APPENDIX

This self-contained appendix presents our paper's technical details, thereby offering supplemental information useful to practitioners (e.g., utility analysts and regulatory staff) of residential optional dynamic pricing (RODP).

1. Adverse selection bias

A RODP pilot should randomly assign volunteering customers among its time-of-use (TOU) and non-TOU and tariffs, so as to mitigate the problem of adverse selection bias. This bias arises because customers with relatively low peak kWh (e.g., a fixed 5% of their total kWh consumption assumed here for exposition clarity) could pick a TOU schedule with a high peak-to-off-peak price ratio to gain bill savings without altering their consumption behavior (Mackie-Mason, 1990; Woo et al., 1995a). Absent this assignment, the peak kWh response estimates based on a side-by-side comparison of the control and treatment groups' kWh data by TOU can falsely inform that RODP has resulted in peak kWh reductions that did not actually occur.

2. Sample selection bias

The aforementioned assignment, however, does not address the sample-selection bias due to voluntary participation (Heckman, 1979; Aigner and Ghali, 1989). For example, our kWh response estimates are conditional on a residential customer who had decided to become a participant. We do not have BC Hydro's customer recruitment data (e.g., who were contacted? and who decided to participate?) to detect the correlation between the random errors of a participation decision regression (e.g., binary probit) and a kWh regression (e.g., the peak kWh regression in the main text). Based on a BC Hydro's post-pilot survey of the participants, the correlation is likely negative, implying an unobservable factor (e.g., idiosyncratic life style or social value) that would encourage a customer's participation could also reduce the customer's post-participation peak kWh level.

Had the recruitment data been available, we could use the Heckman technique by including the Mills ratio based on the participation decision regression (e.g., binary probit) as an additional regressor in our peak and off-peak kWh regressions. Due to the lack of such data, our demand estimation assumes that the participation decision regression's random error is uncorrelated with those of the peak and off-peak kWh regressions. The same assumption is made by studies that do not use recruitment data to account for the sample selection bias (e.g., Faruqui and Sergici, 2010).

In the absence of recruitment data, we compare the demographics of the sample of the pilot's participants and those of BC Hydro's residential customers living in single family homes. Except for household income, the demographic differences in Table 1 between the sample and population are within 10% of the population's demographics, allaying the concern of self-selection bias.

Table A.1: Comparison of Demographics

Variable	Sample	Population	Sample ÷ Population
Average age (years) of main household contacts	54.6	55.0	0.99
Average education (years) of main household contacts	14.2	13.2	1.08
Average household size (persons)	3.0	2.8	1.07
Average household income ($)	82900	71200	1.16
Share of home owners	0.97	0.95	1.02
Average house square footage	2401	2297	1.05
Average annual kWh consumption	11092	12299	0.90

Note: The comparison is based on an internal report provided by BC Hydro to the first author in 2008.

3. Operational importance of a small peak kWh reduction

The operational importance of an estimated peak kWh reduction is underscored by a North American electric grid's daily operating reserve requirement, which is 5% of the grid's daily system peak for a hydro-rich region like BC (www.nerc.com/files/bal-std-002-0.pdf).

Consider an example in which the forecast of the next-day system peak demand is 10000 MW, implying an operating reserve requirement of 500 MW. But only 480 MW of operating reserve is expected to be available due to the failure of a major transmission line. The capacity shortage of 20 MW (= 500 MW – 480 MW) can be eliminated by a 400-MW (= 20 MW ÷ 5%) reduction in the system peak demand, some of which may be achieved under a system-wide residential critical peak pricing (CPP) program.

In this example, the CPP program based on price rationing is considered as a demand response resource that modifies the grid's system peak. Had the program been treated like a direct load control (DLC) program based on quantity rationing (e.g., curtailable service for space heating), a 20-MW load reduction due to the CPP program's activation would have enabled the grid to meet its operating reserve requirement.

The difference between CPP's price rationing and DLC's quantity rationing is largely an artifact of the industry practice dated back to the 1970s. With advanced communication and control technologies now available, however, a CPP tariff can be implemented as a forward contract that permits an electric utility's remote activation of a residential customer's contracted thermostat adjustment (e.g., -2^{0}C) on a CPP day, thereby directly controlling the customer's space heating load (Woo et al., 2014).

4. CPP's peak load reduction as dispatchable capacity

Whether CPP's peak load reduction should be treated like dispatchable generation (e.g., a combustion turbine) is debatable, exemplified by Decision 14-03-026 issued in April 2014 by the California Public Utilities Commission (CPUC) (http://docs.cpuc.ca.gov/DecisionsSearchForm.aspx) in connection to the Order Instituting Rulemaking (OIR) to Enhance the Role of Demand Response in Meeting the State's Resource Planning Needs and Operational Requirements.

A key issue of the OIR is whether a demand response should be seen as demand-modifying vs. capacity-providing. The current industry practice is that a daily occurring kW reduction related to TOU pricing is demand-modifying, whereas a kW reduction due to DLC's activation under system emergency is capacity-providing (WECC, 2014). This distinction is less obvious for a CPP-related load reduction.

A peak kWh response to CPP is obtained with advance notice, arguably weakening its usefulness in resolving an unanticipated forced outage of a large supply resource such as a major power plant or transmission line. Equally applicable to DLC with advance notice, such an argument overlooks CPP's ability to address a foreseeable shortage caused by a demand spike due to extreme weather. Since a grid operator can accurately forecast the weather-related spike on a day-ahead basis (e.g., Woo, et al., 2016), the advance notice requirement is less a concern in the operator's day-ahead scheduling of resources to meet the next day's system demand. Further, the argument ignores that the supply resource's forced outage would become known with certainty after its occurrence, thus lessening the advanced notice's negative effect on the usefulness of a CPP program in a grid's daily operation.

5. Marginal cost estimation

The cost savings of a RODP's program depends on the peak and off-peak marginal cost estimates. Marginal cost estimation, however, is complicated because of wholesale market trading and factors like transmission and distribution (T&D) constraints, resource adequacy requirements, renewable portfolio standards, and emissions reduction targets (Sreedharan et al., 2012). Absent such factors, the hourly marginal energy costs of an electric utility with active trading are the hourly wholesale market prices adjusted for marginal T&D line losses. The peak marginal cost is the marginal capacity cost plus the marginal energy cost for the peak period, and the off-peak marginal cost is the marginal energy cost for the off-peak period.

The annual marginal capacity cost for generation is *MGCC* = per kW-year cost of the marginal peaking capacity used to meet the reserve requirement of a utility not engaging in wholesale trading (Chao, 1983). If the utility uses this capacity to make market-based sales, *MGCC* = per kW-year cost of the marginal peaking capacity – per kW-year profit from market sales (Sreedharan et al., 2012). The marginal T&D capacity cost is *MTDCC* = per kW-year incremental cost of a T&D resource plan due to a peak demand increase (Woo et al., 1995b).

As new peaking facilities are built to serve the peak hours, the peak period's capacity cost per kWh is the sum of *MGCC* and *MTDCC* divided by the annual number of peak hours. For BC Hydro, this number is 400 (= ~80 working weekdays in November – February × 5 peak hours per working weekday).

6. Inferring RODP's kWh effects via electricity demand estimation

A RODP pilot, like BC Hydro's, may not have pre-trial hourly kWh data for a difference-in-difference estimation of the kWh effects. An alternative is to estimate peak and off-peak regressions that characterize the data generating process (DGP) for the participants' observed peak and off-peak kWh.

One may argue that each participant could have its own DGP, rendering a demand estimation approach invalid and therefore useless. Such an argument, however, is unproductive because it can be used to reject TOU demand studies that do not always have pre-trial kWh data (e.g., Lawrence and Aigner, 1979; Aigner, 1984; Faruqui and Sergici, 2010).

7. Estimation process

A RODP pilot like BC Hydro's generates a panel of kWh data by TOU, suggesting the use of random effects in the kWh regressions (Wooldridge, 2010). Commonly used statistical packages like SAS/ETS and STATA, however, do not have readily available routines suitable for estimating a TOU demand system with random effects and cross-equation restrictions. Writing a new routine is a challenging task for many practitioners. Further, the routine may invite extensive questioning in a regulatory hearing in connection to a RODP program's system-wide implementation based on the empirical results of a RODP pilot.

An alternative is to use participant-specific dummy variables in the kWh regressions to account for the *residual* kWh effects not captured by the other regressors. These dummy variables, however, are perfectly collinear with a participant's attributes (e.g., location and electric space heating), rendering the demand estimation infeasible. Estimation by customer segment cannot solve the collinearity problem because a TOU participant's peak-to-peak ratio is a constant number for all days in the sample.

We adopt a feasible estimation process that entails the following steps:

(1) Estimate equations (1.a) and (1.b) in the main text as a system of seemingly regressions with cross-equation restrictions *sans* the participant-specific dummies, producing the regression residuals to be used below.

(2) For each TOU period, estimate an OLS regression (with no intercept) that uses the residual from Step (1) as the regressand and the participant-specific dummy variables as the regressors. Each OLS coefficient estimate serves to proxy a participant-specific residual kWh effect. As the grand mean of the residuals is zero, the grand mean of the participant-specific residual kWh effects is also zero.

(3) Compute the TOU period's adjusted kWh for each participant, which is the participant's actual kWh minus the participant's OLS coefficient estimate from Step (2). The grand mean of the period's adjusted and actual kWh are identical because the grand mean of the residual kWh effects is zero.

(4) Use the adjusted kWh from Step (3) to re-estimate equations (1.a) and (1.b). We verify that the estimated demand curves based on the adjusted kWh match those based on the actual kWh. We gauge the coefficient estimates' precision using customer-clustered standard errors that are heteroscedasticity and autocorrelation consistent.

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