Japan & The World Economy 68 (2023) 101223

Contents lists available at ScienceDirect

Japan & The World Economy

journal homepage: www.elsevier.com/locate/jwe

# Effects of alternative pricing structures on electricity consumption and payments in the commercial and industrial sector

Asahi Oshiro [a], Nori Tarui [b,*]

[a] ExxonMobil., UK

[b] Department of Economics, University of Hawai'i at Mānoa and University of Hawai'i, Economic Research Organization (UHERO), 2424 Maile Way, Saunders Hall, 542, Honolulu, HI 96822, USA

ARTICLE INFO

*JEL classification:*
H8
L9
Q4

*Keywords:*
Real-time pricing
Electricity
Renewable energy
Distributional impacts, fixed cost recovery

ABSTRACT

We investigate the distributional and welfare impacts when commercial and industrial (C&I) electricity end users face a dynamic pricing structure as opposed to a constant volumetric price with demand charge on individual users' peak usage. While demand charge does not necessarily reduce the system-wide peak, it often constitutes a large share of C&I users' payments. Hourly electricity consumption data for C&I users on O'ahu, Hawai'i, reveal that the fixed cost recovery associated with removing demand charge has both significant distributional impacts and considerable efficiency gains. Moreover, the rate reform can be regressive or progressive depending on how the fixed charge is allocated across users.

## 1. Introduction

Intermittent renewable energy (RE) sources, such as solar and wind, are increasingly integrated into energy systems in many parts of the world as a way to reduce reliance on fossil fuel or to reduce greenhouse gas emissions that cause climate change. As a result, mid-day electricity load has decreased over years due to rising solar photovoltaic (PV) penetration in many cities. While such RE integration contributes to decarbonization efforts to mitigate climate change, it imposes its own unique challenges. The associated "duck curve", for example, indicates a steep ramp in the electricity load given peak load in the evening when solar PV output is not available (Fig. 1). Such challenges imply increased need for consumers to shift demand across hours to meet time-varying supply. Increased deployment of energy storage would alleviate the issue, but efficient storage investment – along with efficient generation capacity and transmission plannings in general – requires correct electricity price signals. These considerations all indicate that real-time pricing (RTP), or marginal-cost pricing, has potential benefits of inducing efficient alignment of supply and demand in the electricity markets. Under RTP, a variant of dynamic pricing, retail prices vary with high frequency (often from hour to hour) by reflecting the real-time cost of energy generation.[1]

This paper investigates the effects of RTP on the electricity payments by the commercial and industrial (C&I) sector end users; how the effects would differ across energy users; and the welfare impacts. We address these questions about the distributional and welfare impacts by applying data on customer-level electricity consumption on O'ahu under alternative assumptions about the price elasticity of electricity demand, the marginal cost profile, and the method of the fixed cost recovery. The findings add to the literature on RTP by incorporating the unique issue of fixed cost recovery in the C&I sector and its implications to the efficiency and equity of RTP, as detailed below.

A large body of literature investigates individual peak minimization with pricing schemes such as critical peak pricing (CPP), time of use pricing (TOU), and real-time pricing (RTP) to quantify the efficiency gains relative to traditional electricity pricing that does not reflect the contemporaneous marginal costs. Research has shown that dynamic pricing schemes can help provide a better match between demand and supply as more renewable energy is integrated to the grid (Blonz, 2022). Whether an energy user can shift loads depends on numerous factors including their industrial characteristics and its operation patterns, which shape the price elasticity of the electricity demand as well as the elasticity of substitution of energy usage across hours of a day.

* Corresponding author.
*E-mail addresses:* asahi.oshiro@exxonmobil.com (A. Oshiro), nori@hawaii.edu (N. Tarui).

[1] Coffman et al. (2016) note "the price feedback between the utility and the customer provided by RTP helps send signals to the utility to bring additional generation online during periods of rapid rises in consumption or take them offline during periods of potential curtailment. It helps send signals to customers to encourage electricity usage when costs to generate are low and dissuade electricity usage when costs to generate are high".

https://doi.org/10.1016/j.japwor.2023.101223
Received 28 January 2023; Received in revised form 16 October 2023; Accepted 8 November 2023
Available online 17 November 2023

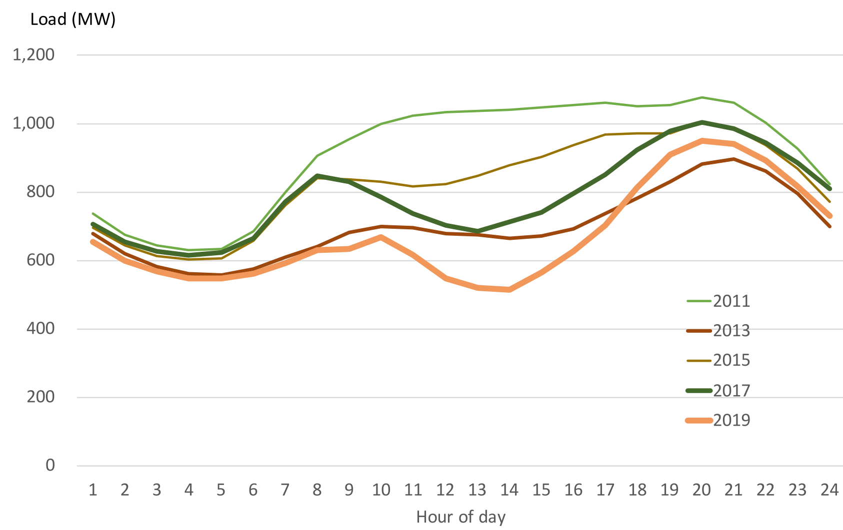



**Fig. 1.** "Duck curve" on O'ahu (net load, March 31,2011–2019). Compiled based on FERC Form 714 data.

The welfare gains that occur under an alternative rate structure can differ among sectors for various reasons. First, varying load profiles can arise due to business operation differences among different sectors. Second, some C&I energy users tend to have fixed business operations that are not easily altered by a change in electricity prices. Finally, peak demands of consumers in different sectors do not occur simultaneously and may not align with the system load. Those energy users with larger usage when the marginal costs are higher may experience a large increase in their volumetric payments.

Current research shows that dynamic pricing schemes such as real-time pricing (RTP) have potential benefits compared to TOU or flat rate pricing schemes, but the full economic impact is uncertain Borenstein (2005). In the residential sector, Ito et al. (2018) find that consumption shifts from on-peak to off-peak hours can occur when consumers face high prices during on-peak hours. With a dynamic pricing experiment on the residential and small-scale C&I consumers, Faruqui et al. (2014) find that small C&I customers are less price responsive than residential customers though overall they provide evidence of statistically significant elasticities of substitution of electricity usage across hours of a day. Blonz (2022) finds that critical peak pricing (when generation costs are high) for small C&I customers in California induced a statistically significant decrease in the electricity usage during the peak period; and hence would lead to considerable efficiency gains by avoiding excessive investment in generation capacity increases. In Hawai'i, where our case study is situated, RTP simulation studies indicate significant aggregate-level efficiency gains through RTP (Coffman et al., 2016; Imelda et al., 2018).

Regarding the distributional impacts, significant decreases or increases in the electricity payments (and hence wealth transfers) can occur if C&I customers were to be billed under a dynamic pricing structure. Under the current flat volumetric rate, those customers who have high energy consumption when the marginal costs are high are subsidized by those who consume low quantities at those times (Borenstein, 2007). The potential winners and losers need to be taken into account when considering alternative pricing structures. In this paper, we investigate how payments change for energy users in different C&I sectors under alternative billing regimes.

While most studies on RTP focus on the residential sector, those that investigate the impacts in the C&I sectors do not address the consequence of eliminating demand charge on fixed cost recovery. Fixed cost recovery is a major challenge associated with RTP. Many electric utilities impose a "demand charge" on C&I customers to help recover fixed costs, and it holds a considerable share of the C&I energy users' overall electricity payments as shown in Fig. 2. Demand charge, also known as the Hopkinson tariff, is typically a charge on the maximum peak demand (in kW) in each month, and hence is distinct from the volumetric charge on electricity usage (in kWh). The time at which the customer pays a peak-demand charge does not necessarily coincide with the system peak time (Mountain and Hsiao, 1986). Therefore, demand charge does not necessarily contain the system peak demand. While some studies estimate the electricity demand given demand charge (Mountain and Hsiao, 1986), the welfare and distributional consequences of dynamic pricing with and without demand charge is not addressed in the literature.

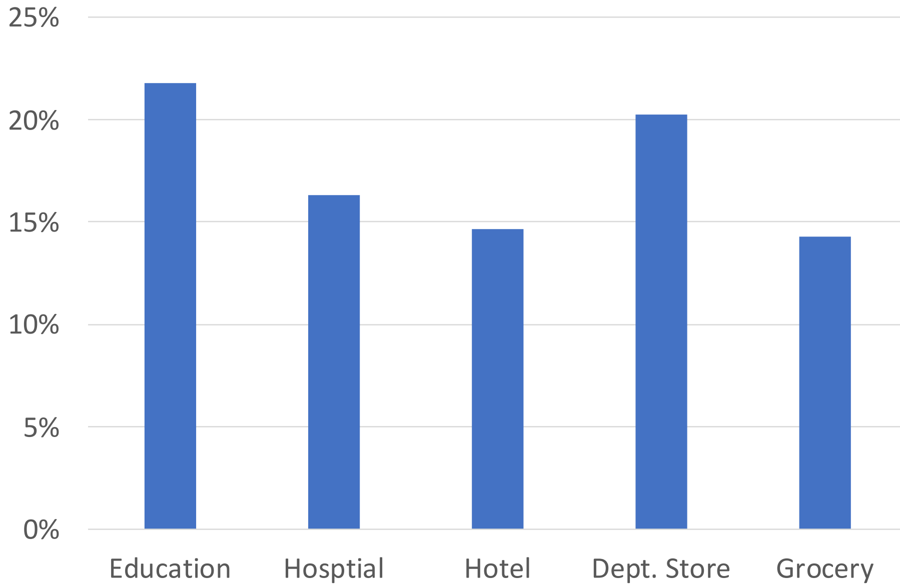
We investigate wealth transfers associated with RTP rate reforms by following Borenstein (2007)'s approach, but we explicitly incorporate demand charge in the analysis. We delineate the consequence of eliminating the demand charge and the resulting increases in the fixed charge, which is necessary for the electric utility's fixed cost recovery under RTP. We also consider the associated welfare impacts. Evaluating welfare impacts requires specification of price-responsive energy demand. We apply a simulation approach that builds on energy users' cost minimization subject to demand charge.

We study the distributional impacts because the equity of energy pricing reforms is receiving renewed concerns as evidence to support decarbonization and dynamic pricing has be come stronger. Recent studies discuss ways to make transitions to RTP equitable, in particular in the residential sector (Borenstein et al., 2021, 2022). We demonstrate how the distributional impacts differ depending on the design of the fixed charge and the treatment of the demand charge.

The C&I energy users on O'ahu (Honolulu County) face a flat volumetric rate, demand charge and fixed charge. The volumetric rate reflects the base rate, fuel cost adjustments, and other fees to cover the cost beyond the variable costs.[2] We apply observations of these customers' hourly electricity usage, along with a proxy of hourly marginal costs of electricity, to our analysis. We first simulate the C&I energy users' electricity payments under RTP by assuming that the energy usage does not change (i.e., the price elasticity of electricity demand is assumed to be zero). In the case of O'ahu, where the current retail rates exceed the marginal costs, the fixed charges to the energy users must increase under RTP in order to maintain the utility's revenue for the fixed cost recovery.[3] We find that, if the fixed charge is distributed equally across energy users, then the RTP transition exhibits a highly

[2] As of 2014, there were no time-of-use rates for C&I consumers in Hawai'i.

[3] The retail volumetric rates are set above the marginal costs in many energy markets for the fixed cost recovery. While the retail rate may be lower than the social marginal costs in some regions where electricity generation




Compiled based on data for March 2014 from Hawaiian Electric Company and FERC.

**Fig. 2.** The share of demand charge payment in the electricity payment by sector.Compiled based on data for March 2014 from Hawaiian Electric Company and FERC.

regressive impact: those with relatively low current energy usage face large payment increases than those with higher energy usage. However, if the fixed charge is allocated across energy users in a way that reflect their relative consumer surpluses from electricity services, then the rate reform can be more equitable and progressive. Under such a fixed charge distribution rule proposed by Wolak (2018), we find that the low energy customers – and those with lower variations in hourly consumption – tend to experience payment reductions while those with large consumption or large usage variations will face increases in their payments. This result illustrates that the design of RTP, and the method of the fixed cost recovery in particular, has a significant implication on the equity of pricing reforms.

We also conduct RTP simulations that incorporate price responses by the energy users. For this purpose, we apply an electricity demand specification that reflect recent estimates of the price elasticity of C&I sector electricity demand and the inter-hourly elasticity of substitution of electricity, along with other parameter values that are consistent with the current energy usage given the demand charge (explained in detail in the following section). The results indicate that the relationship between the change in the electric bill under RTP and the energy users' average electricity usage is less monotonic than in the case with zero price elasticity—reflecting that the price response alters the consumer-specific distributional impacts. The overall distributional impacts – regressivity of the uniform fixed charge and the progressive nature of surplus-proportional fixed charge – is the same.

What is notable is the difference in the welfare impacts with and without demand charge. Compared to the welfare gains of RTP where the demand charge is removed, the welfare gains are considerably smaller if the demand charge is maintained under RTP. While removing the demand charge requires larger adjustments in the fixed charge for the fixed cost recovery, it also leads to large welfare gains.

We also demonstrate that the main results about the distributional impacts of RTP remain the same under the marginal cost schedule that reflects larger penetrations of renewable energy in the energy mix. Such a marginal cost profile reflects larger fluctuations across hours of a day (with very low marginal costs during the daytime) and hence the welfare gains of RTP will be larger by an order of magnitude. Thus the benefits of RTP are expected to be larger in the future as the energy systems are decarbonized.

In what follows, Section 2 presents the theoretical framework for evaluating the distributional welfare impacts of real-time pricing. In Section 3, we introduce the data that is utilized in the analysis. Section 4 presents the findings from our analysis. We conclude this paper with final remarks and future research (Section 5).

## 2. Theoretical background and simulation procedure

### 2.1. Scenarios considered

We consider two cases to investigate the distributional impacts of RTP transitions: (1) when the consumers' energy usage stays the same (i.e., when the price elasticity of electricity demand is zero) and (2) when the consumers' demands are price elastic (the elasticity is nonzero).

The scenarios considered consist of the following.

1. Baseline under the current rate (volumetric and demand charge)
2. RTP with the current marginal costs, with and without demand charge, with or without price elasticity
3. RTP under a high renewable energy penetration scenario, without demand charge, with and without price elasticity

In order to investigate the distributional impacts of RTP, we consider two ways to allocate the fixed charge across different energy users for the fixed cost recovery:

1. Uniform fixed charge (each user pays the same fixed charge); and
2. Surplus-proportional fixed charge.

The surplus-proportional fixed charge follows the principle of benefit taxation. By following Wolak (2018)'s proposal, the fixed charge is set proportional to a proxy of the surplus for each consumer. We detail the specification of the scenarios in what follows.

largely depends on fuels with large negative externalities such as coal, (Borenstein and Bushnell, 2022) find that residential electricity rates exceed average SMC in most of the United States. On O'ahu as well, the social marginal costs are likely lower than the retail rates, which are at the highest level in the United States.

### 2.2. Scenarios with inelastic electricity demand

In this subsection, we present the simulation procedure under inelastic demand. We adopt the simulation procedure by Borenstein (2007) for this scenario. We calculate the current electricity bills for each sector in the sample by applying the current effective electricity rates; and the bill under RTP by applying the marginal costs based on FERC data. Similar to Borenstein (2007), the simulation model accounts for variable and fixed cost recovery for the utility. However, there are two main differences. We do not simulate wholesale costs, but rather utilize actual system lambda data from 2014 to calculate customer bills. Each consumer's volumetric payment changes depending on how its load profile aligns with the marginal cost profile. The second difference is that we explicitly consider fixed cost recovery under RTP with and without the demand charge.

For concreteness, we first compute the baseline payment of each customer $i$ in industry $j$ for a billing period (month) under the current rate as the following.[4] Let $h$ represent hour where $h = 1, \dots, H$ ($H$ would be 24) and $d$ represent day, $d = 1, \dots, D$ ($D$ refers to the number of days in the billing period). Let $x_{dh,ij}$ be the firm $(i,j)$'s load on day $d$ at hour $h$. Then

$$BCvol_{ij} = p \sum_{d=1}^{D} \sum_{h=1}^{H} x_{dh,ij}$$

is the energy charge (or the volumetric rate payment) under the current bill where $p$ is the flat volumetric rate. Let

$$BCdc_{ij} = p_{DC}\bar{x}_{ij}, \text{ where } \bar{x}_{ij} \equiv \max_{d,h}\{x_{dh,ij}\},$$

represent the demand charge payment under the current bill given demand charge $p_{DC} > 0$. (Customers pay for fixed charge under the current bill, but we assume that the current fixed charge is charged the same way under all scenarios.) Hence, the current bill is the sum of the volumetric and demand charge payment.

$$BC_{ij} = BCvol_{ij} + BCdc_{ij}.$$

Given real-time prices $\{p_{dh}\}$, the variable portion of the consumer's payments under RTP is given by

$$BRvol_{ij} = \sum_{d=1}^{D} \sum_{h=1}^{H} p_{dh} x_{dh,ij}.$$

Let $BRfc_{ij}$ be the fixed charge under RTP. Let $BRdc$ be the demand charge. Then the total payment under RTP for customer $i$ in sector $j$ is

$$BR_{ij} = BRvol_{ij} + BRdc_{ij} + BRfc_{ij}.$$

In order to compare alternative rate structures on a common ground, we assume that each RTP specification achieves the same fixed cost recovery:

$$\sum_j \sum_i BC_{ij} = \sum_j \sum_i BR_{ij}.$$

We assume that $\sum_j \sum_i BRvol_{ij}$ represents the variable cost; and hence, we define

$$FC \equiv \sum_j \sum_i BC_{ij} - \sum_j \sum_i BRvol_{ij},$$

to be the fixed cost to be recovered under all RTP scenarios.

#### 2.2.1. RTP with and without demand charge

We consider RTP scenarios with and without demand charge (i.e., $BRdc_{ij} = BCdc_{ij}$ or $BRdc_{ij} = 0$). RTP with demand charge retains the same demand charge as the current rate structure specifies. In this case, the fixed charge satisfies

$$\sum_j \sum_i BRfc_{ij} = \sum_j \sum_i BCvol_{ij} - \sum_j \sum_i BRvol_{ij},$$

i.e, they are equal to the difference between the current total volumetric payments and the total volumetric payments given RTP.

In contrast, under the RTP scenario without demand charge, the fixed charge needs to cover what the consumers pay for the current demand charge:

$$\sum_j \sum_i BRfc_{ij} = \sum_j \sum_i \{BCvol_{ij} + BCdc_{ij}\} - \sum_j \sum_i BRvol_{ij}.$$

#### 2.2.2. Distribution of fixed charge across consumers

We consider two specifications of the fixed charges: uniform charges and surplus-proportional chargers. Under the uniform fixed charge, it is charged equally across all C&I consumers:

$$BRfc_{ij} = \frac{\sum_l \sum_k BRfc_{kl}}{N},$$

where $N$ is the total number of C&I consumers. Given the large variation in the overall electricity usage levels across consumers, the uniform fixed charge is likely to have regressive impacts (i.e., large-scale consumer would face more favorable rate impacts). As an alternative, we consider a fixed cost allocation based on the consumers' "surplus" measures or the benefit taxation principle. Following Wolak (2018), this rate structure allocates fixed costs according to a proxy of each customer's (consumer) surplus from electricity services. For an energy user $(i,j)$ with hourly electricity load profile $x = \{x_{mdh,ij}\}$ ($m = 1, \dots, 12, d = 1, \dots, D_m, h = 1, \dots, 24$ where $x_{mdh,ij}$ represents the usage in hour $h$ on day $d$ in month $m$ with $D_m$ days in the billing cycle) on some base year, the following expression approximates the surplus:[5]

$$CS_{ij} \equiv \frac{1}{2}\frac{1}{24 * 365} * \sum_{m=1}^{12} \sum_{d=1}^{D_m} \sum_{h=1}^{24} x_{mdh,ij}^2 = \left(E[x_{ij}]\right)^2 + Var[x_{ij}].$$

The fixed charge for consumer $i$ is set to be proportional to its share of the total consumer surplus in the base year. Thus consumer $(i,j)$'s share of the fixed charge is given by

$$s_{ij} \equiv \frac{CS_{ij}}{\sum_l \sum_k CS_{kl}}.$$

The intuition behind this specification is that those customers with large electricity mean consumption level (large $E[x_{ij}]$) and large fluctuation (large $Var[x_{ij}]$) would face a larger cost burden.

### 2.3. Scenarios with elastic electricity demand

This section illustrates the derivation of the electricity demand with nonzero price elasticity. We assume two key parameter values—the price elasticity of overall electricity demand and inter-hourly elasticity (the elasticity of substitution of electricity usage across hours of a day). We apply these parameter values to a demand function, which is fitted to each consumer's observed load profile by taking into account the demand charge.

Consider an optimization problem on the allocation of electricity use within a day and across days in a given billing cycle. In what follows, we omit the subscript for the energy user $(i,j)$. Suppose that, in

[4] The bill may vary across periods (months). In the following discussion, we omit the index for periods.

[5] This formula assumes a linear approximation of hourly electricity demand with slope equal to one.

each month (or billing cycle) each firm minimizes the cost of electricity services ($x_{dh}$ in hour $h$ on day $d$) and a composite input ($z_d$ on day $d$):

$$\left(\sum_{d=1}^{D}\sum_{h=1}^{H} p_{dh}x_{dh}\right) + p_{DC}\bar{x} + \sum_{d=1}^{D} wz_d,$$

where $\bar{x} \equiv \max_{d,h}\{x_{dh}\}$ is the maximum demand during the billing period ("billing demand"),[6] $p_{DC}$ the demand charge, and $w > 0$ the unit price of the composite input, subject to a monthly output target $y \geq 0$. Under the flat pricing we have $p_{dh} = p$ for all $d,h$. We have $p_{DC} = 0$ if there is no demand charge. Suppose the firm's production function is given by:

$$f(z_d, q_d) = A\left\{\alpha z_d^{\theta} + (1-\alpha)q_d^{\theta}\right\}^{1/\theta}$$

with

$$q_d = \phi\left\{\sum_{h=1}^{H}\beta_h x_{dh}^{\rho}\right\}^{1/\rho},$$

where $q_d$ is the input of electricity services on day $d$. Notations $A$, $\phi$, and $\alpha$ represent production function parameters. The coefficients $\{\beta_h\}$ represent the share parameters of electricity usage in different hours. Parameter $\theta$ determines the elasticity of substitution between the composite factor and electricity, $\sigma \equiv 1/(1-\theta)$. Note that $\sigma$ also influences the own price elasticity of the electricity demand. On the other hand, $\rho$ determines the size of the elasticity of substitution (e.g., inter-hour substitution of electricity) $\sigma_e \equiv 1/(1-\rho)$. We normalize the parameters so that $\sum_{h=1}^{H}\beta_h^{\sigma_e} = 1$.

The firms' constraint when minimizing the cost of electricity use is given by

$$\sum_{d=1}^{D}\theta_d f(z_d, q(x_{d1}, x_{d2}, \dots, x_{dH})) \geq y,$$

where $\theta_d$ represents daily fluctuations (say due to weather, weekend vs. weekdays etc.),[7] and

$$x_{dh} \leq \bar{x} \quad \text{for all} \quad d,h. \tag{1}$$

The objective is linear while function $f$ is strictly quasiconcave, so there is a unique solution. The Lagrangian function is given by

$$\begin{aligned} L = &-\left(\sum_{d=1}^{D}\sum_{h=1}^{H} p_{dh}x_{dh} + p_{DC}\bar{x} + \sum_{d=1}^{D} wz_d\right) \\ &+ \lambda\left(\sum_{d=1}^{D}\theta_d f(z_d, q(x_{d1}, x_{d2}, \dots, x_{dH})) - y\right) \\ &+ \sum_{h,d}\left\{\mu_{dh}(\bar{x} - x_{dh})\right\}. \end{aligned}$$

Suppose the solution satisfies $z > 0$ and $x_{dh} > 0$ for all $(d,h)$. The first-order condition includes the following.

$$\frac{\partial L}{\partial x_{dh}} = -p_{dh} + \lambda\theta_d\frac{\partial f}{\partial x_{dh}} - \mu_{dh} = 0 \text{ for all } d,h,$$

$$\frac{\partial L}{\partial z_d} = -w + \lambda\theta_d\frac{\partial f}{\partial z} = 0 \text{ for all } d,$$

$$\frac{\partial L}{\partial \bar{x}} = -p_{DC} + \sum_{h,d}\mu_{dh} = 0,$$

$$x_{dh} \leq \bar{x},\ \mu_{dh} \geq 0,\ \mu_{dh}(\bar{x} - x_{dh}) = 0 \text{ for all } d,h.$$

The simulation procedure includes specifications of the function parameters based on the first order conditions for cost minimization matched to the observed load profiles. For this purpose, we need to identify the number of days when the demand charge constraint (1) is binding. It follows from the first order conditions for an interior solution that

$$p_{DC} = \sum_{(d,h)\in D_e}\mu_{dh},$$

where $D_e$ represents the set of hours and days when the load is at the maximum level. (The peak hour $h$ for schools would be when the air conditioning is needed during the day time when it is hottest. The peak for hotels would be in early evening, similar to what typical residential load profiles exhibit, c.f., Figs. 5 and 6.) We specify $D_e$ for each sector based on what the seven-day profile indicates. Fig. 3 demonstrates that, for department stores in the sample, the load profile is almost identical on every day of the week including the weekend. This indicates that the demand charge constraint is binding on seven days a week (i.e., $D_e$ is the set of the peak hour on all days during the billing cycle). In contrast, Fig. 4 illustrates that, for the hospitals in the sample, the weekend load (peak) is considerably lower than the peak on the weekdays. Thus the demand charge constraint is binding only on weekdays (i.e., $D_e$ consists of the peak hour on weekdays).

Hence, the days of a week when the peak demand levels coincide with each other would be different across sectors. The "shadow" price ratio between peak and off-peak periods must be adjusted accordingly, i.e., for each energy user we have

$$\mu_{dh} = \frac{P_{DC}}{\bar{D}_e},$$

where $\bar{D}_e$ represents the number of hours in set $D_e$. Therefore, the effective (relative) shadow price on the peak load is $\frac{p}{p+\frac{p_{DC}}{\bar{D}_e}}$, not $\frac{p}{p+p_{DC}}$. Hence, if the peak hour is unique on each day, we have

$$\frac{p}{p+\frac{p_{DC}}{\bar{D}_e}} = \frac{\text{effective rate}}{\text{effective rate} + \frac{\text{demand charge}}{\text{the number of days where the peak load would coincide}}}.$$

We now explain the simulation procedure when customers are price elastic. Given the functional form assumed earlier, it follows that

$$\frac{p_{dh}}{p_{dh'}} = \frac{\beta_h x_{dh}^{\rho-1}}{\beta_{h'}x_{dh'}^{\rho-1}}$$

for any hours $h, h'$ on day $d$, and hence

$$\frac{x_{dh'}}{x_{dh}} = \left(\frac{p_{dh'}}{p_{dh}}\frac{\beta_{h'}}{1-\beta_h}\right)^{\sigma_e}.$$

for all off-peak periods $h, h'$. Let $(\bar{d}, \bar{h}) \in D_e$. The ratio of the off-peak and the peak consumption on day $\bar{d}$ is given by

$$\frac{\sum_{h\neq\bar{h}}x_{\bar{d}h}}{x_{\bar{d}\bar{h}}} = \frac{\sum_{h\neq\bar{h}}\beta_h^{\sigma_e}}{\beta_{\bar{h}}^{\sigma_e}}\frac{p^{-\sigma_e}}{\left(p+\frac{p_{DC}}{D_e}\right)^{-\sigma_e}} = \frac{1-\beta_{\bar{h}}^{\sigma_e}}{\beta_{\bar{h}}^{\sigma_e}}\frac{p^{-\sigma_e}}{\left(p+\frac{p_{DC}}{D_e}\right)^{-\sigma_e}}.$$

[6] To be precise, the billing demand for period $t$ under Schedule P on O'ahu is given by

$$\bar{x}^t = \max\left\{\max_{d,h}\{x_{dh}^t\}, \frac{1}{2}\max_{d,h}\{x_{dh}^t\} + \frac{1}{2}\max_{s=1,\dots,11}\{\max_{d,h}\{x_{dh}^{t-s}\}\}\right\},$$

i.e., it depends on the maximum demand in the current month relative to the maximum demand in the previous month. The definition of the billing demand reflects the official rule on the demand charge (Hawaiian Electric Company, 2018):

> The maximum demand for each month shall be the maximum average load in kW during any fifteen-minute period as indicated by a demand meter. The billing demand for each month shall be the highest of the maximum demand for such month, or the mean of maximum demand for the current month and the greatest maximum demand for the preceding eleven (11) months, whichever is the higher, but not less than 300 kW.

[7] When specifying the parameter values based on electricity usage observation, we assume $\theta_d$ is the same on all weekdays and on all days for consumers who have the same daily profile on both weekdays and weekend days.

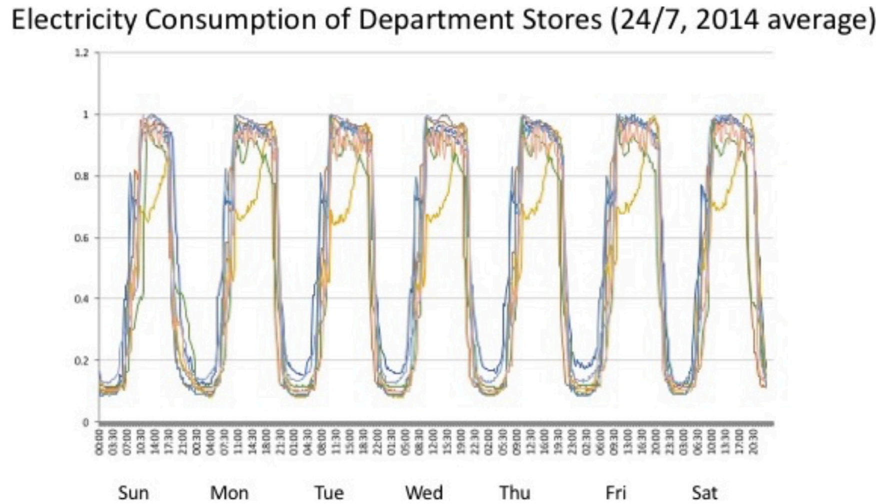



**Fig. 3.** Peak coincides for 7 days a week for general merchandise.

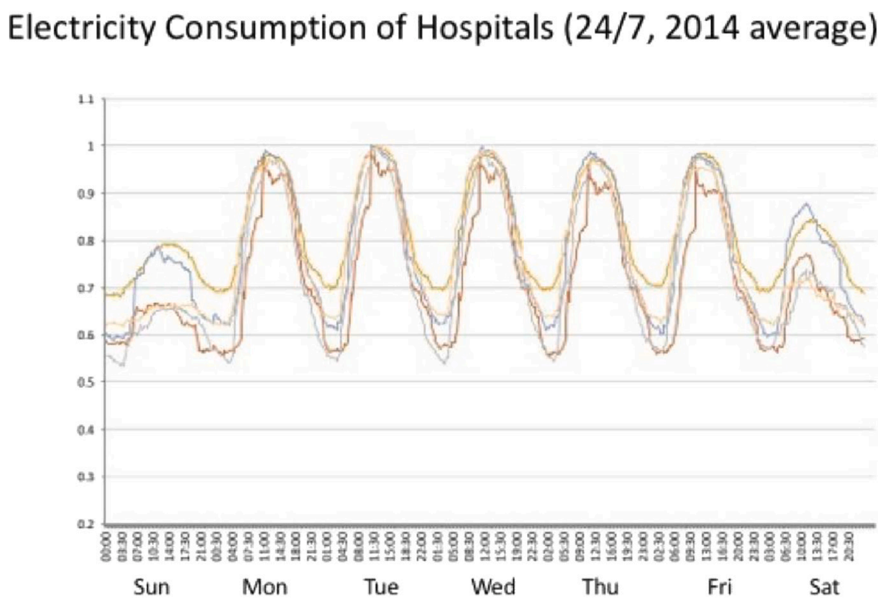



**Fig. 4.** Peak coincides on weekdays for hospitals.

Here we specify $\bar{D}_e$ for each sector depending on whether the demand charge constraint is binding on all days or on all weekdays. The above equality indicates that, under flat pricing with constant rate $p$, we have

$$x_{\bar{d}\bar{h}} p^{-\sigma_e} - x_{\bar{d}\bar{h}} p^{-\sigma_e} \beta_{\bar{h}}^{\sigma_e} = \sum_{h \neq \bar{h}} x_{\bar{d}h} \left(p + \frac{p_{DC}}{D_e}\right)^{-\sigma_e} \beta_{\bar{h}}^{\sigma_e}$$

and hence

$$\beta_{\bar{h}}^{\sigma_e} = \frac{x_{\bar{d}\bar{h}} p^{-\sigma_e}}{\sum_{h \neq \bar{h}} x_{\bar{d}h} \left(p + \frac{p_{DC}}{D_e}\right)^{-\sigma_e} + p^{-\sigma_e} x_{\bar{d}\bar{h}}}.$$

This is how we can pin down the value of $\beta_{\bar{h}}^{\sigma_e}$ based on the observed load profile under volumetric price $p$ and demand charge $p_{DC}$. We also note that

$$\frac{x_{\bar{d}h}}{x_{\bar{d}\bar{h}}} = \frac{\beta_h^{\sigma_e}}{\beta_{\bar{h}}^{\sigma_e}} \frac{p^{-\sigma_e}}{\left(p + \frac{p_{DC}}{D_e}\right)^{-\sigma_e}}$$

for all $h \neq \bar{h}$. Solve for $\beta_h^{\sigma_e}$ to obtain

$$\beta_h^{\sigma_e} = \frac{x_{\bar{d}h}}{x_{\bar{d}\bar{h}}} \frac{\left(p + \frac{p_{DC}}{D_e}\right)^{-\sigma_e}}{p^{-\sigma_e}} \beta_{\bar{h}}^{\sigma_e}$$

for all $h \neq \bar{h}$.

Once $\beta_h$'s are identified, we can compute the electricity consumption for all hours. For off-peak $h$, we have

$$x_{dh} = \beta_h^{\sigma_e} p^{-\sigma_e} \left\{ \left( \sum_{h \neq \bar{h}} \beta_h^{\sigma_e} \right) p^{1-\sigma_e} + \beta_{\bar{h}}^{\sigma_e} \left(p + \frac{p_{DC}}{D_e}\right)^{1-\sigma_e} \right\}^{\frac{\sigma_e - \sigma}{1-\sigma_e}} C,$$

where $C$ is a constant. At the peak hour, the consumption satisfies

$$x_{\bar{d}\bar{h}} = \beta_{\bar{h}}^{\sigma_e} \left(p + \frac{p_{DC}}{D_e}\right)^{-\sigma_e} \left\{ \left( \sum_{h \neq \bar{h}} \beta_h^{\sigma_e} \right) p^{1-\sigma_e} + \beta_{\bar{h}}^{\sigma_e} \left(p + \frac{p_{DC}}{D_e}\right)^{1-\sigma_e} \right\}^{\frac{\sigma_e - \sigma}{1-\sigma_e}} C.$$

Given the solved demand functional form, we assume elasticity values based on the findings from a companion paper (Oshiro, 2018) and the literature (Coffman et al., 2016). We assume the price elasticity of demand to be −0.10 based on an estimate of the price elasticity of demand in the C&I sector on O‘ahu (Oshiro, 2018); and the substitution elasticity parameter to be 0.15 from Coffman et al. (2016). Based on the first order conditions and the hourly load data, we pin down the

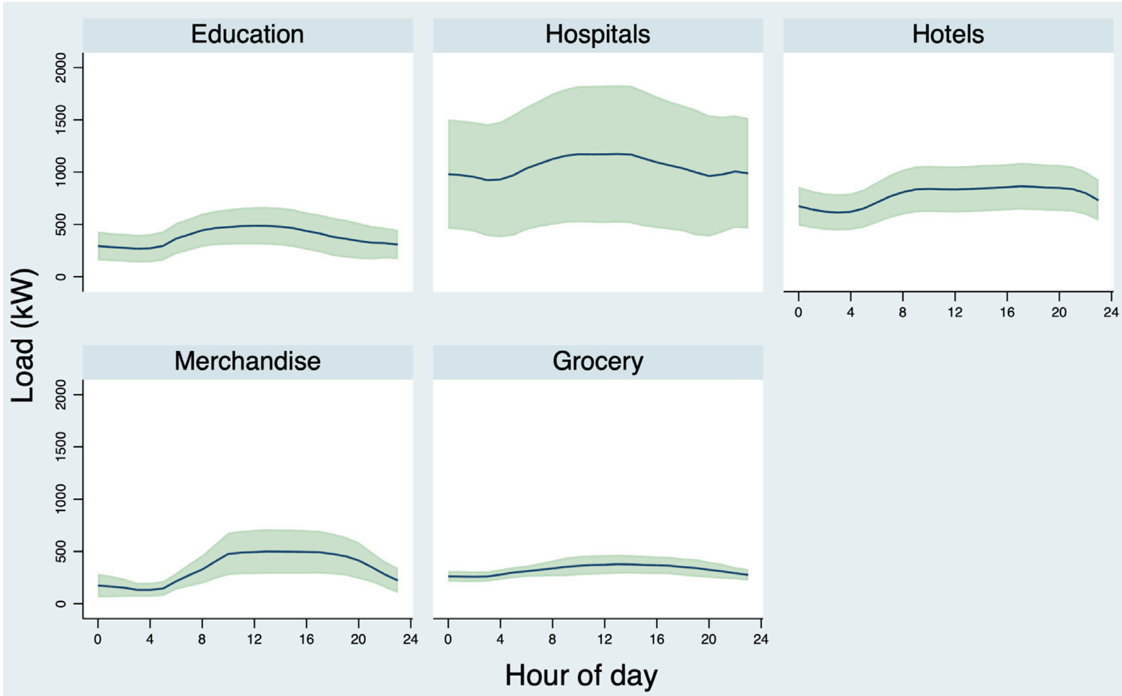



**Fig. 5.** Sectoral average load profile (with the 95% confidence interval, March 2014).

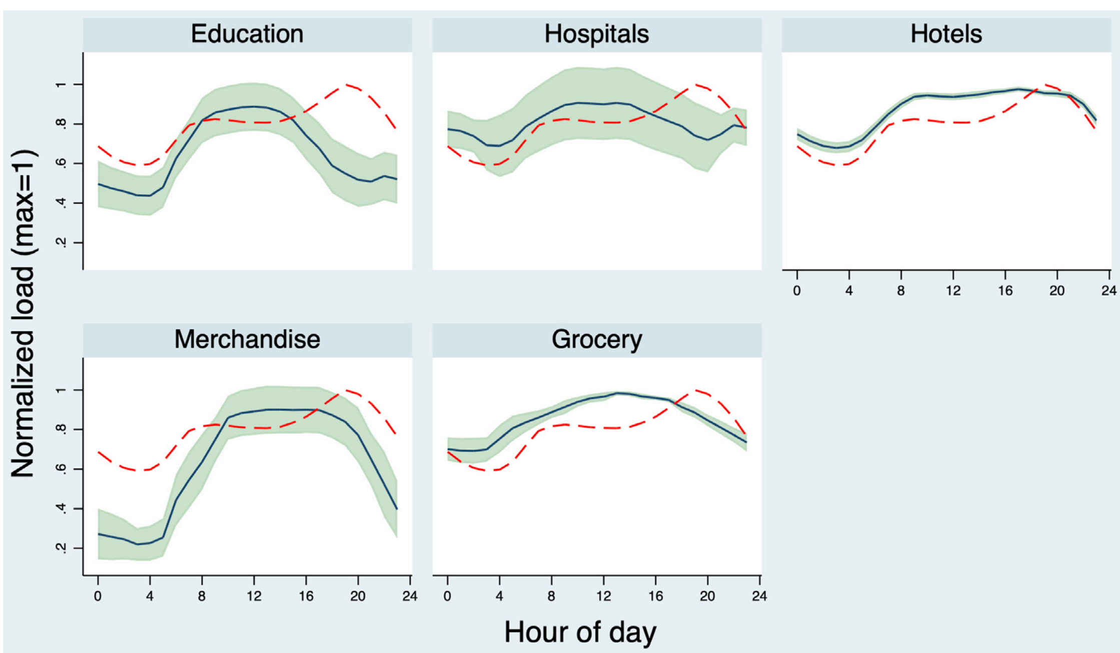



**Fig. 6.** System and Individual Load Overlay.
Note: The figures illustrate the overlay of the average system-level hourly load (red dotted line) and the average sector-level hourly load (blue solid line with the 95% confidence interval). The sector-level load is an average of the individual energy user's load (normalized so that the peak load equals one) in each sector. The data sources are FERC and Hawaiian Electric Company.

values of the share parameters and demand function constants for each customer. We then apply the derived demand functions to simulate load profiles under real-time pricing. With the simulated load profiles, we study how the payments change under RTP.

*2.4. Evaluation of welfare impacts*

With price-elastic demand specification, we can assess the welfare impacts of transitioning from the current flat (above-marginal cost) electricity pricing to RTP.[8] In the short run, RTP reduces price distortions associated with the current retail prices that differ from the

[8] Borenstein (2007) not only computes the total payments for customers, but also consumer surpluses because "total payments fail to capture the benefits to consumers when they increase consumption during low-price hours and would misstate the losses when a customer reduces its bill by lowering consumption during high price periods, but also loses the value of that consumption (Borenstein, 2007)".

social marginal costs (Jacobsen et al., 2020). In the long run, the correct scarcity signals of RTP may alleviate the need to construct additional generation capacity in an inefficient manner. Here we focus on the short-run impacts.

To simulate the welfare impacts, we follow Jacobsen et al. (2020) to approximate the Herberger welfare effects with multiple goods (i.e., electricity services in different hours). The welfare effects (per day) of a shift from vector $p$ to vector $p^*$ is approximately

$$\Delta S(p, p^*) = \frac{1}{2}\sum_{h=1}^{24}\sum_{k=1}^{24}(p_h^* - p_h)(p_k^* - p_k)\frac{\partial x_h}{\partial p_k}.$$

This approximation is correct if the derivatives $\frac{\partial x_h}{\partial p_k}$ are linear. Our demand exhibits nonlinearity. To the extent that the difference between $p$ and $p^*$ are not large, we take this expression as a reasonable approximation of the true welfare effects. We apply this metric, aggregated over all consumers in the sample and as a ratio to their current total electricity payments, in order to assess the welfare impacts under each RTP scenario.

### 2.5. Scenarios with alternative marginal costs under high renewable energy integration

In 2014 (the year this study's baseline data comes from), the Renewable Portfolio Standards (RPS, roughly the share of the sales of electricity generated from renewable sources) was 15.4% on O'ahu. As of 2022, the RPS level has increased to 36%. The State of Hawai'i has adopted a goal to achieve 100% RPS by 2045. We consider a scenario of RTP with a marginal cost profile that represents a high renewable-energy penetration future. Fig. 8 displays the simulated future marginal cost profile, which is based on one of the specifications described in Imelda et al. (2018) for a high renewable energy penetration scenario in 2045.[9] The profile involves a considerable drop in the daytime marginal costs due to high solar PV penetration. A caveat is that these marginal cost profiles will be updated in the future. In addition, the electricity demand will also likely change. The simulations below do not capture uncertainty about the changes in the marginal costs and the electricity demand in the future, but it illustrates the distributional and welfare impacts of RTP when the energy mix is decarbonized.

## 3. Data sources

### 3.1. Commercial and industrial interval consumption data

We apply electricity usage data obtained from Hawaiian Electric Company under a confidential agreement. The sample consists of about 500 large-scale energy users with a meter that collects and stores data on their electrical usage at 15-minute intervals, spread over various sectors on O'ahu, in March and September 2014. Small C&I customers that are in the general non-demand rate schedule (Rate G) are not included in this data set. We classify customers according to the North American Industrial Classification System (NAICS). The major sectors in the sample are hotels, schools, hospitals, general merchandise (department stores), and grocery stores.

We restrict the sample to 100 customers with active energy usage, which are subject to the same rate schedule ("Schedule P").[10] Customers who have solar PV systems are excluded from this sample as they likely have different price responses and distributional consequences of rate reforms.

Fig. 5 displays the average 24-hour load profile by sector. It demonstrates the differences in the level and the shape of the load profile across different sectors.

To better illustrate the relationship between the sectoral usage and the overall profile of O'ahu, Fig. 6 presents the overlay of the sectoral profile (normalized to equal 1 at the respective peak level) and the system load profile. Note that the Renewable Portfolio Standard achievement level on O'ahu was 15.2% in 2014, with more than 382GWh of distributed PV output (5.6% of total sales of electricity, Office (2020)): thus its system daily load already reflected an impact of behind-the-meter PV. We observe that the accommodation sector (hotels) has the load profile closest to the system-wide profile. Specifically, the peak occurs around 8am and at night around 8pm. Other sectors do not have load profiles that coincide with the system. For example, the medical, education, merchandise, and grocery sectors experience peak demand in the daytime when solar is most available (11am to 2pm). These sectors may possibly benefit the most when introducing a marginal cost pricing as their peaks occur when the cost of generation to the utility is relatively low. Moreover, the educational sector may also benefit because the base load is low when the cost of generation for the utility is high.

We note that the customers included in this data have access to their electrical usage through an internet portal. Participation in this service is voluntary, and access to data is possible through contacting a representative of the utility company. Specifically, customers have data on the peak demand and energy usage trends throughout the year. Access to the data is possible through the portal at any time, making it easier for customers to manage demand and energy usage, document the impact of energy-efficient investments, and determine the impact of any new equipment or changes in operations. Therefore, the customers in the sample may be better informed about their usage behavior than other customers, who do not have access to such portal.

### 3.2. Marginal cost data

In addition to consumer demand data, we apply data on the hourly costs of electricity services. This is known as system lambda and obtained from the Federal Energy Regulatory Commission (FERC). System lambda includes the generation, distribution and transmission costs to the utility, and is closely related to the marginal cost of producing electricity incurred by the utility. We use this measure as a proxy to reflect the "real-time" costs of the electricity services.

Fig. 7 presents the overlay of monthly effective rates and monthly-average system lambda. As seen from the figure, system lambda tends to be lower than the effective rates at all year–month combination. This is because the effective rates include fixed cost recovery for the utility while the system lambda only reflects the marginal change in variable costs. The system lambda in March exhibits a peak between 7am and 11am and another between 6pm and 10pm, coinciding with the system peak load during these hours. We use the system lambda and the effective retail rates presented here as inputs to the simulation model (see Fig. 7).

## 4. Results

We first summarize the distributional impacts of alternative RTP options. Then we discuss the welfare impacts of RTP given elastic demand.

### 4.1. Distributional impacts

Fig. 9 illustrates how the electricity payment changes for the C&I energy users in the sample. Panels (a), (b), and (c) represent the results

[9] Imelda et al. (2018) simulate the welfare effects of real-time pricing under optimal and alternative energy mix scenarios in Hawai'i. The marginal cost scenario in Fig. 8 assumes the price elasticity of demand −0.1, electric vehicle share of total vehicle fleet at 50%, 100% renewable energy, with load projected in 2045. The energy mix consists of a large share of solar power, with wind power and battery energy storage meeting the load during the night time. See https://www2.hawaii.edu/~mjrobert/power_production/ for the profile of the resulting energy mix.

[10] Rate Schedule P applies to energy users with monthly peak demand of 300 kW or more (for more than three times within a given year).

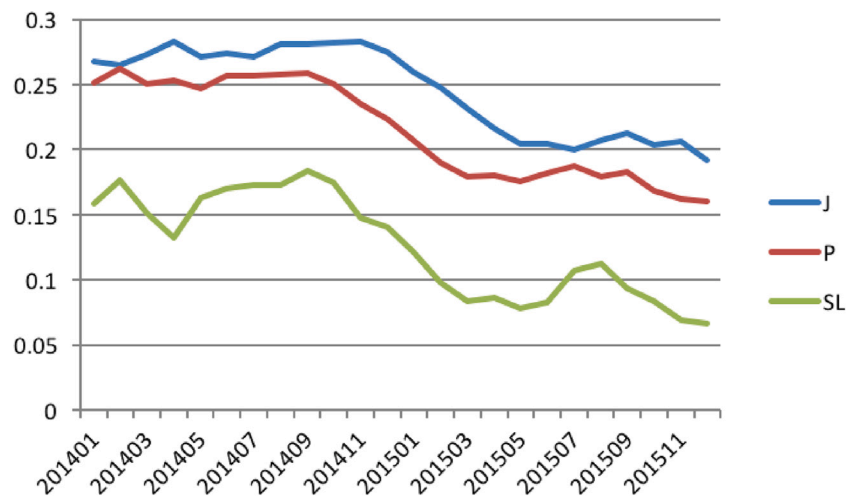



**Fig. 7.** Monthly effective rates with system Lambda.
*Note:* The figure above shows the changes in monthly effective rates (cents/kWh) from 2014 to 2015 for rate schedules J and P, with the monthly system lambda ("SL"). System lambda is available at the hourly level but is aggregated to monthly measures to accommodate the monthly effective rates. For more information on the definition of effective rates refer to the text. Effective rate information are obtained from Hawaiian Electric's public website. https://www.hawaiianelectric.com/billing-and-payment/rates-and-regulations/hawaiian-electric-rates for more details. System lambda data are retrieved from the Federal Energy Regulatory Commission (FERC).

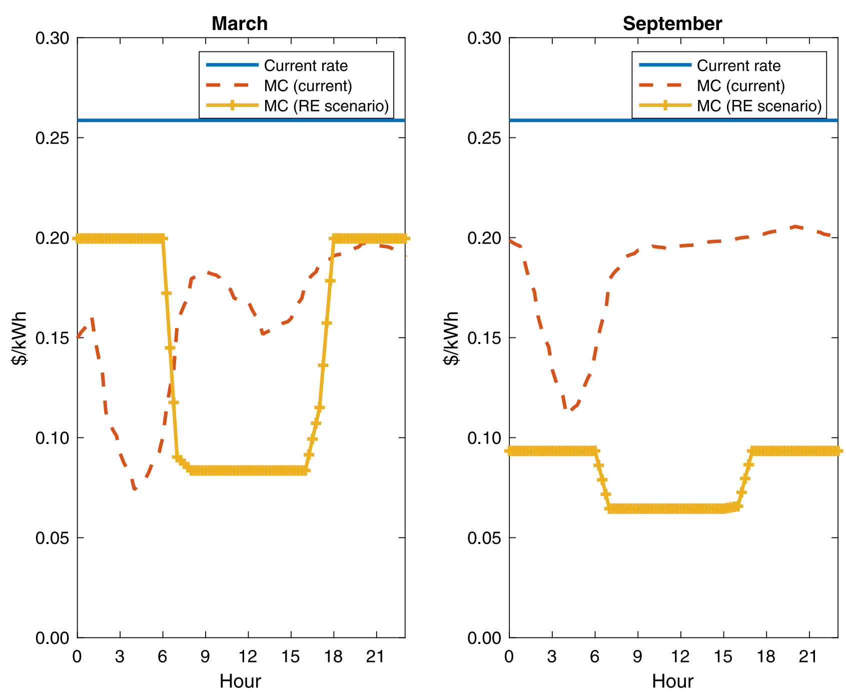



**Fig. 8.** Current retail rates and marginal cost profiles.
*Note:* The figure plots the effective volumetric rates and the average marginal cost profile in the corresponding months in 2014 as well as marginal cost profiles under a future scenario with large-scale renewable energy integration based on Imelda et al. (2018).

with inelastic demand while panels (d), (e), and (f) display the results with price-responsive demand. Panels (a) and (d) demonstrate that the distributional impacts of an RTP reform, if the demand charge is removed and the fixed charge is uniform across consumers, will be highly regressive. That is, while energy users with low mean hourly load experience a large increase in the energy bill, those with high load will face smaller or negative changes in the bill. This is due to the significant level of fixed cost recovery associated with the no-demand-charge scenarios.

Panels (b) and (e) describe the cases in which RTP is introduced while the rate payers still face the same demand charge. The presence of demand charge makes the RTP adoption less regressive than in panels (a), (d). This result occurs because average hourly load and the maximum demand are correlated, so that those with high maximum demand pay more under demand charge. However, the overall distributional impacts are still highly regressive.

Panels (c) and (f) represent the results when the fixed cost recovery is implemented with surplus-proportional allocation across energy users. Clearly, the billing impact is progressive unlike the first two cases. The magnitude of the maximum and the minimum payment changes is also smaller. Thus this result also indicates that surplus-proportional fixed charge allocations may lower the magnitude of the payment changes for all energy users.

While we observe a fairly monotonic relationship between the energy users' mean hourly load and their rate impacts in panels (a), (b), and (c) with no price response, the relationship is less monotonic

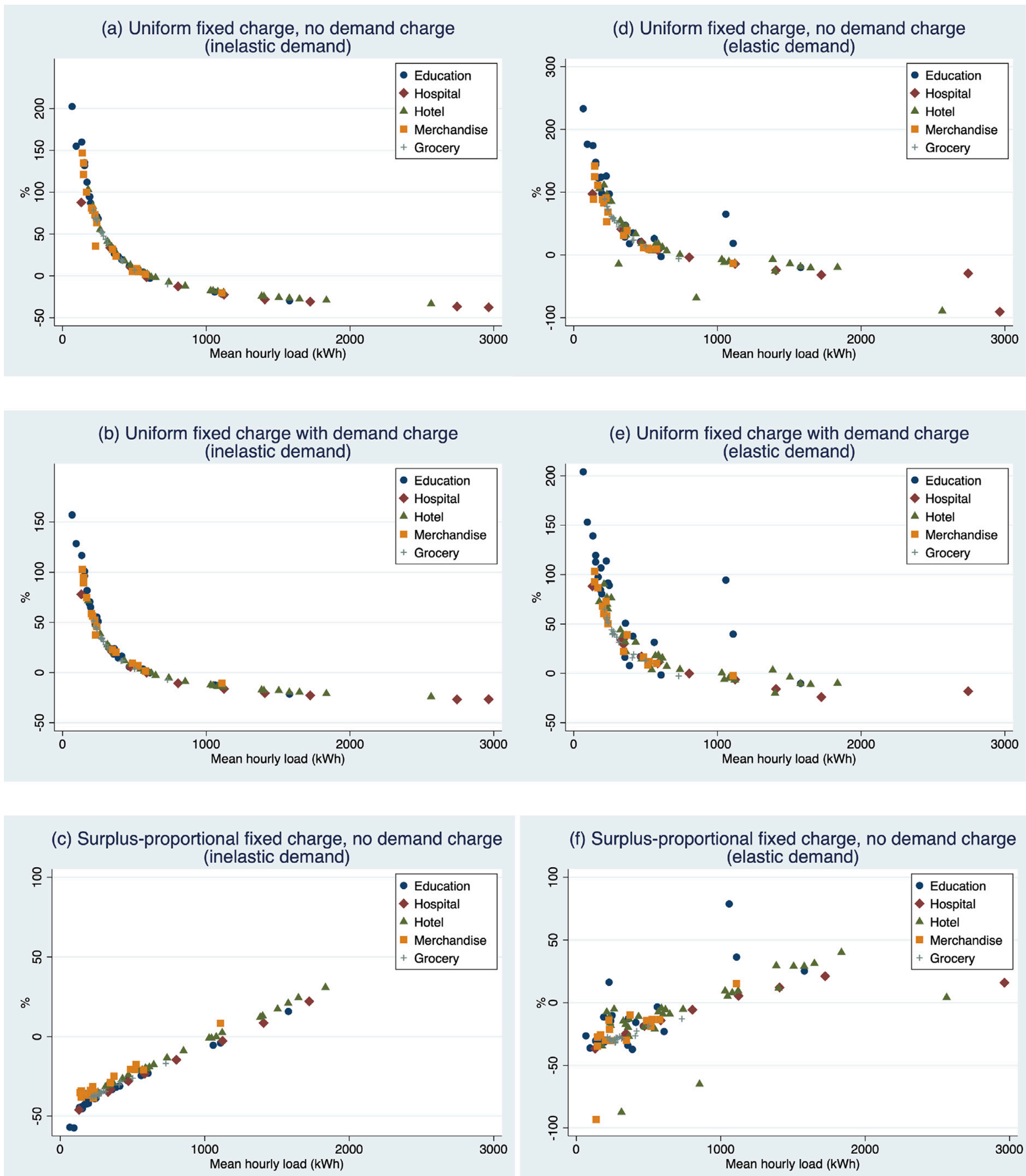



**Fig. 9.** Distributional impacts of changes to real-time pricing.
*Note:* Figure (a) through (f) above illustrates the change in the electricity payments for the C&I consumers in the sample under each RTP introduction. Based on electricity usage and cost data in March 2014.

when we assume nonzero price elasticity of demand (panels d, e, f). Even with fairly limited price elasticity and inter-hourly elasticity, we observe that the rate impacts exhibit larger variances among energy users with similar mean electricity usage.

Fig. 10 displays the distributional impacts under RTP by assuming that the marginal costs reflect energy mix with close to 100% renewable energy integration (the RE scenario). The distributional impacts are similar under this scenario with the uniform fixed charge (panel a, compared to panel d in Fig. 9). With the surplus-proportional fixed charge, the variation appears to be smaller under the RE scenario (panel b, compared to panel f in Fig. 9). In either case, the progressive property of the surplus-proportional demand charge remains the same under the RE scenario.

Table 1 represents the average change in the electricity payment under each RTP scenario by sector. Because of the size distribution in each sector, there are no clear winners or losers under each RTP scenario. However, the surplus-proportional fixed-cost distribution seems to favor the users in education, merchandise, and grocery sectors more

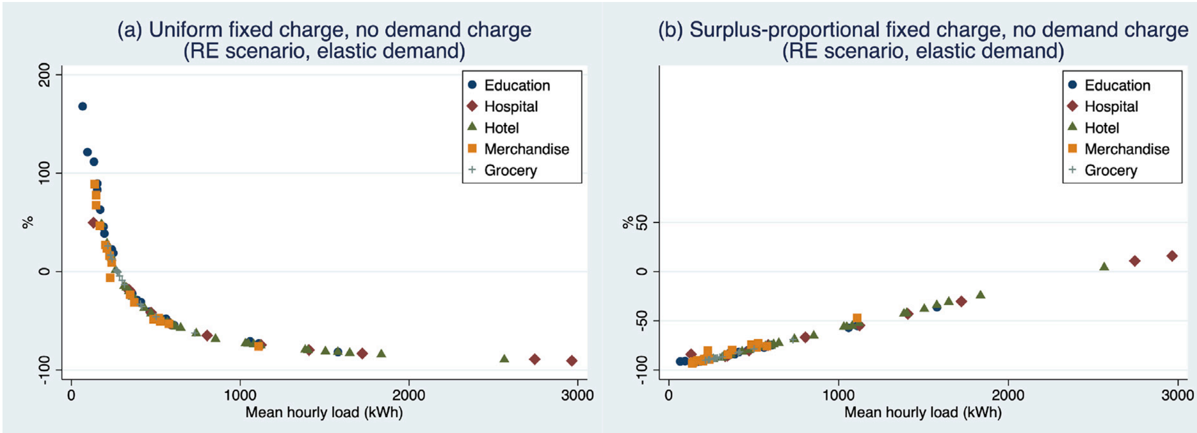



**Fig. 10.** Distributional impacts of changes to real-time pricing (renewable energy future scenarios).
*Note:* Figures (a) and (b) above illustrate the change in the electricity payments for the C&I consumers in the sample under each RTP introduction by assuming a simulated marginal cost profile under a high renewable energy integration scenario.

**Table 1**
Average change in the electricity payments by sector.

| | Education | Hospital | Hotel | Merchandise | Grocery |
|---|---|---|---|---|---|
| Uniform FC, no DC | 61.8 | 2.2 | 12.5 | 55.7 | 44.1 |
| Uniform FC with DC | 46.7 | 2.2 | 7.9 | 41.8 | 28.6 |
| Prop. FC, no DC | −32.8 | −4.5 | −12.2 | −27.9 | −33.6 |
| Uniform FC, no DC (ED) | 81.6 | 4.5 | 18.1 | 59.1 | 50.9 |
| Uniform FC with DC (ED) | 72.8 | 13.5 | 22.8 | 46.6 | 36.7 |
| Prop. FC, no DC (ED) | −13.0 | −2.2 | −6.7 | −24.4 | −26.8 |
| Uniform FC, RE (ED) | 13.0 | −48.6 | −42.6 | 1.2 | −8.1 |
| Prop. FC, RE (ED) | −81.6 | −55.3 | −67.4 | −82.3 | −85.8 |

*Note:* The numbers represent the change (in %) in the customer's electricity payment under the respective RTP reform, averaged by sector. "FC"=fixed charge, "Prop. FC" = surplus-proportional FC, "DC" = demand charge, "ED" = elastic demand, "RE" = RE scenario.

**Table 2**
Welfare impacts of RTP forms (%).

| Current MC, no DC | Current MC, with DC | MC with more RE, no DC |
|---|---|---|
| 0.043 | 0.015 | 2.519 |

*Note:* MC: marginal costs, DC: demand charge, MC with more RE refers to the scenario with a simulated MC profile under large-scale renewable energy integration. The numbers represent the magnitude (in %) relative to the total electricity payments of the C&I energy users in the sample.

than hospitals and hotels. This is largely due to the difference in the average load level (Fig. 5).

### 4.2. Welfare impacts

Table 2 summarizes the welfare impacts under three scenarios with elastic demand. The magnitude of the reduction in deadweight losses due to RTP reforms tends to be small, which is not surprising because the magnitude of the price elasticity of electricity demand tends to be small.[11] What is notable, however, is that retaining the demand charge would make the welfare improvements considerably small. With renewable energy integration and resulting changes in the marginal costs, the welfare impact of RTP is expected to be larger than what we can expect given the current marginal cost profile. Thus the benefit of RTP likely grows under decarbonized energy systems.

## 5. Discussion

Previous studies have theoretically and empirically showed the benefits of dynamic pricing schemes such as RTP in the residential sector. However, studies on the impact of dynamic pricing schemes on sectors within the C&I sector have been sparse while its usage accounts for a large share of total usage in many energy markets (two-thirds in O'ahu's case). Utilizing electricity consumption data for C&I sectors from Hawaiian Electric Company, we estimate the potential bill losses and gains under current and alternative rate structures. We introduce a simulation model of C&I sector energy demand, which takes into account the energy users' responses to demand charge. The findings from the simulations resonate with those of Borenstein (2005): introducing a dynamic pricing structure can harm some customers depending on the load shape of the sector and their load share. Sectors with peak hours that do not align with the system's and have a large load share would benefit the most from dynamic pricing schemes in both elastic and inelastic scenarios. This study can inform policy makers of the winners and losers if RTP were to be adopted and serve as a guide towards efficient pricing in Hawai'i.

Demand charge makes a difference on the fixed-payment impacts for energy users. It also plays a role in demand response. To the extent that the energy users are price responsive, demand charge affects the extent of peak shift; and reduces not only peak demand but the demand in other hours as well though in an inefficient way due to discrepancy in the volumetric price and the marginal costs. Demand charge is not an effective mechanism to contain the system peak when the individual and system peaks do not align with each other. If RTP is coupled with DC, the efficiency gains would be much smaller.

Whether an energy user gains or loses from an RTP rate reform depends on not only its load profile relative to the system's marginal cost profile, but the specification of the utility's fixed cost recovery, i.e., how the fixed cost payments are distributed across customers. While the particular surplus-proportional fixed charge that we consider makes the rate reform progressive, it still leads to a large change in the electric bill for some energy users. We could consider adjusting the formula for fixed charge allocation in order to address the equity needs that are relevant to the local energy markets.

The marginal cost profile considered in this paper does not reflect the social costs of carbon. Incorporating them would change the magnitude of the rate and welfare impacts, but the qualitative nature

[11] For a single market with demand $X$, constant (social) marginal cost $p^*$ and a distorted price $(1+\alpha)p^*$ with $\alpha \neq 1$, the deadweight loss as a fraction of the sales $p^* X(p^*)$ is approximated by $\alpha^2 \eta$ where $\eta \equiv (dX/dp)p^*/X(p^*)$ is the price elasticity of demand. With $\alpha = 0.1$ and $\eta = 0.1$, the deadweight loss is approximately equal to 0.001 or 0.1%.

of the contrast between RTP with and without demand change, and between uniform fixed charge and surplus-proportional fixed charge would remain the same.

The sectoral composition of the C&I sectors is different in different energy markets. While the commercial sectors are dominant in Hawai'i, the share of manufacturing or heavy industries is larger in other cities. The extent of distributional impacts and the alignment of sector-level peak with the system peak may be different in other markets. Future research could address how the fixed charge allocation can be tailored in different markets with different equity concerns.

## Acknowledgments

The primary data set used in this study was provided by Hawaiian Electric Company to the University of Hawai'i Economic Research Organization (UHERO) under a confidentiality agreement "Informing Smart Customer Load (I-Smart)", contract number MSTR-PLA-11-005. The views and opinions expressed in this paper are those of the authors and do not necessarily reflect the official policy or position of the Company. The authors thank Hawaiian Electric Company for making their customer data available for research. An earlier version of this paper was presented at the Workshop on "Environment and Energy Issues in the Asia and the Pacific Region" organized by the Research Institute for Environmental Economics and Management (RIEEM) at Waseda University and funded by the Tokyo Center for Economic Research (TCER). The authors would like to thank the workshop participants and two anonymous reviewers for their helpful comments.

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