP/RT participants of disconnection frequency in the summer pilot period. This plot shows, for example, that 14% of participants were disconnected for only a single event, 6% were disconnected for two events, etc. Altogether 46% of participants were connected for *all* events, and 4% of participants were not connected for any of the events. This figure demonstrates two important points: a) disconnections affect a high proportion of the population, and b) the number of participants that were disconnected for all events is very small. There does not appear to be any meaningful pattern to disconnections – whether or not a participant is disconnected for a given event appears to be random.

Figure 3-11: Distribution of Disconnection Frequency - Summer

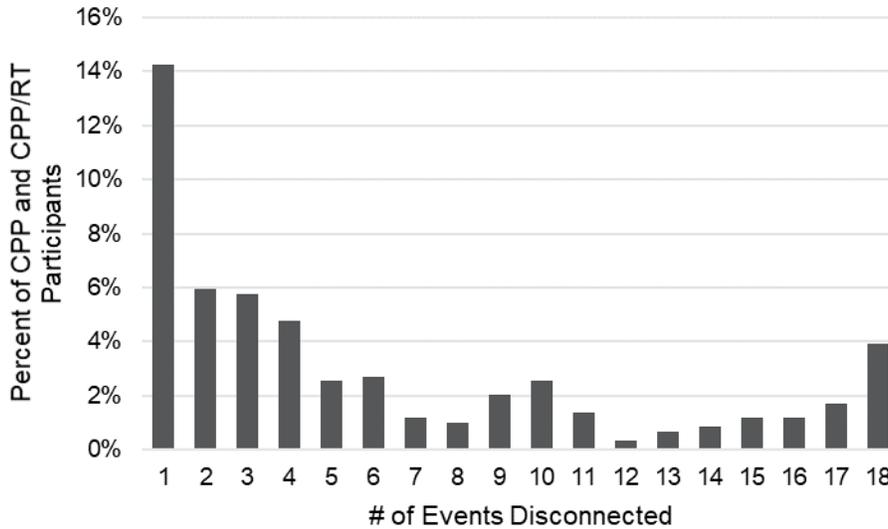
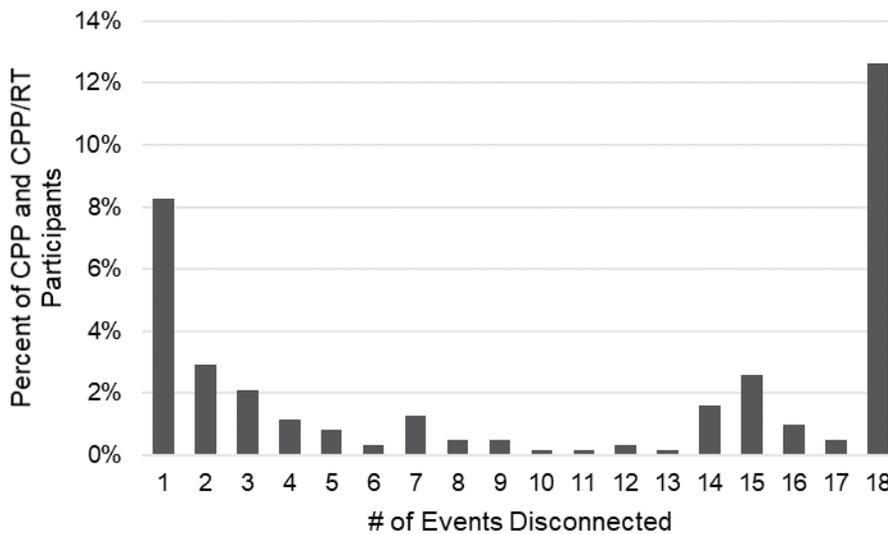


Figure 3-12 shows the distribution across CPP and CPP/RT participants of disconnection frequency in the winter pilot period. This plot differs in two important respects from that shown above: firstly, the overall number of participants disconnected for at least one event is lower—37%, compared to 46% for the summer. This suggests that disconnections in the summer months may have been “teething troubles” related to pilot ramp-up. The other key difference is more troubling – 12% of participants were disconnected for *all* 18 of the winter events. Where in the summer less than 10% of customers that had experienced a disconnection were disconnected for the whole summer, in the winter, a *third* of those customers that experienced a disconnection were disconnected for the whole winter.

Figure 3-12: Distribution of Disconnection Frequency - Winter



These disconnected customers, although result in lower overall estimated impacts, are an advantage for this pilot evaluation, from the standpoint of information gathering.<sup>28</sup> The fact that a meaningful (though relatively small) proportion of the participant population are disconnected for any given event makes it possible to quantify the purely behavioural impact of the CPP event – that is, absent the control technology, are participants still able to respond to the CPP event with 15 minutes' notice?

Note that this “accidental experiment” is much more robust in the summer months, in which there does not appear to be any systematic pattern to the disconnections. In the winter, disconnections are much more clustered, and could be an indication of participant interest (and investment in) the pilot. Long-term disconnections could be an indicator of reduced behavioural investment. Thus, the estimated impacts that result from this “accidental experiment” (i.e., the identification of the purely behavioural impact of the program) should be regarded as much more robust in the summer than in the winter months.

Participants not connected are still subject to the pilot pricing and are therefore still considered pilot participants and still included in Figure 3-2.

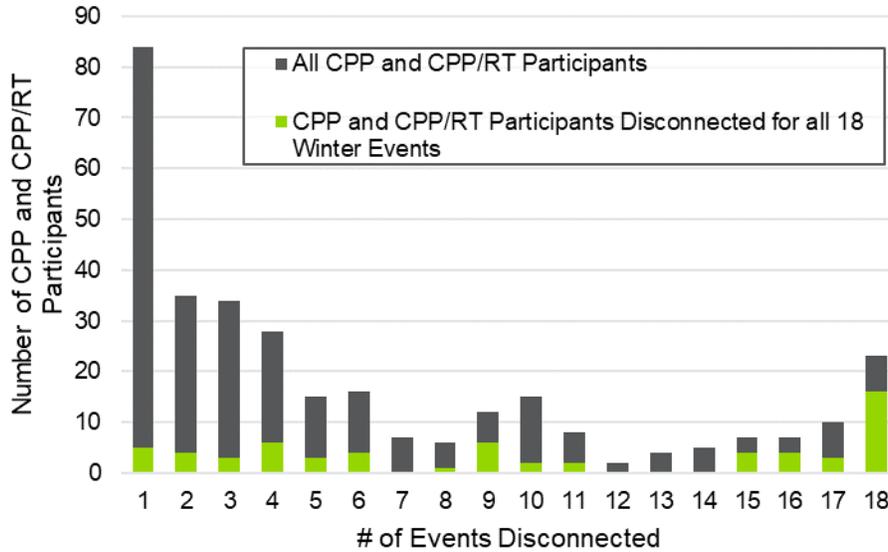
London Hydro noted to Navigant that it continued to offer the same level of support throughout the winter as it had in the summer, so the increased number of participants that were disconnected for all events was not due to utility inaction.

Figure 3-13 compares the distribution of disconnection frequency for all participants in the summer months with the frequency of those participants that were disconnected for all 18 events in the winter. A quarter of the participants that were disconnected for all winter events were also disconnected for all summer events. Note that these participants are included in the estimation sample, and the average impacts reflect the contribution (or lack thereof) to total impacts made by this group.

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<sup>28</sup> It is important to bear in mind that the key goal of a pilot program is *not* primarily about achieving high savings, in either energy or demand response, but to provide actionable intelligence that can be used in decision-making for a wider program roll-out.

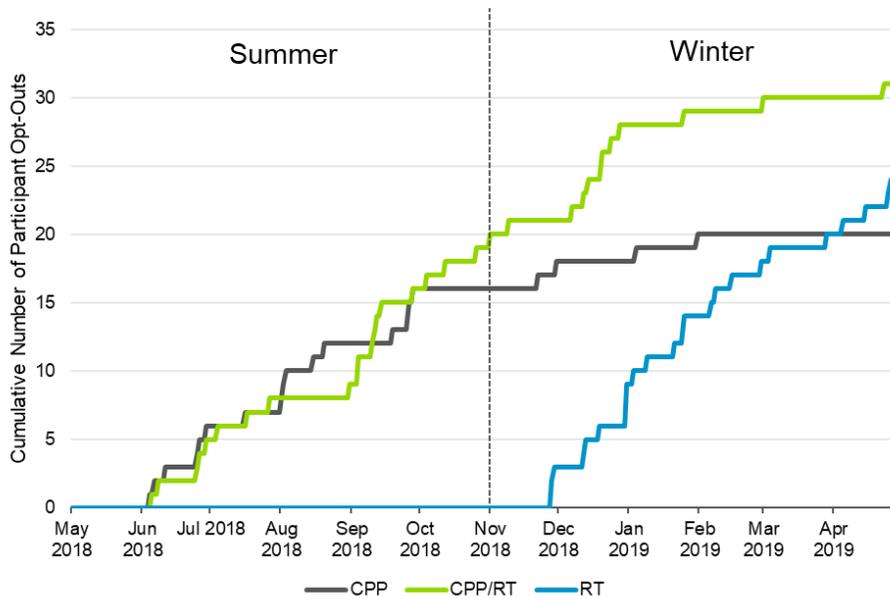
Figure 3-13: Distribution of Disconnection Frequency – Summer, for Participants Disconnected for all Winter Events



### 3.1.5 Pilot Attrition

Some participants elected to exit the pilot before its official date of completion. Altogether, of the participants that enrolled and for which London Hydro provided Navigant with cross-sectional data, approximately 2% of RT participants, 6% of CPP, and 10% of CPP/RT participants exited the pilot before its completion. Note that these figures include both participants electing to leave the pilot and participants that exited the pilot due to a change of address (move-outs). All RT participants that exited the pilot prior to its completion did so due to moving out of their premises. The cumulative attrition is illustrated in Figure 3-14 below.

Figure 3-14: Cumulative Attrition by Treatment Group



It is reasonable to suppose that attrition might have been higher for the CPP and CPP/RT groups absent the program completion incentive (\$75<sup>29</sup>) offered by London Hydro, but Navigant cannot quantify the magnitude (or existence) of such an effect with the data in hand.<sup>30</sup>

### 3.2 Experimental Design

The Uniform Methods Project<sup>31</sup> notes that “*The optimal evaluation scenario for a consumption data analysis is a randomized control trial (RCT) experimental design.*” An RCT is an experimental design in which a sample randomly drawn from a known population is randomly assigned to various treatment groups (usually a treatment group and a control group). This ensures that the expected value of the treatment effect is equal to the true value in the population from which the sample is drawn.

One form of RCT often applied in energy efficiency or demand response evaluations enlists a sampling strategy known as “recruit-and-deny”. The procedure works in the following manner: applicants to a program are either enrolled in the program (and so become treatment participants), or else denied

<sup>29</sup> This is equivalent to approximately 6% of the average annual cost of power to London Hydro CPP and CPP/RT participants

<sup>30</sup> Per the calculations in spreadsheet Appendix B (Tabs 05a and 05b), the annual bill impact calculated when comparing what the average CPP or CPP/RT participant would have paid had they not made any changes in behaviour under the piloted price plan, with what they would have paid under the status quo TOU price plan is approximately one dollar, so for a participant with an average load profile there was a very strong incentive not to exit the pilot.

<sup>31</sup> National Renewable Energy Laboratory, *The Uniform Methods Project: Methods for Determining Energy Efficiency Savings for Specific Measures – Chapter 8: Whole-Building Retrofit with Consumption Data Analysis Evaluation Protocol*, April 2013

<https://www1.eere.energy.gov/wip/pdfs/53827-8.pdf>

enrollment (sometimes by being wait-listed – “recruit-and-delay”) and so act as control customers. Consequently, the underlying population to which estimates of the treatment effect apply are those customers with an interest in enrolling in the program.

The original design of the program called for RCT controls to be developed for both the RT and CPP and CPP/RT groups. During the enrollment process the RT stream had too few applicants to support this design, and RCT controls<sup>32</sup> were drawn only from the population that applied to the CPP and CPP/RT stream.<sup>33</sup>

Navigant validated the RCT allocation through a comparison of participant and control pre-program demand. Navigant’s validation of the control group did so from two perspectives: is the control group valid for estimating the average energy impact per TOU period (by season) and is the control group valid for estimating the average demand impact during CPP events, per season.

To test the validity of the control group for estimating energy impacts, Navigant used twelve months of pre-period data, and estimated a set of regressions similar to those to estimate impacts (see below).<sup>34</sup> None of the coefficients intended to capture the treatment effects (or systematic differences between the two groups in this testing case) were found to be statistically significant, with p-values ranging between 0.575 and 0.995. These results were presented to the OEB via email 2019-01-25, and approval was granted by the OEB to proceed with this control group shortly thereafter.

To test the validity of the control group for estimating CPP event demand impacts, Navigant compared participant and control customers’ average demand on event-like days in three pre-program years. Event-like days were selected on the basis of provincial demand (CPP event days are called at times of system peak). Average participant demand was compared on all of these days using a t-test of independent means. In no case was the estimated event-like demand of participants during the potential event window on event-like days statistically significantly different from zero. The results of this testing were formally presented to London Hydro as a memorandum on 2018-04-03. This document was subsequently provided to the OEB and formal approval to proceed with the experimental design on this basis was provided on 2018-04-11. Additional detail on experimental design validation may be found in Appendix H, in a separate document.

### 3.3 Energy Impact Approach

Participant energy impacts were estimated using only data from the program period. Impacts were estimated using a panel data regression of daily energy consumption by TOU period. Although there are only three TOU periods in Ontario, Navigant estimated impacts for four periods: On-Peak, Mid-Peak, non-holiday weekday Off-Peak, and weekend and holiday Off-Peak. The Off-Peak periods were differentiated to allow for the fact that consumption patterns are substantially different during the overnight Off-Peak than during the weekend or holiday Off-Peak period.

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<sup>32</sup> London Hydro provided cross-sectional data for 474 customers that were enrolled as control customers.

<sup>33</sup> Applicants to the pilot applied for the opportunity to obtain the CPP rate. Those selected for inclusion were randomly allocated to either the CPP or the CPP/RT treatment group.

<sup>34</sup> The estimation model for validating the experimental design included the lagged dependent variable, cooling and heating degree hours and a treatment variable. Aside from the heat and cold-build-up variables, and the treatment dummy interactions, it was identical to the model specification provided for the seasonal energy analysis provided in Appendix A.

The same regression specification was applied to three different sets of participant and control consumption data:

- RT participants and RCT controls
- CPP and CPP/RT participants and RCT controls, excluding CPP event days.
- CPP and CPP/RT participants and RCT controls, including all days (in the given season).

A separate regression was estimated for each season.

The estimated impacts of these regressions are reported and discussed in Section 4.1. The detailed outputs are available in the spreadsheet Appendix B. The confidence intervals and relative precision of all estimates are based on a 90% confidence level.

In an RCT, the simple difference in means provides an unbiased estimate of the treatment effect. This difference in means can be obtained via a regression model involving only the a constant and a treatment dummy variable. Precision of estimates can be improved by adding additional covariates (e.g., weather, etc.)

Navigant's ultimate goal was – where impacts were meaningfully correlated with temperature – to estimate impacts as a function of temperature to allow for ex-ante projection of impacts (if required at some later date). Navigant also wished to identify whether the RT treatment contributed any incremental impacts for participants subject to the critical peak price, above and beyond any energy impacts as a result of that treatment.

To avoid any unnecessary model (and coding) complexity, Navigant began by estimating a simple “dummy” model in which energy impacts were estimated as a function of whether a consumer was a participant or not. This simplified model was used to test whether there was a significant difference between CPP and CPP/RT participants, and to provide Navigant with an indication of whether there exists a statistically significant energy impact of the treatments on daily energy consumption.

This initial testing revealed that, yes, there were statistically significant energy impacts, but no, there was no statistically significant difference between the estimated CPP-only group and CPP/RT group impacts. Further testing indicated that summer impacts were correlated with weather, leading to the final specification. The model is outlined verbally below. This is immediately followed by the algebraic specification.

As noted above, given the RCT, a simple difference in means will deliver an unbiased estimate of the treatment effect. The purpose of adding additional variables (as described below) is to improve the model's precision and to allow (should it be required) for ex-ante prediction of impacts as a function of temperature (where doing so is reasonable, given the findings of the analysis).

Key elements of the estimated regression specification include:

- **TOU Period Dummy Variables.** Four dummy variables (one for each period) were included in the model specification. These were interacted with *all* other variables included in the regression

equation, delivering estimated impacts equivalent to those that would be obtained if a different regression were used for each TOU period.<sup>35</sup>

- Pre-Period Consumption Values.** Based on a series 15 different day-types (capturing differences in weather – see Appendix A for details), Navigant developed a series of 360 individual-specific pre-program average hourly consumption values. These values are applied to the hourly weather series and then aggregated to the daily level (by TOU period) for the energy analysis and are included in the regression specification to control for pre-existing individual customer consumption patterns. This set of values is analogous to including a highly granular set of different individual-level fixed effects in the regression equation.
- Monthly/Day-Type Dummies.** The pre-period consumption values described above are interacted in the regression with a series of dummies representing the averaging periods used to develop them. There are 15 day-type dummies, that capture seasonal effects (month of year) as well as coarser temperature effects (extreme, vs mild temperature days). For more details, please see Appendix A.
- Temperature.** The total number of cooling and heating degree hours observed in the given TOU period on each day of the sample is included to control for any variation in average consumption (not already captured by the pre-period consumption variable discussed above) attributable to weather effects.

Also included is a daily heat-build-up variable and daily cold build-up variable. These 72-hour exponentially decaying moving averages capture the effects on consumption of heat waves or cold snaps.

- Treatment Dummy.** A treatment dummy variable was included to capture the program effect. The estimate parameter associated with this variable captures the impact of the program. It is included as an intercept variable (i.e., interacted only with the TOU dummy, above) and as a slope variable (also interacted with the number of cooling degree hours). The first of these captures the impact of the program on cooler days, and the second captures the incremental impact of each additional cooling degree hour observed in a given TOU period, i.e., effectively identifies the portion of energy savings derived from space-cooling energy savings.

Essentially the same model specification was used to estimate the average treatment impact during the IESO-defined “system coincident peak” period – the period between 1pm and 6pm on non-holiday weekdays in June, July, and August. The key difference is that there was no TOU period dimension (i.e., each date appeared only a single time for a given customer), and that the dependent variable was total consumption in the system coincident peak period (instead of in one of the four specified TOU periods).

Not included in any of the regression specifications is any kind of interaction effect between the CPP and the RT treatments. That is, none of the results presented in this report are derived from a regression equation that controls for the incremental effect on CPP participants’ impacts of *also* being equipped with the RT technologies (online portal and mobile application). These regressions do not differentiate between CPP and CPP/RT group energy impacts.

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<sup>35</sup> The reason for using a single regression, as opposed to one for each TOU period, was to allow the estimation of covariances between different impact parameters, to ensure that the uncertainty associated with aggregated impacts (e.g., across TOU periods) could be accurately estimated.

This is based upon earlier testing that found that this effect was not statistically significant at any conventional level of significance. More specifically, for the CPP and CPP/RT group, Navigant estimated a regression model in which the treatment dummy variable was interacted with another variable flagging whether that customer also had access to the RT technology (but not interacted with any temperature effect). In these test regressions (including and excluding CPP event days), Navigant found that the incremental effect of the RT treatment on CPP participants' changes in behaviour was not statistically significant, and so dropped this interaction from the final analysis. Additional details on this step is presented below.

Equation 1, below, presents the model specification used to estimate the participant summer energy impacts presented above, in the body of this report.

Note that in the equation below, sub-scripts denote differences across rows (e.g., individuals, time periods) and super-scripts denote differences across columns (e.g., batteries of dummy variables).<sup>36</sup>

**Equation 1: Summer Energy Analysis Model Specification**

$$\begin{aligned}
 y_{itp} = & \sum_{p=1}^{P=4} \beta_1^{d,p} \cdot tou_t^p + \sum_{p=1}^{P=4} \sum_{d=1}^{D=15} \beta_2^{d,p} \cdot tou_t^p \cdot daytype_t^d + \\
 & \sum_{p=1}^{P=4} \sum_{d=1}^{D=15} \beta_3^{d,p} \cdot tou_t^p \cdot daytype_t^d \cdot prekWh_{i,d,p} + \sum_{p=1}^{P=4} \beta_4^p \cdot tou_t^p \cdot cdh_{tp} + \\
 & \sum_{p=1}^{P=4} \beta_5^p \cdot tou_t^p \cdot hdh_{tp} + \sum_{p=1}^{P=4} \beta_6^p \cdot tou_t^p \cdot hbu_{tp} + \sum_{p=1}^{P=4} \beta_7^p \cdot tou_t^p \cdot cbu_{tp} + \\
 & \sum_{p=1}^{P=4} \gamma_1^p \cdot tou_t^p \cdot treat_i + \sum_{p=1}^{P=4} \gamma_2^p \cdot tou_t^p \cdot cdh_{tp} \cdot treat_i + \varepsilon_{itp}
 \end{aligned}$$

Where:

$y_{itp}$  = Customer  $i$ 's energy consumption (kWh) in TOU period  $p$  (On-Peak, Mid-Peak, Off-Peak Weekdays, Off-Peak Weekends/Holidays) of day of sample  $t$ .

$tou_t^p$  = A set of four dummy variables. Each one is equal to one when the consumption value on the LHS of the equation is in the same TOU period as that flagged by the dummy. For example: when  $y_{itp=1}$  then,  $tou_t^1 = 1$ ,  $tou_t^2 = 0$ ,  $tou_t^3 = 0$ , and  $tou_t^4 = 0$ .

<sup>36</sup> In some cases, as in the case of  $p$ , an index may appear as both a super-script (there are four TOU dummy variables,  $tou_t^p$ ) and as a sub-script (there is only one value of CDH in each of the four possible TOU periods in a given day,  $t$ , and that is  $cdh_{t,p}$ )

$daytype_t^d$	=	A set of 15 dummy variables. Each is equal to one when the day of sample $t$ is day-type $d$ . See section A.1, below for more details regarding day-types.
$prekWh_{ipd}$	=	The sum of pre-period consumption in TOU period $p$ , of day-type $d$ for customer $i$ . This is the given customer's average TOU period consumption for the given day-type in the pre-program period (summer of 2017).
$cdh_{tp}$	=	The sum of the cooling degree hours (base of 18 degrees Celsius) observed in TOU period $p$ of day of sample $t$ .
$hdh_{tp}$	=	The sum of the heating degree hours (base of 18 degrees Celsius) observed in TOU period $p$ of day of sample $t$ .
$hbu_{tp}$	=	The average heat build-up observed in the hours that fall within TOU period $p$ , on day of sample $t$ . This is a 72-hour geometrically decaying average of cooling degree hours, as observed in hour of sample $s$ . It is calculated in the following manner:
		$cbu_t = \frac{\sum_{h=1}^{72} 0.96^h \cdot cdh_{s-h}}{1,000} \cdot$
$cbu_{tp}$	=	The average cold build-up observed in the hours that fall within TOU period $p$ , on day of sample $t$ . This is calculated in the same way as $hbu_{t,p}$ , except that cooling degree hours are replaced by heating degree hours.
$treat_i$	=	A dummy variable that takes a value of 1 if customer $i$ is a participant, and zero otherwise.
$\varepsilon_{itp}$	=	Errors.

Navigant repeated this estimation (across all three iterations described at the start of this section) using the winter consumption data to support the winter season evaluation. The only difference was that for the winter analysis the temperature interactive term for the treatment effect was excluded. This exclusion was made on the basis of the testing described below and the finding that all winter impacts were statistically non-significant, with p-values of between 0.28 and 0.71. This, the fact that there is almost no price-incentive to shift behaviour, and Navigant's understanding that participants have far fewer options for discretionary behavioural energy shifting behaviour in winter (e.g., the vast majority use natural gas as their primary space-heating fuel), led Navigant to conclude that there were no impacts being delivered, rendering irrelevant any consideration of temperature sensitivity of response.

As noted above, Navigant estimated a slightly simpler model to ascertain whether the RT treatment contributed any incremental savings to the CPP group. The parameter associated with the interactive dummy (capturing the incremental impact of the RT-treatment on CPP participants) was found to be statistically insignificantly different from zero. Based on this and the sign of the interactive point-estimate (which suggested app usage increased consumption), Navigant concluded that differences in impacts

between the two groups are likely simply a result of random variation in the data and elected not to include this interactive variable in the final analysis.

The estimation sample for the testing regression included all CPP and CPP/RT participants as well as all controls. This analysis was repeated for both seasons.

The model specification used for testing was:

**Equation 2: Energy Analysis Model Specification**

$$y_{i,t,p} = \sum_{p=1}^{P=4} \sum_{d=1}^{D=15} \beta_1^{d,p} \cdot tou_t^p \cdot daytype_t^d \cdot prekWh_{i,d,p} + \sum_{p=1}^{P=4} \beta_2^p \cdot tou_t^p \cdot cdh_{t,p} + \sum_{p=1}^{P=4} \beta_3^p \cdot tou_t^p \cdot hdh_{t,p} + \sum_{p=1}^{P=4} \gamma_1^p \cdot tou_t^p \cdot treat_i \cdot cpp_i + \sum_{p=1}^{P=4} \gamma_2^p \cdot tou_t^p \cdot treat_i \cdot rt_i + \varepsilon_{i,t,d}$$

Where:

- $cpp_i$  = A dummy variable equal to one if individual  $i$  was subject to the CPP rate, and zero otherwise.
- $rt_i$  = A dummy variable equal to one if individual  $i$  was subject to the RT treatment, and zero otherwise.

In every case, Navigant found that that the estimated parameter associated with the RT interaction (the incremental impact associated with the RT treatment) was statistically non-significant. In the summer months the p-values associated with this parameter were between 0.33 (Weekend Off-Peak) and 0.835 (On-Peak) and in the winter the p-values associated with these four parameters were between 0.29 (Weekend Off-Peak) and 0.831 (On-Peak). A comparison of the total average treatment effect derived from this model with that provided by the final model reveals that the overall estimated impacts delivered are very close. For example, the final model estimated an impact of 0.297 kWh per day during the summer On-Peak, whereas the test model delivers an average treatment effect of 0.304 kWh – a change of about 2%.

**3.4 CPP Demand Impact Approach**

As with the estimation of energy impacts, Navigant estimated the CPP event day demand impacts separately for the two seasons. The confidence intervals and relative precision of all estimates are based on a 90% confidence level.

**3.4.1 Summer Approach**

Participant demand response impacts on CPP event days were estimated using only data from summer 2018 CPP event days. Impacts were estimated using a panel data regression of hourly energy use. All

impacts were estimated using a single model specification. Immediately below a verbal description of Navigant’s regression model is provided. This is followed by the algebraic specification.

Navigant’s regression model specification is designed to estimate four impacts:

- **Ex-Post Total Impact.** An estimate of the total impact of the program during CPP events in Summer 2018. That is, an estimate of the difference between a participant’s demand during the CPP event, and what it would have been had there been no program at all. This defines the estimated *total* impact of the program.
- **Ex-Post DR Impact.** An estimate of the historical impact of CPP events, given that the program is in place. Put another way, this is an estimate of the difference between what a participant’s demand was during the CPP event, and what it would have been had there been no event on that day, but in all other respects (including the existence of the program) the days were the same. This defines the estimated “*DR only*” impact of the program.
- **Ex-Ante Total Impact.** A prediction of total impacts across a range of temperatures. This defines the estimated *capability* of the program.
- **Ex-Ante DR Impact.** A prediction of the DR-only impacts across a range of temperatures.

Key variables included in the regression specification are:

- **Hour-of-Day Dummies.** A set of 24 hourly dummies. These are interacted with all other non-treatment variables (and in some cases some treatment variables).
- **Temperature.** Heating degree hours, cooling degree hours, and heat build-up.
- **Hourly Pre-Period Consumption Values.** Average participant-specific pre-period consumption for the given day-type. These act as highly granular fixed effects in the energy regression. See Appendix A for more details.
- **Non-DR Program Dummies.** A set of variables (the treatment dummy interacted with the hourly dummies) intended to capture the non-CPP-event treatment effects on a CPP event day – i.e., to capture the effect on participant demand of their anticipating when an event *may* occur. This set of variables is included as both intercept dummies, and as slope dummies (interacted with cooling degree hours).
- **DR Event Dummy.** A dummy variable intended to capture CPP event “DR only” impacts. This is included both as an intercept dummy and a slope dummy (interacted with cooling degree hours), both of which are included as-is and interacted with a variable that captures whether the enabling technologies are connected and able to be automatically controlled via London Hydro’s curtailment signal.
- **Snapback Variables.** Four dummy variables (one for each of the four hours immediately following the DR event) interacted with the cooling degree hours observed during the event. These variables are designed to control for any snapback effects.<sup>37</sup>

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<sup>37</sup> Snapback is a phenomenon commonly observed in direct load control programs. If participant A/C is controlled for long enough that indoor temperature materially rises, this can result in more A/C compressor cycles than usual in the hours immediately following the event as the A/C unit works harder usual to restore the home to the set-point temperature.

Equation 2 below, presents the model specification used to estimate the participant CPP summer event demand impacts presented above, in the body of this report. Important note: Equation 1 use the subscript “*t*” to denote the day of sample. Equation 2, below, uses the “*t*” subscript to denote the *hour* of the sample. Note that in the equation below, sub-scripts denote differences across *rows* (e.g., individuals, time periods) and super-scripts denote differences across *columns* (e.g., batteries of dummy variables).<sup>38</sup>

**Equation 3: CPP Event Demand Model Specification**

$$\begin{aligned}
 y_{i,t} = & \sum_{h=1}^{H=24} \beta_1^h \cdot he_t^h + \sum_{h=1}^{H=24} \beta_2^h \cdot he_t^h \cdot cdh_t + \sum_{h=1}^{H=24} \beta_3^h \cdot he_t^h \cdot hdh_t + \\
 & \sum_{h=1}^{H=24} \beta_4^h \cdot he_t^h \cdot hbu_t + \sum_{h=1}^{H=24} \beta_5^h \cdot he_t^h \cdot EMACdh_t + \sum_{h=1}^{H=24} \beta_6^h \cdot he_t^h \cdot prekWh_{th} + \\
 & \sum_{h=1}^{H=24} \rho_1^h \cdot he_t^h \cdot treat_i + \sum_{h=1}^{H=24} \rho_2^h \cdot he_t^h \cdot treat_i \cdot cdh_t + \\
 & \gamma_1 \cdot treat_i \cdot event_t + \gamma_2 \cdot treat_i \cdot event_t \cdot cdh_t + \\
 & \gamma_3 \cdot treat_i \cdot event_t \cdot connected_{it} + \gamma_4 \cdot treat_i \cdot event_t \cdot cdh_t \cdot connected_{it} + \\
 & \sum_{s=1}^{S=4} \delta_1^s \cdot s_{it}^s \cdot eventcdh_t + \sum_{s=1}^{S=4} \delta_2^s \cdot s_{it}^s \cdot eventcdh_t \cdot connected_{it} + \varepsilon_{it}
 \end{aligned}$$

Where:

- $y_{i,t}$  = Customer *i*'s demand (kW)<sup>39</sup> in hour of sample *t*.
- $he_t^h$  = A set of 24 dummies, one for each hour of the day, equal to 1 when hour of sample *t* falls in hour of day *h*, and zero otherwise.
- $cdh_t$  = The number of cooling degree hours observed in hour of sample *t*, with a base of 18 degrees Celsius.
- $hdh_t$  = The number of heating degree hours observed in hour of sample *t*, with a base of 18 degrees Celsius.

<sup>38</sup> In some cases, as in the case of *p*, an index may appear as both a super-script (there are four TOU dummy variables,  $tou_t^p$ ) and as a sub-script (there is only one value of CDH in each of the four possible TOU periods in a given day, *t*, and that is  $cdh_{t,p}$ )

<sup>39</sup> Interval data in fact show consumption, but since the goal of this is to estimate demand impacts, and hourly consumption and average hourly demand are equivalent values, it is shown as demand here.

- $hbu_t$  = The average heat build-up hour of sample  $t$ . This is a 72-hour geometrically decaying average of cooling degree hours. It is calculated in the following manner:
- $$cbu_t = \frac{\sum_{h=1}^{72} 0.96^h \cdot cdh_{t-h}}{1,000} \cdot$$
- $EMAc dh_t$  = The five-hour exponential moving average of cooling degree hours observed in hour of sample  $t$ .
- $prekWh_{idh}$  = Customer  $i$ 's average demand during hour of day  $h$ , in day-type  $d$  of the pre-program (i.e., summer 2017) period. The day-type is that of the day on which hour of sample  $t$  falls. See A.1 for more details.
- $treat_i$  = A dummy variable equal to one if customer  $i$  is a participant, and zero otherwise.
- $event_t$  = A dummy variable equal to one if hour of sample  $t$  is a CPP event, and zero otherwise.
- $connected_{it}$  = A dummy variable equal to one if participant  $i$  is connected to London Hydro's automatic curtailment system on the event day on which hour of sample  $t$  falls, and zero otherwise.
- $s_{it}^s$  = A set of four dummy variables to capture the effects (if any) of snapback. Each variable is equal to 1 when hour of sample  $t$  is the  $s$ -th hour observed since the end of the event observed on the day on which hour of sample  $t$  occurs. For example, if the event occurs between 5pm and 6pm, at 7pm these four variables will take the following values:  $s_{it}^{s=1} = 1$ ,  $s_{it}^{s=2} = 0$ ,  $s_{it}^{s=3} = 0$ , and  $s_{it}^{s=4} = 0$ .

This model is estimated once. The estimated values of the  $\rho$  parameters capture the “energy impact” of the treatment, whereas the  $\gamma$  parameters capture the “DR only” impact. That is, this second set of parameters capture the difference between what average demand during the event would have been had there been no event, *but the program was still in place*, and what average demand was. The “total” program impact is the “sum product” of both sets of parameters and the appropriate variable values.

### 3.4.2 Winter Approach

Navigant’s approach for estimating the winter impacts was materially different from the approach to estimating summer impacts. Most importantly, the specification is much simpler, as there is no need to split out hourly energy impacts from the demand-response type impacts. The fact that none of the treatment groups delivered any statistically significant energy impacts removes this requirement.

Further, as part of the initial exploratory analysis of the data, Navigant noted that there appeared to be no observable relationship between temperatures and impacts. This suggested that it would be inappropriate to estimate impacts as a function of temperature, as was done for summer impacts.

Likewise, observation of event-day load profiles made it apparent that while the CPP rate was clearly delivering demand response there appeared to be very little, if any snapback. This is consistent with the observation that impacts do not appear to be correlated with temperature. When space-conditioning is curtailed (turning the home into a thermal battery), snapback is an inevitable outcome of the HVAC system restoring set-point temperature. When other end uses are controlled (as appears to be the case here and is consistent with the very high penetration of natural gas heating in London Hydro’s customer base), snapback is less common. For example: if CPP response is dominated by extinguishing lighting, home entertainment systems, etc. no snapback would be expected.

There are, therefore, three key differences between the summer and winter model specifications.

- **No Non-DR Program Dummies.** With no energy impacts to control for, these are unnecessary.
- **No Snapback Variables.** With no snapback observable in the load profiles, and the observation that impacts do not appear to be a function of outdoor temperatures, these are also unnecessary.
- **DR Event Dummies.** Whereas the summer analysis uses only a single dummy variable to flag CPP events (and interacts this with temperature values), for the winter analysis a “battery of dummies” approach is used. Each event receives a separate dummy variable. For the 18 hours of CPP events in the winter, there are 18 dummy variables. Each dummy variable takes a value of one only once in each individual participant’s time series.

Equation 4 below, presents the model specification used to estimate the winter participant CPP event demand impacts presented above, in the body of this report. Important note: Equation 1 and Equation 2 use the subscript “*t*” to denote the day of sample. Equation 4, below, uses the “*t*” subscript to denote the *hour* of the sample.

**Equation 4: CPP Event Demand Model Specification**

$$\begin{aligned}
 y_{i,t} = & \sum_{h=1}^{H=24} \beta_1^h \cdot he_t^h + \sum_{h=1}^{H=24} \beta_2^h \cdot he_t^h \cdot hdh_t + \sum_{h=1}^{H=24} \beta_3^h \cdot he_t^h \cdot month_t \\
 & \sum_{h=1}^{H=24} \beta_4^h \cdot he_t^h \cdot cbu_t + \sum_{h=1}^{H=24} \beta_5^h \cdot he_t^h \cdot EMAhdh_t + \sum_{h=1}^{H=24} \beta_6^h \cdot he_t^h \cdot prekWh_{idh} + \\
 & \sum_{v=1}^{V=18} \gamma_1^v \cdot cpp\_event_t^v \cdot treat_t + \sum_{v=1}^{V=18} \gamma_2^v \cdot cpp\_event_t^v \cdot treat_t \cdot connected_{it} + \varepsilon_{it}
 \end{aligned}$$

Where:

*cbu<sub>t</sub>* = The average cold build-up hour of sample *t*. This is a 72-hour geometrically decaying average of heating degree hours. It is calculated in the same manner as the heat build-up variable included in the summer

$EMAh_{dh_t}$	=	CPP event analysis, except that cooling degree hours are replaced by heating degree hours.
$c_{pp\_event_t}^v$	=	The five-hour exponential moving average of cooling degree hours observed in hour of sample $t$ .
	=	A set of 18 dummy variables. The $v$ -th dummy variable is equal to one when the $v$ -th CPP event of the season occurs in hour $t$ , and zero otherwise. This is a “battery of dummies” approach. For each individual participant’s time series each of these 18 variables can take a value of no more than once. See below for a short description of why this approach was used.

And all other variables are as defined for the summer estimation.

This model is estimated once. Key differences between the winter and summer CPP period regression equations include:

- No variables to control for energy (as opposed to CPP event-day specific DR) impacts. As there is no statistically significant energy impact, these variables are not required.

No variables to interact impacts with outdoor temperature. Navigant began by estimating a model that included a temperature interaction (i.e., very similar to the summer model) but found that the temperature interaction term was so small that even wide swings in temperature left the estimated event-specific impacts very similar, and that this parameter was not statistically significant. This led to the re-specification above, which adopts a more agnostic approach, with a separate dummy variable applied for each event.

### 3.5 Elasticities

As per the OEB evaluation metrics requirements<sup>40</sup>, Navigant used the outputs from the analysis described above to develop estimates of two different metrics of price sensitivity for the group of participants subject to the CPP rate:

- **Own/daily price elasticity of demand.** This describes the relationship between CPP and CPP/RT participants’ average daily demand. More specifically: Navigant has used outputs from the energy and CPP event demand estimation to calculate the average percentage change in quantity of average daily energy demanded divided by the percentage change in the effective price paid for daily energy demanded.
- **Inter-period elasticity of substitution.** This describes the relative relationship between electricity pricing and demand for two different time periods – analogous to a cross-price elasticity. The two time periods applied for this analysis are the Mid-Peak and the Off-Peak periods (no CPP events occurred outside of the Mid-Peak period).

<sup>40</sup> The OEB’s EM&V Metrics output spreadsheet requires all RPP pilot proponent LDCs’ technical consultants provide: the own/daily price elasticity and the inter-period substitution elasticity. These are required for each treatment group subjected to an alternative price plan, and for each season (summer and winter). For the second metric this is a comparison between the substitution elasticity between Mid-Peak and Off-Peak periods (the only two periods in which price changes – relative to the status quo price plan – occur).

All of the RPP pilots procured by the OEB require the technical consultant to provide an estimate of the own/daily price elasticity of demand and the inter-period substitution elasticity for all treatment groups that include a price treatment.

Given the nature of the London Hydro pilot – the use of enabling technology to deliver very fast-ramp demand response – Navigant determined that it was more appropriate to evaluate impacts using an approach more aligned with the demand response evaluation literature than the elasticity estimation literature. To deliver the required estimates of elasticities, Navigant committed in its approved evaluation plan to using the estimated outputs from the energy and demand regressions to derive a point estimate of these two values.

Each of these is defined in greater detail below.

### 3.5.1 Own/Daily Price Elasticity

The own-price elasticity of daily consumption is the elasticity associated with any overall conservation effect and compares the percentage change in the effective average daily price of consumption (by season) with the percentage change in daily consumption.

Algebraically, this can be expressed:

$$e = \frac{\% \Delta Q}{\% \Delta P}$$

Where  $e$  is the estimated own-price elasticity of demand,  $\% \Delta Q$  is the percentage change in overall quantity of electricity demanded, and  $\% \Delta P$  is the percentage change in the average price paid for electricity over the period in question (i.e., the season).

The numerator is a straight-forward calculation. The percentage change is calculated by comparing actual total<sup>41</sup> observed average energy consumption in all periods with average counterfactual<sup>42</sup> estimated energy consumption in all periods. The change in average price is more subject to interpretation. Since the purpose of an elasticity is to quantify a behavioural response, the question of what constitutes the price for the commodity must be considered from the perspective of the consumer. When a consumer considers the average cost of their overall electricity consumption, what is the price signal? Note that since the behavioural decision relates to overall consumption (and not TOU-period specific consumption), the prices of the individual TOU periods are relevant only inasmuch as they affect the bottom line dollar amount paid by the consumer: the bill total.

If the bill total is considered the price for seasonal consumption, what values are used to assess the percentage change?

The average “base” price of electricity is the average seasonal cost to the participant assuming they were still subject to status quo TOU prices (counterfactual prices) and thus had made no change to their consumption (counterfactual consumption). The average base price is therefore the counterfactual seasonal bill.

<sup>41</sup> Note that although seasonal totals are used for this calculation instead of daily averages, the end results

<sup>42</sup> Counterfactual consumption is the consumption that is estimated would have been observed had there been no pilot program.

The new price, to which the participants are responding is the cost that they would observe if they did not change their behaviour to respond to the new pilot price but *were* subject to that price. If they don't respond to the incentive, what does it cost? This seasonal cost is calculated by applying the actually observed prices (the pilot prices) to the counterfactual consumption – what participants would have consumed had they not changed their behaviour.

The detailed derivation of all these values is provided in tabs 05a and 05b of the Appendix B spreadsheet.

### 3.5.2 Inter-Period Substitution Elasticity

The own/daily price elasticity captures the change in energy consumption relative to the change in price for that consumption, whereas the inter-period substitution elasticity captures the relationship between consumption and relative price between two periods. More specifically, as defined by the OEB for this engagement, the inter-period elasticity of substitution “...indicates the percentage change in the ratio of peak to offpeak consumption due to one percent change in the ratio of peak to offpeak prices”.

In the summer months of the pilot the On-Peak price of electricity did not change, so the inter-period elasticity of substitution was calculated using the Off-Peak and Mid-Peak periods. In the winter months of the pilot the Mid-Peak price of electricity did not change, so the inter-period elasticity of substitution was calculated using the Off-Peak and On-Peak periods.

Equation 5, below provides the equation used to calculate the inter-period substitution elasticity for the summer months. The winter equation is identical, but (per above) the “mid” subscripting (indicating the Mid-Peak period) should be replaced by “on” subscripting to reflect the use of the On-Peak period.

**Equation 5: Summer Inter-Period Elasticity of Substitution**

$$S = \frac{\left( \frac{Q_{mid}^{post}}{Q_{off}^{post}} - \frac{Q_{mid}^{pre}}{Q_{off}^{pre}} \right) \frac{Q_{mid}^{pre}}{Q_{off}^{pre}}}{\left( \frac{P_{mid}^{post}}{P_{off}^{post}} - \frac{P_{mid}^{pre}}{P_{off}^{pre}} \right) \frac{P_{mid}^{pre}}{P_{off}^{pre}}}$$

Where:

- $Q_{mid}^{post}$  = The average consumption during the pilot Mid-Peak period (summer).
- $Q_{off}^{post}$  = The average consumption during the pilot Off-Peak period (summer).
- $Q_{mid}^{pre}$  = The average counterfactual consumption during the pilot Mid-Peak period (summer).

- $Q_{off}^{pre}$  = The average counterfactual consumption during the pilot Mid-Peak period (summer).
- $P_{mid}^{post}$  = The average price (variable cost per kWh<sup>43</sup>) during the pilot Mid-Peak period (summer).
- $P_{off}^{post}$  = The average price (variable cost per kWh) during the pilot Off-Peak period (summer).
- $P_{mid}^{pre}$  = The average price (variable cost per kWh) under the status quo TOU price plan during the pilot Mid-Peak period (summer).
- $P_{off}^{pre}$  = The average price (variable cost per kWh) under the status quo TOU price plan during the pilot Mid-Peak period (summer).

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<sup>43</sup> Includes variable non-commodity charges.

## 4. IMPACT RESULTS

This chapter provides the results of Navigant's impact evaluation of the London Hydro RPP pilot program.

This chapter is divided into two main sections:

- **Energy Impacts.** This section provides and discusses the estimated impacts on daily energy consumption of the program for all participants.
- **Critical Peak Event Demand Impacts.** This section provides and discusses the estimated CPP event demand impacts delivered by the CPP and CPP/RT participants.

### 4.1 Energy Impacts

Navigant's key findings from the energy impact analysis include:

- **The pilot treatments deliver energy savings only in the summer.** Navigant did not estimate any statistically significant energy savings during the winter months for any of the treatment groups.
- **CPP participants delivered summer On-Peak and Mid-Peak energy savings that are statistically significant at the 90% confidence level.** CPP and CPP/RT participants reduced their daily summer:
  - On-Peak consumption by approximately 5% on average (+/- 58%)<sup>44</sup>
  - Mid-Peak consumption by approximately 3% on average (+/- 90%)
- **RT participants delivered modest On-Peak energy savings, although these results are less certain.** RT participants reduced their summer On-Peak consumption by approximately 2%, although these results are less certain than those of the CPP group – being just barely statistically non-significant, with a relative precision of +/- 101%. Navigant presents evidence in Section 4.1.4 that although these impacts are not statistically significant at the 90% level, it seems probable that these estimates reflect actual conservation, and not just random variation in the underlying data, that is that there is a real, though highly uncertain, impact during the On-Peak period.
- **CPP participants also equipped with the RT technology are saving the same as CPP-only participants in the summer months.** Navigant found no statistically or practically significant difference between the energy savings achieved by CPP and CPP/RT participants in the summer months and concluded from this that the RT treatment did not deliver any incremental savings.
- **Statistically significant energy savings have been estimated only in summer months and are, in those months, correlated with temperature.** Although Navigant cannot categorically state what behaviour is driving energy savings, the fact that the CPP groups' estimated energy savings are statistically significantly correlated with temperature and are statistically significant only in summer months, suggests that response is driven in large part by changes in A/C use.

This section of the impact chapter is divided into five sub-sections:

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<sup>44</sup> All confidence intervals (relative precision) provided in this report are based on a 90% confidence level applied to cluster-robust standard errors.

- Summary of Energy Impacts
- CPP and CPP/RT Participants – Summer Energy Impacts
- CPP and CPP/RT Participants – Winter Energy Impacts
- RT Participants – Summer Energy Impacts
- RT Participants – Winter Energy Impacts

**4.1.1 Summary of Energy Impacts**

Figure 4-1, below, provides a tabular summary of all estimated energy impacts. These are discussed in detail in the sub-sections that follow. Note that CPP and CPP/RT groups are presented together based on the finding (detailed in section 3.3) in an early testing phase that the incremental impact of the RT treatment is statistically insignificant, of the wrong sign, leading Navigant to conclude that the RT treatment is having no incremental impact on CPP participant energy consumption.

**Figure 4-1: Summary of all Energy Impacts**

Treatment Group(s)	Season	Time-Period	Daily Savings		P-Value	Relative Precision +/- % (90% Confidence)
			kWh	%		
RT	Summer	On-Peak	0.16 (N/S)	2.36% (N/S)	0.105	101%
RT	Summer	Mid-Peak	0.03 (N/S)	0.42% (N/S)	0.755	528%
RT	Summer	Off-Peak	-0.2 (N/S)	-1.62% (N/S)	0.222	135%
RT	Summer	Weekend Off-Peak	-0.15 (N/S)	-0.53% (N/S)	0.659	373%
<i>RT</i>	<i>Summer</i>	<i>Total Energy</i>	<i>-10.21(N/S)</i>	<i>-0.21% (N/S)</i>	<i>0.860</i>	<i>934%</i>
RT	Winter	On-Peak	0.07 (N/S)	1.28% (N/S)	0.363	181%
RT	Winter	Mid-Peak	0.05 (N/S)	0.87% (N/S)	0.596	310%
RT	Winter	Off-Peak	0.06 (N/S)	0.54% (N/S)	0.714	449%
RT	Winter	Weekend Off-Peak	-0.19 (N/S)	-0.77% (N/S)	0.560	282%
<i>RT</i>	<i>Winter</i>	<i>Total Energy</i>	<i>11.45(N/S)</i>	<i>0.28% (N/S)</i>	<i>0.838</i>	<i>803%</i>
<b>RT</b>	<b>Annual</b>	<b>Total Energy</b>	<b>1.24(N/S)</b>	<b>0.01% (N/S)</b>	<b>0.988</b>	<b>10696%</b>
CPP and CPP/RT	Summer	On-Peak	0.297	0.050	0.004	58%
CPP and CPP/RT	Summer	Mid-Peak	0.174	0.029	0.066	90%
CPP and CPP/RT	Summer	Off-Peak	-0.22 (N/S)	-1.96% (N/S)	0.228	136%
CPP and CPP/RT	Summer	Weekend Off-Peak	0.08 (N/S)	0.3% (N/S)	0.827	751%
<i>CPP and CPP/RT</i>	<i>Summer</i>	<i>Total Energy</i>	<i>36.1(N/S)</i>	<i>0.79% (N/S)</i>	<i>0.582</i>	<i>299%</i>
CPP and CPP/RT	Winter	On-Peak	0.1 (N/S)	1.74% (N/S)	0.276	151%
CPP and CPP/RT	Winter	Mid-Peak	-0.04 (N/S)	-0.68% (N/S)	0.714	448%
CPP and CPP/RT	Winter	Off-Peak	-0.19 (N/S)	-1.74% (N/S)	0.301	159%
CPP and CPP/RT	Winter	Weekend Off-Peak	-0.4 (N/S)	-1.61% (N/S)	0.277	151%
<i>CPP and CPP/RT</i>	<i>Winter</i>	<i>Total Energy</i>	<i>-37.92(N/S)</i>	<i>-0.92% (N/S)</i>	<i>0.548</i>	<i>274%</i>
<b>CPP and CPP/RT</b>	<b>Annual</b>	<b>Total Energy</b>	<b>-1.82(N/S)</b>	<b>-0.02% (N/S)</b>	<b>0.984</b>	<b>8221%</b>

Note that an estimate is statistically significant at the 90% level when the relative precision is less than 100%, or the p-value is less than 0.1. Estimates that are not statistically significant are followed by “(N/S)”. Finally note that statistical insignificance (the finding that an estimate is not statistically significantly different from zero) formally means that the null hypothesis (that the estimated value’s true value is zero) cannot be rejected at the selected level of confidence.

This does not necessarily mean that no impact is being delivered, simply that the estimated value is highly uncertain. Such highly uncertain impacts may be interpreted in a number of ways. Two of the most common interpretations are: there is an impact, but the signal/noise ratio is simply too small to achieve much certainty, or there is no impact, and the estimated value is just the result of random variation in the underlying data generation process. Pilot evaluations often, out of prudence, apply the second

interpretation. Navigant has, *except in cases where other compelling evidence exists to suggest the presence of an impact*, applied this second interpretation: that statistical non-significance suggest the likelihood that no impact was achieved.

### 4.1.2 CPP and CPP/RT Participants – Summer Energy Impacts

This section provides and discusses the estimated energy impacts for the CPP and CPP/RT groups in the summer months (May through October 2018). As noted in both the section introduction and Section 3.3, initial exploratory regression estimation found that the incremental energy impact of the RT treatment for the participants exposed to the CPP treatment was not statistically significant. These interaction terms were then dropped from the model specification for the remainder of the analysis. For the remainder of this section, references to the “CPP group” or “CPP treatment” should be understood to encompass both the CPP and the CPP/RT participants.

Navigant estimated the energy impacts of the CPP group twice, both times with the same model specification, but with slightly different data sets. Navigant’s initial estimation included *all* summer days. Navigant then re-estimated the same model specification, dropping all CPP event days from the data set.

Although both sets of results are presented below, the final results presented in this report (and in Appendix B, the accompanying output spreadsheet of program metrics for the OEB) are those estimated when CPP event days are *excluded* from the data set.<sup>45</sup>

Average impacts in the summer of 2018 are presented in Figure 4-2, below. This table shows the average daily reduction in consumption (kWh) in the given TOU period, the percentage reduction in the consumption of the given TOU period, and the relative precision of the estimated impact at the 90% confidence level.<sup>46</sup>

Positive values indicate a savings, and negative values indicate an increase in consumption. Statistically non-significant estimates are followed by “(N/S)”. A value is considered statistically not significantly different from zero<sup>47</sup> when the relative precision at the 90% confidence level exceeds 100%.

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<sup>45</sup> When event days are included then estimated energy savings capture two effects: energy shifting on non-event days *and* the event-period CPP response, but averaged over many days. The goal of the energy analysis is to understand what changes participants made to their average daily consumption patterns. Including the event day obscures this goal and means that any calculation of system avoided costs (e.g., for the purposes of cost-effectiveness testing) that also considered the CPP event day impact would double-count some savings and overstate societal benefits.

<sup>46</sup> All estimates of uncertainty presented in this report have been estimated using cluster-robust standard-errors, with clustering applied at the individual customer level.

<sup>47</sup> A statistically non-significant estimate is an estimate for which the hypothesis that the true value of the estimated parameter is zero cannot be rejected. This makes such impacts highly uncertain. Such results may be interpreted in one of two ways: there is an impact, but it is highly uncertain, or there is no impact and the estimate is simply the result of statistical noise in the data.

**Figure 4-2: CPP Summer Energy Impacts – Excludes CPP Event Days**

TOU Period	Daily Savings		P-Value	Relative Precision +/-% (90% Confidence)
	kWh	%		
On-Peak	0.30	5.0%	0.004	58%
Mid-Peak	0.17	2.9%	0.066	90%
Off-Peak	-0.22 (N/S)	-1.96% (N/S)	0.228	-136%
Weekend Off-Peak	0.08 (N/S)	0.3% (N/S)	0.827	751%

Note that the savings values above are average daily consumption savings, by TOU period. These values, divided by the number of hours in each period, deliver the average demand (kW) impact in each period. The an average energy reduction of 0.3 kWh over the six hours of the On-Peak period is equivalent to a reduction in On-Peak hourly demand of 0.049 kW and an average energy reduction of 0.17 kWh in the Mid-Peak period is equivalent to an average reduction in Mid-Peak demand of 0.029 kW.

When the model was re-estimated using the system coincident peak demand data set (i.e., a daily frequency data set where the dependent variable is the total daily consumption between 1pm and 6pm on non-holiday weekdays in June, July, and August), Navigant estimated a statistically significant average reduction in energy consumption of 0.46 kWh, or approximately 6% of baseline consumption in that period. The average estimated demand impact in this period is 0.077 kW.

Figure 4-3, below, provides the estimated impacts when CPP event days are *included*. Note that the estimated impact in the On-Peak period barely changes, whereas the Mid-Peak impact nearly doubles when CPP event days are included. This effect is because in the summer of 2018 CPP events all began at either 5pm or 6pm; no CPP events took place within the TOU On-Peak period.

**Figure 4-3: CPP Summer Energy Impacts: Includes CPP Event Days**

TOU Period	Daily Savings		P-Value	Relative Precision +/-% (90% Confidence)
	kWh	%		
On-Peak	0.33	5.1%	0.003	55%
Mid-Peak	0.28	4.4%	0.005	58%
Off-Peak	-0.23 (N/S)	-1.9% (N/S)	0.227	-136%
Weekend Off-Peak	0.08 (N/S)	0.3% (N/S)	0.827	751%

The savings values above are average daily consumption (energy, kWh) savings, by TOU period. These values, divided by the number of hours in each period, deliver the average demand (kW) impact in each period. The average energy reduction of 0.33 kWh over the six hours of the On-Peak period is equivalent to a reduction in On-Peak hourly demand of 0.054 kW and an average energy reduction of 0.28 kWh in the Mid-Peak period is equivalent to an average reduction in Mid-Peak demand of 0.046 kW.

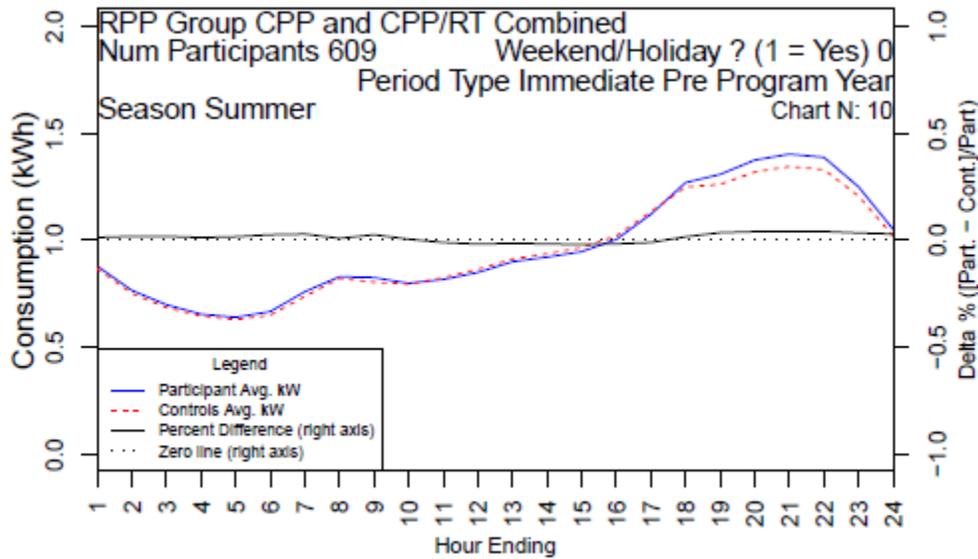
Estimated impacts in the On-Peak and Mid-Peak periods are evident when comparing current and prior summer seasonal load profiles.

Consider Figure 4-4, below. This plot shows the average summer 2017 (one year prior to program implementation) load profile of non-holiday weekday consumption for:

- CPP participants (blue line) and
- RCT control customers (red dotted line).

Note how close the two lines are throughout most of the day. Some separation exists in the evening, with CPP participants on average consuming slightly more electricity in the nighttime hours.<sup>48</sup>

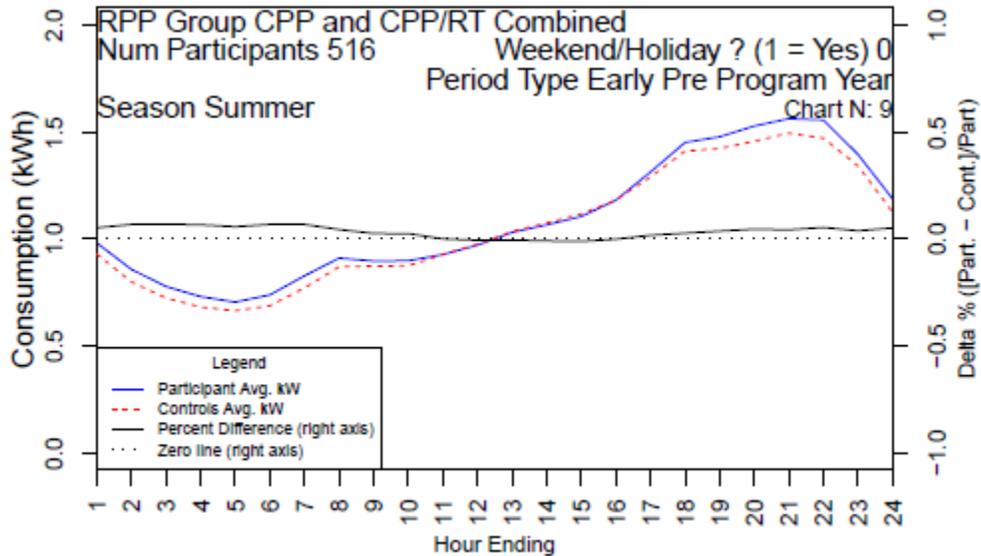
Figure 4-4: CPP Participants – Summer 2017 Weekday Load Profile



Aside from the late evening hours, the two profiles are nearly identical. Now consider the same profiles one year farther back in time, in the summer of 2016. These are shown below in Figure 4-5. Although there are now some small differences in the overnight and very early morning hours, the differences between the two profiles are consistent with those observed in the summer of 2017

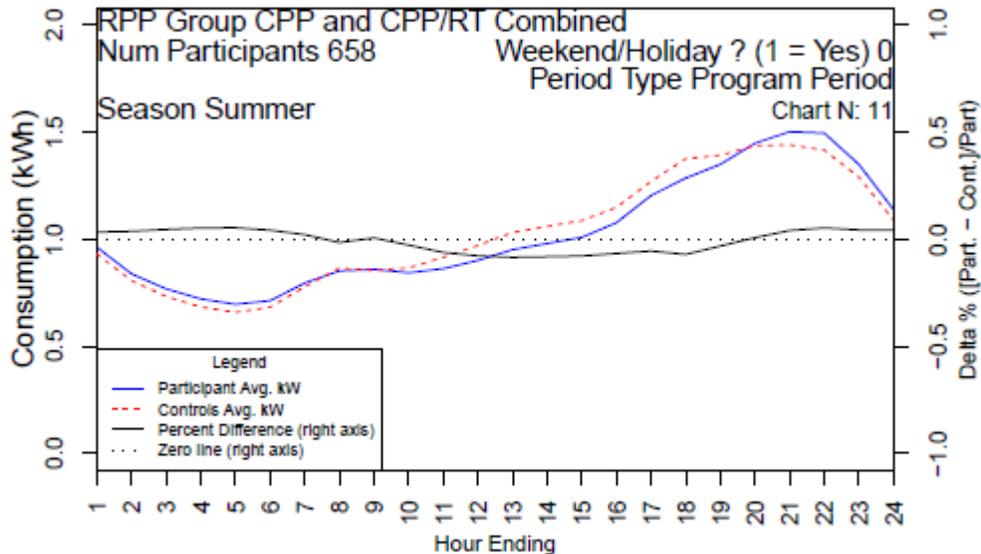
<sup>48</sup> This difference is controlled for using the pre-period consumption values included in the regression equation. That is, impacts are estimated in the program period conditional on this structural difference observed in the pre-period.

Figure 4-5: CPP Participants – Summer 2016 Weekday Load Profile



Finally, consider the same two sets of load profiles from the summer of 2018, the program period. There is a distinct separation between the two profiles that begins close to the beginning of the morning Mid-Peak period, extends consistently across the On-Peak period, and tails off at the end of the afternoon Mid-Peak period.

Figure 4-6: CPP Participants – Summer 2018 (Program Period) Weekday Load Profile



Observing the patterns across three years of data it seems clear that the change in consumption observed in the program period – a relatively consistent change across the hours of the day in which a CPP event is most likely – is motivated by the program treatment.

As indicated in Section 3.3, Navigant estimated energy impacts as both a function of the program participation and as a function of the interactive effect between program participation and the weather. That is, the regression-estimated parameters provide an estimate of the average program impact on cooler days (when there are no cooling degree hours) as well as the incremental impact of each cooling degree hour observed in the given period.

Figure 4-7, below, provides the regression-estimated parameters when CPP event days are excluded from the analysis. This shows both:

- The intercept parameters for On-Peak and Mid-Peak (i.e., estimated annual kWh impact when no cooling degree hours are observed in the period in question), and;
- The slope parameters (i.e., the incremental impact for each cooling degree hour observed in the given period).

In this table, a negative value indicates a reduction in consumption (energy savings).

**Figure 4-7: CPP Energy Impact Parameters of Interest**

	Intercept Dummy		Slope (Temperature) Dummy	
	Estimate	P-Value	Estimate	P-Value
On-Peak	-0.079	0.327	-0.008	0.001
Mid-Peak	-0.068	0.399	-0.007	0.014

Note that although the intercept parameters for both TOU periods are not statistically significant, the combined effect across intercept and slope parameters (as shown in Figure 4-2, above) *is* statistically significant.

Based on all the estimated model parameters, CPP participants' consumption over the entire summer of 2018 decreased by a statistically non-significant 36 kWh, or about 0.79%.<sup>49</sup> Put another way, there appears to have been no conservation effect, a not unexpected result given the revenue-neutral nature of the design of the price-plan.

This result (the lack of statistical significance of the savings) is likely a result of noise in the non-On-Peak and non-Mid-Peak periods distorting the result. If only the On-Peak and Mid-Peak (both of which test as statistically significant) savings are considered, and consumption in all other periods (where impacts were found to be non-significant) is assumed to not have changed as a result of the program, then overall summer savings would be approximately 59 kWh, or about 1.3%.

#### **4.1.3 CPP and CPP/RT Participants – Winter Energy Impacts**

This section covers the estimated energy impacts for the CPP and CPP/RT groups in the winter months (November 2018 through April 2019). As noted above, Navigant found (unlike in the summer months) that there was no statistically significant impact on energy consumption from the treatments applied. As the parameter associated with the variable included to test the degree to which the RT treatment delivered incremental impacts was also statistically insignificant, Navigant has provided the results below in a

<sup>49</sup> The p-value associated with this estimate is 0.58, indicating that it would be statistically significant only at the 42% level of confidence.

manner consistent with the summer impacts: CPP and CPP/RT participants are combined as a single group.

Navigant estimated the energy impacts of the CPP group twice, both times with the same model specification, but with slightly different data sets. Navigant’s initial estimation included *all* winter days. Navigant then re-estimated the same model specification, dropping all CPP event days from the data set.

Although both sets of results are presented below, the final results presented in this report (and in Appendix B, the accompanying output spreadsheet of program metrics for the OEB) are those estimated when CPP event days are *excluded* from the data set.

Average impacts in the winter of 2018/2019 are presented in Figure 4-10, below. This table shows the average daily reduction in consumption (kWh) in the given TOU period, the percentage reduction in the consumption of the given TOU period, and the relative precision of the estimated impact at the 90% confidence level.<sup>50</sup>

Positive values indicate a savings, and negative values indicate an increase in consumption. Statistically non-significant estimates are followed by “(N/S)”. A value is considered statistically not significantly different from zero<sup>51</sup> when the relative precision at the 90% confidence level exceeds 100%.

**Figure 4-8: CPP Winter Energy Impacts – Excludes CPP Event Days**

TOU Period	Daily Savings		P-Value	Relative Precision +/-% (90% Confidence)
	kWh	%		
On-Peak	0.1 (N/S)	1.74% (N/S)	0.276	151%
Mid-Peak	-0.04 (N/S)	-0.68% (N/S)	0.714	-448%
Off-Peak	-0.19 (N/S)	-1.74% (N/S)	0.301	-159%
Weekend Off-Peak	-0.4 (N/S)	-1.61% (N/S)	0.277	-151%

Note that the savings values above are average daily consumption savings, by TOU period. None of these estimates is statistically significant. These values, as well as the average demand (kW) savings per period are also presented in spreadsheet Appendix B.

When the model was re-estimated using the system coincident peak demand data set (i.e., a daily frequency data set where the dependent variable is the total daily consumption between 6pm and 8pm on non-holiday weekdays in December, January, and February), Navigant estimated a statistically non-significant average reduction in energy consumption of 0.035 kWh, or approximately 1.3% of baseline consumption in that period. The average estimated demand impact in this period is 0.017 kW.

Figure 4-11, below, provides the estimated impacts when CPP event days are *included*.

<sup>50</sup> All estimates of uncertainty presented in this report have been estimated using cluster-robust standard-errors, with clustering applied at the individual customer level.

<sup>51</sup> Generally speaking (though exceptions exist), impact estimates that are statistically no different from zero should be considered the same as no impact at all.

Figure 4-9: CPP Winter Energy Impacts: Includes CPP Event Days

TOU Period	Daily Savings		P-Value	Relative Precision +/-% (90% Confidence)
	kWh	%		
On-Peak	0.1 (N/S)	1.76% (N/S)	0.283	153%
Mid-Peak	-0.05 (N/S)	-0.92% (N/S)	0.630	-341%
Off-Peak	-0.19 (N/S)	-1.71% (N/S)	0.322	-166%
Weekend Off-Peak	-0.4 (N/S)	-1.61% (N/S)	0.277	-151%

Given the statistical non-significance of all impacts, and the counter-intuitive signs of the parameters (e.g., estimated increases in demand during the On-Peak period and decreases during the Off-Peak periods), Navigant has concluded that this treatment group did not make any material changes in energy consumption behaviours that delivered savings in the winter months.

#### 4.1.4 RT Participants – Summer Energy Impacts

This section will provide and discuss the estimated energy impacts for the RT group in the summer months.

None of the estimated parameters of interest for this group are statistically significant at the 90% level of confidence. A summary of average daily savings (negative values indicate increases in consumption) is provided in Figure 4-10, below.

Normally, for an evaluation such as this, the observation of a statistically non-significant of a parameter of interest (i.e., one designed to capture program savings) would mean that Navigant would not be able to confidently conclude that any savings were achieved. In many cases, where an evaluator of a pilot program cannot confidently conclude that any savings were achieved, risk-averse conservation policy planners treat this as an indication that in fact no savings were delivered. In this case, Navigant believes that evidence exists of savings being delivered (despite the non-significance of the result), albeit savings that are highly uncertain in value.

Figure 4-10: RT Energy Impacts<sup>52</sup>

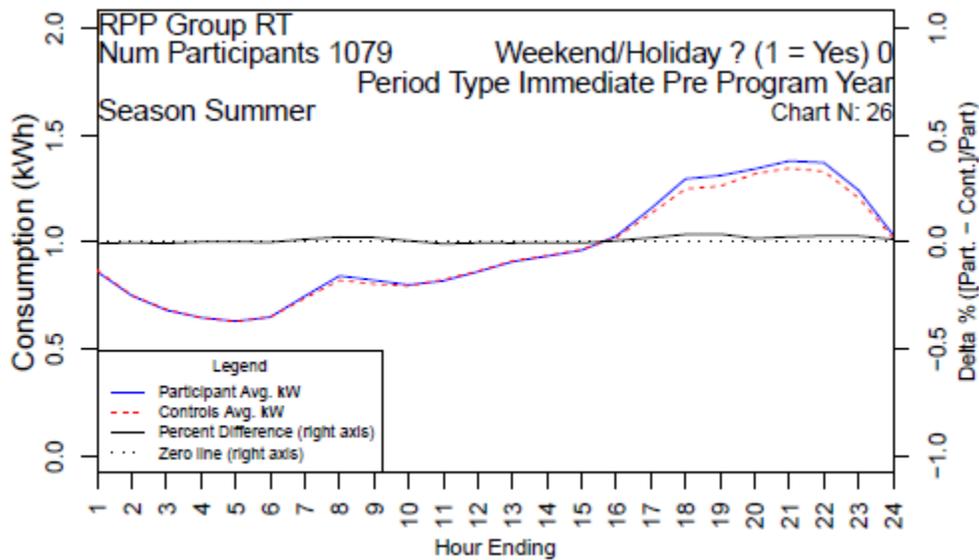
TOU Period	Daily Savings		P-Value	Relative Precision +/-% (90% Confidence)
	kWh	%		
On-Peak	0.16 (N/S)	2.36% (N/S)	0.105	101%
Mid-Peak	0.03 (N/S)	0.42% (N/S)	0.755	528%
Off-Peak	-0.2 (N/S)	-1.62% (N/S)	0.222	-135%
Weekend Off-Peak	-0.15 (N/S)	-0.53% (N/S)	0.659	-373%

First, consider the uncertainty associated with On-Peak period savings. Although the savings are not statistically significant at the 90% level (the relative precision is more than 100%), they are only *just barely* non-significant. The relative precision is 101%, meaning that if the hypothesis had been tested with only a slightly less stringent confidence level (e.g., 89% instead of 90%), then the result would have been to reject the null hypothesis, delivering a statistically significant impact..

<sup>52</sup> The savings values in this table are average daily consumption savings, by TOU period. This is equivalent to an average reduction in On-Peak demand of 0.026 kW.

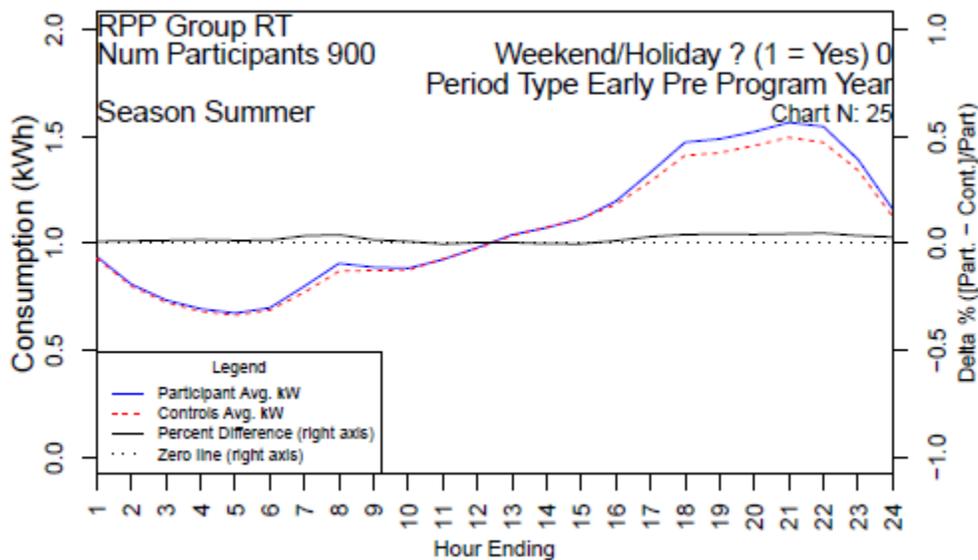
Second, when considering the seasonal non-holiday load profiles – as was done above for the CPP participants – a clear (but small) change in mid-day (On-Peak) consumption is clearly visible. As above, begin by observing the seasonal non-holiday load profiles in the summer of 2017, as shown in Figure 4-11.

Figure 4-11: RT Participants – Summer 2017 Weekday Load Profile



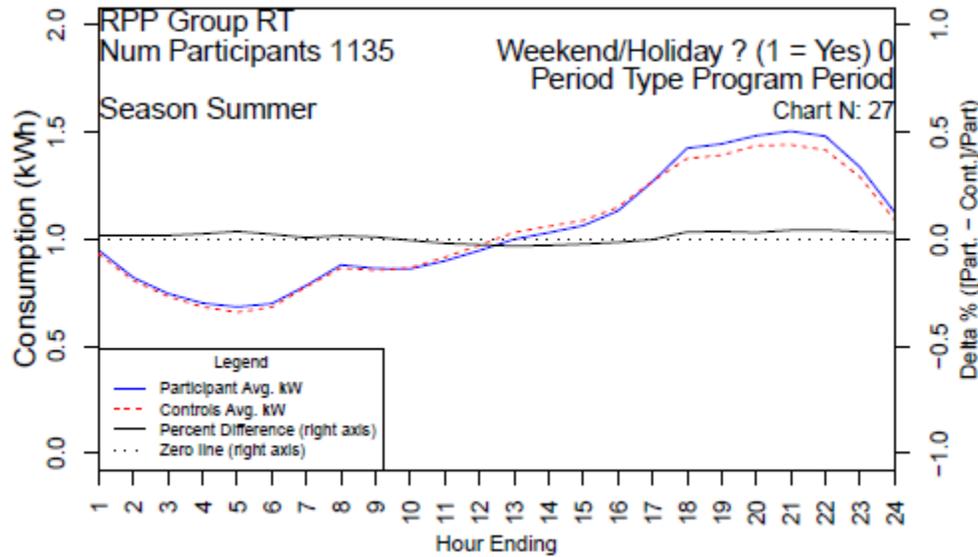
Next, observe the load profiles in the summer before that, summer 2016, as shown in Figure 4-12. This shows essentially the same pattern – the control and participant profiles are very close during the mid-day period (from about 9am to 5pm) but deviate in the early and later evening. Recall that these consistent differences between the participants and controls are accounted for via the inclusion on the right-hand side of the regression equation of customer-specific pre-period consumption values.

Figure 4-12: RT Participants – Summer 2016 Weekday Load Profile



Finally, observe the two profiles in Figure 4-13, the program period (summer of 2018). There is now a small, but distinct, separation between the control and participant profiles in the mid-day On-Peak period. It is this separation that the regression equation is capturing in the estimated impacts provided above.

Figure 4-13: RT Participants – Summer 2018 (Program Period) Weekday Load Profile



Despite the statistical non-significance of the estimated On-Peak impact, the fact that the parameter is so close to being statistically significant, and the fact that the program effects are intuitive and observable in plots of participant and control hourly load profiles is sufficient for Navigant to conclude that the estimated On-Peak impact shown above as the best available impact of the RT group.

Figure 4-14, below, shows the estimated values for the key parameters of interest for the RT group. As above, in Figure 4-7, this table shows the estimated intercept parameter (estimated impact on days where no cooling degree hours are observed during the TOU period of interest) as well as the estimated slope parameter (the incremental impact for each additional cooling degree hour observed during the period of interest). Note that the point estimate of the slope variable for the On-Peak period is not statistically significant for the RT participants but is for the CPP and CPP/RT participants.

Figure 4-14: RT Energy Impact Parameters of Interest

	Intercept Dummy		Slope (Temperature) Dummy	
	Estimate	P-Value	Estimate	P-Value
On-Peak	-0.091	0.194	-0.002	0.313
Mid-Peak	-0.001	0.991	-0.001	0.543

This contrast between the RT and CPP participants' estimated slope impact parameters suggests that while the majority of CPP participants' savings are driven by adjustments in space-cooling, the same may not be the case for the RT participants. A potential driver of this difference may be the combination of the price effects faced by CPP participants, and their expectations regarding CPP event scheduling. The CPP participants know, from the program education provided to them by London Hydro, that CPP event

scheduling is driven by system need, and that system needs tend to be greatest on very hot days. Likewise, CPP participants have tool to not available to RT participants – the remote control functionality of the Trickle app. This functionality allows them to control the circuit to which their load switch is attached, potentially using it reduce A/C use.

The appropriate response then, for the CPP participants, is to focus changes in behaviour in reducing consumption in periods when temperature is highest. The simplest method of doing this is to reduce A/C consumption.

RT customers face a different set of incentives. Where CPP participants' expected unit cost for electricity is correlated with temperature, RT participants' expected unit cost is not. Regardless of the temperature, RT participants pay the same unit cost in the On-Peak period across the whole summer. The benefit to an RT participant in reducing consumption during the On-Peak in October is the same as reducing consumption during the On-Peak of the hottest day of the summer. The "cost" (in terms of the personal discomfort of a house that's too warm) is not the same, however.

Based on all the estimated model parameters, RT participants' consumption over the entire summer of 2018 *increased* by a statistically non-significant 10 kWh, or about 0.2%.<sup>53</sup> This result is likely a result of noise in the non-On-Peak periods distorting the result. If only the On-Peak savings are considered (and consumption in all other periods is assumed to not have changed as a result of the program), then overall summer savings would be approximately 20 kWh, or about 0.2%.

When the model was re-estimated using the system coincident peak demand data set (i.e., a daily frequency data set where the dependent variable is the total daily consumption between 1pm and 6pm on non-holiday weekdays in June, July, and August), Navigant estimated a statistically non-significant average reduction in energy consumption of 0.21 kWh, or approximately 2.4% of baseline consumption in that period. The average estimated demand impact in this period is 0.036 kW. Although the estimated impact is statistically non-significant, the p-value of 0.1047 indicates that there is strong likelihood that the true effect is not zero, consistent with the findings reported above for the On-Peak period.

#### **4.1.5 RT Participants – Winter Energy Impacts**

This section provides and discusses the estimated energy impacts for the RT group in the winter months.

None of the estimated parameters of interest for this group are statistically significant at the 90% level of confidence. A summary of average daily savings (negative values indicate increases in consumption) is provided in Figure 4-18, below. Based on these findings, Navigant cannot conclude that energy savings in the winter are different from zero.

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<sup>53</sup> The p-value associated with this estimate is 0.86.

**Figure 4-15: RT Energy Impacts**

TOU Period	Daily Savings		P-Value	Relative Precision +/-% (90% Confidence)
	kWh	%		
On-Peak	0.07 (N/S)	1.28% (N/S)	0.363	181%
Mid-Peak	0.05 (N/S)	0.87% (N/S)	0.596	310%
Off-Peak	0.06 (N/S)	0.54% (N/S)	0.714	449%
Weekend Off-Peak	-0.19 (N/S)	-0.77% (N/S)	0.560	-282%

When the model was re-estimated using the system coincident peak demand data set (i.e., a daily frequency data set where the dependent variable is the total daily consumption between 6pm and 8pm on non-holiday weekdays in December, January, and February), Navigant estimated a statistically non-significant average reduction in energy consumption of 0.01 kWh, or approximately 0.4% of baseline consumption in that period, equivalent to an estimated average demand impact in this period is 0.012 kW (statistically non-significant at the 90% confidence level).

## 4.2 Critical Peak Event Demand Impacts

Navigant’s key findings include:

- **CPP response is very different between summer and winter.**
  - *Summer CPP response is substantial and correlated with temperature.* In the summer months, CPP impacts were on average 0.67 kW and were positively correlated with temperature: the hotter the day, the higher the CPP impacts. During the hottest event of the summer, the demand response averaged 1kW per customer. This aligns with the hypothesis developed above in the introduction to section 4.1 that summer energy impacts are highly correlated with temperature.
  - *Winter CPP response is small and does not appear to be meaningfully correlated with temperature.* Winter impacts, in contrast with those estimated in the summer, are much lower, on average, 0.13 kW per event. Winter impacts do not appear to be correlated with weather, with the highest event impact being estimated to have occurred on only a moderately cold day (0.23 kW, at -8 degrees Celsius).
- **There is a behavioural element to CPP event impacts in the summer months.** CPP participants are equipped with enabling technologies (a switch at the panel, and one smart plug) that respond automatically to London Hydro’s price signal. Even though participants receive 15 minutes’ notification of an event, there are clear behavioural elements to their response over and above the automated response delivered by the switches and smart plugs.
  - *Participants reduced consumption during hours in which CPP events were likely to occur.* CPP participants reduce their exposure to the CPP rate by making changes to their consumption habits in anticipation of CPP events – substantial savings are achieved in hours of the CPP event day leading up to the CPP event, despite participants not having any knowledge of when the event will occur until 15 minutes before it does.
  - *Disconnected participants still delivered demand response.* For any given event, approximately 20% of participants’ devices could not receive, or respond to, London Hydro’s curtailment signal. On average these participants were still able to reduce

demand by 0.3 kW.<sup>54</sup> The approach for estimating these impacts is described in Section 3.4.

- It is unclear to what degree CPP impacts in the winter months rely on the enabling technology.** The estimated CPP impacts of participants whose enabling technology was disconnected were statistically significant only for two events. This does not however necessarily indicate that behavioural response was muted. A key feature of summer disconnections was their apparently random distribution: half of participants were subject to at least one, but less than 4% of all participants were disconnected for all events. This apparent randomness makes it reasonable to consider the DR impact of disconnected participants as a proxy for the behavioural element of price response (as opposed to the equipment-automated element). In the winter, disconnections do not appear to be randomly distributed. Whereas in the summer, approximately 10% of participants that were disconnected were disconnected for the entire summer, in the winter a third of all participants (that were disconnected at some point) were disconnected for the whole winter.

The lack of response from disconnected participants in the winter may not necessarily be representative of the behavioural contribution of price response in the same way that the summer response of disconnected participants may be. The high proportion of participants disconnected for the entire season in the winter months may be indicative of a high proportion of disconnected participants simply giving up on price response.

In summary, while Navigant believes that the estimated impacts from disconnected participants provide a reasonable proxy for behavioural impacts in the summer months, Navigant is much less certain that the estimated impacts from disconnected participants provide a reasonable proxy for behavioural impacts in the winter months.

- Real-time information on consumption did not affect demand reductions.** The impacts of the CPP and CPP/RT group were not statistically significantly different from one another in either season – the availability of the online portal and energy tracking app did not impact participants' ability to deliver demand reductions

The remainder of this section of Chapter 4 is divided into three sub-sections:

- Summer 2018 Average Impacts (Ex-Post).** This sub-section provides the estimated summer CPP impacts by event for all participants, on average. This sub-section provides both the “total” program impacts (the impact compared to if there had been no program at all), and the “DR only” impacts (the impact compared to if the program was in place but on the given day there had been no CPP event).
- Winter 2018/2019 Average Impacts (Ex-Post).** This sub-section provides the estimated winter CPP impacts by event for all participants, on average. As there are no winter energy impacts, winter CPP impacts are not distinguished into the two categories of “total” and “DR only” impacts in the manner of the summer impacts.

<sup>54</sup> Participants' whose enabling technologies were not connected to London Hydro's dispatch system continued to receive event notification via the Trickl app. Note that approximately 0.09 kW of this demand reduction was due to daily shifts achieved as part of the pilot.

- **Summer 2018 Average Impacts (Ex-Post) by Connectivity Status.** This sub-section provides the estimated total impact of participants during CPP events, split by whether the participant was connected to London Hydro's direct load control dispatch system at the time of the event.
- **Summer Capability Estimates (Ex-Ante).** This sub-section provides a graphic illustration of the ex-ante program impacts, by connectivity status, across a range of potential outdoor temperatures. Ex-ante impacts are Navigant's estimate of the program's capability for delivering demand response under a range of different temperature conditions.

### 4.2.1 Summer 2018 Average Impacts (Ex-Post)

CPP event impacts are a combination of two distinct types of impact: an energy impact driven by participants anticipating the possibility of a CPP event, and a demand response impact driven by the actual occurrence of a CPP event. As noted above, CPP customers are achieving consumption (and thus average demand) savings across the entire summer. This program effect (the energy impact) is one component of the estimated CPP event impact. There is also an incremental demand impact achieved specifically due to, on the given day, London Hydro dispatching a critical peak pricing event.

Program impacts in this section are therefore presented in two ways:

- **Total Program Impact** is the estimated impact of the program at the time of the CPP event. This combines both energy and DR impacts and provides the overall demand reduction achieved in the CPP period by the program. In this case the counterfactual (baseline) is participants' consumption, had there been no program at all.
- **Demand Response Impact** is the estimated incremental impact of just the DR component. In this case the counterfactual (baseline) is participants' consumption, assuming the existence of the program but no CPP event.

Although the DR-only results are presented below, some caution should be used in interpreting these results. The variables used to estimate the two different types of program effects are, inevitably, quite correlated – there is no CPP event that is affected *only* by the DR impact. This makes isolating this effect challenging and may mean some of the parameters associated with the DR only impact may be biased and inappropriate for out-of-sample projection.<sup>55</sup>

For this reason, and since they capture the entire program impact, the main results reported by Navigant in its outputs to the Ontario Energy Board and in the summaries of results presented above are the total program results.

Total ex-post average impacts ranged from 0.4 (+/- 26%) kW on September 6<sup>th</sup>, to 1 kW (+/- 41%) on July 4<sup>th</sup>. Individual event estimates of the total program impact for each CPP event (and on average across events) are presented in Figure 4-16, below. This table also provides the average event temperature.

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<sup>55</sup> The same caveat is not the case for the total program impact – these parameters may be confidently used to project total (i.e., the combination of demand response and daily energy shifting) impacts as a function of average event temperature short distances out of sample. For example, the hottest event day observed in the summer months has an event temperature of approximately 29 degrees Celsius. Navigant is confident that the estimated parameters would reasonably accurately predict the total demand impact of an event for which the temperature was 31 degrees. Navigant would be less confident in projecting only the “demand response” impact in this circumstance, given the issues identified above.

Figure 4-16: Total Program Summer CPP Event Impacts, Average Connectivity<sup>56</sup>

Event Date	Total Demand Savings		Relative Precision +/-% (90% Confidence)	P-Value	Mean Temperature (°C)
	kW	%			
2018-06-01	0.60	31%	11%	0.000	24
2018-06-18	0.65	33%	9%	0.000	25
2018-06-29	0.83	36%	9%	0.000	28
2018-07-03	0.90	40%	9%	0.000	30
2018-07-04	1.00	41%	9%	0.000	31
2018-07-05	0.68	35%	10%	0.000	25
2018-07-16	0.64	33%	9%	0.000	25
2018-07-17	0.47	31%	13%	0.000	22
2018-07-24	0.63	35%	9%	0.000	25
2018-08-07	0.65	33%	9%	0.000	26
2018-08-15	0.76	37%	9%	0.000	27
2018-08-16	0.53	32%	11%	0.000	23
2018-08-17	0.56	33%	11%	0.000	24
2018-08-20	0.61	35%	10%	0.000	25
2018-08-27	0.81	38%	9%	0.000	29
2018-09-05	0.83	35%	9%	0.000	29
2018-09-06	0.40	26%	17%	0.000	21
2018-09-17	0.54	30%	11%	0.000	24
<b>Average Across Events</b>	<b>0.67</b>	<b>34%</b>	<b>9%</b>	<b>0.000</b>	<b>26</b>

Figure 4-17 provides a summary of event “DR only” impacts. These are the estimated impacts when the baseline already accounts for a customer being enrolled in the program. These demand reductions include only participant response to the notification of a CPP event, and not general daily participant response motivated by participants’ understanding that an event *could* occur. The difference between the estimated impacts below and those above is the average non-event impact on participant demand.

<sup>56</sup> Note that a p-value of 0.000 indicates a p-value of less than 0.001.

Figure 4-17: DR Component of Summer CPP Event Impacts, Average Connectivity

Event Date	Demand Response Savings		Relative Precision +/-% (90% Confidence)	P-Value	Temperature (°C)
	kW	%			
2018-06-01	0.53	29%	8%	0.000	24
2018-06-18	0.58	30%	7%	0.000	25
2018-06-29	0.68	32%	7%	0.000	28
2018-07-03	0.77	36%	7%	0.000	30
2018-07-04	0.80	36%	8%	0.000	31
2018-07-05	0.58	31%	7%	0.000	25
2018-07-16	0.58	30%	7%	0.000	25
2018-07-17	0.45	30%	12%	0.000	22
2018-07-24	0.57	33%	7%	0.000	25
2018-08-07	0.58	31%	7%	0.000	26
2018-08-15	0.63	32%	7%	0.000	27
2018-08-16	0.49	31%	10%	0.000	23
2018-08-17	0.51	31%	9%	0.000	24
2018-08-20	0.55	33%	8%	0.000	25
2018-08-27	0.70	34%	7%	0.000	29
2018-09-05	0.71	32%	7%	0.000	29
2018-09-06	0.39	26%	16%	0.000	21
2018-09-17	0.49	28%	9%	0.000	24
<b>Average Across Events</b>	<b>0.59</b>	<b>31%</b>	<b>7%</b>	<b>0.000</b>	<b>26</b>

As can be seen, the average difference between the total program impact and the DR-only impact is approximately 0.08 kW – this is the “energy impact” contribution to the total program impact. This is higher than the average summer-wide demand impact of the program in the Mid-Peak period shown above (just below Figure 4-2) of 0.029 kW (all CPP events occurred between 5pm and 6pm or between 6pm and 7pm – in the Mid-Peak period).

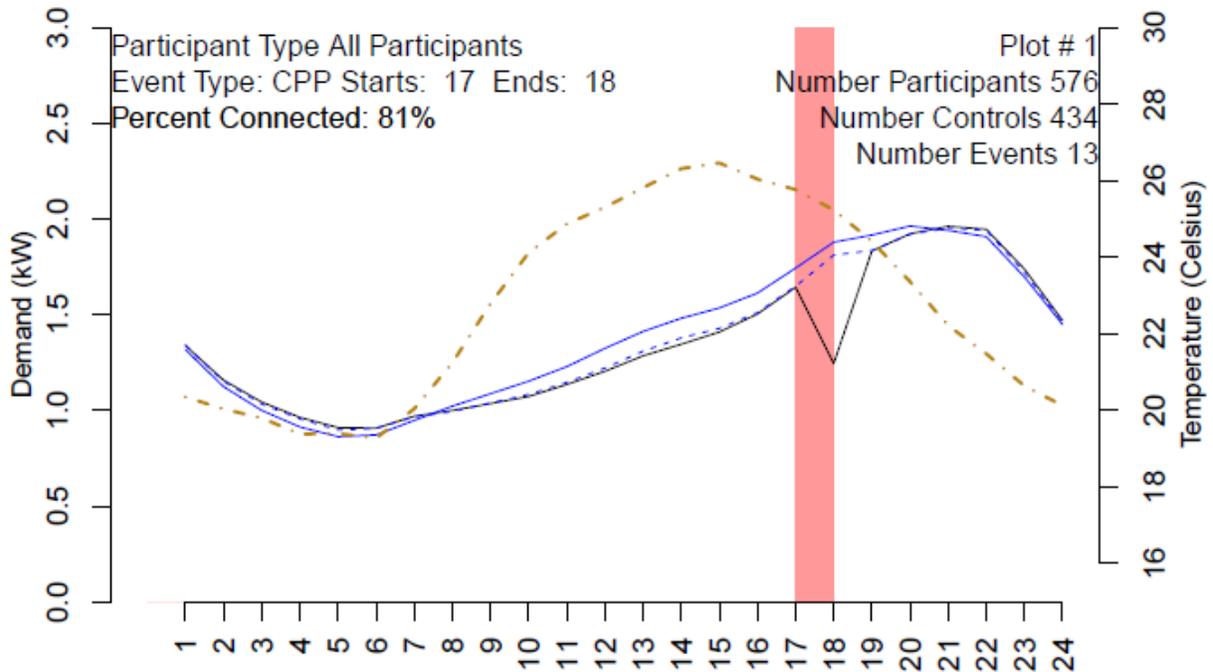
The CPP event day “energy impact” is higher than the summer average because event days are, on average, much warmer than typical summer days. For example, the average CPP event period temperature was 26 degrees Celsius. In contrast, the average temperature observed in all Mid-Peak periods across the summer was only 18.75 degrees Celsius.

The contrast between the two types of impacts can clearly be seen in Figure 4-18, below, which applies to the 13 CPP event days where events ran from 5pm to 6pm..

- The **black solid line** is the actual (observed) average load of all participants included in the estimation data..
- The **blue solid line** is the predicted average load of participants *had there been no program at all*. The difference between the blue and black solid lines is the “total program impact” reported above.
- The **blue dashed line** is the predicted average load of participants, assuming the presence of a program, but assuming *no CPP event occurred on that day*. The difference between the blue dashed and black solid lines is the DR only impact reported above.
- The **goldenrod dot-dashed line** is the average temperature observed in the given hour (read on the right axis).

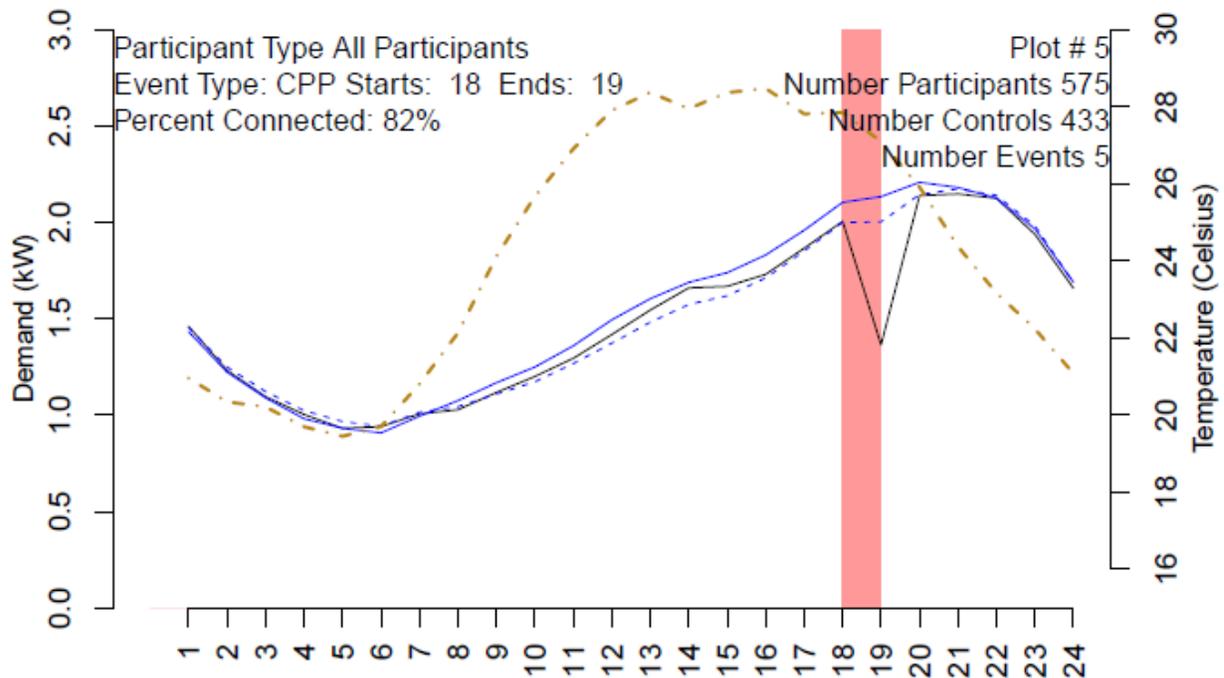
The red box highlights the hour in which the event occurs (from 5pm to 6pm).

Figure 4-18: Average Summer CPP Event Day Load Profile – Events Beginning at 5pm



The average load profiles for the five events running from 6pm to 7pm show a similar pattern, as seen in Figure 4-19.

Figure 4-19: Average Summer CPP Event Day Load Profile – Events Beginning at 6pm



The CPP event response is clear in both these plots – the sharp decrease in demand (black line) during the event hour is obvious, and characteristic of residential direct load control programs. One interesting feature of these plots is the apparent lack of any material snapback.

“Snapback” is a characteristic phenomenon of A/C direct load control DR programs; in the hours immediately following an event, participant loads are typically higher than the baseline. During the event, A/C compressor runtime is restricted (for A/C cycling programs), reducing demand. This leads to higher-than normal temperatures in the building, which results in longer than normal compressor run-times in the period immediately following the event.

The lack of estimated snapback for this pilot is likely due to a combination of three factors:

- **Events are short.** Shorter events mean less time for a home with curtailed A/C to heat up. Provided the indoor temperature doesn’t increase very much beyond the set-point temperature, snapback should be minimal. Navigant has noted this behaviour in previous A/C direct load control evaluations.<sup>57</sup>
- **Events are late.** The snapback period is coincident with the beginning of the evening cooling period. As can be seen in Figure 4-18, for example, the average outdoor temperature goes from approximately 25 degrees Celsius during the event, to just 21 degrees three hours later. One reason there may not be much snapback is that participants may rely to some degree on letting in cooler outside air for evening space-cooling.

<sup>57</sup> See for example, Figure 3 and footnote #9 of Navigant Consulting, presented to Progress Energy Carolinas, *EM&V Report for the EnergyWise Home Program – Summer 2011 and Winter 2011 – 2012*, September 2012 <https://dms.psc.sc.gov/attachments/matter/2BB3B03A-155D-141F-1D48A6BCE191C362> Public Service Commission of South Carolina, Docket N. 2008-251-E and Docket No. 2012-93-E

- **Not all response is driven by space-cooling.** There is some evidence (see below) to suggest that demand response impacts are not driven wholly by space-cooling, but that participants are controlling other end-uses (whether manually, via the panel-located switch, or the smart plugs) to achieve bill savings. Snapback is characteristic only of controlled space-conditioning and water-heating end-uses. Lighting, pump, or motor curtailment will not typically result in any snapback.

#### 4.2.2 Winter 2018/2019 Average Impacts (Ex-Post)

Navigant estimated no statistically significant energy impacts in the winter months. Unlike summer CPP impacts, winter CPP impacts include only a demand response impact.

Total ex-post average impacts ranged being not statistically significant to a lowest statistically significant impact of 0.1 (+/- 60%) kW on February 6<sup>th</sup>, to the highest statistically significant impact of 0.23 kW (+/- 29%) on January 16<sup>th</sup>. Individual event estimates of the total program impact for each CPP event (and on average across events) are presented in Figure 4-16, below. This table also provides the average event temperature.

**Figure 4-20: Total Program Winter CPP Event Impacts, Average Connectivity**

Event Date	Total Demand Savings		Relative Precision +/-% (90% Confidence)	P-Value	Temperature (°C)
	kW	%			
2018-12-04	0.13	10%	56%	0.003	-2
2018-12-06	0.17	13%	39%	0.000	-3
2018-12-13	0.16	13%	40%	0.000	0
2019-01-11	0.18	13%	40%	0.000	-7
2019-01-16	0.23	17%	29%	0.000	-8
2019-01-21	0.06(N/S)	0.04(N/S)	1.22(N/S)	0.176	-14
2019-01-22	0.07(N/S)	0.05(N/S)	1.1(N/S)	0.136	-5
2019-01-28	0.13	9%	57%	0.004	-10
2019-01-29	0.07(N/S)	0.05(N/S)	1.08(N/S)	0.129	-13
2019-02-01	0.02(N/S)	0.01(N/S)	4.55(N/S)	0.718	-17
2019-02-06	0.10	8%	60%	0.006	0
2019-02-12	0.05(N/S)	0.04(N/S)	1.13(N/S)	0.146	0
2019-02-19	0.22	16%	33%	0.000	-9
2019-02-20	0.11	9%	53%	0.002	-1
2019-02-27	0.17	13%	36%	0.000	-8
2019-03-04	0.22	16%	42%	0.000	-11
2019-03-05	0.17	12%	53%	0.002	-11
2019-03-06	0.17	12%	52%	0.002	-11
<b>Average Across Events</b>	<b>0.13</b>	<b>10%</b>	<b>31%</b>	<b>0.000</b>	<b>-7</b>

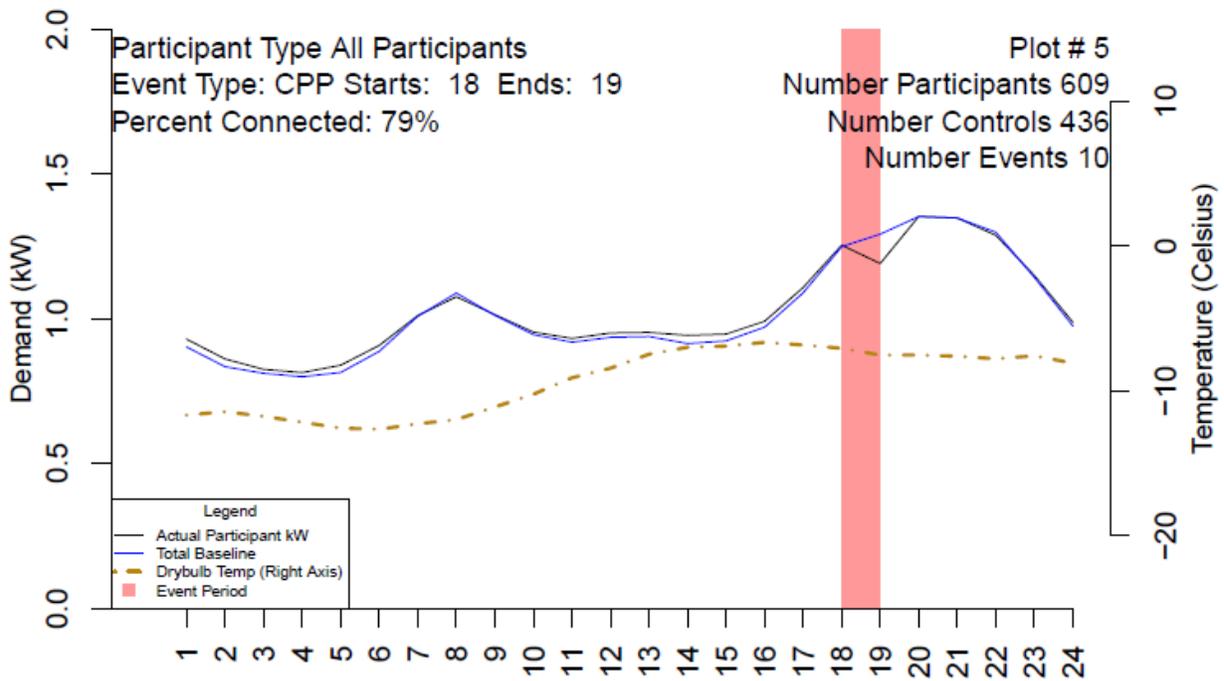
The average actual and counterfactual (baseline) loads of participants on the ten days in which the CPP events were from 6pm to 7pm are shown in Figure 4-21, below.

- The **black solid line** is the actual average load of all participants.
- The **blue solid line** is the predicted average load of participants *had there been no program at all*. The difference between the blue and black solid lines is the estimated program impact.

- The **goldenrod dot-dashed line** is the average temperature observed in the given hour (read on the right axis).

The red box highlights the hour in which the event occurs (from 6pm to 7pm).

Figure 4-21: Average Winter CPP Event Day Load Profile – Events Beginning at 6pm



#### 4.2.3 Summer 2018 Average Impacts (Ex-Post) by Connectivity Status

As noted above, in Section 3.1.4, a key asset for this evaluation was the availability of participant connectivity data. This data source, and the fact that approximately 20% of participants were not connected for any given event, allowed Navigant to effectively isolate impacts driven by the enabling technologies, and impacts that are purely behavioural, via the inclusion of an appropriate dummy variable in the regression.

Navigant’s initial hypothesis was that, given the very short notification lead time provided to participants the “DR only” impact for disconnected participants would be very small, perhaps not even statistically significant. That is, Navigant anticipated that participants that were disconnected would respond only to the longer-term price signal – there could be a CPP event at any time – rather than the event-specific price signal. Based on Navigant’s analysis, however, it appears as though some participants can respond to the CPP event notifications and undertake purely behavioural demand reductions in response to the CPP event notification.

First, for context, consider the average impacts of participants that *were* connected, as shown in Figure 4-22, below Impacts are materially higher than those presented in Figure 4-16, which shows the total program impact under the *average* connectivity rate. Under the average connectivity rate, the average

total program impact is 0.67 kW per participant. Assuming 100% connectivity, the average impact is 0.09 kW higher, at 0.76 kW.

**Figure 4-22: Total Program Summer CPP Event Impacts, 100% Connectivity**

Event Date	Total Demand Savings		Relative Precision +/-% (90% Confidence)	P-Value	Temperature (°C)
	kW	%			
2018-06-01	0.67	36%	10%	0.000	24
2018-06-18	0.72	37%	9%	0.000	25
2018-06-29	0.94	42%	8%	0.000	28
2018-07-03	1.03	45%	8%	0.000	30
2018-07-04	1.13	47%	9%	0.000	31
2018-07-05	0.76	38%	9%	0.000	25
2018-07-16	0.71	36%	9%	0.000	25
2018-07-17	0.51	35%	13%	0.000	22
2018-07-24	0.71	40%	9%	0.000	25
2018-08-07	0.74	39%	8%	0.000	26
2018-08-15	0.86	41%	8%	0.000	27
2018-08-16	0.59	35%	10%	0.000	23
2018-08-17	0.63	36%	10%	0.000	24
2018-08-20	0.69	39%	9%	0.000	25
2018-08-27	0.93	43%	8%	0.000	29
2018-09-05	0.96	41%	8%	0.000	29
2018-09-06	0.43	29%	16%	0.000	21
2018-09-17	0.61	34%	10%	0.000	24
<b>Average Across Events</b>	<b>0.76</b>	<b>39%</b>	<b>8%</b>	<b>0.000</b>	<b>26</b>

Now, consider Figure 4-23, below. This shows the average total program impact per participant, but only for those participants that *were not* connected. Although the average impact is much lower than for the fully-connected participants it is still both material and statistically significant – on average 0.3 kW per customer. For context, this is the same estimated impact as delivered by peaksaverPLUS® during the 29-degree test event that occurred on August 26, 2014.<sup>58</sup>

Note however that estimated impacts of disconnected participants do not appear to be nearly as sensitive as those of connected participants to temperature. The average impact of the 100% connected group during the July 4 event (the hottest event day) was 1.13 kW, half again as much demand response as delivered on average across all events. In contrast, the impact of the disconnected participants on that same day was only 0.39 kW, only a 30% jump over the average across events for that group of participants.

**Figure 4-23: Total Program Summer CPP Event Impacts, 0% Connectivity**

The results above are the total program impact. These include both the general reduction in energy consumption motivated by the participant’s understanding that he or she could – at a moment’s notice – become exposed to very high critical peak prices. As such, it is conceivable this element of response could be the entirety of demand response – i.e., that no incremental demand response is motivated when CPP event notification is received by the participant. Intriguingly, the model estimated parameters

<sup>58</sup> See Table 1-1 of Nexant, Inc. prepared for the Independent Electricity System Operator, *peaksaverPLUS® Program 2014 Load Impact Evaluation*, August 2015

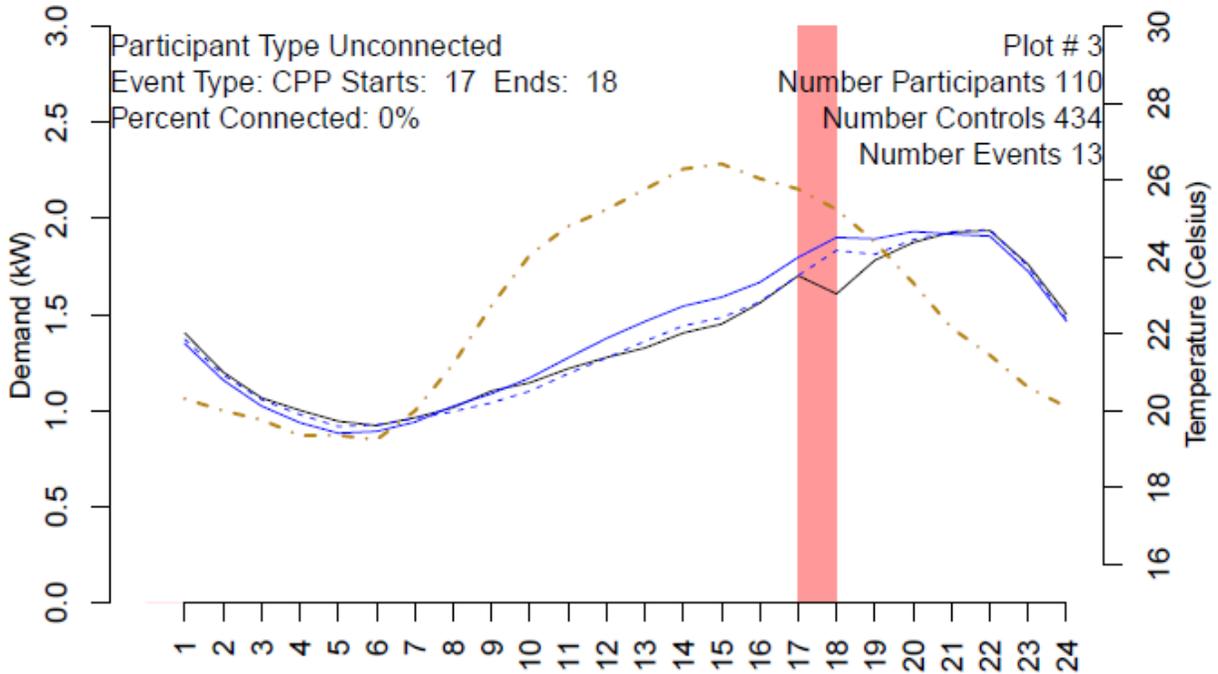
suggest that approximately two thirds of the total program effect for disconnected customers is the “DR only” effect, see Figure 4-24, below.

**Figure 4-24: DR Component of Summer CPP Event Impacts, 0% Connectivity**

Event Date	Total Demand Savings		Relative Precision +/-% (90% Confidence)	P-Value	Mean Temperature (°C)
	kW	%			
2018-06-01	0.30	15%	32%	0.000	24
2018-06-18	0.28	14%	33%	0.000	25
2018-06-29	0.35	15%	33%	0.000	28
2018-07-03	0.33	15%	42%	0.000	30
2018-07-04	0.39	14%	40%	0.000	31
2018-07-05	0.31	16%	31%	0.000	25
2018-07-16	0.28	15%	33%	0.000	25
2018-07-17	0.26	14%	38%	0.000	22
2018-07-24	0.28	15%	33%	0.000	25
2018-08-07	0.29	14%	33%	0.000	26
2018-08-15	0.33	16%	32%	0.000	27
2018-08-16	0.27	17%	35%	0.000	23
2018-08-17	0.27	16%	34%	0.000	24
2018-08-20	0.28	18%	33%	0.000	25
2018-08-27	0.31	15%	38%	0.000	29
2018-09-05	0.32	13%	40%	0.000	29
2018-09-06	0.25	16%	44%	0.000	21
2018-09-17	0.27	15%	34%	0.000	24
<b>Average Across Events</b>	<b>0.30</b>	<b>15%</b>	<b>32%</b>	<b>0.000</b>	<b>26</b>

These results are also reflected in the plotted actuals and baselines for the group of participants not connected, see for example Figure 4-25, below. Although there is a significant impact across the On-Peak and Mid-Peak hours (in anticipation that an event *might* be called), there is clearly some kind of CPP-event specific response, distinguished by the characteristic sharp drop in demand during the event.

Figure 4-25: Average Summer CPP Event Day Load Profile – Events Beginning at 5pm, Disconnected Participants



Although an unexpected result, Navigant is confident in the robustness of the finding: there is some group of participants that is, without the benefit of the enabling technology, receiving the event notification, and, within fifteen minutes, sufficiently reducing demand to deliver the distinctive DR-shaped load profile. Gaining a better understanding of how these impacts are distributed across as well as what strategies are being used to deliver the demand response could be a valuable goal of further research into this group. Some intuition regarding the latter question may be assessed by examining the estimated regression parameters that deliver the impacts.

The estimated parameters associated with the DR only impacts are presented in Figure 4-26, below. The first row presents the parameters that deliver the estimated impacts achieved by all participants, with or without a connection. The second row presents the parameters that deliver the incremental estimated impact due to that participant being connected.

Two types (columns) of parameter are estimated for each effect type (connected versus disconnected): an intercept parameter (which captures the impact when no cooling degree hours are observed during the event period), and a slope parameter (which captures the estimated incremental effect of each additional cooling degree hour observed on impacts). The table presents both parameter estimates (where a negative value denotes a demand *reduction*) and p-values. Recall that the p-values are a measure of uncertainty. An estimate with a p-value of more than 0.1 is not statistically significant at the 90% level of confidence.

**Figure 4-26: Summer DR Impact Parameters and P-Values**

Type of Impact	Intercept Dummy		Slope (Temperature) Dummy	
	Estimate	P-Value	Estimate	P-Value
Without Connection	-0.25	0.00	0.01	0.60
Incremental Impact when Connected	-0.03	0.73	-0.06	0.00

These values seem to suggest that the “base impact” delivered by a participant, before considering the incremental effects of the enabling technology that depends on a connection is not only not very weather sensitive (the effect has a p-value of 0.6, making it statistically non-significant), but what temperature sensitivity there is moves in the opposite from expected direction – that is, as temperatures increase, the base “DR only” impacts fall.

The opposite appears to be the case for the incremental impacts delivered when a participant is connected. In that case, nearly the entirety of the incremental effect is a function of the weather.

These results suggest two things:

- Most automated, DR only response is achieved via A/C curtailment of some kind.
- Purely behavioural DR only response may be driven primarily by non-A/C end-uses.

Note that some caution should be used in interpreting these values. Although these capture the DR only effects of the program, the other variables included to capture the longer-term effects (hourly dummies interacted with a treatment/participant dummy, and the same variable interacted with cooling degree hours) are likely to be correlated with the DR only parameters. Projecting impacts out of sample should be done cautiously, given the possibility that some estimated parameters may be spurious as a result of multi-collinearity.<sup>59</sup>

**4.2.4 Winter 2018/2019 Average Impacts (Ex-Post) by Connectivity Status**

Navigant’s analysis of the purely behavioural impact of CPP events above rests on the assumption that participant disconnections are, for the most part, purely random events – that disconnections provide a fortuitous “accidental experiment”. In the summer months, the distribution of participant disconnections appears to support this assumption: no clear pattern exists, half of all participants appear to have been disconnected at least once, and two-thirds of participants that have been disconnected were disconnected four or fewer times (out of a possible 18).

The pattern of disconnections in winter months suggests that these disconnections may no longer be random events, and thus that treating them as an accidental experiment to motivate the estimation of purely behavioural impacts may be problematic. Recall, from Figure 3-12, earlier, that in the winter months, disconnections appeared much more clustered – a third of those disconnected at some point in the winter were, in fact, disconnected for the *whole winter*. If this indicates – for example – that a subset of participants’ devices disconnected and were never fixed because those participants had lost interest in the program then a selection issue exists, and the “purely behavioural” impact estimates (derived from disconnected participants) may be biased. Conversely, if these participants took no action to remedy their disconnection over the winter because their enabling technology (the load switch) was connected to their

<sup>59</sup> As above, the total effect across all the parameters is robust, it is only when considering the DR only “sub-effect” that more caution should be exercised.

central air conditioning unit, and they recognized that remedying the connection wouldn't make a difference to their bill (i.e., wouldn't be worth the hassle of contacting support, etc.) then it would still be a reasonably robust design for estimating purely behavioural impacts.

It is impossible to know which of these narratives is accurate, or if either of them is. The key point here is that readers should recognize that greater uncertainty (relative to summer impacts) exists as to whether the "behavioural" impacts below truly capture the purely behavioural aspect of winter CPP response, or whether they are influenced by other, confounding factors.

First, for context, consider the average impacts of participants that *were* connected, as shown in Figure 4-27, below. Estimated impacts are slightly higher than those presented in Figure 4-20, which shows the total program impact under the *average* connectivity rate. Under the average connectivity rate, the average total program impact is 0.13 kW per participant. Assuming 100% connectivity, the average impact is 0.03 kW higher, at 0.16 kW. Also, with *average* connectivity, the impacts of the CPP events on January 22, January 29, and February 12 are not statistically significant, whereas under 100% connectivity, they are.

**Figure 4-27: Total Program Winter CPP Event Impacts, 100% Connectivity**

Event Date	Total Demand Savings		Relative Precision +/-% (90% Confidence)	P-Value	Temperature (°C)
	kW	%			
2018-12-04	0.14	11%	53%	0.002	-2
2018-12-06	0.17	13%	40%	0.000	-3
2018-12-13	0.18	15%	36%	0.000	0
2019-01-11	0.21	16%	36%	0.000	-7
2019-01-16	0.25	18%	29%	0.000	-8
2019-01-21	0.08(N/S)	0.05(N/S)	1.04(N/S)	0.114	-14
2019-01-22	0.08	7%	96%	0.087	-5
2019-01-28	0.15	11%	55%	0.003	-10
2019-01-29	0.09	7%	91%	0.070	-13
2019-02-01	0.05(N/S)	0.04(N/S)	1.57(N/S)	0.294	-17
2019-02-06	0.13	11%	48%	0.001	0
2019-02-12	0.07	6%	81%	0.042	0
2019-02-19	0.26	18%	32%	0.000	-9
2019-02-20	0.13	11%	49%	0.001	-1
2019-02-27	0.20	15%	34%	0.000	-8
2019-03-04	0.26	19%	36%	0.000	-11
2019-03-05	0.19	14%	49%	0.001	-11
2019-03-06	0.21	15%	44%	0.000	-11
<b>Average Across Events</b>	<b>0.16</b>	<b>12%</b>	<b>28%</b>	<b>0.000</b>	<b>-7</b>

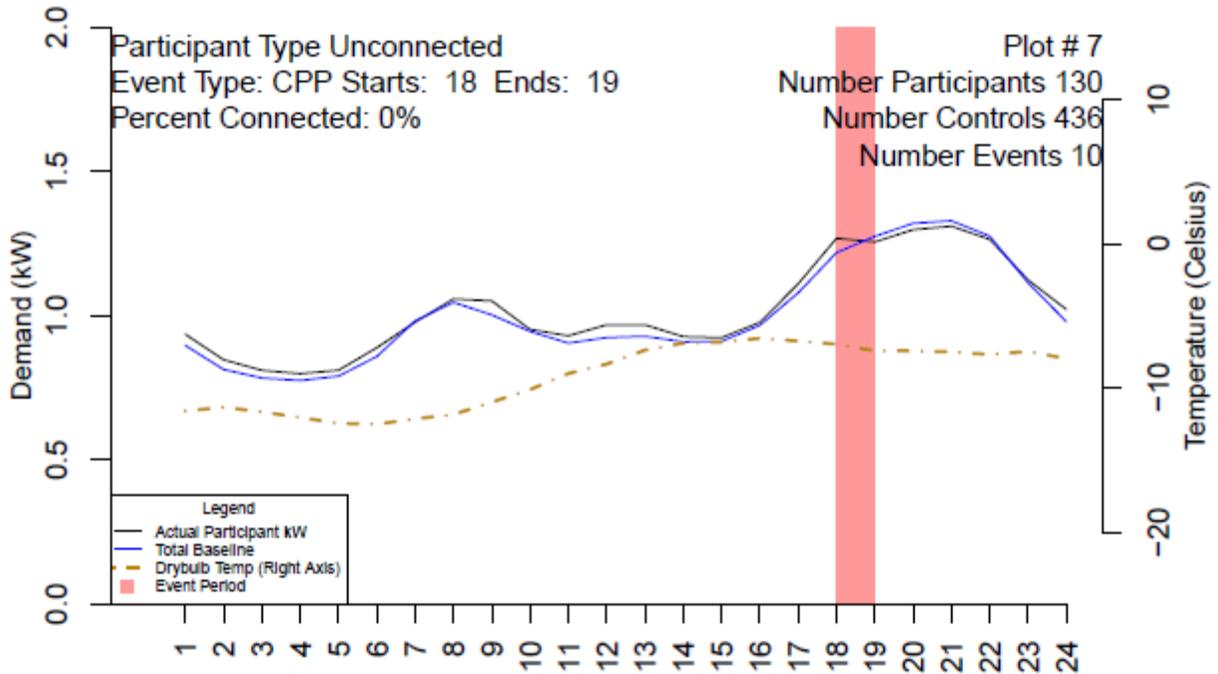
Now, consider Figure 4-34, below. This shows the average total program impact per participant, but only for those participants that *weren't* connected. Unlike the summer (where disconnected impacts were all statistically significant), winter disconnected participant impacts are only statistically significant for two of the eighteen events, and in fact the average disconnected impact is not statistically significant either.

**Figure 4-28: Total Program Winter CPP Event Impacts, 0% Connectivity**

Event Date	Total Demand Savings		Relative Precision +/-% (90% Confidence)	P-Value	Temperature (°C)
	kW	%			
2018-12-04	0.07(N/S)	0.05(N/S)	2.26(N/S)	0.467	-2
2018-12-06	0.15	11%	79%	0.037	-3
2018-12-13	0.06(N/S)	0.05(N/S)	2.11(N/S)	0.435	0
2019-01-11	0.07(N/S)	0.05(N/S)	2.01(N/S)	0.412	-7
2019-01-16	0.18	13%	59%	0.005	-8
2019-01-21	0(N/S)	0(N/S)	62.45(N/S)	0.979	-14
2019-01-22	0.01(N/S)	0.01(N/S)	9.31(N/S)	0.860	-5
2019-01-28	0.07(N/S)	0.05(N/S)	1.5(N/S)	0.274	-10
2019-01-29	-0.01(N/S)	0(N/S)	20.23(N/S)	0.935	-13
2019-02-01	-0.12(N/S)	-0.09(N/S)	1.12(N/S)	0.142	-17
2019-02-06	-0.02(N/S)	-0.02(N/S)	5.08(N/S)	0.746	0
2019-02-12	-0.03(N/S)	-0.03(N/S)	3.3(N/S)	0.619	0
2019-02-19	0.1(N/S)	0.07(N/S)	1.08(N/S)	0.129	-9
2019-02-20	0.03(N/S)	0.02(N/S)	3.29(N/S)	0.617	-1
2019-02-27	0.07(N/S)	0.06(N/S)	1.62(N/S)	0.309	-8
2019-03-04	0.06(N/S)	0.04(N/S)	2.5(N/S)	0.511	-11
2019-03-05	0.09(N/S)	0.07(N/S)	1.61(N/S)	0.308	-11
2019-03-06	0.03(N/S)	0.02(N/S)	5.49(N/S)	0.764	-11
<b>Average Across Events</b>	<b>0.04(N/S)</b>	<b>0.03(N/S)</b>	<b>1.42(N/S)</b>	<b>0.247</b>	<b>-7</b>

Figure 4-29, below, shows the average counterfactual (predicted baseline) and actual demand, on average across the ten events that took place between 6pm and 7pm (the January 16 event where Navigant estimated a statistically significant impact for disconnected participants took place in this window of time). As can be seen from an examination of the observed actual demand, if there is a CPP response at all (on average across these 10 events) it is very small, particularly given the noise in the prediction.

Figure 4-29: Average Winter CPP Event Day Load Profile – Events Beginning at 6pm, Disconnected Participants



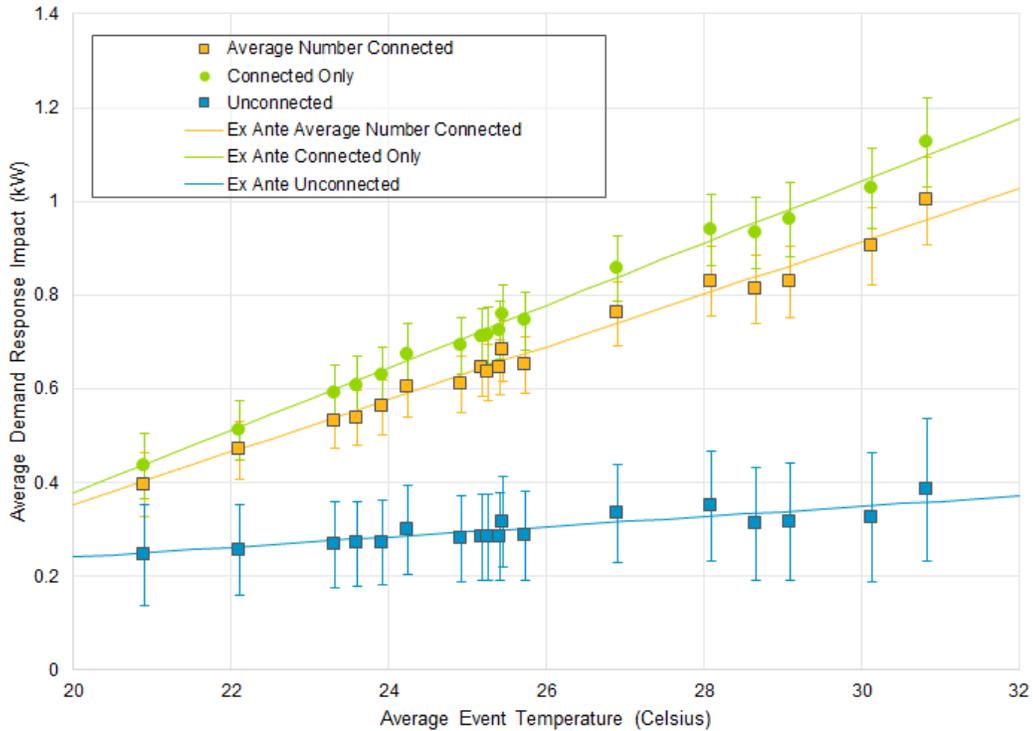
#### 4.2.5 Summer Capability Estimates (Ex-Ante)

A standard output for most evaluations of programs with a DR component is a set of “ex-ante” estimates. An ex-ante impact estimate is the estimated impact of a program under certain pre-specified conditions. Typically, these are weather-related – for example presenting a program’s estimated DR capability under a utility’s 1-in-2, 1-in-10 (as in California), or “design criterion” (as in Florida) weather. Also – when no design criterion weather values have been established – is to present ex-ante impacts across a range of different temperatures. Figure 4-30 illustrates the estimated relationship between the average demand response capability of the program under a range of outdoor temperatures: the ex-ante DR impacts of the pilot – a key output of this study.

Navigant has estimated the total program impact of a CPP event at a range of temperatures from 20 degrees to 32 degrees Celsius. Three sets of ex-ante impacts have been produced: one set assuming all participants are connected, one set assuming the average connectivity rate observed in the summer of 2018, and a third set, assuming all participants are disconnected. These ex-ante values are represented in Figure 4-30 below as a set of solid lines.

The ex-ante impacts are presented alongside the individual event ex-post impacts, which are represented by the markers in Figure 4-30. The whiskers around each marker represent the 90% confidence interval associated with that estimated impact. The solid lines represent the series of estimated ex-ante impacts, or program capability under a range of different temperatures. Note that the impacts presented here are the total program impacts, not the DR-only impacts.

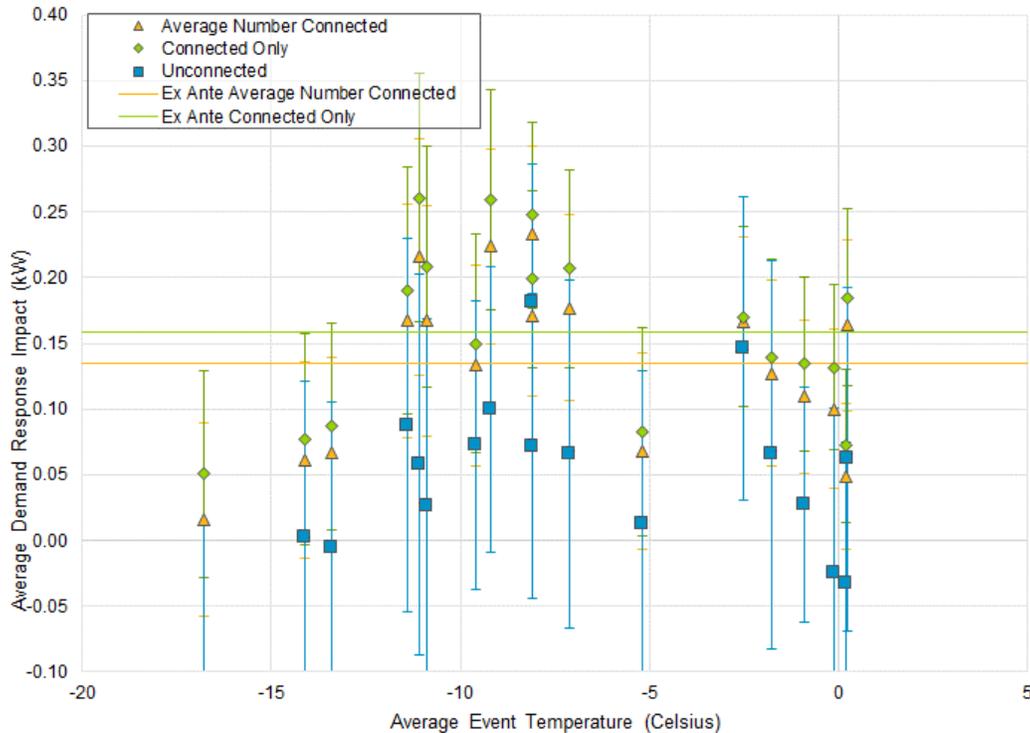
Figure 4-30: Summer Ex-Ante and Ex-Post Impact Scatter Plot



#### 4.2.6 Winter Capability Estimates (Ex-Ante)

A key finding of Navigant’s winter analysis of CPP event impacts is that, unlike in the summer, they are not correlated with outdoor temperatures. As such, for predictive purposes, Navigant would recommend that the average impact across all 18 CPP events be used as the ex-ante predictive value. This is represented as the straight green line (all connected, 0.16 kW) and the straight yellow line (average number connected, 0.13 kW) in Figure 4-31. The average impact estimated for disconnected participants is not statistically significantly different from zero, so ex-ante prediction of impacts should assume zero impact for participants that are disconnected in winter.

Figure 4-31: Winter Ex-Ante and Ex-Post Impact Scatter Plot



### 4.3 Elasticity Findings

Based on the results above, Navigant estimated both an own-price elasticity of daily electricity consumption (by season), an inter-period elasticity of substitution between the Mid-Peak period and the Off-Peak Period (summer)<sup>60</sup>, and an inter-period elasticity of substitution between the On-Peak period and the Off-Peak Period (winter).<sup>61</sup>

#### 4.3.1 Summer Elasticity Findings

As specified in Navigant’s approved evaluation plan and in correspondence between Navigant and the OEB in January of 2019, the two required elasticity outputs – the own/daily price elasticity and the inter-period substitution elasticity are calculated values based on historical prices, observed consumption, and the estimated linear regression model parameters. No separate (e.g., log-log) model is estimated.

The point estimate of the own-price elasticity of demand, derived from the parameters estimated as part of the regression described above is -3.97. This indicates that average daily consumption, as a percentage of counterfactual (baseline) consumption, fell by nearly four times the percentage increase in

<sup>60</sup> Under the pilot, average summer On-Peak prices did not differ from the status quo RPP TOU as no CPP events began prior to 5pm. In the summer months, the On-Peak period runs from 11am to 5pm.

<sup>61</sup> Under the pilot, average winter Mid-Peak prices did not differ from the status quo RPP TOU as no CPP events began prior to 5pm. In the winter months, the Mid-Peak period runs from 11am to 5pm.

the effective average daily cost of electricity. Demand for electricity is typically regarded as quite inelastic in the short-run, whereas the estimated value suggests that it is in fact highly elastic.

This result is driven by the fact that the average daily cost of electricity for CPP and CPP/RT participants (absent any changes to behaviour in response to the change in cost) increased by 0.3%, and average daily consumption fell by 1.2%.

Navigant would recommend that this estimated value be used only very cautiously, for several reasons. Firstly, the average change in the effective price of daily consumption is *very* small, as is the average change in daily consumption. It should be remembered that rates were set to be revenue neutral under the assumption of no behaviour change, so any average change in daily electricity costs (as calculated for this evaluation) may be at least partly reflective of structural differences between this sample and that used to set the prices.

Secondly, this value may well capture a major disconnect between *perceived* electricity costs, and actual costs. Even though the rate is intended to be revenue neutral when participants make no changes to behaviour, the relatively large value of the CPP price, the sudden nature of events (with only 15 minutes' warning), may have led participants to perceive not responding to the rate to be much more costly than actual non-response would have been.

The estimated inter-period elasticity of substitution is -0.26. The negative sign indicates that the two "goods" – Mid-Peak and Off-Peak consumption – are gross substitutes. The complete calculation of this value may be found in Appendix B.

#### 4.3.2 Winter Elasticity Findings

The point estimate of the own-price elasticity of demand, derived from the parameters estimated as part of the regression described above is -1.83. This is an unusually large (in absolute) value, though not as large as that derived from the estimated impacts in the summer. Demand for electricity is typically regarded as quite inelastic in the short-run, whereas the estimated value suggests that it is in fact highly elastic.

This result is driven by the fact that the average daily cost of electricity for CPP and CPP/RT participants decreased by 0.4%, and average daily consumption increased by 0.8%.

As with the summer estimate, Navigant would recommend that this estimated value be used only very cautiously, for several reasons. Firstly, the average change in price is *very* small, as is the average change in consumption. It should be remembered that rates were set to be revenue neutral under the assumption of no behaviour change, so any average change in daily electricity costs (as calculated for this evaluation) may be at least partly reflective of structural differences between this sample and that used to set the prices.

Secondly, this value may well capture a major disconnect between *perceived* electricity costs, and actual costs. Even though the rate is intended to be revenue neutral when participants make no changes to behaviour, the relatively large value of the CPP price, the sudden nature of events (with only 15 minutes' warning), may have led participants to perceive not responding to the rate to be much more costly than actual non-response would have been.

The estimated inter-period elasticity of substitution is -0.29. The negative sign indicates that the two “goods” – On-Peak and Off-Peak consumption – are gross substitutes. The complete calculation of this value may be found in Appendix B.

#### 4.4 Revenue Adequacy

An evaluation requirement of the OEB for the evaluation of this pilot is the publication of a table indicating the revenue adequacy of this program.

Figure 4-32, provides a comparison of aggregate consumption volumes and revenues associated with the participants included in the energy analysis. All revenues shown below include only the commodity cost (i.e., the TOU rate) and do not reflect delivery charges, taxes, etc.

**Figure 4-32: Annual Revenue Adequacy**

Participant Group	Consumption Volumes in kWh	Revenues (Pilot Price Plan)	Revenues (Status-Quo TOU)	Average Revenue (Pilot Price Plan)	Average Revenue (Status-Quo TOU)
CPP	2,362,642	\$189,301	\$191,202	\$0.080	\$0.081
CPP/RT	2,468,464	\$197,148	\$199,401	\$0.080	\$0.081
RT	9,679,748	N/A	\$786,418	N/A	\$0.081
RCT Control	3,743,329	N/A	\$305,463	N/A	\$0.082

These values are drawn from London Hydro’s billing system. These values were calculated using participant and control customer bills with a billing cycle start date no earlier than 2018-04-15, and a billing cycle end date no later than 2019-05-15 (winter data).<sup>62</sup> This includes only those participants that were included in the energy analysis, only those that completed the pilot (drop-outs are excluded) for both seasons, and only those for whom the billing cycle resulted there being fewer than 370 days included in their analysis period, after applying the billing period assumptions above.<sup>63</sup>

Figure 4-32 shows that the difference between actual commodity revenues collected by London Hydro and the revenue that would have been collected under standard TOU rates - had the same program effects been observed under those rates - is very small on a relative basis. The average difference between the two sets of revenue is 1% in absolute value.

Navigant calculated the differential between CPP and CPP/RT customers’ commodity costs, and what they would have paid had these bills been calculated using standard TOU commodity rates. The frequency distribution of these differences is shown in Figure 4-33 (CPP-only) and Figure 4-34 (CPP/RT) below.

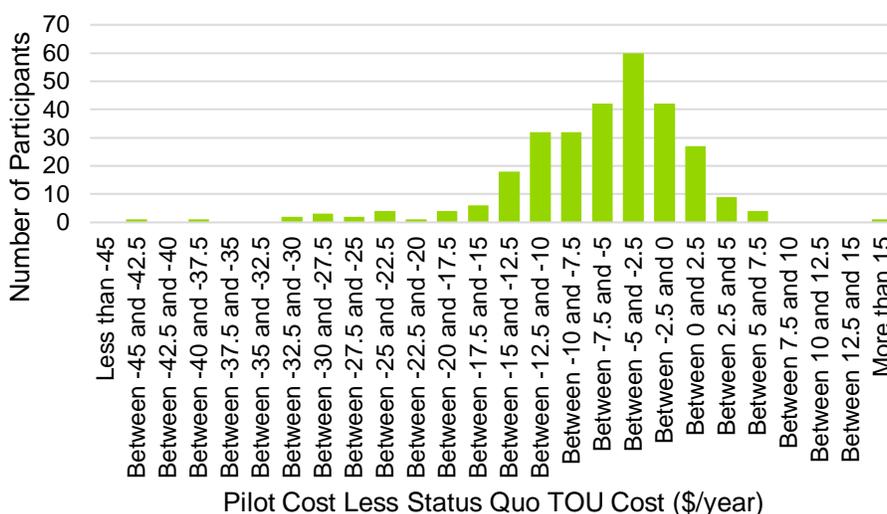
<sup>62</sup> Billing cycles do not match calendar months exactly, so some imprecision exists in attributing consumption to the defined summer program period. Billing data values were calculated separately for winter and summer and aggregated together, as shown in tab 08 of the Appendix B spreadsheet.

<sup>63</sup> Again, because of the uneven distribution of the billing cycle, it is impossible to match all customer bills to a 365 day year beginning and ending on a specific day. The revenue adequacy sample includes 291 CPP participants, 306 CPP/RT participants, 1,087 RT participants, and 438 RCT controls.

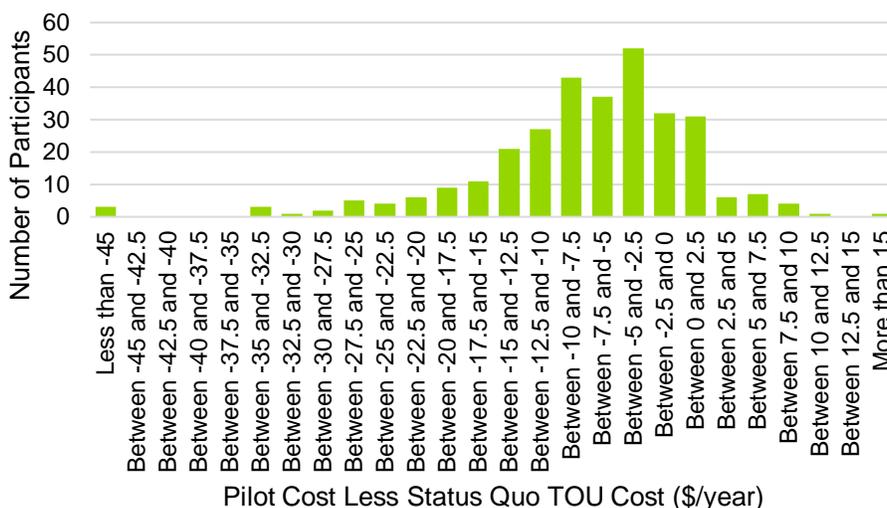
Note that these are *not* bill impacts. A participant's bill impact is the difference between what the participant actually paid, and what that participant would have paid under standard TOU rates *had their consumption not changed in response to the program*.

The distribution of commodity revenue differences by customer indicates that overall changes in behaviour were, on an LDC revenue basis, trivially small. Most participants paid less under the CPP price plan than they would have had they been billed under the standard RPP price plan (but still behaved as though they were being billed under the CPP price plan), and the shape of the distribution (approximately normal, skewed to the left) suggests that most of the difference between LDC revenues for a *given* customer under the two price plans is due to non-price response variation in consumption patterns.

**Figure 4-33: Distribution of CPP-Only Participant Cost Differentials**



**Figure 4-34: Distribution of CPP/RT Participant Cost Differentials**





## 5. ENERGY LITERACY ANALYSIS

The pilot offers a unique opportunity to understand what, if any, impact increasing the energy literacy of the consumer can have on effectively managing of energy consumption.

Navigant's sub-contractor, Ipsos Public Affairs conducted a mixed methodology survey including both telephone and online surveys among pilot participants and non-participants in order to effectively evaluate the effects of the three treatments on energy literacy. Both the telephone and online survey were completed following the conclusion of the pilot. Respondents were offered different ways to respond to the survey in order to achieve a higher response rate than could be otherwise achieved utilizing only one methodology.

### 5.1 Research Objectives

Navigant commissioned Ipsos Public Affairs to conduct an energy literacy survey as part of the evaluation of the Regulated Price Plan (RPP) Pilot program. The research was used to help assess the energy literacy of program participants and included a survey of program participants (CPP/RT, CPP Only, RT Only) and non-participants (for comparative purposes).

The key objectives of the energy literacy analysis were to measure:

- **Participant Energy Literacy:** How well do participants understand their real-time usage data? How do they use this information to inform or adjust their behaviour?
- **Differences Between Participant and Non-Participant Energy Literacy:** How does participant energy literacy differ from that of non-participants? Approximately how much of this difference is attributable to the program, and how much is attributable to differing base levels of energy literacy?
- **Differences Between Participant and Non-Participant Consumption Behaviour:** To what degree do key self-reported electricity consumption habits of interest differ between participants and non-participants? How much of this difference may be attributed to the program?

The survey questionnaire was designed in close collaboration with the Project Team, London Hydro, and the OEB and sought to address several topics, all designed to meet the goals outlined above and control for the possibility of selection bias resulting from (potential) structural differences between the participant and non-participants groups.

### 5.2 Methodology

The survey was conducted through a mixed methodology approach including both an online and telephone survey. The online survey was launched first and sent to all contacts. After a week of fieldwork, the telephone survey was launched among those who had yet to complete the online survey to offer respondents the option to complete the survey at the time over the phone.

Sample for participants and non-participants was provided by London Hydro. Participants included anyone who participated in each of the three streams of the pilot program (CPP/RT, RT Only, CPP Only). Non-participants were those London Hydro customers who expressed interest in the RPP pilot program

but were not selected to participate. The following number of participants and non-participants were offered the opportunity to respond to the survey.

**Table 5-1: Available Sample (Number of Potential Respondents)**

Participants	1714
RT	1105
CPP	311
CPP + RT	298
Non-Participants	1158

In total, n=1,173 completed interviews were achieved overall across both Participant (n=821) and Non-Participant (n=352) groups. A sample of this size has a margin of error of +/- 2.2%, nineteen times out of twenty). The figure below details the number of completed interviews by program stream and the corresponding margin of error. Completed interviews by methodology include n=775 online and n=398 by telephone.

**Table 5-2: Attained Sample (Number of Achieved Survey Respondents)**

Participants	821	(+/-2.9%)
RT	436	(+/-4.3%)
CPP	198	(+/-6.7%)
CPP + RT	187	(+/-6.9%)
Non-Participants	352	(+/-4.9%)

Fieldwork took place between May 23rd to June 24th (the telephone survey launched June 4th, 2019).

The survey yielded a response rate of 41% overall which is considered high when compared to typical response rates to consumer surveys.

### 5.3 Key Findings

- A majority of program participants in all treatment groups had a positive experience with the program and would welcome the opportunity to participate in a similar program in the future.

- Energy literacy as it relates to managing electricity consumption is high among all consumers (including non-participants) and a strong majority have taken most of the steps presented in the survey to reduce their household energy consumption.
- Despite limited differences in energy literacy between participants and non-participants overall, the program helped to build knowledge in specific areas related to energy consumption.
- Program participants (except for CPP participants) have higher proven knowledge about how time of use works (daytime vs. evening/ overnight usage), that electronic devices continue to use power even when turned off and that major appliances and electronics contribute most to usage.
- In terms of stated actions to reduce electricity consumption, non-participants are equally as likely as participants to have taken most of the electricity reduction actions presented to them in the survey. However, non-participants are less likely to use some form of home automation or to use major appliances in the evening or overnight which, given the experimental design, could be attributed to educational elements of the pilot program.
- Participation in outreach events had a greater impact on participants level of knowledge about how to manage household electricity consumption than the use of the Trickl app.
- Engagement in the pilot program had a considerable impact on trust in organizations within the electricity system in Ontario. Program participants express higher trust in all parties, and London Hydro in particular, compared to non-participants.
- CPP/RT participants are most likely to feel the program improved their knowledge and to have frequently taken steps to reduce their electricity consumption. They are also more likely to have used the Trickl app more frequently and to feel it had an impact on their level of knowledge.
- Energy literacy is consistently higher among those 55+, males and homeowners regardless if they were a participant or non-participant. Future consideration should be given to how such programs can be made more engaging to younger consumers and renters who are generally less interested in reducing their electricity consumption than other segments.
- Notably, non-participants are more likely to be a homeowner than participants in each of the three treatments. The findings of the survey show that homeowners place more importance on their electricity bill and have higher perceived and proven knowledge than renters. These aspects contribute to the high-level of engagement and energy literacy among non-participants.

### 5.4 Key Differences by Demographics

There are consistent statistically significant differences across all consumer groups (participant and non-participant) by age, gender and homeownership.

- Those age 55+ are statistically more likely than those under 55 to place importance on their electricity bill, to feel knowledgeable about how to manage their electricity consumption and to have a high-degree of proven knowledge. Among program participants, those age 55+ report using the Trickl more frequently and are more likely to have attended an outreach event than those under 55. They also express a higher degree of trust in all parties in the electricity system.
- Respondents age 18-34 are least likely to feel the Trickl app improved their understanding of how to reduce electricity consumption and to feel participation in the program overall improved their level of knowledge.

- Men are statistically more likely than women to feel knowledgeable about how to manage their electricity usage and to have a high-degree of proven knowledge. They also express a higher degree of trust in all parties in the electricity system.
- Women are statistically more likely than men to place importance on their electricity bill and among program participants to say they never used the Trickl app.
- Homeowners are more likely to place importance on their electricity bill and to have a high-degree of proven knowledge than those who rent. Among participants, homeowners are more likely to have attended an outreach event.

## 5.5 Energy Literacy and Actions Taken

A majority of all consumers surveyed (participant and control) place a high degree of importance on the amount they pay for their energy bill (Figure 5-1), feel knowledgeable about how to manage their electricity consumption (Figure 5-2) and have a high degree of energy literacy on the subject (Figure 5-4, 5-5 and 5-6).

CPP/RT participants have consistently higher degrees of perceived and proven knowledge (Figure 5-3, 5-4 and 5-5). They place a higher degree of importance on their electricity bill than CPP and RT participants (Figure 5-1) and are more likely to have frequently taken actions to reduce their electricity usage (Figure 5-7).

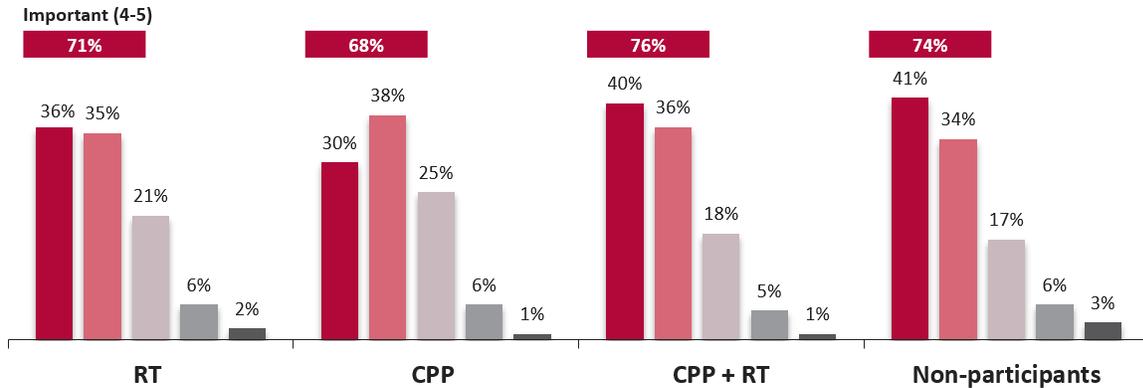
The control group are a highly engaged group of consumers who place a high degree of importance on their electricity bill (more so than CPP or RT participants) and have high energy literacy (Figure 5-1 and Figure 5-6).

However, gaps versus participants and the control group exist related to understanding how time of use works (daytime vs. evening/ overnight usage), which major appliances and electronics contribute most to household electricity usage and that electronic devices continue to use power even when turned off (Figure 5-4 and 5-5).

Figure 5-1: Importance of Electricity Bill Amount

Importance of Electricity Bill Amount

EXTREMELY IMPORTANT (5) ■  
 4 ■  
 3 ■  
 2 ■  
 NOT AT ALL IMPORTANT (1) ■



As shown in Figure 5-2, pilot volunteers (both participants and those assigned to the control group) feel most knowledgeable about how time-of-use pricing works, ways to reduce the amount you pay for electricity and which appliances and electronics use the most electricity. Fewer feel knowledgeable about how much electricity their heating and cooling systems use.

Figure 5-2: Knowledge of Managing Electricity Consumption

Knowledge of Managing Electricity Consumption

EXTREMELY KNOWLEDGEABLE (5) ■  
 4 ■  
 3 ■  
 2 ■  
 NOT AT ALL KNOWLEDGEABLE (1) ■

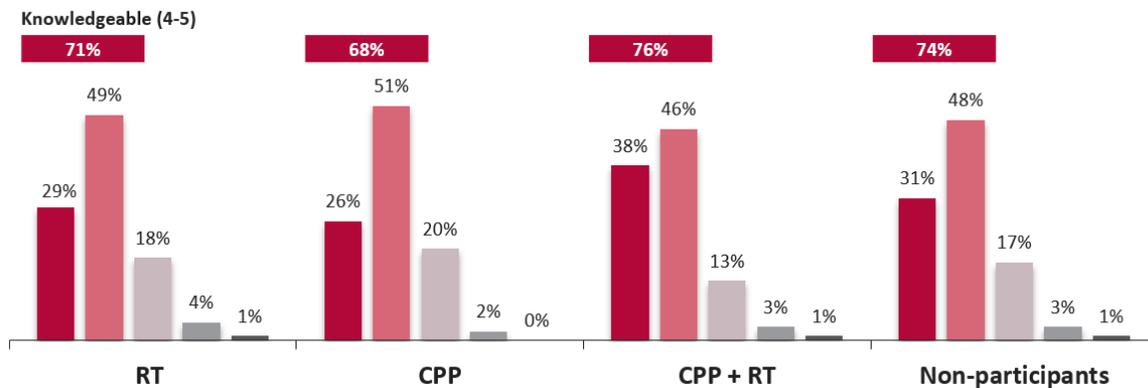
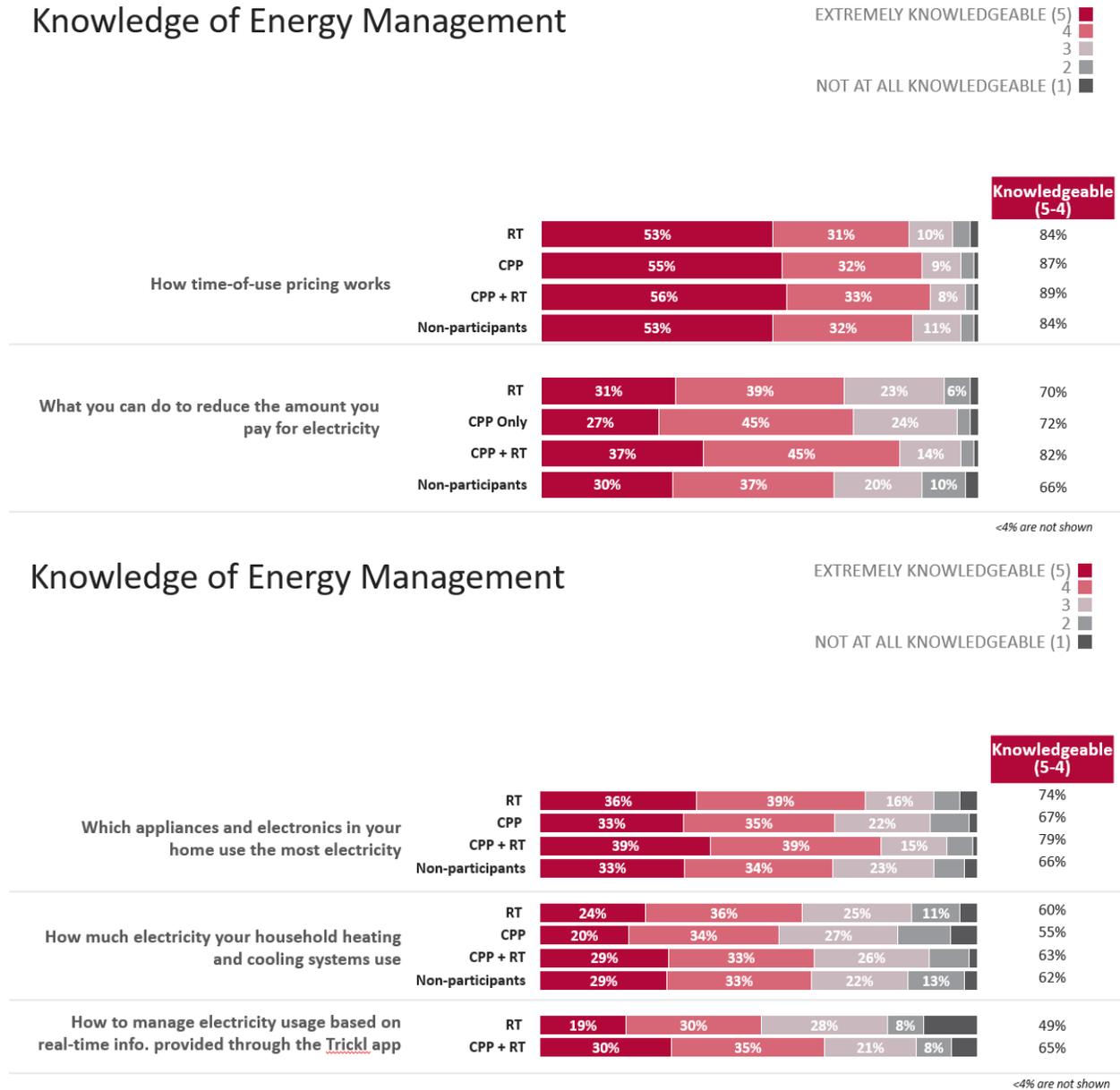


Figure 5-3: Knowledge of Energy Management



On a proven basis (see Figure 5-4, 5-5, 5-6), energy literacy is high across all consumer groups surveyed (participants and controls). Across all consumer groups, knowledge is lower relative to other areas that using less electricity during the day will save more money than reducing consumption in the evening or overnight and that large household appliances account for the most electricity usage.

Figure 5-4: Proven Energy Knowledge I

Proven Energy Knowledge

TRUE ■  
DON'T KNOW ■  
FALSE ■

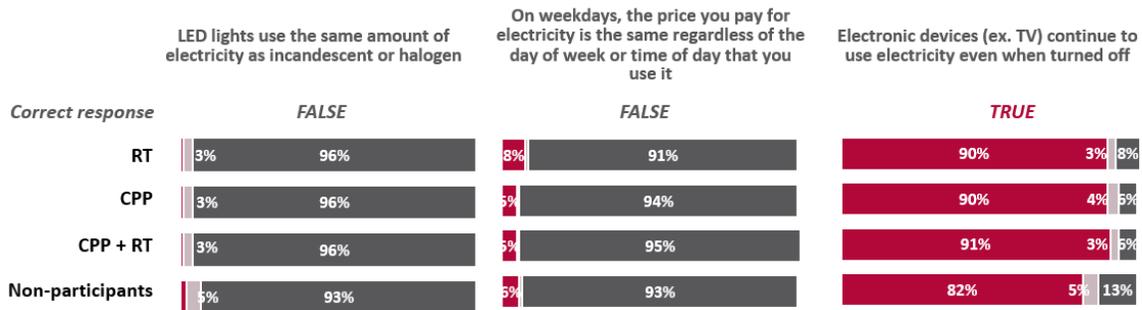


Figure 5-5: Proven Energy Knowledge II

Proven Energy Knowledge

TRUE ■  
DON'T KNOW ■  
FALSE ■

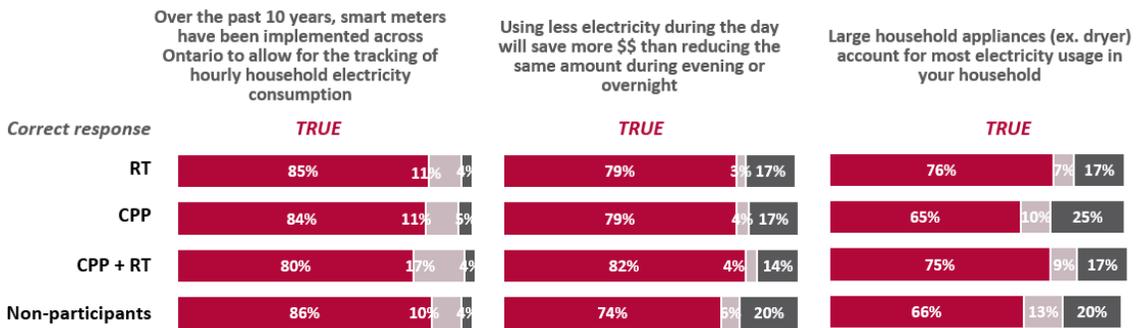
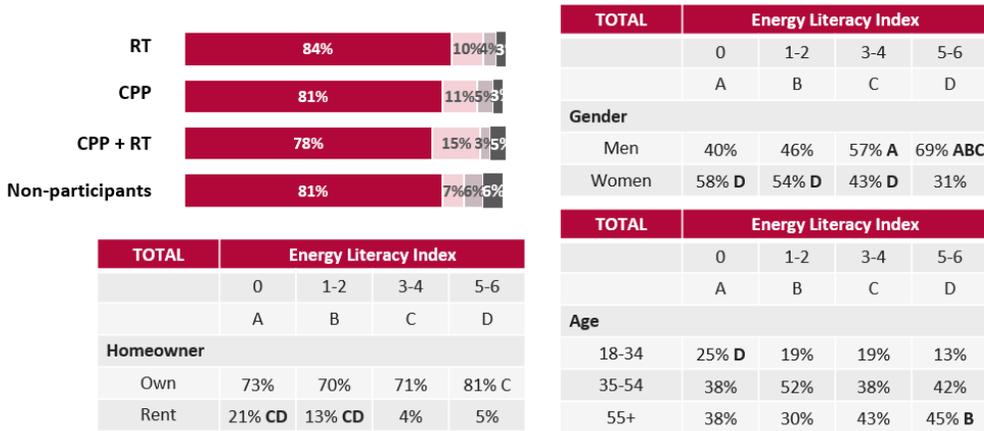


Figure 5-6: Proven Energy Knowledge- Energy Literacy Index

Proven Energy Knowledge- Energy Literacy Index

5-6 Correct ■  
 3-4 Correct ■  
 1-2 Correct ■  
 0 Correct ■



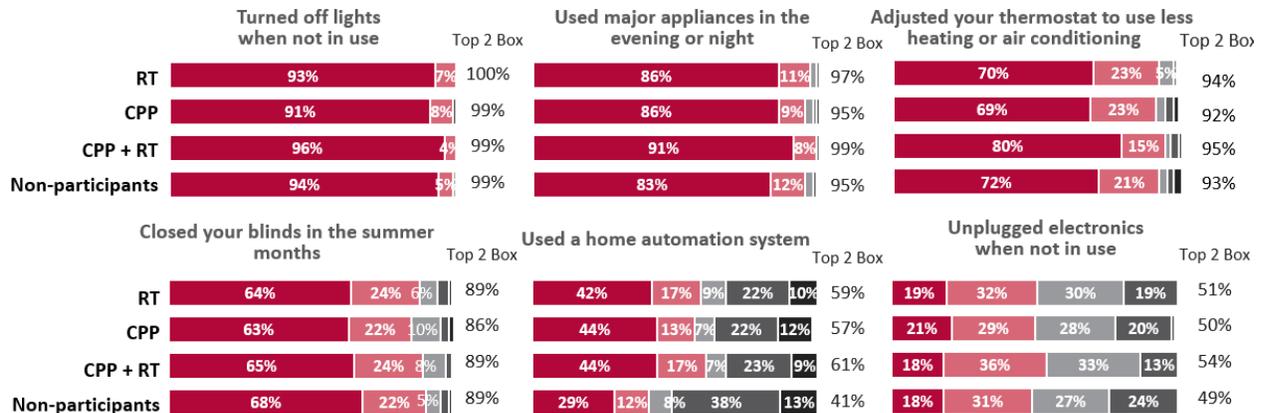
In terms of stated actions (Figure 5-7), virtually all consumers turn off lights when not in use or adjust their thermostat to use less electricity on a frequent basis. Consumers are less likely to use major appliances in the evening or night or close blinds in the summer months as frequently, while considerably fewer use a home automation system or unplug electronics when not in use.

The control group are equally as likely as participants to have taken most actions, however they are less likely to use a home automation system or use major appliances in the evening or overnight.

Figure 5-7: Frequency of Energy Actions

Frequency of Energy Actions

FREQUENTLY ■  
 SOMETIMES ■  
 RARELY ■  
 NEVER ■  
 NOT APPLICABLE ■



### 5.6 Customer Engagement Evaluation

Among program participants, use of the Trickl app (Figure 5-8) and the perceived impact on their level of knowledge (Figure 5-9) differs by treatment group. CPP/RT participants are most likely to have frequently used the app, followed by CPP Only participants while RT participants used the app least frequently.

More than half of CPP/RT participants say that use of the Trickl app improved their understanding of how to reduce household electricity usage. Comparatively, opinions are mixed among RT Only and CPP Only participants and roughly one-third feel the app improved their knowledge.

CPP/RT participants used the Trickl app more frequently (Figure 5-8), to feel knowledgeable about how to use it (Figure 5-3) and to feel it had a positive impact on their ability to manage their household electricity usage (Figure 5-9).

Figure 5-8: Trickl App Usage

#### Trickl App Usage

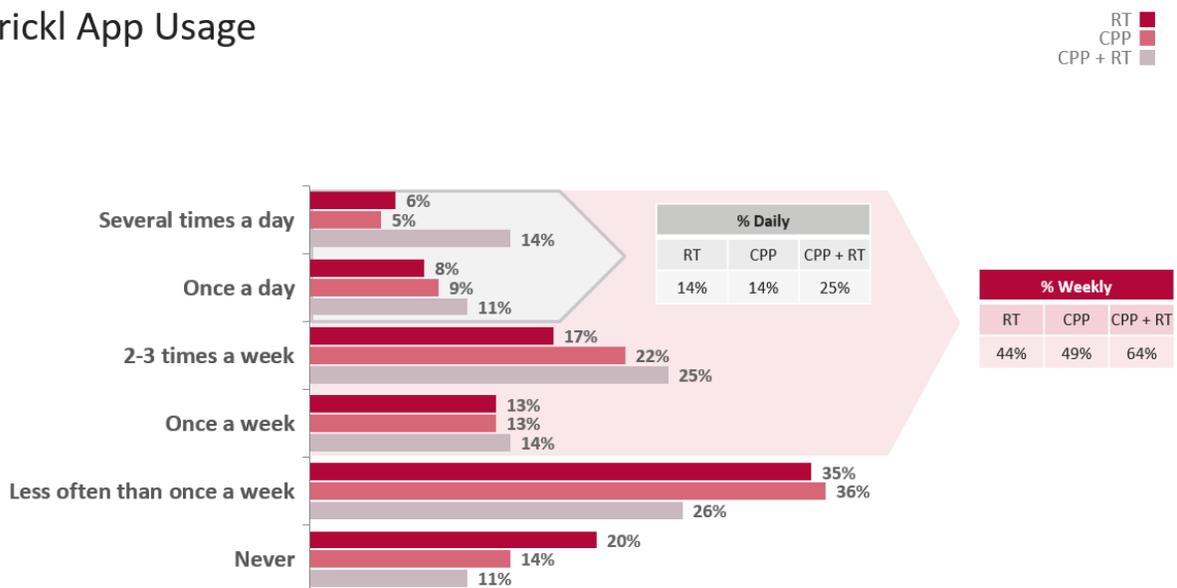
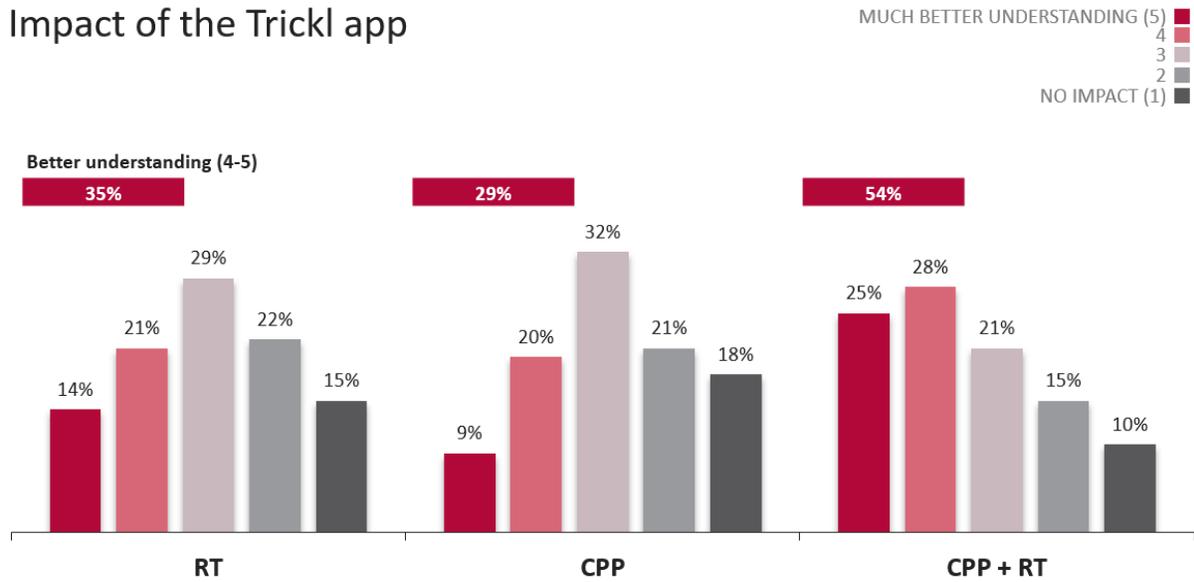


Figure 5-9: Impact of the Trickl app

Impact of the Trickl app



Attendance at outreach events also differs by treatment group (Figure 5-10), however perceived impact is consistent across groups (Figure 5-11). One-third of CPP/RT participants report having attended at least one event, compared to one-quarter of CPP or RT participants. Roughly half of all participants who attended an outreach event say it improved their understanding of how to reduce household electricity usage.

Figure 5-10: Attendance of Outreach Events

Attendance of Outreach Events

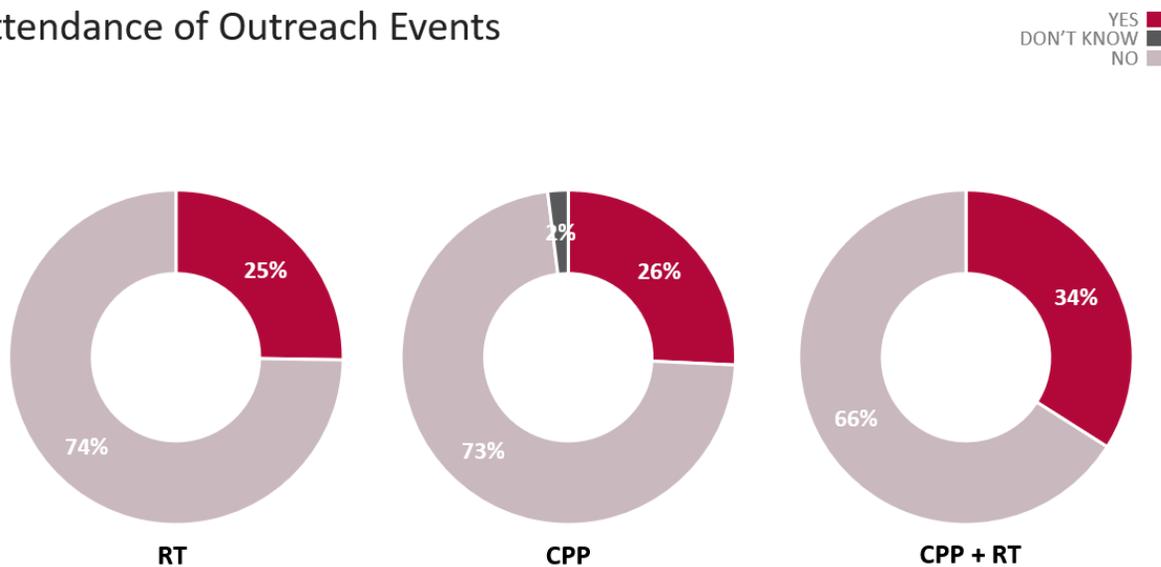
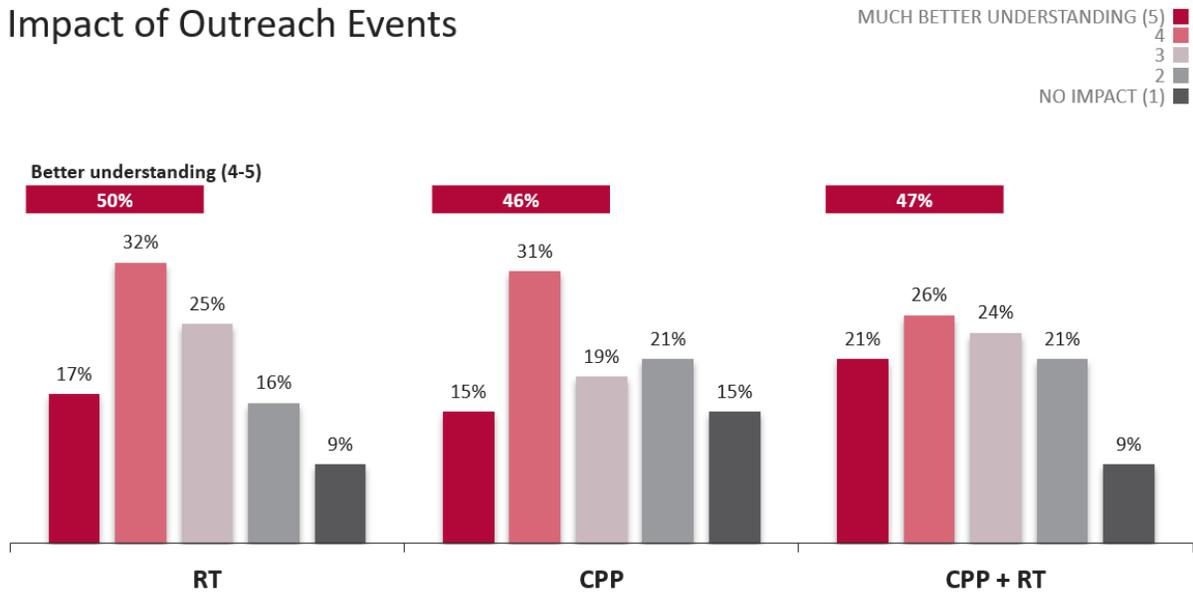


Figure 5-11: Impact of Outreach Events

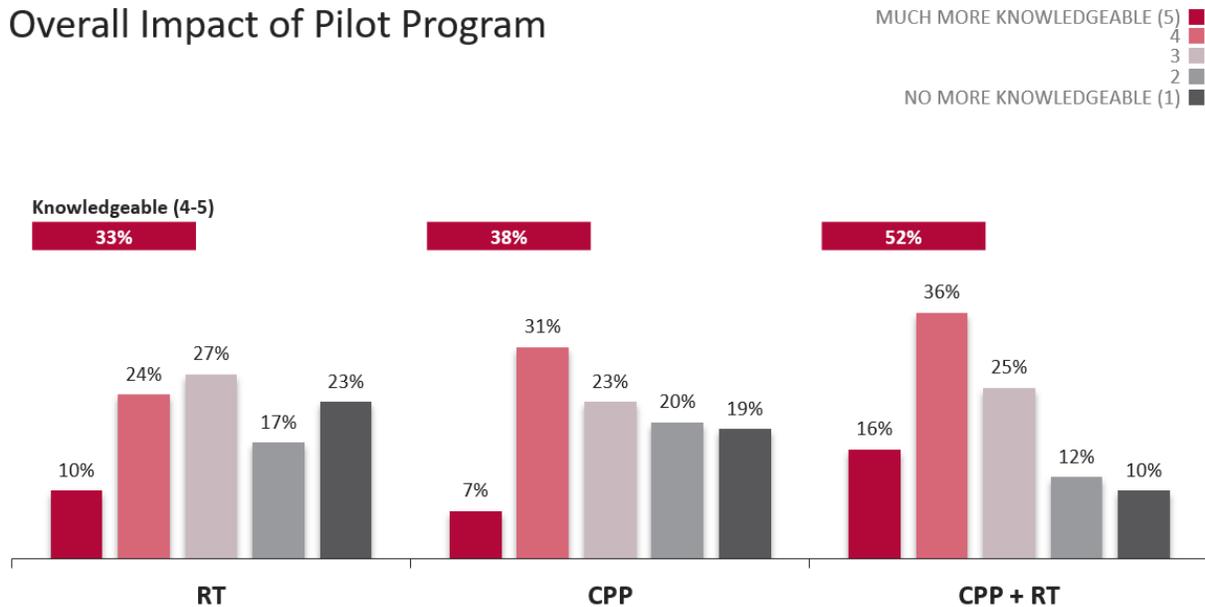
Impact of Outreach Events



Overall, the impact of the program on participants' understanding of how to manage household electricity consumption varies by treatment group (Figure 5-12). Most CPP/RT participants feel their knowledge increased as a result of participating, compared to nearly four in ten CPP participants and one third of RT participants.

Figure 5-12: Overall Impact of Pilot Program

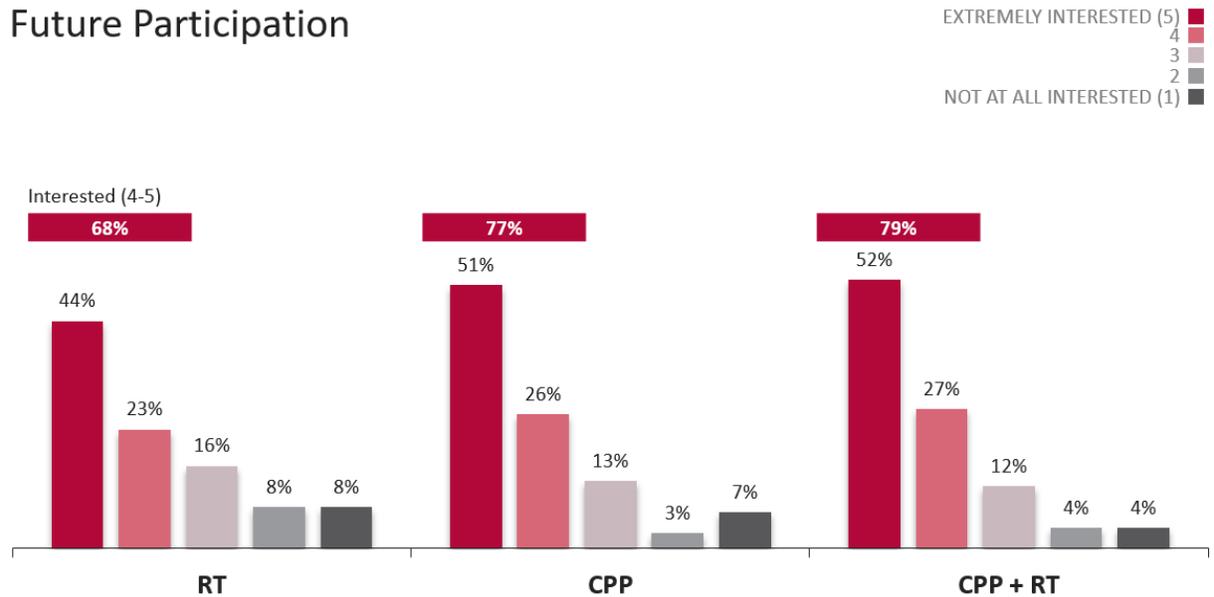
Overall Impact of Pilot Program



Interest in participating in future program is high among all groups and most participants would be interested in similar future programs (Figure 5-13).

Figure 5-13: Future Participation

Future Participation

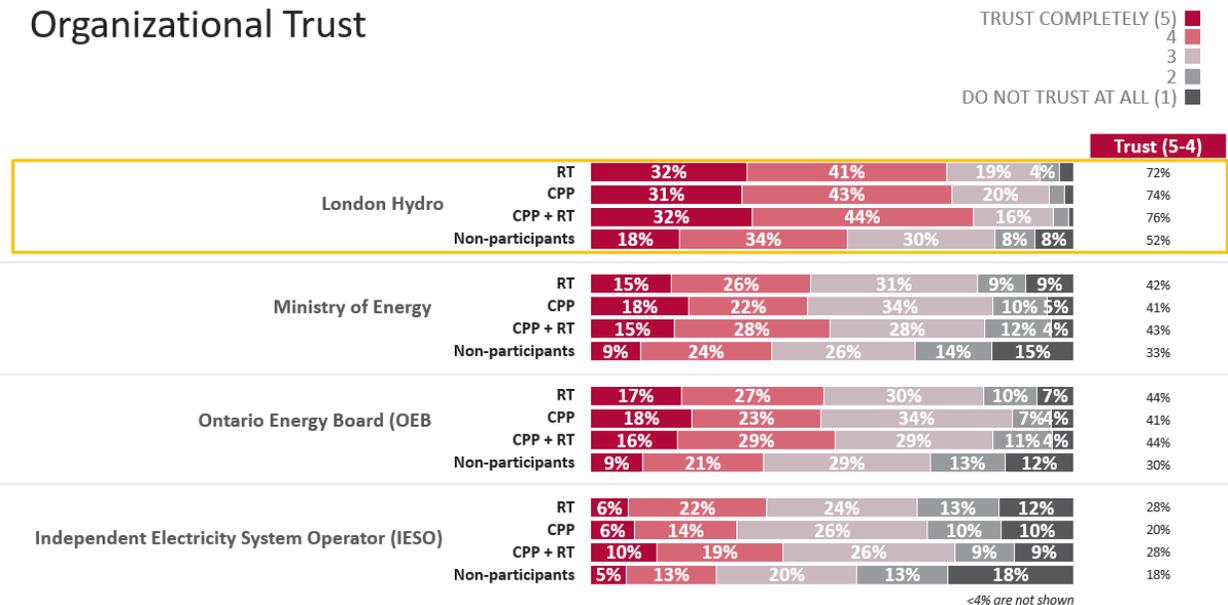


5.7 Engagement in Electricity System

At roughly seven in ten, most participants in all treatment groups express trust in London Hydro, the highest of any of the organizations presented (Figure 5-14). Closer to four in ten participants express trust in the Ministry of Energy or the OEB, while fewer than three in ten trust the IESO. The control group are significantly less likely to express trust in each party and London Hydro in particular.

Figure 5-14: Organizational Trust

Organizational Trust

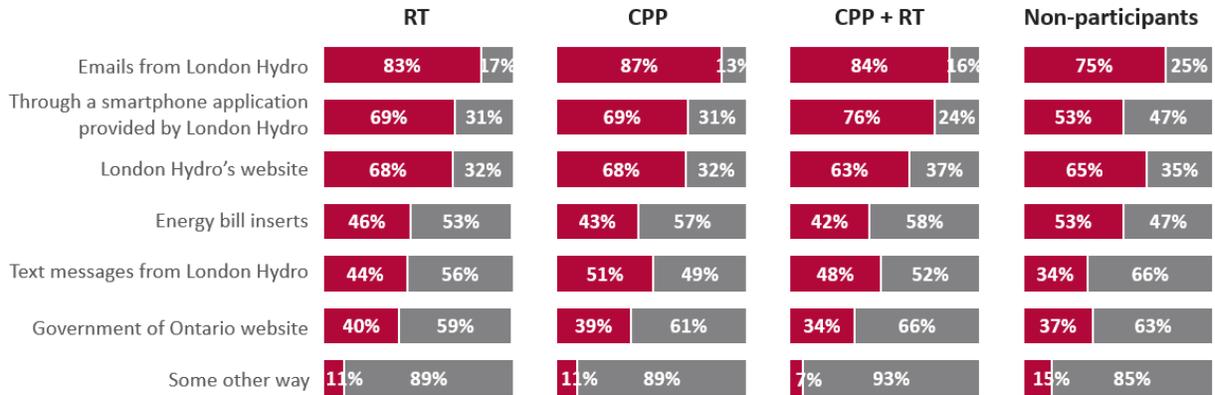


Respondents from all consumer groups (participants and controls) prefer to receive information about the electricity system by email from London Hydro, followed by through a smartphone app provided by London Hydro or on London Hydro’s website (Figure 5-15). The control group are less likely to prefer to receive communication by email, through a smartphone app or text messages from London Hydro.

Figure 5-15: Preferred Methods of Communication

Preferred Methods of Communication

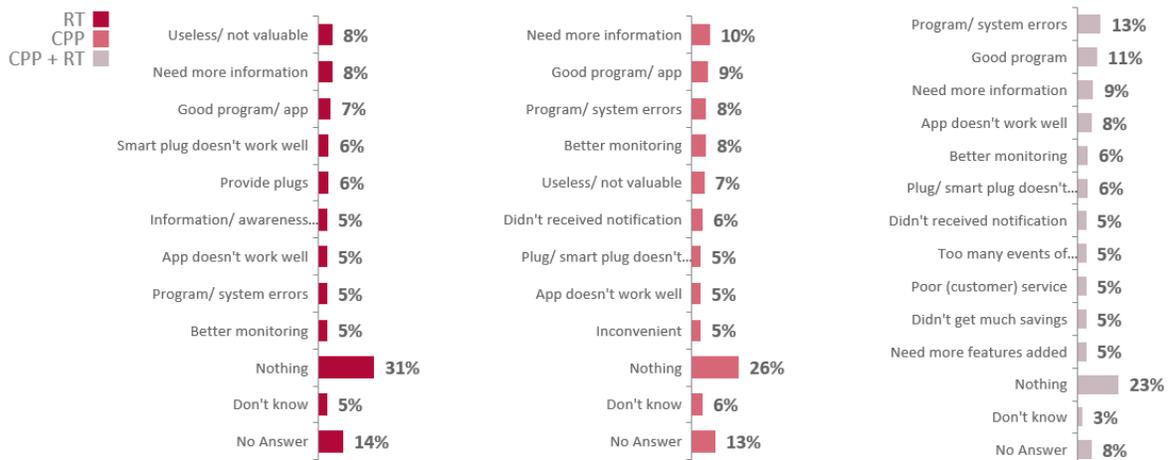
YES ■  
NO ■



When asked for feedback on the Pilot program, participants are most likely to highlight the need for more information while also noting that the program/app was good. Some also mentioned system errors or issues they encountered with the Trickl app.

Figure 5-16: Additional Feedback

Additional Feedback



<5% are not shown

## 6. KEY FINDINGS AND CONCLUSIONS

This final chapter of the report is divided into two sections.

- **Key Findings.** This section provides some of the most important quantitative outputs of the two main analyses undertaken.
- **Conclusions.** This section contextualizes the quantitative findings and interprets the implications of those findings.

### 6.1 Key Findings

There are three sets of key findings for this report: those associated with the energy savings impact analysis, those associated with the CPP event demand reduction analysis, and those associated with the energy literacy analysis.

#### 6.1.1 Energy Impact Key Findings

Navigant's key findings from the energy impact analysis include:

- **The pilot treatments deliver energy savings only in the summer.** Navigant did not estimate any statistically significant energy savings during the winter months for any of the treatment groups.
- **CPP participants delivered summer On-Peak and Mid-Peak energy savings that are statistically significant at the 90% confidence level.** CPP and CPP/RT participants reduced their daily summer:
  - On-Peak consumption by approximately 5% on average (+/- 58%)<sup>64</sup>
  - Mid-Peak consumption by approximately 3% on average (+/- 90%)
- **RT participants delivered modest On-Peak energy savings, although these results are less certain.** RT participants reduced their On-Peak consumption by approximately 2%, although these results are less certain than those of the CPP group – being just barely statistically non-significant, with a relative precision of +/- 101%. Navigant presents evidence in Section 4.1.4 that although these impacts are not statistically significant at the 90% level, it seems probable that these estimates reflect actual conservation, and not just random variation in the underlying data, that is that there is a real, though highly uncertain, impact during the On-Peak period.
- **CPP participants also equipped with the RT technology are saving the same as CPP-only participants in the summer months.** Navigant found no statistically or practically significant difference between the energy savings achieved by CPP and CPP/RT participants in the summer months and concluded from this that the RT treatment did not deliver any incremental savings.
- **Statistically significant energy savings have been estimated only in summer months and are, in those months, correlated with temperature.** Although Navigant cannot categorically state what behaviour is driving energy savings, the fact that the CPP groups' estimated energy

<sup>64</sup> All confidence intervals (relative precision) provided in this report are based on a 90% confidence level applied to cluster-robust standard errors.

savings are statistically significantly correlated with temperature and are statistically significant only in summer months, suggests that response is driven in large part by changes in A/C use.

### 6.1.2 CPP Event Demand Impact Key Findings

Navigant's key findings from the demand impact analysis include:

- **CPP response is very different between summer and winter.**
  - *Summer CPP response is substantial and correlated with temperature.* In the summer months, CPP impacts were on average 0.67 kW (34%) and were positively correlated with temperature: the hotter the day, the higher the CPP impacts. During the hottest event of the summer, the demand response averaged 1kW per customer. This aligns with the hypothesis developed above in the introduction to section 4.1 that summer energy impacts are highly correlated with temperature..
  - *Winter CPP response is small and does not appear to be meaningfully correlated with temperature.* Winter impacts, in contrast with those estimated in the summer, are much lower, on average, 0.13 kW per event. Winter impacts do not appear to be correlated with weather, with the highest event impact being estimated to have occurred on only a moderately cold day (0.23 kW, at -8 degrees Celsius).
- **There is a behavioural element to CPP event impacts in the summer months.** CPP participants are equipped with enabling technologies (a switch at the panel, and one smart plug) that respond automatically to London Hydro's price signal. Even though participants receive 15 minutes' notification of an event, there are clear behavioural elements to their response over and above the automated response delivered by the switches and smart plugs.
  - *Participants reduced consumption during hours in which CPP events were likely to occur.* CPP participants reduce their exposure to the CPP rate by making changes to their consumption habits in anticipation of CPP events – substantial savings are achieved in hours of the CPP event day leading up to the CPP event, despite participants not having any knowledge of when the event will occur until 15 minutes before it does.
  - *Disconnected participants still delivered demand response.* For any given event, approximately 20% of participants' devices could not receive, or respond to, London Hydro's curtailment signal. On average these participants were still able to reduce demand by 0.3 kW (15%).<sup>65</sup>

Some additional context may clarify how remarkable this is: an evaluation of San Diego Gas and Electric's voluntary CPP rate<sup>66</sup> (notification provided no later than 3pm on the day *prior* to the event) found the average response (at an average temperature of 99 degrees Fahrenheit, or approximately 37 degrees Celsius) was only 0.14 kW.

<sup>65</sup> Participants' whose enabling technologies were not connected to London Hydro's dispatch system continued to receive event notification via the Trickl app.

<sup>66</sup> Christensen Associates Energy Consulting, *2016 Load Impact Evaluation of San Diego Gas and Electric's Voluntary Residential Critical Peak Pricing (CPP) and Time-of-Use (TOU) Rates*, CALMAC Study ID SDGE0304, April 2017

[http://www.calmac.org/publications/PY16\\_TOU\\_and\\_CPP\\_Ex\\_Post\\_and\\_Ex\\_Ante\\_Report.pdf](http://www.calmac.org/publications/PY16_TOU_and_CPP_Ex_Post_and_Ex_Ante_Report.pdf)

- **Real-time information on consumption did not affect demand reductions.** The impacts of the CPP and CPP/RT group were not statistically significantly different from one another in either season – the availability of the online portal and energy tracking app did not impact participants’ ability to deliver demand reductions.

### 6.1.3 Energy Literacy Analysis Key Findings

- **Energy literacy as it relates to managing electricity consumption is high amongst all applicants to the RPP pilot program.** Approximately three quarters of all pilot participants and non-participants score in the top two (of five) categories for knowledge of how to manage electricity consumption. Eighty percent of survey respondents answered five or six (out of six) questions proving their energy knowledge correctly.
- **Despite starting from a high base of knowledge, the pilot appears to have built knowledge in specific areas related to energy consumption amongst participants.** Program participants have a higher proven knowledge about how time-of-use rates work, and better understand the concept of appliance phantom power, than non-participants. For example, 79% of RT and CPP, and 82% of CPP/RT, participants could identify as “True” the statement that reducing consumption during the day will reduce bills more than reducing consumption overnight, whereas just under three-quarters of non-participants could also correctly identify that reducing consumption during the days will reduce bills more than reducing consumption overnight. This difference is statistically significant at the 90% level for the RT and CPP/RT groups.
- **Despite the impact analysis finding no statistically significant difference between CPP/RT and CPP participants’ impacts, the literacy analysis indicates that CPP/RT participants are most likely to feel that the pilot improved their knowledge.** A quarter of CPP/RT participants indicated that the Trickle app provided them with a much better understanding of their energy consumption, in contrast to 14% of RT participants and 9% of CPP-only participants.
- **Energy literacy is consistently highest amongst men of 55 years or more.** Forty-five percent of respondents in this demographic answered five or six of the proven energy knowledge questions correctly, in contrast to 42% of those 35 – 54 and only 13% of those 18 – 34 (this difference is statistically significant at the 90% confidence level)..

## 6.2 Conclusions

This section is divided into two sub-sections. The first summarizes Navigant’s retrospective conclusions – observations and hypotheses about the impacts and participant energy literacy that occurred as part of this pilot. The second set of conclusions are prospective: a summary of considerations for future deployment on a broader scale based on the evidence provided by Navigant’s evaluation.

### 6.2.1 Evaluation Conclusions

Navigant has drawn four main conclusions from this final evaluation of the London Hydro RPP Pilot:

- **London Hydro’s residential customers are able to reduce more consumption and event-period demand in the summer months than in the winter months.** This is likely because summer discretionary loads are much larger than winter discretionary loads.

The largest residential end-uses in Ontario, as a proportion of average provincial annual consumption, are (in order): space-heating, plug loads, refrigeration, lighting, miscellaneous, water heating, space cooling, washing and drying appliances, ventilation and circulation, and cooking.<sup>67</sup> All of these end-uses, with the exception of refrigeration, include some discretionary use.

Most of London Hydro's customers use natural gas as their primary space-heating fuel, eliminating this as a discretionary (electric) load. In examining the other residential loads, the only one where loads are: concentrated in a single piece of equipment (and so are convenient to control), significant in size, and sometimes non-essential is the space-cooling end-use.

It should come as no surprise that shorter-run behavioural impacts will be dominated by changes in how consumers use space-cooling, and thus are much smaller in the winter months.

- **The available evidence suggests that education and customer engagement are key factors in enabling participant response.** Education and engagement are key elements of *all* programs and pilots that seek to motivate a behavioural response from participants. The question may be asked, why does Navigant single this as a key factor rather than attributing impacts *only* to the pricing and informational/technological treatment? This hypothesis is driven by two findings:
  - *The RT treatment motivates no incremental energy or demand impact from CPP/RT participants, but delivers summer energy savings for RT participants.* For both energy impacts and CPP event demand impacts, Navigant found that the combined CPP/RT treatment did not deliver any incremental statistically significant impacts, which Navigant has interpreted to mean that the RT treatment provided no additional benefit to participants already subject to CPP.

Yet, the RT treatment *did* deliver material summer energy savings. These two findings seem at odds – if the RT treatment on its own delivers summer savings, and the CPP treatment on its own delivers summer savings, why would the two treatments combined not deliver more savings than one of the treatments alone?

Navigant believes that the most likely explanation is that in fact the RT technology – the app – isn't what's responsible for the energy savings.<sup>68</sup> Rather, these offerings are an incentive that entices customers to participate in the program, and savings are delivered through the concerted effort of the utility to educate participants – or to motivate participants to educate themselves – as part of the program, in effective, practical strategies that deliver energy savings.

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<sup>67</sup> Navigant on behalf of the IESO and OEB, *2019 Conservation Achievable Potential Study*, 2019 See Chapter 3: Reference Forecast.

<sup>68</sup> Evaluations of real-time information pilots often yield savings estimates that are very low, or are statistically insignificant, suggesting that simply providing customers with data is insufficient for motivating real savings. Participants require an intermediary, such as the utility or some third-party home energy report provider to translate those data into *information*.

For a summary of real-time information studies and the associated impacts, see for example Table 13 on PDF page 41/95 of:

Navigant, prepared for Newfoundland Labrador Hydro, *Real Time Monitor Pilot Program: Impact and Process Evaluation*, March 2016

[https://www.exec.gov.nl.ca/exec/occ/publications/RTM\\_Complete\\_Rpt\\_F\\_Mar31\\_2016.pdf](https://www.exec.gov.nl.ca/exec/occ/publications/RTM_Complete_Rpt_F_Mar31_2016.pdf)

- *The price-only treatment (CPP) motivates a change in summer consumption behaviour even when there is no direct price signal to do so.* Most of the energy savings achieved by the CPP-only group were achieved in summer non-event periods.<sup>69</sup>

Certainly, this behaviour may be explained through the lens of expected value – participants assessing when peak prices will occur and making behavioural adjustments on this basis. The problem with this hypothesis is that it cannot explain why impacts were greatest in the On-Peak period, and yet, *by design*, the CPP price can only occur in the final hour of that period (from 4pm to 5pm).

A rational economic actor responding purely to price might adjust their behaviour in the window from 4pm to 5pm, but otherwise is not motivated to adjust their behaviour in the On-Peak period.

It is based on these two observations regarding the estimated impacts that Navigant infers that the customer engagement strategy used by London Hydro to support the deployment of the pilot design was a critical factor in empowering customer decision-making, and, ultimately, delivering the final reported results.

- **Critical peak pricing can be a tool for summer energy conservation as well as demand reduction.** CPP participants are provided with 15 minutes' notice when a CPP event occurs. This limits the scope of what actions participants can take in the short term when they receive event notification. In response to this challenge, it appears that participants have worked to limit their exposure to the critical peak rate by reducing consumption in hours in which events are likely to occur.

Participants have been educated to understand that CPP events are driven by system needs, and that system needs are driven (in the summer) by weather, and so they understand that daily energy impacts (even when no event takes place) are correlated with temperature. Participants undertake actions that reduce their risk exposure even as the risk of a CPP event climbs (i.e., temperature increases). Put another way, participants are provided with a qualitative understanding of the factors that drive the prices they will face and develop rules of thumb for responding to those prices.<sup>70</sup>

It should be noted that Navigant has only had a single summer to quantify impacts. It may be that these changes in behaviour are short-lived. If bill savings achieved by participants don't match what they perceive to be the efforts they have made to achieve them, such savings may not be sustainable over the longer term.

- **Participants can be remarkably nimble in responding to very short-term changes in price in the summer, as demonstrated by the statistically significant average summer CPP event response (0.3 kW) delivered by disconnected participants.** What this appears to demonstrate

<sup>69</sup> CPP events only account for 18 hours of the summer.

<sup>70</sup> It has previously been noted that when participants are provided with prices that change too frequently to allow a true "real-time" response (e.g., real-time pricing), they develop a set of rules for behaviour changes that reflect their average expectations of price changes. See for example:

Navigant, submitted to Ameren Illinois Utilities, *Power Smart Pricing 2009 Annual Report*, April 2010

<https://www2.illinois.gov/sites/ipa/Documents/CUB-Comments-Appendix-D-2009-Navigant-Power-Smart-Pricing-Annual-Report.pdf>

is that enabling technology is not *required* to deliver a demand response impact that nearly as high as that which might be delivered by a more conventional A/C cycling direct load control program,<sup>71</sup> Caution should be applied in extrapolating this result. Despite participants not being controlled delivering 0.3 kW of demand response, these are all participants that enrolled in a pilot program for which a key feature was automatic control. It is unclear to what degree these results might be reproduced in a program that does not offer enabling technology to support CPP response.

### 6.2.2 Considerations for Broader Deployment

The OEB's letter to RPP Pilot proponents of 2019-07-31 provides a set of additional reporting requirements for the final report. These include a requirement that pilot reporting address considerations for deployment of the pilot at a broader scale. This sub-section addresses those considerations identified by Navigant that flow from its impact and energy literacy analysis. Additional considerations (e.g., addressing program costs) for elements not considered by Navigant as part of its evaluation are included in Appendix J, drafted by London Hydro staff.

Key considerations for future deployment include:

- **Consider the value of winter CPP events.** At present Ontario is, and, absent any widespread electrification of space heating, will remain a summer-peaking jurisdiction. There is therefore no avoided generation capacity benefit associated with winter demand reductions. Furthermore, should the OEB wish to expand deployment of London Hydro's enabling technology solution (the panel-connected load switch), the incentive to reduce demand on winter CPP events may lead consumers make sub-optimal choices when selecting which circuit to control. *Prior a wider deployment, the OEB should consider not deploying winter CPP events.*
- **Consider an alternative curtailment technology.** Deploying and maintaining equipment is costly. It is possible that program cost-effectiveness could be improved under a "bring-your-own-thermostat" (BYOT) model. Under a BYOT model, participants that already own a "smart" thermostat cede control of that device to the utility during critical peak events. Such an approach would also mitigate against the potentially lost opportunities where participants may have elected to connect the pilot-deployed load control switch to a less impactful end-use (e.g., water heater, pool pump, area lighting, etc.). Note that thermostat control is typically not applied as aggressively as the load switch control applied in this pilot. In this pilot the switch was used to entirely switch of the A/C unit. Whether using smart thermostats or load switches if anything less than 100% cycling<sup>72</sup> is applied, impacts are likely to be less than those estimated in this pilot. *Prior to a wider deployment, the OEB should consider exploring the use of already-deployed thermostats as a potential enabling technology to support critical peak price response.*

<sup>71</sup> In the most recent year it was evaluated, the IESO's peak saver PLUS® program delivered an average of 0.43 kW per participant at an average temperature of 31 degrees Celsius (five degrees higher than the average summer CPP event temperature observed for this evaluation).

Nexant, prepared for Independent System Electricity Operator, *peaksaverPLUS® Program 2015 Load Impact Evaluation*, September 2016

<http://www.ieso.ca/en/Sector-Participants/Energy-Efficiency/Evaluation-Measurement-and-Verification>

<sup>72</sup> Most residential direct load control programs typically deploy 30%, 50, or 65-75% cycling strategies (sometimes applying 100% cycling in emergency situations). The cycling percentage generally refers to the proportion of the time within a given window (e.g., 20 minutes) that the A/C compressor is allowed to run.

- **Consider identifying the overall societal benefit delivered by the Trickl app.** The scope of Navigant's evaluation was relatively narrow: quantify the impact on energy consumption and peak demand of the Trickl app. In conducting a benefit/cost analysis, the benefit of avoided costs delivered by the app are important, but not considering other benefits may understate the societal value of the app. For example: can the app be used to drive uptake in other consumer CDM programs? Can the app be used to reduce payment lags through reminders (reducing working capital needs and therefore ratepayer costs)? Can the app be used as a more reliable and immediate communications channel to customers (e.g., regarding outages), potentially reducing call centre costs? *Prior to a wider deployment the OEB should consider comprehensively cataloguing the different benefit streams a mobile app can offer to ensure that benefit/cost ratios are not understated.*
- **Consider explicitly defining the incremental value that fast-ramp, short-term demand response through CPP offers over longer-notice, longer period CPP events.** The London Hydro pilot was designed evaluate the potential for very fast-ramp price-motivated demand response. What incremental value does this capability offer, and what might the benefit/cost trade-offs (in terms of enrollment, etc.) of allowing more notice. To what degree would DR impacts extend over a longer period? Caution should be applied in extrapolating the London Hydro CPP event impacts over longer periods. Participants may not be able to continue to provide very large adjustments over a period of more than an hour. *Prior to a wider deployment, the OEB should consider explicitly quantifying the value of the short-ramp aspect of the treatment and should carefully consider how impacts might be affected by extending the CPP period.*

## APPENDIX A. APPROACH – ADDITIONAL DETAIL

This appendix provides additional technical details regarding Navigant's approach to estimating the impacts reported in this analysis.

This Appendix is divided into two sections:

- **Pre-Period Consumption Variable Creation.** This section provides additional detail regarding how the pre-period consumption variable was developed.
- **Participant Incentives and the Question of Bias.** This section address feedback provided to Navigant based on its interim report, addressing the question of the degree to which the incentive offered to CPP and CPP/RT participants could potentially bias the results.

### A.1 Pre-Period Consumption Variable Creation

As noted in several instances in both the body of the report and in the earlier sections of this Appendix, Navigant includes on the right-hand side of the regression equation a variable capturing an average of each participant's pre-program consumption. In the summer this variable is a 720-element<sup>73</sup> vector of average pre-period consumption values.

The 720 elements are the product of 30 day-types, and 24 hours in each day. Day-types are defined by three components:

- Month of year
- Day of week
- Average daily temperature

Figure 6-1, below, shows how day-types are assigned. So, for example:

- Day-type F\_1 would be assigned to all non-holiday weekdays in July or August with an average dry bulb temperature exceeding 23 degrees.
- Day-type D\_5 would be assigned to all weekends and holidays in May and October
- Etc.

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<sup>73</sup> Altogether this vector has 720 elements for a whole year, but only 360 for the summer, and 360 for the winter.

**Figure 6-1: Day-Type Definitions**

		Day Type				Weekends/ Holidays
		Weekdays				
		1	2	3	4	
Winter	<b>Period A: Jan &amp; Feb</b>	<= -11	-7 to -11	-3 to -7	> -3	All Days
	<b>Period B: Mar &amp; Dec</b>	<= -10	-6 to -10	1 to -6	> 1	
	<b>Period C: Apr &amp; Nov</b>	<= 1	2 to 1	6 to 2	> 6	
Summer	<b>Period D: May &amp; Oct</b>	>= 18	15 to 18	11 to 15	< 11	All Days
	<b>Period E: Jun &amp; Sept</b>	>= 23	21 to 23	16 to 21	< 16	
	<b>Period F: Jul &amp; Aug</b>	>= 23	21 to 23	20 to 21	< 20	

The thresholds are selected with reference to the pre-program period observed temperatures. Specifically, thresholds are selected such that, in the pre-program period, approximately:

- 10% of non-holiday weekdays are type 1 (most extreme temperatures)
- 20% of non-holiday weekdays are type 2
- 30% of non-holiday weekdays are type 3
- 40% of non-holiday weekdays are type 4 (mildest seasonal days)

Once day-types are assigned to each day, each customer’s 720 element (360 in the summer, 360 in the winter) vector of pre-program period consumption is calculated by averaging their consumption, grouped by hour of day and day-type.

These are then associated with the appropriate program period observation by defining the program period day-types based on the criteria in Figure 6-1, above, and joining the pre-period values based on that and the hour of day.

## A.2 Participant Incentives and the Question of Bias

Following its review of Navigant’s interim impact evaluation of the LH RPP pilot, the OEB requested that Navigant respond to the following:

*Please provide a discussion of the \$25/\$75 incentive and any impact offering that incentive might have by introducing or inflating customer bias.*

In the context of pilot program evaluation “bias” can take on different meanings, but the two most common definitions used are that of “omitted variable bias”, and “sample bias”.

### Omitted Variable Bias

The question here is this: *is there some systematic way in which the treatment and control groups are different from one another that has not been controlled for* (typically either through the selection of the control group or the inclusion of a variable on the right-hand-side of the regression)?

Failing to control for some systematic difference between the two groups that is correlated with the treatment effect would lead to the (erroneous) attribution of that systematic difference to the treatment effect, biasing results.

Since the offer of the incentive is made to all program applicants (treatment and controls), there is no consistent difference here between the two groups, and therefore it is possible to rule out that the offer of the incentive has biased estimated impacts. This is one of the great benefits of a randomized control trial.

### Sample Bias

Sample bias identifies an instance in which a sample collected for a study is not representative of a broader population to which sample impacts are to be extrapolated.

By making the pilot opt-in (as opposed to mandatory), it is biased by construction. Since only a sample of the population will volunteer to participate, participant self-selection means that it is probable that unobservable characteristics (characteristics, like enthusiasm for energy conservation, that may be correlated with electricity consumption) of the sample would not match those of the overall residential electricity consumer population.

The LH RPP pilot impacts cannot be considered representative of what could be achieved by *imposing* the pilot treatments on the entire population but can be considered representative of what could be achieved by *offering* the same pilot treatments to the overall population, with the same incentives. In other words, the question of sample bias depends entirely on the context to which one wishes to apply the impacts.

The experience of the pilot provides valuable information, when considering a wider implementation, particularly on the question of incentives. Consumers appear to be relatively risk-averse when it comes to alternative rate structures: prior to offering the incentive, there were concerns that London Hydro would not be able to attain the enrollment required for the participant group, let alone the control group.

In effect, the incentive is a form of first-year bill protection. The incentive protects a customer from some of the down-side risk of the rate but does so in a fashion that interferes only minimally with the price signal on a day-to-day basis. The key process lesson here is that enticing consumers to try something different requires offering them a risk-free trial. This is not an isolated observation, but one borne out by other programs in the utility rate space, as well as numerous other industries.

Consider, for example, OG&E's SmartHours program. This is a variable peak pricing program with a quite aggressive price differential – a critical peak price more than eight times the Off-Peak price. And yet, despite this, the program maintains an enrollment of approximately 120,000 customers<sup>74</sup>, or

<sup>74</sup> OG&E, *SmartHours – End of SmartHours Season*, accessed 2019-04-03

approximately 15% of its *total* customer count.<sup>75</sup> A key feature of the program is first-year bill protection – a risk-free trial of the alternative rate.

[https://www.oge.com/wps/portal/oge/save-energy/smarthours/!ut/p/z1/IZFNC4JAEIZ\\_SwevzqQm1m1tY\\_0qsEK0vYSFrYK6opZ\\_PyEvQfYxp5nheedlZoBDDLxK7rllulxWSTHUR26eL11uHA-1LbMPJpK9vWSMLXRmGhCNAK7RNTQPvSEla4v6u6Wto2MA\\_0vPfG2DxKd0twjo3LV\\_1ONEEPzVfxLgn8dHwEeL6Qu8Am9W\\_GbiAReFPD\\_QaqzbgngTXpNm7RRb83QzrqublcKKti3vSqkFEWqXmSp4DtJJtsO4lcS6jIMwxizolyslsxmD02c2DA/dz/d5/L2dBISEvZ0FBIS9nQSEh/](https://www.oge.com/wps/portal/oge/save-energy/smarthours/!ut/p/z1/IZFNC4JAEIZ_SwevzqQm1m1tY_0qsEK0vYSFrYK6opZ_PyEvQfYxp5nheedlZoBDDLxK7rllulxWSTHUR26eL11uHA-1LbMPJpK9vWSMLXRmGhCNAK7RNTQPvSEla4v6u6Wto2MA_0vPfG2DxKd0twjo3LV_1ONEEPzVfxLgn8dHwEeL6Qu8Am9W_GbiAReFPD_QaqzbgngTXpNm7RRb83QzrqublcKKti3vSqkFEWqXmSp4DtJJtsO4lcS6jIMwxizolyslsxmD02c2DA/dz/d5/L2dBISEvZ0FBIS9nQSEh/)

<sup>75</sup> OG&E has approximately 840,000 customers of all classes. Navigant was not able to determine what proportion of these are residential customers at the time of writing, but per the Q4 2018 company financial statement, residential sales account for only about a third of total sales. This suggests that SmartHours customers could represent nearly a quarter of total residential customers.