NBER WORKING PAPER SERIES

THE EFFICIENCY AND DISTRIBUTIONAL EFFECTS OF ALTERNATIVE RESIDENTIAL ELECTRICITY RATE DESIGNS

Scott P. Burger
Christopher R. Knittel
Ignacio J. Pérez-Arriaga
Ian Schneider
Frederik vom Scheidt

Working Paper 25570
http://www.nber.org/papers/w25570

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2019

We thank, without implicating, Carlos Batlle, Richard Schmalensee, Paul Joskow, and Bentley Clinton for their support and insights. We thank Dave Kolata and Jeff Zethmayr for their support in accessing the data used in this study. The usual disclaimer applies. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Efficiency and Distributional Effects of Alternative Residential Electricity Rate Designs
Scott P. Burger, Christopher R. Knittel, Ignacio J. Pérez-Arriaga, Ian Schneider, and Frederik vom Scheidt
NBER Working Paper No. 25570
February 2019
JEL No. H23,L5,Q41,Q58

ABSTRACT

Electricity tariffs typically charge residential users a volumetric rate that covers the bulk of energy, transmission, and distribution costs. The resulting prices, charged per unit of electricity consumed, do not reflect marginal costs and vary little across time and space. The emergence of distributed energy resources—such as solar photovoltaics and energy storage—has sparked interest among regulators and utilities in reforming electricity tariffs to enable more efficient utilization of these resources. The economic pressure to redesign electricity rates is countered by concerns of how more efficient rate structures might impact different socioeconomic groups. We analyze the bill impacts of alternative rate plans using interval metering data for more than 100,000 customers in the Chicago, Illinois area. We combine these data with granular Census data to assess the incidence of bill changes across different socioeconomic groups. We find that low-income customers would face bill increases on average in a transition to more economically efficient electricity tariffs. However, we demonstrate that simple changes to fixed charges in two-part tariffs can mitigate these disparities while preserving all, or the vast majority, of the efficiency gains. These designs rely exclusively on observable information and could be replicated by utilities in many geographies across the U.S.

Scott P. Burger
MIT Energy Initiative
77 Massachusetts Avenue
Cambridge, MA 02139
sburger@mit.edu

Christopher R. Knittel
MIT Sloan School of Management
100 Main Street, E62-513
Cambridge, MA 02142
and NBER
knittel@mit.edu

Ignacio J. Pérez-Arriaga
Instituto de Investigacion Tecnologica (IIT)
Universidad Pontificia Comillas, Alberto Aguilera,
28015 Madrid, Spain
ignacio.perez@iit.upcomillas.es

Ian Schneider
MIT
77 Massachusetts Avenue
Cambridge, MA 02139
ischneid@mit.edu

Frederik vom Scheidt
Karlsruhe Institute of Technology (KIT)
Fritz-Erler-Straße 23
76133 Karlsruhe, Germany
frederik.scheidt@kit.edu

1 Introduction

Residential electricity tariffs typically distort—and thus do not allow consumers to respond to—the marginal cost of energy consumption. Rates are typically constant across time and location, despite the fact that short-run marginal costs can vary dramatically. As of the end of 2016, less than one quarter of one percent of residential customers in the U.S. faced electricity prices that reflected the real-time marginal cost of energy production (U.S. Energy Information Administration, 2017). Furthermore, the bulk of system costs[1] are recovered through volumetric charges—that is, charges per-unit of energy consumed—despite the fact that a substantial fraction of these costs are fixed[2] in the short term. More economically efficient rate designs—enabled in part by the proliferation of smart metering infrastructure—could substantially improve market efficiency (Borenstein, 2005a). However, the potential distributional impacts across customer types and incomes of transitioning from today's tariffs to more efficient designs have historically impeded progress (Joskow and Wolfram, 2012).

This paper examines the distributional and economical efficiency implications of residential electricity tariffs. Using interval metering data—measuring electricity consumption every 30 minutes—for more than 100,000 customers in the Chicago, Illinois area, we assess the economic benefits of efficient tariffs relative to alternative tariff designs. We then use census data to understand the demographics—i.e. income levels—of the customers in our sample. A regulator might seek to shift from the current tariff structure to a two-part tariff, because the two-part tariff has higher economic efficiency. If this two-part tariff has an equal fixed charge for all customers, we demonstrate that this shift is regressive; the change in monthly bills is larger, as a share of income, for lower income consumers. However, we show that a two-part tariff that bases the fixed charge on income or other measures that correlate strongly with income can improve distributional outcomes without substantially sacrificing economic efficiency.

The issues addressed in this paper are likely to increase in importance as distributed energy resources (DERs), such as rooftop solar, become more prevalent. When located and operated appropriately, DERs can deliver substantial benefits (Cohen et al., 2016). However, if

[1] Tariffs are designed to recover all energy costs, transmission and distribution network costs, as well as the costs of taxes, and additional regulatory and policy costs. In locations where payments are made to support generation capacity, tariffs recover these costs as well. A large portion of non-energy costs cannot be recovered through marginal cost pricing, and can therefore be considered residual costs. The structure of the tariff —that is, the mix of per-kilowatt-hour, per-kilowatt, and per-customer charges— varies widely and is typically determined by a mix of regulatory and market-based decisions.

[2] As we will detail in Section 2, the challenge of network cost recovery is not solely that network costs are fixed. Non-convexities in the cost function and policy and regulatory intervention also present challenges.

investment and operation decisions are not aligned with system objectives, DERs can substantially increase system costs (Schmalensee et al., 2015). The lack of spatial variation in retail prices distorts where DERs are placed within a network and how they are operated. In addition, remunerating transmission and distribution costs through volumetric charges over-incentivizes solar adoption by driving a wedge between the private and social returns to solar adoption. Adopters of some DERs, for example, rooftop solar, are able to reduce, or eliminate, their payments for transmission, distribution, and other regulated costs, despite the fact that these DER owners remain connected to and continue to use the network. Given utility revenue sufficiency constraints, this leads to increases in the transmission and distribution volumetric charges faced by other customers (Pérez-Arriaga et al., 2016).

This can also have large distributional consequences. Because solar adoption tends to be positively correlated with income, high-income consumers are effectively passing on their contributions to transmission and distribution costs to lower-income consumers. Finally, widespread adoption of renewables can lead to larger diurnal price swings (Seel et al., 2018), exacerbating the difference between time invariant rates and the social marginal cost of consumption.

These converging challenges have led many regulators, policy makers, consumer advocates, and utilities to call for improved tariff designs. For example, the New York Department of Public Service recently called for "more precise price signals...that will, over time, convey increasingly granular system value" (New York Department of Public Service, 2016b). New York is not an anomaly. In 2017, regulators in 45 of 50 U.S. states and the District of Columbia opened dockets related to tariff design or made changes to tariff design (Proudlove et al., 2018). Similarly, in November 2016, the European Commission issued a sweeping set of rulings, with tariff design as a centerpiece (European Commission, 2016).

The economic pressure to redesign electricity rates is countered in part by concerns among policy makers and regulators of how more efficient rate structures might impact different socio-economic groups in terms of both average bills and bill volatility (Burger et al., 2018). For example, the Massachusetts Department of Public Utilities (MADPU), the New York Department of Public Service (NYDPS), and the California Public Utilities Commission (CPUC) all list concerns about the distributional impacts of rates in their principles for rate design (Massachusetts Department of Public Utilities, 2016; New York Department of Public Service, 2016a; Commission, 2018). Distributional concerns are not unfounded. For example, the U.S. Energy Information Administration recently found that 31% of U.S. households struggled to pay the costs of meeting energy needs (Berry et al., 2018). In practice, regulatory decisions highlight these concerns: in the U.S. in the second quarter of 2018, state electricity regulators rejected over 80% of utility requests to increase fixed charges, frequently citing the potential impacts on low-income customers (Trabish, 2018; Proudlove et al., 2018).

Our work leads us to a number of novel findings. First, we find that, holding the proportion of fixed and volumetric charges in the tariff constant, annual electricity expenditures tend to decrease for low-income customers from movements towards more time-varying rates. However, increases in customer fixed charges tend to increase expenditures for low-income customers who, on average, consume less electricity than their more affluent counterparts. The net effect of a rate design with real-time energy prices and uniform fixed charges for residual cost recovery is a near monotonic negative relationship between income and changes in expenditures. Second, in our sample, the economic distortions of recovering residual network and policy costs through volumetric tariffs likely outweigh the distortions that emerge from charging an energy price that does not reflect the underlying time- and location-varying cost of energy.[3] Finally, we find that changes to fixed charge designs can preserve the efficiency gains of transitioning to efficient residual cost recovery while mitigating undesirable distributional impacts. We highlight three methods for designing fixed-charges for residual cost recovery —based on customer demand characteristics, income, or geography— that mitigate the regressiveness of fixed charges.

The paper proceeds as follows. Section 2 provides an overview of the literature on equity and efficient retail tariffs, as well as a summary of the data and methods used in this study. Section 3 assesses the surplus gains and distributional impacts of moving to alternative rate designs. This section motivates the benefits of efficient pricing, as well as the need for efficient two-part tariff designs that avoid the distributional challenges of uniform fixed charges. Section 4 demonstrates that simple mechanisms for designing fixed charges in two-part tariffs can improve distributional outcomes—in particular, distributional outcomes related to low-income customers. Section 5 summarizes and concludes.

2 Background, Data, and Methods

The literature on efficient electricity tariff design is vast. The theoretical benefits of efficient price signals are well established, with economic literature dating back to the early-20th

[3] Borenstein and Bushnell (2018) compares the distortion created by inefficient residual cost allocation with the the inefficiency created by the lack of meaningful prices on externalities such as greenhouse gas emissions across the U.S. They find that these two countervailing distortions cancel in some locations, while one dominates the other in other locations.

century.[4] The benefits of real-time pricing have been empirically demonstrated as well (Jessoe and Rapson, 2014; Wolak, 2011; Allcott, 2011). This paper touches primarily on two strands of this literature: recovery of non-convex costs in the monopoly setting and the equity or distributional impacts of rate design.

Energy costs vary, often by orders of magnitude, over time and space due to the changing marginal cost of power generation, the physical laws that govern the flow of power over transmission and distribution networks, and the need to constantly balance electricity supply and demand (Schweppe et al., 1988). At any given point in time and location in the power system, the efficient energy price is the short-run social marginal cost of delivering power to that point, adjusted for losses, congestions, externalities, and the potential for scarcity.[5] Under a restrictive set of assumptions, short-run social marginal cost-based pricing (with appropriate scarcity pricing) can recover all fixed and variable energy generation costs (Schweppe et al., 1988). The same theoretical logic holds for network costs. However, the necessary assumptions typically do not hold in practice for networks (Pérez-Arriaga et al., 1995) or generation capacity (Vázquez et al., 2002; Joskow, 2008). Pricing based on marginal costs leaves a set of residual costs—network, capacity, and policy and regulatory costs that cannot be recovered through marginal rates. Residual costs emerge either because of non-convex cost curves—energy production for network capacity, for example—or from policy and regulatory intervention.

A central challenge in utility pricing is recovery of residual costs in a manner that minimally impacts welfare (Joskow, 2007; Schweppe et al., 1988). Because residual costs arise from non-convexities in the long-run cost function of supplying power, it is impossible to attribute these fixed costs to any one individual on the basis of cost-causation (i.e. marginal cost) pricing. The optimal method for residual cost recovery depends on a variety of assumptions. In general, two-part (i.e. containing both a fixed, per-customer charge and a volumetric charge) tariffs will generally be substantially more efficient than optimal linear (i.e. purely volumetric) tariffs[6] (Brown and Sibley, 1986). We therefore focus our atten-

[4] Coase (1946) contains early discussion of two-part tariffs, designed to distinguish between marginal and residual cost recovery. Houthakker (1951) expanded upon earlier calls for two-part tariffs by distinguishing between the impacts of peak- and non-peak-coincident demand. Vickrey (1971) presented one of the first descriptions of the benefits of real-time pricing based on short-run marginal costs. This theory has been expanded upon in more recent work (see, for example, Borenstein (2005a)).

[5] Note that while the nature of efficient energy prices is well understood, the optimal strategies for eliciting efficient customer response are less clear. Schneider and Sunstein (2017) highlight how transaction costs and behavioral biases impact the optimal type and frequency of price notifications.

[6] The optimal linear (i.e purely volumetric) tariff—the "Ramsey-Boiteux" tariff—recovers residual costs through mark-ups on the marginal cost that vary in inverse proportion to the elasticity of demand (Ramsey, 1927; Boiteux, 1956). Feldstein (1972a) expands on this work by considering optimal linear prices while accounting for a measure of distributional impacts.

tion on two-part tariffs.[7] Two-part tariffs with volumetric charge set to the marginal social cost of consumption and a fixed charge to recover residual costs are optimal so long as the fixed charge does not change any customer's marginal consumption or production decisions (Feldstein, 1972b).[8]

In this analysis, we assume that customers respond to *marginal* prices as opposed to *average* prices[9] or any other function of fixed and variable prices.[10] Ito and Zhang (2018) find that consumers can differentiate between marginal and fixed charges (and, therefore, between marginal and average prices) in their short-term response (in the context of Chinese heating bills). In designing efficient fixed charges, two factors must be kept in mind.

1. If the sum of fixed and variable charges that any given customer faces exceed his or her total consumer surplus, this customer may "defect" from the grid—either by investing in self-generation or simply ceasing consumption.

2. Should customers—for example, due to wealth effects or budget constraints—adjust their marginal behavior in response to the magnitude of the fixed charges they face, optimal fixed charges would account for these behaviors.

In our dataset, more than 99% of customers have positive consumer surplus at the magnitudes of fixed charges explored in this paper, even with relatively modest assumptions about

[7] In areas of growing peak-demand and tight network capacity margins over peak net demand, the marginal energy cost may not reflect the long-run marginal cost of consuming energy during times of peak network utilization. Such conditions may warrant the use of peak-coincident charges that reflect a customer's contribution to future network capacity costs (Pérez-Arriaga et al., 2016). This would be a component of the variable cost in a two-part tariff. Given the lack of network topology and network loading data, we ignore these conditions and assume all network costs are residual. This likely slightly overstates the quantity of residual costs that we recover through fixed charges in our study.

[8] If: 1) resale of power is restricted, 2) customers have the potential to grid defect, and 3) the value of grid connection for any given customer is unknown, then the optimal residual cost recovery method involves a menu of contracts designed to elicit customers to express their value of connecting to the grid (Braeutigam, 1989). These menus contain a set of tariffs with inversely varying fixed and variable charges. Such designs are unlikely to be optimal at the residential level for two primary reasons. First, resale is possible through the ownership of distributed generation, opening the possibility for inefficient bypass of grid-supplied electricity. Second, the costs of grid defection at a high-level of reliability are likely substantial for the vast majority of residential customers (Khalilpour and Vassallo, 2015; Hittinger and Siddiqui, 2017). Thus, the benefits of grid connection for residential customers will likely be greater than the costs under a relatively wide range of fixed charges. This range will change as alternatives to grid-supplied energy proliferate and increase in economic competitiveness.

[9] That is, the average of all fixed and variable costs over a given time period.

[10] Ito (2014) demonstrates that, in certain contexts, electricity consumers respond to average prices, not marginal prices. However, Ito (2014) focuses on consumer response to inclining block prices, a fairly complicated pricing structure in which the volumetric charge increases as the total volume of consumption increases. Furthermore, the customers in Ito (2014) face predominately volumetric charges, and the study does not shed light on the issue of whether customers would distinguish between marginal and average prices in the presence of fixed charges.

customer own price elasticity.[11] We therefore do not consider grid defection to be a substantial issue. In practice, wealth effects are very challenging to measure. In this paper we do not explicitly incorporate wealth effects on customer marginal responses. In Section 4, we demonstrate several mechanisms for charging lower fixed charges to low-income customers that may increase efficiency relative to a uniform fixed charge in the presence of wealth effects.

Economic efficiency is not, of course, the only consideration in residential rate design. Equity is a central consideration in Bonbright (1961)'s widely used guiding principles for rate making. Indeed, regulation has long been used as a means of distributing benefits—a task typically associated with the government (Posner, 1971). Recently, Levinson and Silva (2019) found that utilities in regions with higher levels of income inequality and higher percentages of Democratic voters had more income redistributive electricity rates. This implies that income redistribution is an explicit regulatory goal, and that this goal is expressed in rate design.

There is relatively limited literature on how different tariff designs (and the transitions from today's designs) impact customers of different socioeconomic groups. This paper assesses the distributional impacts of two salient tariff design distortions: (1) the distortions that arise from recovering residual costs in volumetric charges, and (2) the distortions that arise from price signals that do not pass on the temporal volatility in the price of energy.[12]

The literature on the distributional impacts of increasing fixed charges and decreasing volumetric charges for residual cost recovery consistently points to the regressive nature of such transitions. Feldstein (1972b) derives optimal two-part electricity tariffs under the constraint that all customers must face the same fixed charge. Borenstein (2011) finds that such charges are regressive in California. Similarly, Borenstein and Davis (2012) explore the efficiency and distributional impacts of increasing fixed charges and improved two-part tariffs for natural gas consumption using a nationally representative sample of customers. Borenstein (2012) finds that California's increasing block tariffs have a moderate redistributional impact relative to a pricing structure with lower volumetric charges for high-consuming customers, a finding that underscores the regressive nature of a transition to a tariff with higher fixed charges and lower variable charges. We expand upon this literature by relaxing the requirement that all customers must face identical fixed charges. We then outline economically efficient mechanisms for mitigating the distributional impacts of transitioning to tariffs with

[11] See Appendix 6.5 for detailed calculations.

[12] These are not the only distortions present in electricity tariffs. Specifically, in most markets across the U.S., the full social cost of pollution is not included in the tariff. Borenstein and Bushnell (2018) suggests that the net impact of the failure to price externalities into tariffs differs across markets.

higher fixed charges for residual cost recovery.

The literature on the distributional impacts of transitioning to more time granular pricing shows mixed results. Borenstein (2013) explores the impacts of opt-in dynamic pricing programs on those that do not opt-in, finding the impacts to be relatively minor. Hledik and Greenstein (2016) find that charges based on peak demand do not harm low-income customers on average, and present these customers with large opportunities to save with peak-shaving. Horowitz and Lave (2014) argue that real-time pricing may negatively impact low-income customers on average, and that, as a result, real-time pricing programs should only be offered on an opt-in basis. On the contrary, Simshauser and Downer (2016) find that today's flat rates negatively impact vulnerable customers on average, and that default dynamic pricing could improve efficiency and equity. In recent years, scholars have begun to assess the extent to which DER adoption is equitable under existing rate structures. For example, Nelson et al. (2011) argue that the mechanism for supporting rooftop solar PV in Australia is regressive, benefiting high-income customers at the expense of lower income customers. The results surrounding the distributional impacts of residential electricity rates tend to vary widely based on system characteristics, customer demographics, and energy usage patterns. We expand on this literature by exploring the design of mechanisms for maintaining *desired* protections for vulnerable customers in the transition to more efficient rate designs.

2.1 Data

The residential electricity consumption data used in this work come from Commonwealth Edison (hereafter: ComEd). ComEd —a subsidiary of Exelon Corporation— is one of the largest electric utilities in the U.S., serving over four million customers in the state of Illinois (Exelon, 2018). The data contain anonymous electricity consumption data for 100,170 residential customers for 2016. Electricity consumption is reported in 30-minute intervals. All customers in the data contain complete and clean consumption information for the entire 2016 calendar year. The data set states each customer's *Delivery Service Class*, which differentiates between Single Family Homes and Multi Family Homes as well as between customers with Electric Space Heat and those without. In addition, the data specify each customer's U.S. 9-digit zip code ("Zip+4 Code"), indicating the city block or apartment group of the respective household. For confidentiality reasons, ComEd applied a "15/15-rule" to the data. This rule removes any customers or Zip+4 areas that:

1. contain fewer than 15 customers per Customer Service Class, or

2. contain one customer that represents more than 15% of the total consumption of the corresponding Customer Service Class (Illinois Commerce Commission, 2014).

As the data used in this study predominately cover the densely populated regions of Chicago, we expect that few areas will be affected by this rule. Nonetheless, this may bias our sample towards containing relatively few areas with very large consumers.

Table 1 summarizes the breakdown of customer service classes represented in the sample. The breakdown of single family versus multi family homes in our data is roughly representative of the broader ComEd service territory. 61.2% of the customers in our sample live in single family homes and 38.7% in multi family homes, compared to roughly 58.7% and 40.2% respectively for the total ComEd service territory (Commonwealth Edison, 2011).[13] Customers without electric space heat make up the majority of the customers in the data.

Table 1: Breakdown of customer service classes

Heating Type	Single Family		Multi Family	
	Number	Percent	Number	Percent
Electric Space Heat	96	0.01%	3,987	4.1%
No Electric Space Heat	60,095	61.2%	34,017	34.6%

Electricity consumption is strongly correlated with housing type. Table 2 highlights the annual consumption in kilowatt-hours of the different customer service classes in our sample. Customers in single family homes consume nearly twice as much energy customers in the multi-family homes. As one would expect, electric space heat is also a significant driver of energy consumption. The average customer living in a multi family home with electric space heat consumes nearly twice as much energy as the average customer living in a multi family home without.

We enrich the consumption data with corresponding 2016 socioeconomic data from the American Community Survey (ACS) (U.S. Census Bureau, 2018a). The smallest, most detailed geography for which ACS publishes public data is a Census Block Group (CBG). CBGs contain 600 to 3,000 people (U.S. Census Bureau, 2018b). In total, our sample contains customers in 2,315 CBGs, meaning each CBG contains an average of 43 customers. While the primary focus of our analysis is the impacts on customers of different income levels, we gather and assess data related to the distribution of age, education, race, unemployment,

[13]Note that ComEd does not publish data on the breakdown of electric versus non electric space heat customers in its service territory.

Table 2: Breakdown of annual electricity consumption by customer service classes (kWh)

	Single Family	Multi Family	Multi Family-ESH	Single Family-ESH
Minimum	26.56	38.61	121.92	1142.15
1st Quartile	4927.43	2236.50	5184.78	15761.78
Median	6993.93	3437.01	7657.55	18084.09
Mean	7436.61	3956.70	8536.50	19076.21
3rd Quartile	9451.34	5129.14	10804.36	22826.22
Maximum	44238.23	84726.89	37992.99	31068.12

the frequency of individuals on social security (as a measure of customers on a fixed-income stream). Note that, in 2016, the federal poverty limit for a 4-person household was $24,300 (U.S. Department of Health & Human Services, 2018). Throughout this study, we refer to low-income customers as those making below $25,000 per year. We estimate that roughly 24% of the customers in our sample meet this definition of low-income.

The geographic boundaries of CBGs do not match directly with those of 9-digit zip-code areas. We use a commercial data set—provided by Melissa Data—to match 9-digit zip areas to CBGs.[14] In the course of the data merging 1,975 customers (2%) are dropped from the set because they are lacking corresponding data in the census.

Table 6 in the appendices compares the demographic characteristics of the customers in our sample with the characteristics of the broader ComEd service territory. Note that, due to the hierarchical design of our sample—with demographic data represented at the CBG geography—the demographic data for our customer sample are actually the demographic data for the CBGs contained in our sample. The sample in our analysis over represents low-income and high-income customers, and under represents middle-income customers relative to the ComEd service territory more broadly. Additionally, our sample over represents black and African American customers and under represents white customers relative to the ComEd service territory. This is consistent with our sample being predominately an urban population. Our sample is broadly representative across all other demographic characteristics.

[14] https://www.melissa.com/

2.2 Methods

In our analysis we are interested in the average and sorted bill changes for customers in specific income groups. We can model a bill change (Δ) for a given customer $i \in \{1, ..., 100170\}$ and tariff r according to $\Delta_{i,r} = Y_i' \beta_r + \epsilon_{i,r}$, where $Y_i = e_j$ is a one-shot vector representing the income level, $j \in \{1, ..., 9\}$, and $\epsilon_{i,r}$ represents the residual. For example, if $X_i = e_j$ then X_i is a vector of zeros with a single 1 at location j, representing that customer i is in income quantile j. With customer-level data on Y_i, we could calculate the average bill change from tariff r by regressing $\Delta_{i,r}$ on Y_i.

However, in our hierarchical design, we do not know the income of any individual customer; we only know their Census Block Group. We have a frequency distribution over income levels for each customer i's CBG, $p_i = \mathbb{P}(Y_i = e_j)$, where $p_i \in \mathbb{R}^9$ describes the probability that a random customer in customer i's Census Block Group has income level j, for each income $j \in 1, ..., 9$. We assume that each customer is randomly chosen given their CBG, so p_i provides a probability distribution of incomes for customer i.

Our assumption, that all customers within a given CBG face the same probability of being in any income level j, implies that factors like housing stock or consumption profiles do not affect p_i. Borenstein (2012) highlights the fact that, for example, income and annual electricity consumption are correlated, and that using this information can provide a more accurate estimate of p_i. Of course, in practice, we may wish to use the distribution of incomes in a CBG as a prior and update this distribution using additional consumption, housing, or demographic data. Additionally, many utilities or regulators may have much more granular data on the demographics of their customers.

We are interested in the average bill change for customers in each income level j, represented by β_r, as well as the distribution of individual effects, given by $\beta_r + \epsilon_{i,r}$. The formula for average bill change for a hypothetical customer of a given income level is given by Equation 1, where $\beta_r \in \mathbb{R}^9$ is a vector containing the average impact for each income level j, and the matrix $P \in \mathbb{R}^{100170 \times 9}$ contains the vector of probabilities that customer i has income level j (that is, $p_{i,j}$). The derivation for Equation 1 is provided in Appendix 6.2.

$$\beta_r = \Big(\sum_i diag(p_i) \Big)^{-1} P' \Delta_r \tag{1}$$

In order to obtain standard errors and sorted expenditure effects, we bootstrap the data. We stratify by CBG and randomly select M income levels according to the distributions of incomes in the respective CBGs. We then randomly assign a customer from the population within the relevant CBG to this income. Customer i's income level during run m is y_i^m, and the bootstrap income matrix is Y^m.

We obtain the bootstrap estimate β_r^m by regressing the variable of interest (in most cases, Δ_r) on Y^m, and note that $\beta_r \approxeq \mathbb{E}_m[\beta_r^m]$. The distribution of β_r across m provides our confidence intervals for the average impacts. Additionally, by sorting the $\Delta_{i,r}^m$ within each bootstrap run, we can obtain the sorted effects. The distribution of $\Delta_{i,r}$ across bootstrap runs within each sorted quantile provides the confidence intervals for the sorted impacts.

We use this method to estimate expenditure impacts across socioeconomic variables beyond income, as well as to measure other variables of interest beyond changes in expenditures.

2.3 Rate Designs

In Section 3, we analyze the efficiency and distributional impacts of various rate designs relative to the default tariff in the ComEd geography. The primary purpose is to compare the efficient benchmark tariff (described below) to other commonly proposed designs, and to motivate our discussion of equitable residual cost allocation methods. This section briefly describes the various tariffs involved, and more detail is provided in Appendix 6.3.

In our model, total utility revenue R is equal to the sum of revenues from fixed charges (F_i) and variable charges for energy ($p_{i,t}^e$) and residual costs ($p_{i,t}^r$) across all customers i and times t: $R = \sum_{i,t} \Big(F_i + x_{i,t}(p_{i,t}^e + p_{i,t}^r) \Big)$. Where $x_{i,t}$ is again the demand of customer i in time t.

We design all tariffs to be revenue neutral in residual (network and policy) costs compared to the default tariff. We allow the total quantity of energy costs recovered to vary in the scenarios in which customers respond to prices (described more in Section 3), as a reduction in consumption leads to a reduction in the total cost of producing energy. Revenue neutrality in network and policy costs is critical, as these costs must be recovered, regardless of the total quantity of energy purchased.[15] In practice, if any network or policy costs were under recovered in a given year, these costs would most likely be recovered in a future year. Thus, any apparent cost savings resulting from lower overall network or policy cost recovery would simply be an inter-temporal shift, and not a true cost saving. We focus on tariff designs that have garnered significant attention by utilities, regulators, and academics.

First a note on externalities. In this paper our primary focus is on the impacts of alternative

[15] The "regulatory compact" between the regulator and the regulated utility has historically lead to conditions in which utilities recover all costs, even in circumstances of "stranded" costs (Sidak and Spulber, 1996). While there is legal precedence for not allowing the recovery of "stranded" costs, in the majority of cases, all network and policy costs are ultimately recovered by utilities.

mechanisms of residual and energy cost allocation on certain socioeconomic groups. While externalities are clearly important in the electricity sector, given the lack of momentum for pricing those externalities, we ignore the impacts of externalities in each of our tariff specifications. Certain tariff designs may lead to an increase in emissions (see, for example, Holland and Mansur (2008)'s analysis of the emissions impact of real-time pricing). Inclusion of externalities might slightly exacerbate or mitigate the impacts modeled in our paper.

2.3.1 Default-Flat

The default tariff in the ComEd footprint—serving 95.8% of residential customers as of the end of 2016—is comprised of a flat, time- and location-invariant volumetric charge of roughly \$0.10/kilowatt-hour (kWh) and a small fixed, per-customer charge of roughly \$10 to \$14 per month. The default tariff differentiates between customers of different Delivery Service Classes (e.g., residential or industrial customers); prices change slightly throughout the year to reflect changes in the total sum of energy, network, and policy costs to be recovered.[16] Throughout this paper we refer interchangeably to this tariff as the flat or default tariff.

The default tariff distinguishes between energy charges, transmission services charges, distribution facilities charges, metering and customer charges, and policy charges related to taxes, energy efficiency programs, and other environmental programs. Using the customer load profiles and the tariff data retrieved from the Illinois Commerce Commission, we compute the total costs to be recovered in three categories: energy (containing the energy charges), network (containing transmission services, distribution facilities, metering, and customer charges), and policy and regulatory costs (containing all other charges). The total costs and the structure of the charges under the default tariff are presented in Table 3. We compute the costs in Table 3 by multiplying customer consumption profiles by the corresponding volumetric charges (that is, the energy, transmission services, distribution facilities, and policy and regulatory charges), and adding in the corresponding customer fixed charges (that is, the customer and metering charges).[17]

Average annual expenditures and 95% confidence intervals for these average expenditures

[16]The rates are determined according to formulas approved by the Illinois Commerce Commission (Edison, 2016).

[17]In our analysis we assume that all customers begin on the flat default rate. This should not bias the numbers in Table 3, as all of ComEd's tariffs are designed to be revenue neutral. However, this assumption likely slightly overstates the potential consumer surplus and efficiency gains from a transition to more time-granular pricing schemes. The impact of this is likely small given the relatively small number of customers currently facing time varying rates. The results presented in section 3 can be considered upper bounds on the overall impact.

Table 3: Costs and tariff structure under the default tariff

Total	Energy	Distribution			Transmission	Policy and other
		Distribution Facilities	Customer	Metering		
	$/kWh	$/kWh	$/customer	$/customer	$/kWh	$/kWh
$78,024,552	$31,990,302	$19,510,770	$10,671,363	$5,255,667	$7,645,008	$2,951,442

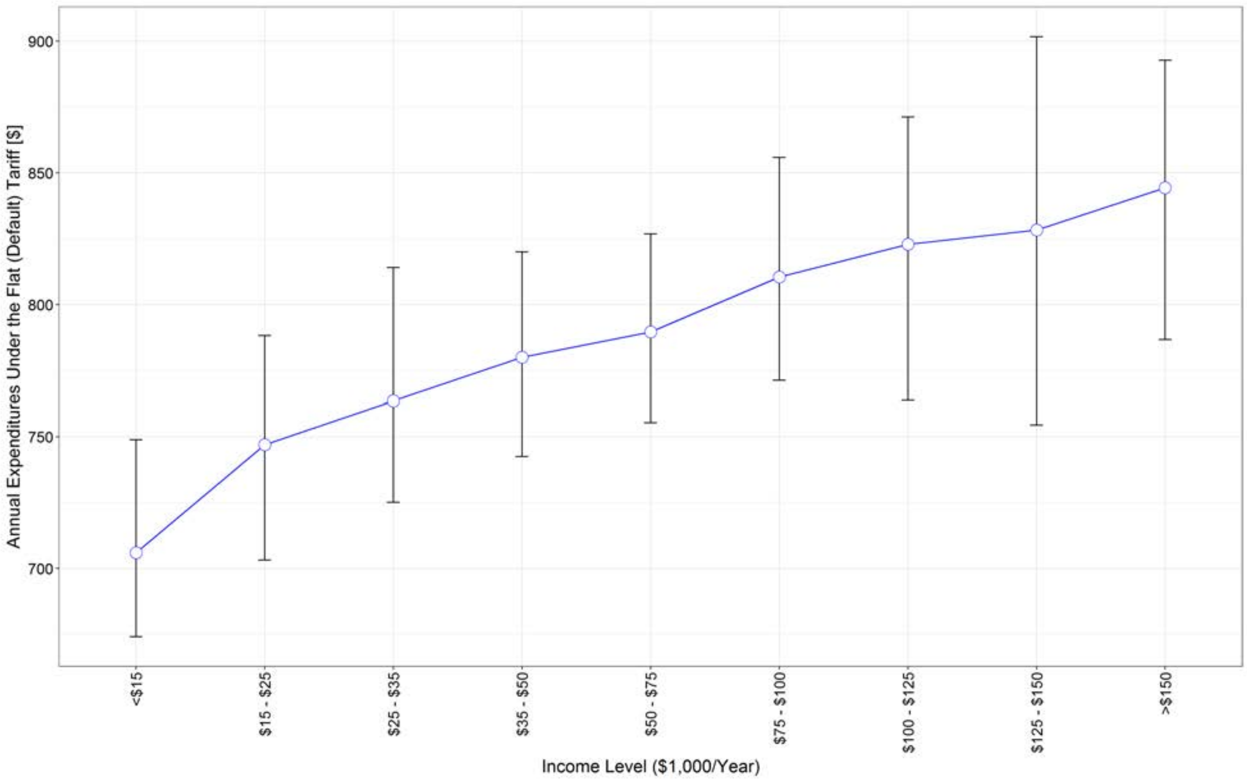
under the Flat ComEd tariff are depicted in Figure 1. Figure 1 makes it clear that, under the default tariff, customers in the lowest income bracket pay less in annual electricity bills than do higher income customers. This trend holds true when controlling for housing type (that is, single family versus multi-family home, electric space heat versus non-electric space heat). This is driven almost exclusively by the fact that, in our data, low-income customers consume less energy on average than higher income customers. This finding is consistent with other studies (for example, Borenstein (2012)) as well as with other data sources that track the relationship between average household energy consumption and income (U.S. Energy Information Administration, 2015). The confidence intervals on the mean impact are quite wide, reflecting both the variance in expenditures across income groups and the uncertainty in the assessment of which customers are in which income bracket. We observe high variance in expenditures in areas with low median incomes and high concentrations of low-income customers. Nonetheless, the mean expenditures from the lowest income bracket is statistically significantly different from the mean expenditures of all customers making more than $35,000 per year.

For the purposes of this analysis, we assume that all network and policy costs are residual and must be recovered. While network costs are driven in the long run by the need to develop network infrastructure to meet peak injections and/or withdrawals, the costs of existing network infrastructure largely do not change in the short term with the amount of energy consumed or produced (Borenstein, 2016).

2.3.2 Flat tariff with non-coincident peak demand charge: Flat-NCDC

Under the flat tariff with a non-coincident peak demand charge ("Flat-NCDC"), the volumetric charges for energy and policy costs and the fixed charges remain the same as under the default tariff. However, under the Flat-NCDC design, distribution facilities and transmission costs are recovered via a charge applied to each customer's peak demand in each month, regardless of when this demand occurs (the revenue-neutral charge is roughly $3.735 per kilowatt). Thus, the Flat-NCDC tariff is identical to the default tariff in all ways but network cost recovery. See Appendix 6.3 for more detail.

Figure 1: Annual electricity expenditures under the Flat (default) ComEd tariff



2.3.3 Critical Peak Price tariff: CPP-10

The "CPP-10" tariff comprises a fixed charge identical to that under the default tariff, combined with a volumetric "critical peak price" designed to reflect the periods of peak price in the ComEd system. In typical critical peak pricing programs, off-peak prices are constant or varying according to a deterministic time-schedule; peak price periods are announced some time—commonly 24 hours—ahead of the "event period" (for many design characteristics, see U.S. Department of Energy (2016)). In our design, the off-peak price is \$0.0825/kWh, and the peak price is \$0.825/kWh for all customers, leading to a peak to off-peak ratio of 10. We hold fixed customer and metering charges identical to those in the default flat tariff. Consistent with existing critical peak pricing programs, we choose 18 event periods, all lasting between 3:00PM and 9:00PM. The event days are chosen based on the 18 highest electricity price days for the ComEd load zone in 2016.

The CPP-10 and RTP-Volumetric rate (described below) are designed to have the same average volumetric rate as the default flat rate. See Appendix 6.3 for more detail.

2.3.4 Real-time price tariff with volumetric network cost recovery: RTP-Volumetric

The RTP-Volumetric tariff charges the hourly locational marginal cost of energy at the ComEd load zone, and recovers all distribution facilities, transmission services, and policy and tax costs through a volumetric rate. Customer and metering charges remain fixed as under the default tariff. Recovering residual costs through volumetric charges distorts the marginal price signal that network users see. Nonetheless, we include this case to align with previous studies that have considered such volumetric cost recovery for residual costs (Borenstein, 2005a, 2012, 2013).

The CPP-10 and RTP-Volumetric tariff differ from the default flat tariff only in the time granularity of the energy price signal and the connection to wholesale energy prices. Contrasting the results of the CPP-10 and RTP-Volumetric tariffs with those of the Flat tariff allows us to understand the impacts of passing on increasingly efficient energy price signals while holding all else equal. See Appendix 6.3 for more detail.

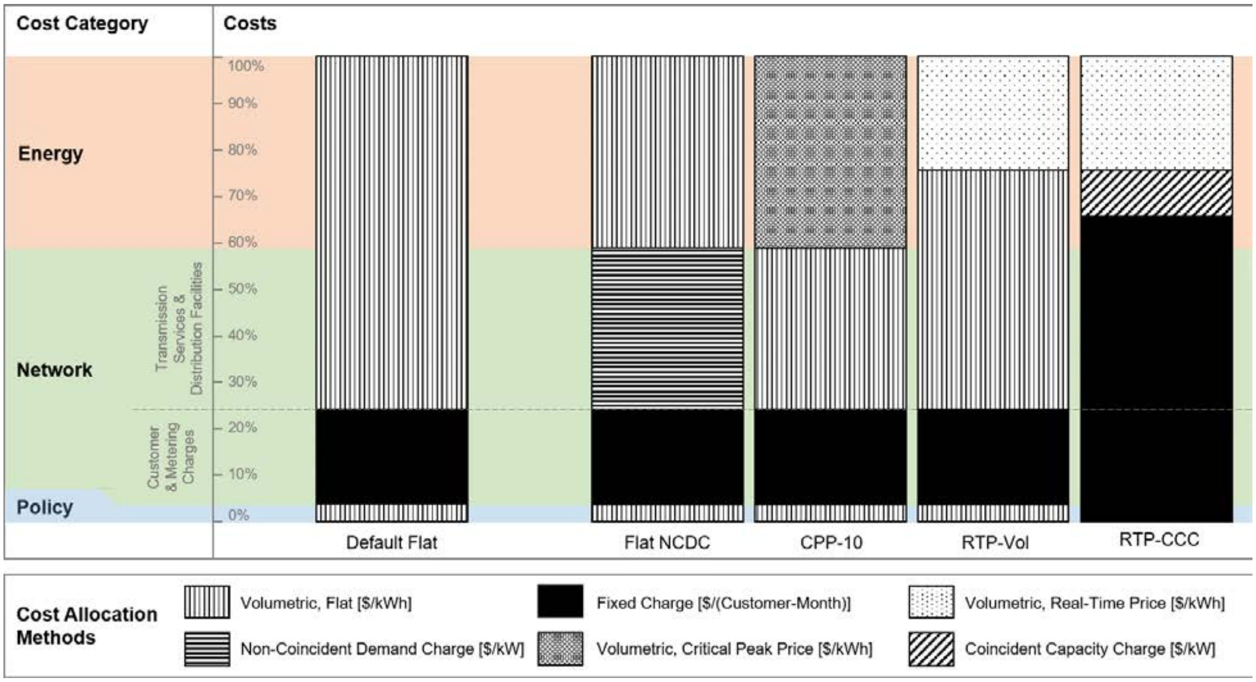
2.3.5 Real-time price tariff with coincident peak capacity charges: RTP-CCC

The final tariff in our study, the real-time price tariff with a coincident capacity charge (the "RTP-CCC tariff"), is our benchmark economically efficient tariff. The RTP-CCC rate charges the hourly locational marginal price of energy at the ComEd load zone. The tariff recovers all network and policy costs through a fixed charge. Finally, we include a charge coincident with the PJM system peak intended to reflect a customer's contribution to future generation capacity costs. We briefly introduce the RTP-CCC tariff here; please see Appendix 6.3 for more detail.

The volumetric energy charge in the default ComEd tariff generates roughly 14.5% more revenue than the sum of revenues from the real-time energy prices and the coincident capacity charges. This is due to the fact that the default energy price charged by ComEd recovers a number of non-energy costs, including but not limited to the risk premium for charging a flat price, and the costs of PJM capacity charges from previous years. We recover these costs in all tariffs. In the RTP-CCC tariff, we assume these costs are residual and recover them through a fixed charge. Capacity costs from previous years are residual, as changes to customer load profiles do not impact ComEd's need to pay these costs. However, passing along the real-time price of energy would eliminate risk premium, so classifying these costs as residual slightly overstates the total amount of residual costs.

Figure 2 provides an overview of the structure of the tariffs introduced above. For example, we see that under the default tariff, all customer and metering costs are recovered through a fixed charge (the black fill), while all other costs are recovered through volumetric charges (the dark gray fill).

Figure 2: Breakdown of costs under the tariff designs in this study



In Section 3, we explore tariff impacts under the premise that all residential customers face identical fixed charges for residual cost recovery. In Section 4, we describe alternative fixed charge designs and explore their economic underpinnings and impacts.

3 Estimating bill and consumer surplus impacts from efficient retail tariffs

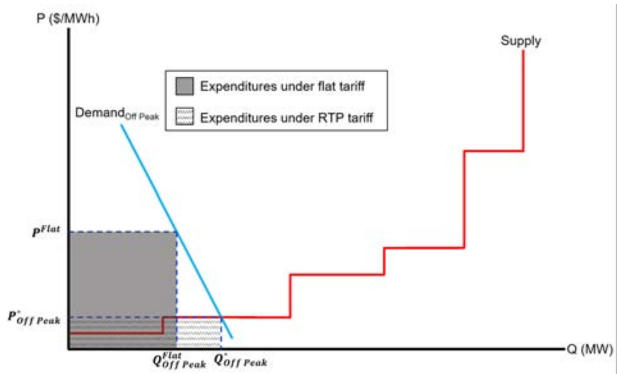
To understand the impacts and relative efficiency of the tariffs introduced in Section 2.3, we compute customer expenditure and volatility impacts under three different cases. First, we compute customer bills assuming no price response from consumers—demand has an elasticity of zero. In the zero-elasticity case, all expenditure changes are simply transfers between customer groups and bill changes reflect changes in consumer surplus. In addition, because demand is perfectly inelastic, there is no inefficiency (deadweight loss) from mis-pricing hourly electricity prices. When demand elasticity is not zero, changes in hourly prices will lead to changes in consumption levels and bill and consumer surplus changes will no longer be equivalent. The presence of demand elasticity also implies that mis-pricing leads to efficiency losses and a move toward more efficient pricing can, in principle, increase the consumer surplus of *all* consumers. This is especially true given the presence of volumetric transmission and distribution charges since the average hourly (marginal) price will be too high. We compute expenditure and consumer surplus impacts for two cases with non-zero elasticity to gauge the importance of consumer response.

3.1 Zero-elasticity case

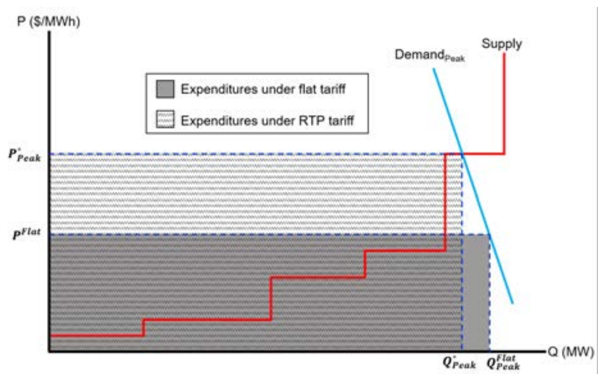
Figure 3 illustrates the the calculations of expenditure changes in the transition from the flat default tariff to a real-time price tariff, in the case where the elasticity of demand is non-zero. While the private marginal cost that each customer faces (i.e. the volumetric charge) is only equal to the short-run marginal cost in the RTP-CCC tariff, the same concepts depicted in Figure 3 hold for the Flat-NCDC, CPP-10, and the RTP-Volumetric tariffs. That is, when the marginal price falls below the flat tariff, bill change is calculated as shown Figure 3(a), and when the marginal price rises above the flat tariff, bill change is calculated as shown Figure 3(b). In the zero-elasticity case, the demand curve would be vertical, resulting in zero quantity change. In addition to computing the changes in expenditures due to changes in the volumetric rate, we also calculate the changes in expenditures resulting from changes in fixed or demand-based charges.

Figure 4 shows the average change in annual expenditures relative to the default tariff for all of the tariffs in the zero-elasticity case. The figure also includes the 95% confidence intervals on the average change for each tariff and income group. Negative changes correspond to a *decrease* in expenditures under the tariff relative to the flat tariff, while positive changes correspond to an increase in bills. The RTP-CCC tariff creates the largest overall distributional impacts, with monotonically decreasing expenditure changes as income increases. Two tariffs keep the same fixed charges as under the default tariff, and change only the time granularity of the volumetric price signal: the CPP-10 and RTP-Volumetric tariffs. Transitioning to these tariffs benefits low-income customers on average in our sample, highlighting the fact that increasing the time granularity of the energy price signal will not inherently negatively impact low-income customers. Instead, it is RTP-CCC's increase in fixed charges (and decrease in average volumetric charge) that has negative impacts on low-income customers. No income group under the demand charge tariff—Flat-NCDC—has an average effect statistically distinguishable from zero.

Figure 3: Illustration of bill change in the transition from flat default to real-time price tariff



(a) Off peak demand

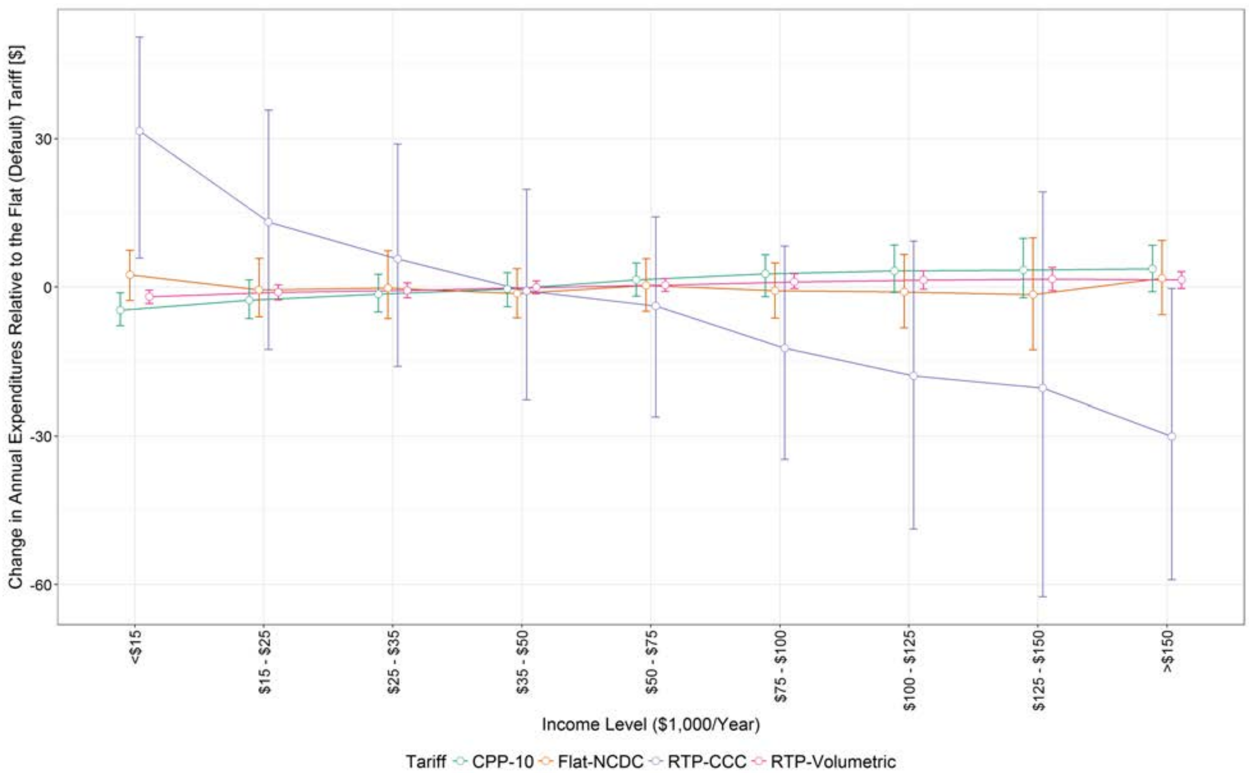


(b) Peak demand

The drivers of the impacts seen in Figure 4 vary by tariff. We explore these drivers using simple linear regression analysis in Appendix 6.4.

Figure 5 shows the coefficient of variation (CV) of monthly expenditures for all of the tariffs analyzed in this study, including the Flat (default) tariff. The CV can be interpreted as the deviation from the mean for roughly two-thirds of the bills and measures bill volatility across the different tariff designs. For example, a CV of 0.4 implies that roughly two-thirds of the bills—or 8 months-worth of bills—are within 40% of that customer's mean bill. The CV of the default tariff is extremely low across all income levels, implying that bills are relatively consistent throughout the year for most customers. All designs except the Flat-NCDC design increased CVs, as expected with an increase in time variability. Perhaps counter-intuitively, the inclusion of a demand charge in the Flat-NCDC tariff had only a minor impact on the average month-to-month bill variation. The RTP-CCC tariff creates the largest CVs, implying the greatest month-to-month variability in customer bills. Perhaps

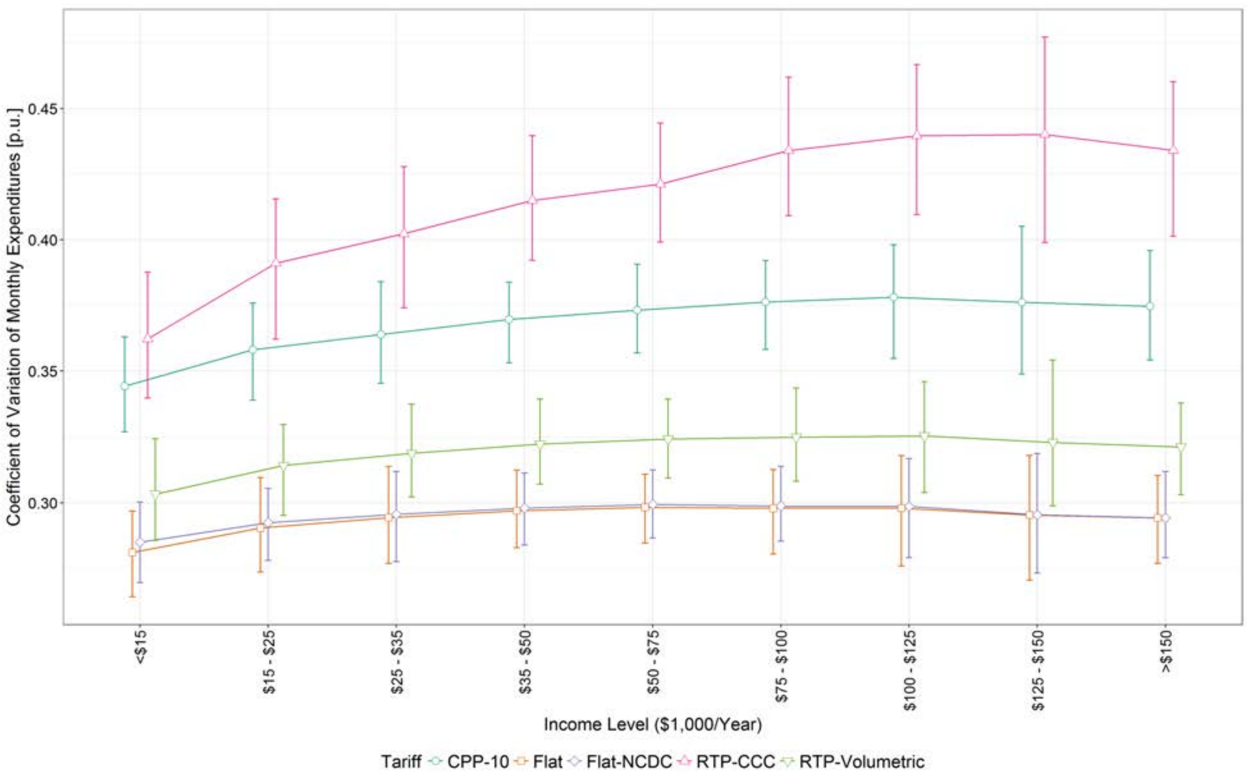
Figure 4: Change in annual expenditures by tariff and income level, zero-elasticity case



counter-intuitively, CVs are lowest for low-income customers under the RTP-CCC tariff, despite the fact that low-income customers see bill increases on average. This stems from the fact that the dominant driver of bill increases for low-income customers is the increase in fixed charges, which do not change from month-to-month.

While price volatility—and the resulting month-to-month expenditure volatility—is a concern for many customers and the regulators and advocates that represent them, we focus primarily on aggregate customer expenditures for the remainder of the paper. There are many methods to hedge bill volatility (Borenstein, 2007, 2005b). Among them, contracts for differences and other types of option contracts maintain the efficiency of marginal price signals while providing protection. Other types of payment plans—such as those already offered by many utilities today—can also alleviate the potential impacts of unexpectedly high bills in a given month. One example, detailed in Borenstein (2005b), is to automatically enroll customers with unusually high costs in given month into a payment plan. Such "spark loans" are one of many proposals for mitigating month-to-month expenditure volatility that maintain efficient marginal incentives.

Figure 5: Coefficient of variation of monthly expenditures, zero-elasticity case



3.2 Price elasticity and change in consumer surplus

In addition to the zero-elasticity case, we model two cases for price elasticity. Consistent with the existing literature (for example, Borenstein (2005a)), we consider only own-price elasticity and do not consider cross-price elasticity. Additionally, consistent with existing literature, we assume no customer response to non-coincident peak-demand charges (see, for example, Mays and Klabjan (2017)). In this sense, we can consider the Flat-NCDC tariff to be a tariff in which a fixed charge is allocated to customers based on their peak demand in each month.

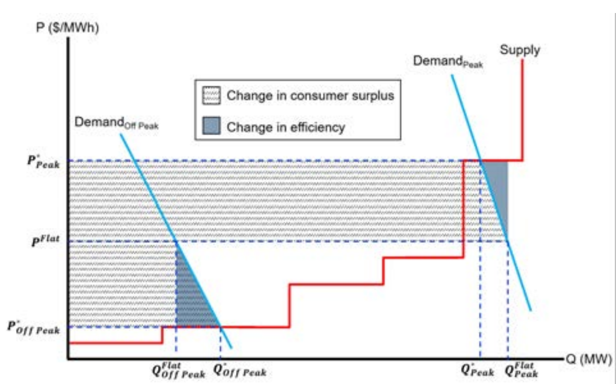
Empirical estimates of the price elasticity of customers vary widely and depend on a variety of factors including time of day, season, availability of information, and level of automation. We consider two values for own-price elasticity: one value on the low end of the range of empirically measured elasticities (-0.1), and one value on the high end of the range (-0.3). We model price response according to Equation 2. For RTP-CCC and RTP-Volumetric, a few hours of nonpositive prices occur in 2016. For these cases we manually set a very low positive price, i.e. 10^{-7} to guarantee mathematical applicability of the formula. This leads to relatively large (roughly 4x) increase in demand over baseline during negative price hours.

$$x'_{i,h} = x^{flat}_{i,h} \left(\frac{p'_h}{p^{flat}_h} \right)^{\epsilon} \tag{2}$$

In all of our demand response cases, we maintain revenue neutrality for all network and policy costs. We do not maintain revenue neutrality in energy costs, as a reduction or increase in demand in one time period corresponds to a reduction or increase in energy production costs. Residual network and policy costs, however, do not decrease with volume of consumption. Following the calculation of demand using Equation 2, we compute the deviation from the total required network and policy revenue. We then increase or decrease fixed charges accordingly, and recalculate all expenditures.[18] All results presented below are of expenditures following tariff rebalancing.

Figure 6 illustrates the change in consumer surplus and efficiency (dead weight loss) that emerges from the transition from the flat to the RTP-CCC tariff. As depicted in the graphic we assume demand curves to be linear. Note that in the zero-elasticity case, the change in consumer surplus is equivalent to the change in expenditures, as there is no change in efficiency. Thus, in the zero-elasticity case, changing the tariff affects only the distribution of consumer surplus, and not the total quantity of consumer surplus. We subtract any changes in fixed or demand charges from the consumer surplus change depicted in Figure 6 to arrive at our final estimate of consumer surplus change.

Figure 6: Illustration of consumer surplus and efficiency change in the transition from the flat default to the real-time price tariff



[18] Rebalancing with fixed charges will, of course, have distributional impacts. However, given the relatively small magnitude of the charges required by rebalancing, this impact is minor compared to the impacts of the transition from one tariff design to another.

Table 4 displays the aggregate consumer surplus change in the transition to each of the four tariffs assessed. Table 8 in Appendix 6.1 contains the mean per-customer change in consumer surplus and the 95% confidence intervals on the mean impact for each socioeconomic group for the high elasticity case. As expected, we see the largest aggregate gain in consumer surplus under the RTP-CCC tariff.

Table 8 highlights that *all* socioeconomic groups benefit on average in every tariff, but for the Flat-NCDC, CPP-10, and RTP-Volumetric cases, some individual customers in each socioeconomic group experience losses in surplus. Under the RTP-CCC tariff, we see substantial surplus gains, with average per-customer surplus gains between 28% and 48% of annual expenditures for different socioeconomic groups (in the high elasticity case). This is an important point. While the policy debate often focuses on bill changes assuming no demand elasticity, this shows that this can be misguided; consumers whose bills might be projected to increase, assuming no demand response, may in fact benefit from the tariff change once demand response is accounted for.

Perhaps less intuitively, we see substantially larger consumer surplus gains under the Flat-NCDC tariff than we do under the CPP-10 and RTP-Volumetric tariff. This stems from the fact that, under the Flat-NCDC and RTP-CCC tariffs, a substantial portion of residual costs are removed from the volumetric portion of the tariff. The volumetric portion of the tariff is thus much closer to the actual marginal cost of energy much more often under the Flat-NCDC tariff than under the CPP-10 and RTP-Volumetric tariffs. This implies that the distortion arising from the recovery of residual network and policy costs through volumetric rates is likely larger than the distortion arising from the fact that the energy component of the flat default tariff does not reflect the time- and location-varying marginal cost of energy.

Our discussion above focuses only on changes in *consumer* surplus; we do not calculate change in social welfare because we leave the discussion of environmental externalities outside the scope of the current accounting. As highlighted by Borenstein and Bushnell (2018), the cost of environmental externalities may roughly equal volumetric residual charges in the Chicago area implying that the average marginal price may be closer to the optimal marginal price when transmission and distribution are remunerated through a volumetric charge. Nonetheless, if an emissions surcharge were efficiently applied to all tariffs, we would still expect to see a tariff with efficient network cost allocation be closer to the social marginal cost than a tariff with inefficient network cost allocation.

As we would expect, the primary effect of increasing the elasticity of demand is to increase the number of customers who benefit from the transition to a more efficient tariff. Figure 7 highlights the consumer surplus change for customers in the lowest income bracket (<$15,000

Table 4: Aggregate change in consumer surplus by tariff

Elasticity Case	Flat-NCDC	CPP-10	RTP-Volumetric	RTP-CCC
ϵ = -0.1	\$983,429	\$445,683	\$125,181	\$10,036,693
ϵ = -0.3	\$3,130,361	\$1,478,859	\$390,054	\$29,237,459

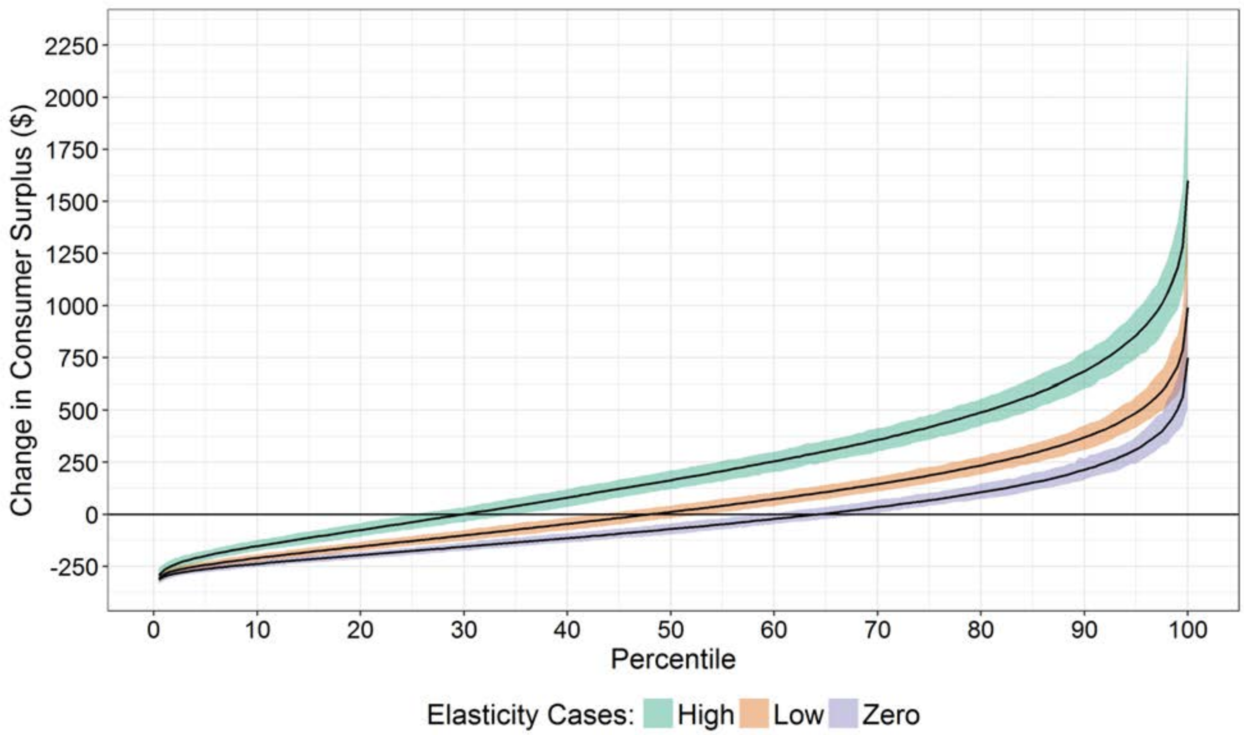
per year) under the RTP-CCC tariff for the three elasticity cases. A positive change is an increase in consumer surplus, while a negative change is a decrease. The shaded regions in the plot are the 95% confidence intervals for the ranked effects. The consumer surplus change in the zero-elasticity case is equal to the change in expenditures. In the zero-elasticity case, between 60% and 68% of customers making less than \$15,000 per year see their bills increase under the RTP-CCC tariff with uniform fixed charges. However, as consumers become more elastic, we see that average changes in surplus relative to the Flat default tariff begin to be positive. This leads to an interesting insight: while conversation surrounding tariff design change tends to focus on changes in expenditures, a better focus may perhaps be on changes in consumer surplus.

In practice, customers will have a distribution of elasticities, rather than a single value as modeled here. Thus, in practice, while the average elasticity across all customers may lead to an average net gain in consumer surplus, some customers may still see negative changes in surplus.

4 Mitigating bill impacts with progressive fixed charges

Section 3 demonstrates that transitioning to a retail tariff that more accurately reflects the marginal cost of consumption—the RTP-CCC tariff in our design—would create substantial consumer surplus gain relative to other design options. However, in Section 3, we naively charge every residential customer the same fixed, per-customer charge for residual cost recovery, regardless of the customer's socioeconomic status, consumption, or any other variable. This approach to allocating residual costs creates substantial distributional concerns. Some socioeconomic groups benefit far less than others in the transition to the RTP-CCC tariff with uniform fixed charges. Low-income customers are particularly impacted, experiencing annual expenditure increases of roughly \$30 on average, with some customers experiencing substantially larger expenditure increases (see Figure 7). Even in a scenario with negative or zero average expenditure changes, we may still want to protect against substantial bill

Figure 7: Change in consumer surplus in the transition from the Flat to RTP-CCC tariff
Annual income: Less than \$15,000



increases for vulnerable customer groups.

When moving to an efficient rate design, one pathway for mitigating undesired distributional impacts is to utilize or enhance existing programs for lowering energy costs for low-income customers. The two primary existing programs in the ComEd service territory, the federal Low-Income Home Energy Assistance Program (LIHEAP)[19] and the ComEd CARE[20] programs are need-tested. That is, customers must demonstrate need by providing proof of a qualifying income level or proof of enrollment in another need-tested support program (such as the Supplemental Nutrition Assistance Program). However, need-tested programs often receive very low enrollment due to a variety of reasons. In 2012, only 22% of individuals eligible for LIHEAP nationwide actually received support under the program (Falk et al., 2015). Eligibility for ComEd's CARE program requires enrollment in LIHEAP, so enrollment among eligible customers is likely low. As a result, these programs are often overlooked when considering new tariff designs; regulators are understandably skeptical of the ability of

[19] www.LIHEAPIllinois.com
[20] www.comed.com/MyAccount/CustomerSupport/Pages/ResidentialHardship.aspx

these programs to mitigate concerns affecting low-income customers.

However, based on the principles of monopoly cost recovery, and as discussed in Section 2, a wide range of fixed charges are approximately economically efficient. This insight opens the door to bill protection mechanisms for vulnerable customer groups that capture all—or the vast majority—of the benefits of the economically efficient tariff options discussed in Section 3.

In this section, we illustrate three different methods for recovering residual costs through fixed charges. We demonstrate that these methods can mitigate many of the distributional impacts of moving towards more efficient tariff designs.[21] Because these methods enable network cost recovery while preserving marginal cost signals, they maintain the efficiency benefits of the RTP-CCC tariff explored in Section 3. In the presence of wealth effects, wherein low-income customers change their demand functions in response to changes in fixed charges, progressive pricing mechanisms may be *more* efficient than a uniform fixed charge approach.

We explore several methods for progressive fixed charges. First, we explore fixed charges based on historical consumption data that correlate with income. We then explore fixed charges based directly on customer income. Finally, we explore fixed charges based on geographical information. The three designs we highlight have different tradeoffs. In practice, the design chosen for a given geography will need to be tailored to the regulatory and stakeholder objectives and the available data.

While we focus here on designing fixed charges to mitigate distributional impacts, regulators could use the same data and methods described here to accomplish any number of regulatory goals. For example, regulators could set fixed charges to achieve "gradualism" or "rate stability." Such charges would be designed to minimize the bill changes that any customer experiences, regardless of income or other variables (Burger et al., 2018).

4.1 Progressive fixed charges based on customer demand characteristics

Many customer consumption characteristics correlate strongly with income. Table 5 presents the average value for different consumption characteristics at each income level, normalized to the value associated with the lowest income group (computed according to the method

[21] We refer broadly to the mechanisms explored here as "progressive pricing" mechanisms, as the underlying impact in each case is to mitigate the additional burden of transitioning to efficient tariffs created by uniform fixed charges.

described in Section 2.2).[22] The non-normalized data are presented in Table 9 in Appendix 6.8. For example, customers in the highest income bracket have, on average, 29% higher annual peak demand than customers in the lowest income bracket. The variables that are most predictive of income may vary across geographies.

Table 5: Average Profile Variables by Income

Income ($1,000 USD)	Average Monthly Consumption	Annual Peak Demand	Peak-To-Off-Peak Ratio	May Peak Demand	June Peak Demand	July Peak Demand	August Peak Demand	Consumption: 5:30PM-6:00PM	Consumption: 6:00PM-6:30PM	Consumption: 6:30PM-7:00PM
<$15	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
$15 – $25	1.07	1.03	0.95	1.05	1.06	1.05	1.05	1.08	1.08	1.08
$25 – $35	1.10	1.06	0.95	1.09	1.09	1.09	1.09	1.12	1.12	1.11
$35 – $50	1.12	1.09	0.95	1.12	1.13	1.13	1.12	1.15	1.15	1.15
$50 – $75	1.14	1.13	0.97	1.17	1.17	1.17	1.16	1.18	1.18	1.18
$75 – $100	1.18	1.17	0.97	1.22	1.22	1.22	1.21	1.23	1.23	1.23
$100 – $125	1.20	1.19	0.97	1.25	1.26	1.25	1.25	1.26	1.26	1.26
$125 – $150	1.21	1.21	0.98	1.27	1.28	1.27	1.27	1.28	1.28	1.27
>$150	1.25	1.29	1.02	1.36	1.35	1.34	1.33	1.32	1.33	1.32

Regulators wishing to create more progressive fixed charges may exploit these demand characteristics. That is, fixed charges could be designed based on these characteristics. In order to avoid customer responses to the fixed charges —and thus decreasing the efficiency of the tariff— the fixed charges must be held constant for some period of time.[23] Given that network costs are driven in the long run by coincident peak demand, charges determined according to a customer's coincident peak demand are likely to be more well aligned with regulatory objectives of cost-causality.

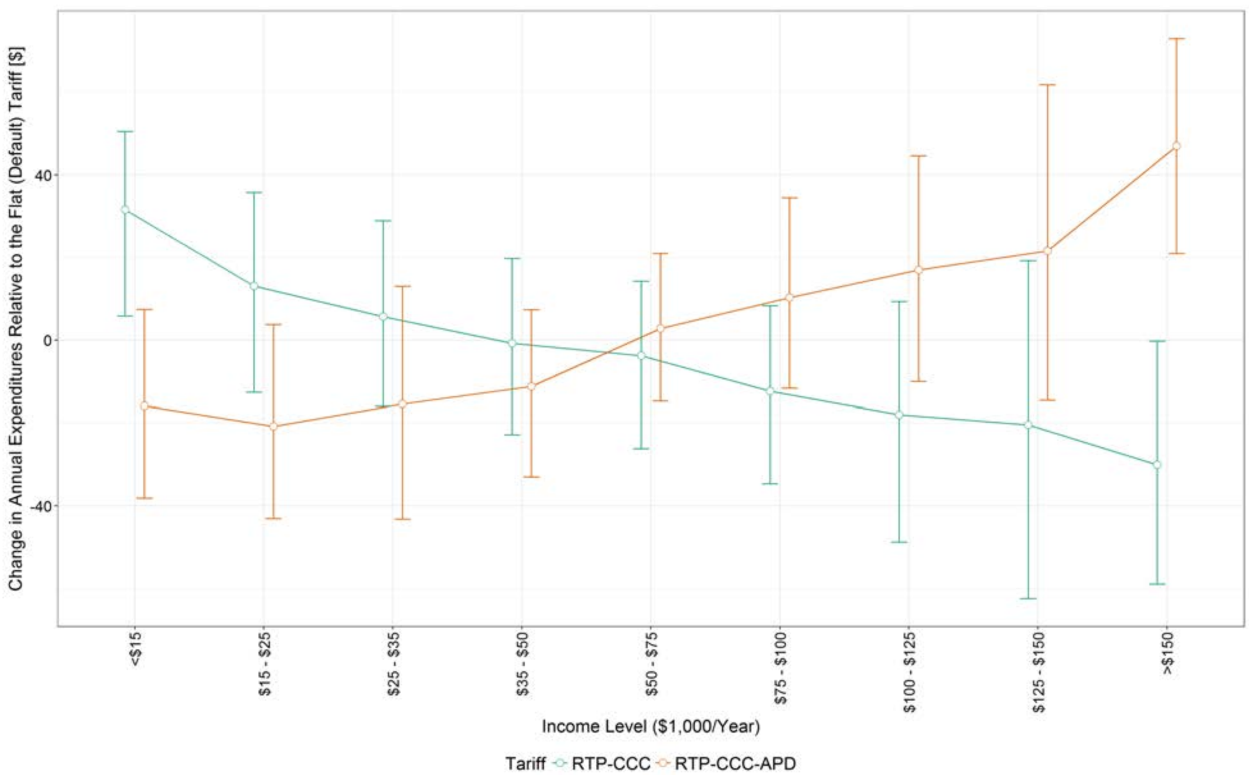
Figure 8 compares the average bill change for customers of different income levels under two different fixed charge scenarios. In the RTP-CCC tariff, fixed charges are uniform across all customers, as presented in Section 3. The marginal prices under the RTP-CCC-APD tariff are identical to the RTP-CCC tariff. However, fixed charges for residual cost recovery are determined according to the customer's annual peak demand (APD stands for "annual peak demand").[24] Given the strong correlation between a customer's peak demand and income, the RTP-CCC-APD is substantially more progressive than the RTP-CCC tariff.

[22] Peak-to-Off-Peak ratio is the ratio of the customer's peak demand over the entire year to the customer's average half-hourly consumption. The various monthly peak demands correspond to the peak demands in the specified month. Finally, the consumption data in different time slots (e.g. "Consumption: 6:00PM-6:30PM") correspond to the consumption during the specified time slot, summed over the entire year. These demand characteristics are chosen due to their strong correlation with income.

[23] That is, a fixed charge based on historical consumption would need to be held constant for, for example, ten years following the implementation of the fixed charge. The longer this time period, the lower the customer response to the fixed charge is likely to be. Regulators could update the customer fixed charges based on a rolling average of the customer demand characteristic of interest (for example, the average annual peak demand over the past 10 years). If fixed charges based on demand characteristics are updated frequently, customers would face inefficient incentives to modify their consumption and production decisions to modify their residual cost payments.

[24] Each customer's monthly fixed charge is determined by multiplying the customer's peak demand over

Figure 8: Change in annual expenditures under the RTP-CCC and the RTP-CCC-APD tariffs, zero-elasticity case



This structure is similar to contracted capacity tariffs used in locations like France and Spain today.[25] However, demand subscriptions assessed annually allow customers to lower their contributions to residual costs by changing their peak demand.

Fixed charges based on demand characteristics have the benefit of simplicity. However, they face two primary drawbacks. First, if updated frequently to reflect changes in demand characteristics, such fixed charges could effectively mimic the inefficient incentives created by marginal charges for residual cost recovery. Second, while low-income customers may benefit on average from such charges, some low-income customers may experience higher expenditures.

---

the year by $8.90 per kilowatt.

[25] See, for example, Électricité de France's Tarif Bleu (Électricité de France, 2018)

4.2 Progressive fixed charges based on customer income

Rather than determining fixed charges according to customer demand characteristics, regulators may wish to design fixed charges based directly on income. Such mechanisms could replace or complement existing bill protection programs such as CARE. We highlight two potential methods for designing progressive fixed charges based on income. First, we examine a method in which low-income customers are provided discounted fixed charges, financed by higher fixed charges for non-low-income customers. Second, we examine a method in which changes in expenditures for low-income customers are capped (hedged) through discounted fixed charges. We refer to both fixed charge discounts and hedges as "bill protections" for simplicity.

The data used in this analysis do not contain customer-level income data, as discussed in Sections 2.1. In order to explore income-based discounts and hedges, we assume that each customer's income is equal to the median income in the Census Block Group in which the customer lives.[26] In practice, customer-level income data could be obtained through credit agencies, means-testing, or other sources.

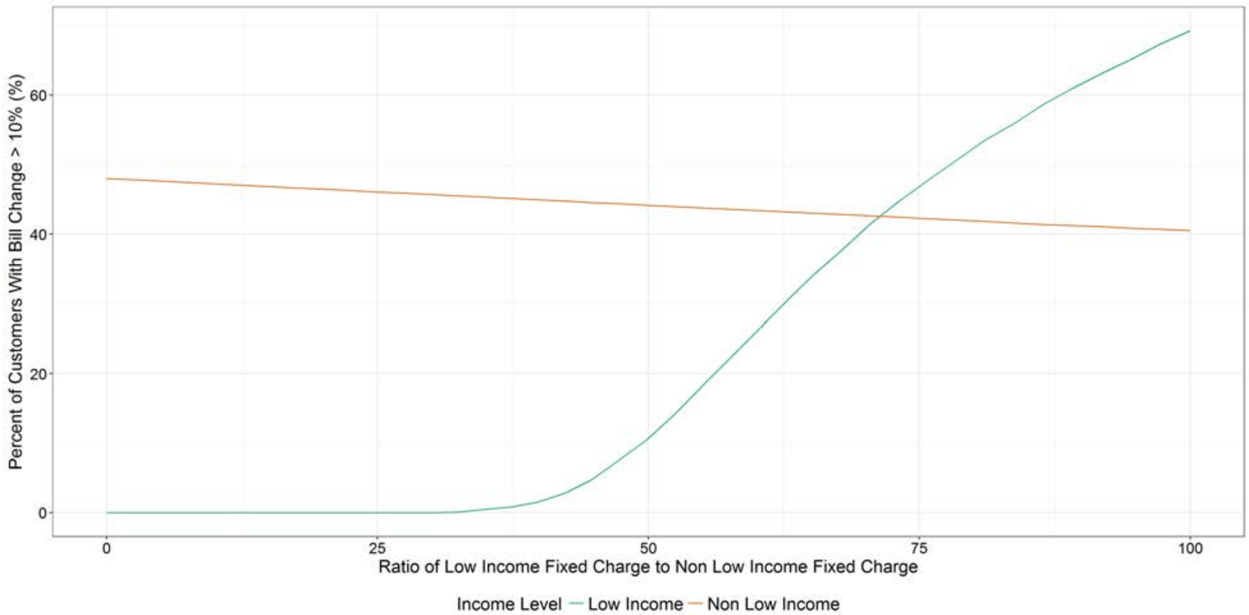
Under both the hedging and fixed charge regimes, the expected impact of the program can be tuned to produce the desired level of protection. That is, the maximum change in expenditures (e.g. 10%) and the number of vulnerable customers experiencing the specified bill change are decision variables.

For example, Figure 9 shows the percent of low-income[27] and non-low-income customers that experience bill changes greater than 10% in the transition to the RTP-CCC tariff as a function of the fixed charge for low-income customers. With fixed charges for low-income customers equal to roughly \$13.30 per-customer per-month, or roughly 33% of the magnitude of the fixed charges for non-low income customers (roughly \$40.39 per-customer per-month), no low-income customers experience bill increases greater than 10%. Intuitively, the impact on non-low income customers is relatively small, as non-low-income customers vastly outnumber low-income customers in our data. In this case, the fixed charge for non-low-income customers increases from roughly \$38.30 per-customer per-month (under the RTP-CCC tariff with uniform fixed charges) to \$40.39 per-customer per-month.

[26] This is a common simplifying assumption made in many analyses that leverage census data, as noted by Borenstein (2012).

[27] We define low-income customers as customers in Census Block Groups with median incomes less than \$25,000 per year. The federal poverty limit for a family of four in 2016 was \$24,300 per year.

Figure 9: Bill change as a function of fixed charge: Transition from the flat to the RTP-CCC tariff, zero-elasticity case.

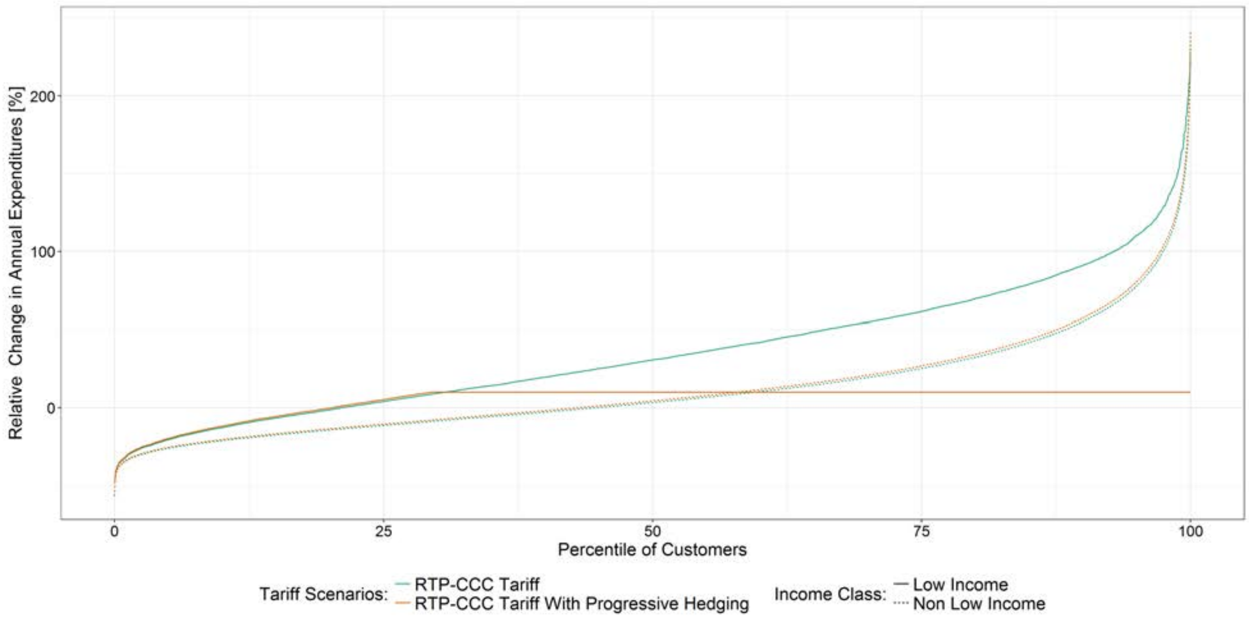


An alternative method would be to provide hedges that cap the bill changes experienced by vulnerable customers. These hedges could be financed through higher fixed-charges on all other customers. Figure 10 shows one example of such a mechanism for the zero-elasticity case. Figure 10 highlights the limited expenditure impacts that such bill caps could have on non-hedged customers. While progressive hedges create lower overall cost impacts on non-low-income customers relative to low-income discounts[28], they do not provide efficient marginal incentives for all customers.[29]

[28]Fewer customers receive fixed charge discounts, as discounts are only provided to the subset of customers that would otherwise face bill increases. Thus, the total cost to be recovered from non-low-income customers is lower than under the discount method.

[29]A customer that expects to see a bill increase relative to the flat default tariff has no incentive to consume efficiently if his or her bill is capped.

Figure 10: Progressive hedging example, zero-elasticity case.



4.3 Progressive fixed charges based on geography

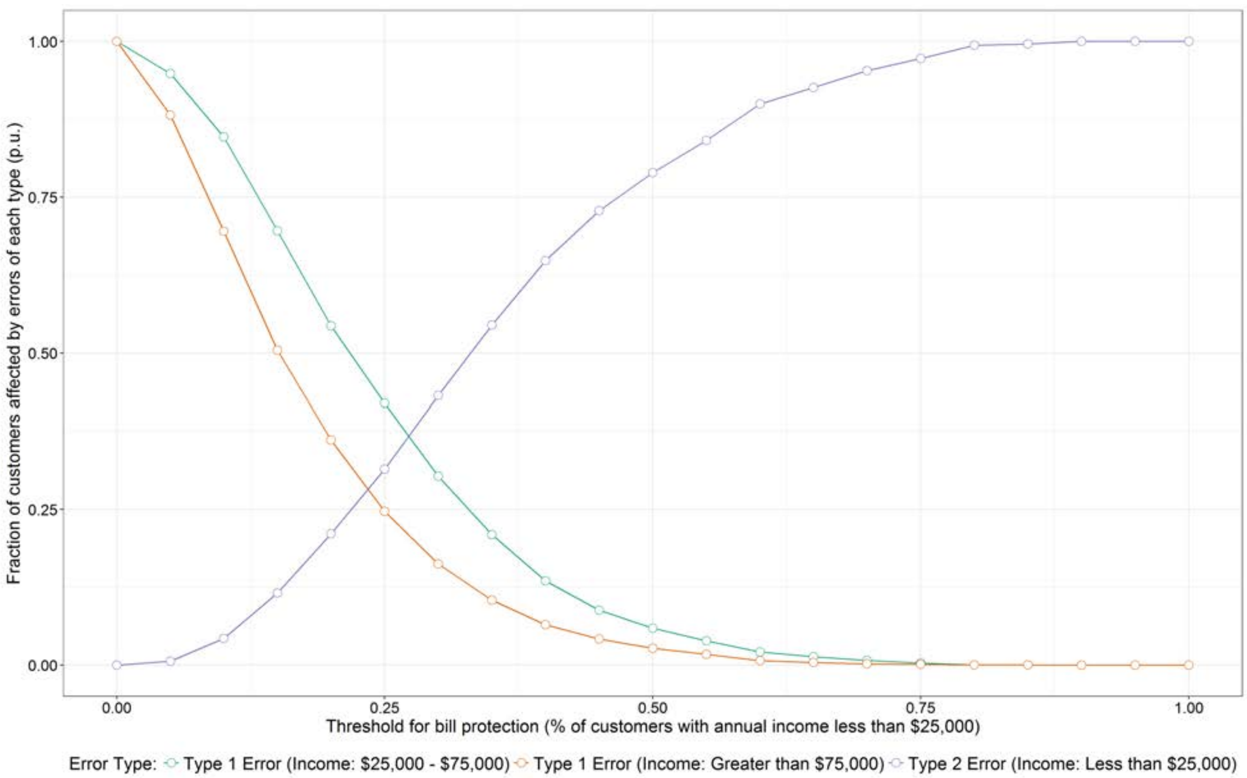
In practice, regulators and utilities may not know customer incomes, and may need to use alternative data sources to determine the appropriate fixed charge. Section 4.1 highlights how regulators could use demand characteristics, but regulators may also wish to use other observable information that correlates with income, such as home size or value.[30] Here we explore the use of geographical and census data—specifically, the characteristics associated with a customer's Census Block Group—to determine whether or not a customer receives bill protection.

Of course, no proxy variable will be perfect. Figure 11 shows the magnitude of type 1 and 2 errors created when using customer geography and the income characteristics of the customer's Census Block Group to determine eligibility for bill protection. Type 1 errors refer to non-low-income customers that receive bill protections that are intended for low-income customers. Type 2 errors refer to low-income customers that are eligible for bill protections but that do not receive them. In Figure 11, the threshold for protection is the percent of customers in a given Census Block Group with income below $25,000 per year. Intuitively, when the threshold for protection is that 0% of customers in a given CBG are low-income,

[30]There is long standing precedent for using information such as home size in designing efficient and equitable two-part tariffs (Lewis, 1941).

0% of low-income customers are overlooked, and 100% of non-low-income customers are also protected. Similarly, when the threshold for protection is that 100% of customers in a given geography are low-income, 0% of low-income customers receive protection, as no CBG is comprised entirely of low-income customers. As noted, LIHEAP has historically had a Type 2 error rate of roughly 78%. In this example, if the threshold for bill protection was that 50% of customers in a given geography were low-income, the Type 2 error rate would be roughly equivalent to LIHEAP, and the Type 1 error rate would be less than 10%.[31]

Figure 11: Type 1 and 2 errors in using Census Block Group data to determine bill protections



5 Conclusions

The emergence of DERs has brought tariff design to the fore of regulatory issues globally. There is now broad acceptance that rate designs must be updated to better reflect the underlying cost of service for different customers. Such tariffs would reflect the time and

[31] It is worth noting that geographically-based fixed charges could ultimately be reflected in rents or land values, as low-tariff regions could be more desirable. This would mitigate the benefit of a geography-based approach.

location-varying marginal cost of energy and would recover residual system costs through fixed charges that do not change as a customer changes his or her consumption profile. However, the implementation of improved tariffs has been stymied in part by the perceived distributional impacts of transitioning to more efficient tariffs. This paper demonstrates that simple changes to fixed charge designs for residual cost recovery make it possible for regulators to improve the economic efficiency of retail tariffs without harming distributional equity. This paper demonstrates that the goals of designing economically efficient and distributionally equitable tariffs need not be in conflict.

Section 3 assesses the consumer surplus gains and distributional impacts of transitioning to many commonly discussed rate designs, including a design with economically efficient marginal prices and a uniform fixed-charge for residual cost recovery. We found five key outcomes:

1. Any transition creates winners and losers, even within customer segments that are benefited by or hurt on average from a transition.

2. Updating the energy component of the tariff to better reflect the real-time marginal costs of energy benefits low-income customers on average, although the gains are relatively modest (1% to 5% of expenditures) if no changes are made to the design of residual cost recovery mechanisms.

3. Transitioning to uniform fixed charges for residual cost recovery is likely to cause higher average expenditures for low-income customers on average. This is due primarily to the low average consumption levels of low-income customers relative to higher-income customers.

4. Nonetheless, with relatively limited price elasticity, nearly all socioeconomic groups are likely to see average consumer surplus benefits in the transition to an efficient tariff with fixed charges for residual cost recovery, even if bills increase for certain groups.

5. The recovery of residual network and policy costs through volumetric rates appears to be a larger economic distortion than the recovery of energy costs through time invariant rates.

Next, Section 4 demonstrates that simple deviations from uniform fixed charge designs can mitigate some or all of the undesirable distributional impacts of transitioning to an efficient rate design while maintaining nearly all of the desired economic efficiency benefits. A close examination of the economics of rate design reveals that the feature that makes designing electricity rates so challenging provides the key to improving the efficiency and equity of retail electricity rates. Due to the existence of non-convex costs that cannot be efficiently allocated to individual users' marginal consumption or production decisions, there is a wide array of potential fixed charges for residual cost recovery, all of which have equal or approximately equal economic efficiency.

We explore three possible designs for economically efficient residual cost recovery that alleviate the distributional challenges of uniform fixed charges. We demonstrate that fixed charges designed using observable information such as customer demand profiles or geography can provide more efficient bill protections than existing needs-tested programs such as the Low-Income Home Energy Assistance Program.

We introduce two progressive bill protection schemes: one based on discounted fixed charges for low-income customers, and one based on bill caps for low-income customers. While discounted fixed charges are relatively simple mechanisms, these mechanisms tend to have larger expenditure impacts on non-low-income customers than the bill cap protection scheme. However, while bill caps have relatively small impacts on non-low-income customers, they do not provide efficient marginal signals to all protected customers.

There is substantial room for additional research into the issues raised in this paper. In particular, what are the optimal mechanisms and thresholds for identifying which customers are eligible for bill protections? How might customers respond to the types of progressive fixed charges and hedges introduced in this paper? Stakeholder and regulator engagement can inform an agenda for future work towards practical tariff improvements with enhanced protection for low-income customers.

References

Allcott, H. (2011): "Rethinking real-time electricity pricing." *Resource and Energy Economics*, 33, 820–842.

Berry, C., C. Hronis, and M. Woodward (2018): "One in three U.S. households faces a challenge in meeting energy needs." https://www.eia.gov/todayinenergy/detail.php?id=37072, accessed: 2018-09-30.

Blonz, J. A. (2018): "Making the Best of the Second-Best: Welfare Consequences of Time-Varying Electricity Prices." Working paper, Resources for the Future.

Boiteux, M. (1956): "Sur la gestion des monopoles publics astreints à l'équilibre budgétaire," *Econometrica, Journal of the Econometric Society*, 22–40.

Bonbright, J. C. (1961): *Principles of Public Utility Rates*, Columbia University Press.

Borenstein, S. (2005a): "The Long-Run Efficiency of Real-Time Electricity Pricing." *The Energy Journal*, 26, 93–116.

——— (2005b): "Time-varying retail electricity prices: Theory and practice," *Electricity deregulation: choices and challenges*, 4, 317–356.

——— (2007): "Customer risk from real-time retail electricity pricing: bill volatility and hedgability," *The Energy Journal*, 28, 111–132.

——— (2011): "Regional and income distribution effects of alternative retail electricity tariffs," *Energy Institute at Haas Working Paper*, 225.

——— (2012): "The Redistributional Impact of Nonlinear Electricity Pricing." *American Economic Journal: Economic Policy*, 4, 56–90.

——— (2013): "Effective and Equitable Adoption of Opt-In Residential Dynamic Electricity Pricing." *Review of Industrial Organization*, 42, 127–160.

——— (2016): "The economics of fixed cost recovery by utilities." *The Electricity Journal*, 29, 5–12.

Borenstein, S. and J. B. Bushnell (2018): "Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency," Working Paper 24756, National Bureau of Economic Research.

Borenstein, S. and L. W. Davis (2012): "The equity and efficiency of two-part tariffs in US natural gas markets." *The Journal of Law and Economics*, 55, 75–128.

Braeutigam, R. R. (1989): "Optimal policies for natural monopolies," in *Handbook of Industrial Organization*, ed. by R. Schmalensee and R. Willig, Elsevier, vol. 2.

Brown, S. J. and D. S. Sibley (1986): *The Theory of Public Utility Pricing*, Cambridge University Press.

Burger, S. P., I. Schneider, A. Botterud, and I. J. Pérez-Arriaga (2018): "Fair, Equitable, and Efficient Tariffs in the Presence of Distributed Energy Resources," Working Paper 2018-012, MIT Center for Energy and Environmental Policy Research.

Coase, R. H. (1946): "The Marginal Cost Controversy," *Economica*, 13, 169–182.

Cohen, M., P. Kauzmann, and D. Callaway (2016): "Effects of distributed PV generation on California?s distribution system, part 2: Economic analysis." *Solar Energy*, 128, 139–152.

Commission, C. P. U. (2018): "Residential Rate Reform / R.12-06-013," http://www.cpuc.ca.gov/General.aspx?id=12154.

Commonwealth Edison (2011): "PopFacts - Demographic Snapshot – ComEd Northern Illinois Service Territory," https://www.comed.com/SiteCollectionDocuments/ComEd_Service_Territory_Demographics_Update_122311.pdf, accessed: 2018-10-09.

Edison, C. (2016): "Schedule of Rates for Electric Service." .

Électricité de France (2018): "Grille de prix de l'offre de fourniture d'électricité ¡¡Tarif Bleu¿¿," https://particulier.edf.fr/content/dam/2-Actifs/Documents/Offres/Grille_prix_Tarif_Bleu.pdf, accessed: 2019-01-14.

European Commission (2016): "COM(2016) 769 final: Report from the Commission to the European Parliament, the Council, the European Economic and Social Committee, and the Committee of the Regions: Energy prices and costs in Europe." https://ec.europa.eu/energy/sites/ener/files/documents/com_2016_769.en_.pdf.

Exelon (2018): "Our companies - ComEd," http://www.exeloncorp.com/companies/comed.

Falk, G., A. Mitchell, K. E. Lynch, M. McCarty, W. R. Morton, and M. L. Crandall-Hollick (2015): "Need-Tested Benefits: Estimated Eligibility and Benefit Receipt by Families and Individuals," Report R44327, Congressional Research Service.

Faulhaber, G. (1975): "Cross-Subsidization: Pricing in Public Enterprises." *The American Economic Review*, 65, 966–977.

Feldstein, M. S. (1972a): "Distributional equity and the optimal structure of public prices," *The American Economic Review*, 62, 32–36.

——— (1972b): "Equity and efficiency in public sector pricing: the optimal two-part tariff," *The Quarterly Journal of Economics*, 176–187.

Hittinger, E. and J. Siddiqui (2017): "The challenging economics of US residential grid defection." *Utilities Policy*, 45, 27–35.

Hledik, R. (2014): "Rediscovering Residential Demand Charges." *The Electricity Journal*, 27, 82–96.

Hledik, R. and G. Greenstein (2016): "The distributional impacts of residential demand charges." *The Electricity Journal*, 29, 33–41.

Holland, S. and E. Mansur (2008): "Is real-time pricing green? The environmental impacts of electricity demand variance." *The Review of Economics and Statistics*, 90, 550–561.

Horowitz, S. and L. Lave (2014): "Equity in Residential Electricity Pricing." *The Energy Journal*, 35, 1–23.

Houthakker, H. S. (1951): "Electricity Tariffs in Theory and Practice," *The Economic Journal*, 61, 1–25.

Ito, K. (2014): "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review*, 104, 537–563.

Ito, K. and S. Zhang (2018): "Do Consumers Distinguish Marginal Cost from Fixed Cost? Evidence from Heating Price Reform in China." in *National Bureau of Economic Research Conference Paper*.

Jessoe, K. and D. Rapson (2014): "Knowledge Is (Less) Power: Experimental Evidence from Residential Energy Use." *American Economic Review*, 104, 1417–1438.

Joskow, P. L. (2007): "Regulation of the Natural Monopoly," in *Handbook of Law and Economics*, ed. by A. M. Polinsky and S. Shavell, Elsevier B.V., vol. 2.

——— (2008): "Capacity payments in imperfect electricity markets: Need and design." *Utilities Policy*, 16, 159–170.

Joskow, P. L. and J. Tirole (2007): "Reliability and competitive electricity markets." *RAND Journal of Economics*, 38, 60–84.

Joskow, P. L. and C. D. Wolfram (2012): "Dynamic pricing of electricity," *American Economic Review*, 102, 381–85.

Khalilpour, R. and A. Vassallo (2015): "Leaving the grid: An ambition or a real choice?" *Energy Policy*, 82, 207–221.

Levinson, A. and E. Silva (2019): "The Electric Gini: Income Redistribution through Energy Prices," Working paper.

Lewis, W. A. (1941): "The Two-Part Tariff." *Economica*, 8, 249–270.

Massachusetts Department of Public Utilities (2016): "D.P.U. 15-155," https://www.mass.gov/files/documents/2017/08/30/15-155.pdf, accessed: 2018-10-09.

Mays, J. and D. Klabjan (2017): "Optimization of time-varying electricity rates." *The Energy Journal*, 38, 67–91.

Nelson, T., S. P., and S. Kelley (2011): "Australian Residential Solar Feed-in Tariffs: Industry Stimulus or Regressive form of Taxation." *Economic Analysis and Policy*, 41, 113–129.

New York Department of Public Service (2016a): "CASE 14-M-0101 ? Proceeding on Motion of the Commission in Regard to Reforming the Energy Vision: Order Adopting a Ratemaking and Utility Revenue Model Policy Framework," http://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=%7BD6EC8F0B-6141-4A82-A857-B79CF0A71BF0%7D, accessed: 2018-10-09.

——— (2016b): "Case 15 - E - 0751 - Staff Report and Recommendations in the Value of Distributed Energy Resources Proceeding Staff Report and Recommendations," https://www.nyserda.ny.gov/-/media/Files/Programs/Clean-Energy-Standard/Staff-Report-Recommendations-Value-Distributed-Energy-Resources.pdf.

Newell, S. and A. Faruqui (2009): "Dynamic Pricing: Potential Wholesale Market Benefits in New York State." Report, New York Independent System Operator, Inc.

Pérez-Arriaga, I., F. Rubio, J. Puerta, J. Arceluz, and J. Marin (1995): "Marginal pricing of transmission services: An analysis of cost recovery." *IEEE Transactions on Power Systems*, 10, 546–553.

Pérez-Arriaga, I. J., C. Knittel, A. Bharatkumar, M. Birk, S. P. Burger, J. P. Chaves-Ávila, P. Dueñas Martinez, I. Herrero, J. D. Huntington, Sam Jenkins, M. Luke, R. Miller, P. Rodilla, R. Tabors, C. Tapia-Ahumada, Karen Vergara, and N. Xu (2016): "Utility of the Future: An MIT Energy Initiative response to an industry in transition," Report, Massachusetts Institute of Technology.

PJM Interconnection (2017): "Summer 2016 - Peaks and 5CPs," https://www.pjm.com/-/media/planning/res-adeq/load-forecast/summer-2016-pjm-5cps-and-w-n-zonal-peaks.ashx?la=en, accessed: 2018-10-09.

Posner, R. A. (1971): "Taxation by regulation." *The Bell Journal of Economics and Management Science*, 2, 22–50.

Proudlove, A., B. Lips, and D. Sarkisian (2018): "50 States of Solar: Q2 2018 Quarterly Report," Report, NC Clean Energy Technology Center.

Ramsey, F. P. (1927): "A Contribution to the Theory of Taxation," *The Economic Journal*, 37, 47–61.

Schmalensee, R., V. Bulovic, R. Armstrong, C. Batlle, P. Brown, J. Deutch, H. Jacoby, R. Jaffe, J. Jean, R. Miller, F. O'Sullivan, J. Parsons, J. I. Perez-Arriaga, N. Seifkar, R. Stoner, and C. Vergara (2015): "The Future of Solar Energy: An Interdisciplinary MIT Study," Report, Massachusetts Institute of Technology.

Schneider, I. and C. R. Sunstein (2017): "Behavioral considerations for effective time-varying electricity prices," *Behavioural Public Policy*, 1, 219–251.

Schweppe, F., M. Caramanis, R. Tabors, and R. Bohn (1988): *Spot Pricing of Electricity*, Springer US.

Seel, J., A. D. Mills, and R. H. Wiser (2018): "Impacts of High Variable Renewable Energy Futures on Wholesale Electricity Prices, and on Electric-Sector Decision Making," Working Paper LBNL-2001163.

Sidak, J. G. and D. F. Spulber (1996): "Deregulatory takings and breach of the regulatory contract," *NYUL Rev.*, 71, 851.

Simshauser, P. and D. Downer (2016): "On the Inequity of Flat-rate Electricity Tariffs." *The Energy Journal*, 37, 199–229.

Spees, K., S. A. Newell, and J. P. Pfeifenberger (2013): "Capacity Markets: Lessons Learned from the First Decade." *Economics of Energy and Environmental Policy*, 22, 1–26.

Trabish, H. (2018): "Are regulators starting to rethink fixed charges?" https://www.utilitydive.com/news/are-regulators-starting-to-rethink-fixed-charges/530417/, accessed: 2018-10-22.

U.S. Census Bureau (2018a): "American Community Survey (ACS)," https://www.census.gov/programs-surveys/acs/.

——— (2018b): "Geographic Terms and Concepts - Block Groups," https://www.census.gov/geo/reference/gtc/gtc_bg.html.

U.S. Department of Energy (2016): "Final Report on Customer Acceptance, Retention, and Response to Time Based Rates from the Consumer Behavior Studies," https://www.smartgrid.gov/files/CBS_Final_Program_Impact_Report_20161107.pdf.

U.S. Department of Health & Human Services (2018): "Poverty Guidelines," https://aspe.hhs.gov/poverty-guidelines.

U.S. Energy Information Administration (2015): "2015 Residential Energy Consumption Survey: Energy Consumption and Expenditures Tables: Table CE1.3," https://www.eia.gov/consumption/residential/data/2015/c&e/pdf/ce1.3.pdf.

——— (2017): "Form EIA-861," https://www.eia.gov/electricity/data/eia861/.

Vázquez, C., M. Rivier, and I. Pérez-Arriaga (2002): "Marginal pricing of transmission services: An analysis of cost recovery." *IEEE Transactions on Power Systems*, 17, 349–357.

Vickrey, W. (1971): "Responsive Pricing of Public Utility Services," *Bell Journal of Economics*, 2, 337–346.

Wolak, F. A. (2011): "Do Residential Customers Respond to Hourly Prices? Evidence from a Dynamic Pricing Experiment." *American Economic Review*, 101, 83–87.

6 Appendices

NOT FOR PUBLICATION

6.1 Data

The original sample obtained from ComEd contained 344,717 customers, including housing-type data and half-hourly electricity consumption data from 2016. However, a substantial number of customers in this sample contained missing or potentially flawed data, and were therefore removed. Out of the initial 344,717 customers only 278,821 appear in each of the monthly files. There are two primary causes for incomplete time series. First, the smart meters that are used to measure and report consumption data were deployed in a step-wise fashion. Half-hourly consumption data are only available for customers following the installation of smart meters, which happened mid year for certain customers. Second, customers may move throughout the year, thus changing their meters and corresponding customer IDs.

Next, in an effort to use only high quality customer data, we removed all customers with incomplete or inconsistent data. We removed all customer accounts with any missing consumption values for any half-hourly period. Additionally, for numerous customers the daily sum of the half-hourly consumption reads did not equal the reported total daily sum. That is, there were inconsistencies—in some cases, substantial inconsistencies—in the raw data provided by ComEd. The majority of cases with this issue occur in January, February and March. We removed all customers with at least one case of more than a 5% deviation between the reported daily energy consumed and the sum of the half-hourly consumption reads.

Finally, we removed 62 customers from non-residential rate classes. As noted in 2.1, the final sample contains 100,170 residential customers with complete half-hourly consumption data for 2016.

Table 6: Demographic characteristics of the ComEd Service territory and the data used in this study

	Demographic variable	ComEd Service Territory	Customer Sample
Income	Less than \$15,000	10.49%	13.72%
	\$15,000 - \$24,999	8.43%	10.33%
	\$25,000 - \$34,999	9.25%	9.35%
	\$35,000 - \$49,999	14.36%	12.37%
	\$50,000 - \$74,999	20.06%	16.73%
	\$75,000 - \$99,999	13.89%	11.83%
	\$100,000 - \$124,999	9.08%	8.36%
	\$125,000 - \$149,999	5.29%	5.20%
	More than \$150,000	9.15%	12.11%
Age	0-17	25.37%	22.82%
	18-24	9.41%	9.79%
	25-64	53.52%	54.97%
	65+	11.7%	12.42%
Race	White alone	65.05%	55.91%
	Black or African Amer. alone	16.91%	23.19%
	Amer. Indian & Alaska native alone	0.33%	0.30%
	Asian alone	5.43%	6.82%
	Native Hawaiian & other Pac. Isl. alone	0.06%	0.04%
	Other racial designations	12.22%	13.74%
Educational attainment	Less than 9th Grade	6.89%	8.32%
	Some High School, no diploma	7.62%	7.45%
	High School Graduate (or GED)	25.44%	23.94%
	Some College, no degree	20.20%	19.07%
	Associate Degree	6.69%	6.36%
	Bachelor's Degree	20.43%	21.22%
	Master's Degree	9.22%	9.88%
	Professional School Degree	2.39%	2.47%
	Doctorate Degree	1.12%	1.29%
Employ.	Civilian employed	61.73%	60.00%
	Civilian unemployed	6.41%	6.39%
	Armed forces	0.16%	0.02%
	Not in labor force	31.70%	33.59%

Note: 2011 demographic data for the ComEd service territory used Commonwealth Edison (2011).

6.2 Derivation of Equation 1

Customer bill change is given by $\Delta_i = Y_i'\beta + \epsilon_i$ where $p_i = \mathbb{P}(Y_i)$. We seek to minimize the expected square error:

$$\beta = \arg\min_b \sum_i \mathbb{E}(\Delta_i - Y_i'b)'(\Delta_i - X_i'b) \tag{3}$$

The objective function in (3) is equivalent to

$$\begin{aligned}
\sum_{i,j} p_{ij}(\Delta_i - e_j'b)'(\Delta_i - e_j'b) &= \sum_{i,j} p_{ij}(\Delta_i - e_j'b)'(\Delta_i - e_j'b) && (4)\\
&= \sum_{i,j} p_{ij}\Delta_i\Delta_i - p_{ij}b'e_j\Delta_i - p_{ij}e_j'b + p_{ij}e_je_j'b && (5)\\
&= \sum_i \Delta_i\Delta_i - 2\Delta_i p_i'b + b'\text{diag}(p_i)b && (6)
\end{aligned}$$

Taking the derivative of (6) with respect to b we obtain the first order condition for the optimization problem in (3):

$$0 = \sum_i -2\Delta_i p_i + 2\text{diag}(p_i)\beta \tag{7}$$

By rearranging this expression, we get the initial result in Equation 1. Note that the second derivative equals $\sum_i 2\text{diag}(p_i)$, which is a diagonal matrix with non-negative entries along the diagonal; hence, it is positive semi-definite. This confirms that (3) is a convex optimization problem with the solution β as the unique optimum.

6.3 Tariff designs

Notes on Flat-NCDC: Non-coincident peak demand charge designs have garnered some attention in recent years as alternatives to volumetric charges (see, for example, Hledik (2014)). However, individual peaks often do not align well with the network or system-demand peaks that drive costs. Further, residual costs are not affected by individual customer peak demands. NCDCs are therefore distortionary mechanisms for recovering residual charges. We include this case to highlight the impacts of non-coincident peak-demand charges. We test multiple levels of NCDCs and find similar results in all cases. We present only one NCDC case for concision.

Notes on CPP-10: As of the end of 2016, there were 23 residential critical peak pricing programs in the U.S. (U.S. Energy Information Administration, 2017). Critical peak pricing programs are commonly considered improvements over flat pricing schemes, as they capture some of the time variability in the price of electricity. However, because these schemes are typically limited to a finite number of event days per year, and because the price of electricity is typically administratively determined during event- and non-event-periods, these programs tend to capture only a small fraction of the efficiency of real-time pricing programs (Blonz, 2018). We test a number of peak-to-off-peak price ratios and find similar results in all cases. We present only one critical peak price case for concision.

Notes on RTP-CCC: All U.S. wholesale electricity markets—with the exception of ERCOT in the state of Texas—operate some form of organized capacity market designed to ensure that the system maintains a desired margin of generation capacity above electricity demand. These capacity remuneration mechanisms have the effect of suppressing short run electricity prices below the levels necessary to maintain an "adequate" level of capacity (where the adequate level is most often defined by a regulatory authority or system operator) in the system (Spees et al., 2013).[32] Critically, prices during periods of scarcity do not rise to the long run marginal cost and do not adequately signal a consumer's contribution to future capacity costs (Joskow and Tirole, 2007). Using simulation models of varying degrees of complexity, Mays and Klabjan (2017) and Newell and Faruqui (2009) demonstrate that, in markets with capacity remuneration mechanisms, adding a peak-coincident charge to the real-time price of energy during periods of scarcity can increase efficiency relative to a pure real-time price. The rational for forward-looking capacity charges for transmission and distribution is the same as that outlined here. However, as noted, we do not have network topology or loading data, and thus don't assess such charges.

[32]This follows directly from the fact that the current system capacity is supported by both energy and capacity market revenues.

The efficient signal equals the expected marginal change in capacity market costs C for a marginal change in demand at any point in time x_t. If capacity demand at the capacity market clearing price P^* is $D(P^*)$, then capacity market costs are as in Equation 8. The optimal coincident capacity charge is then as in Equation 9.

$$C = D(P^*)P^* \tag{8}$$

$$E\left[\frac{\partial C}{\partial x_t}\right] = E\left[\frac{\partial D(P^*)}{\partial x_t}P^* + D(P^*)\frac{\partial P^*}{\partial x_t}\right] \tag{9}$$

We assume the marginal change in price with respect to demand to be zero. In other words, we assume that P^* is a function of the capacity supply curve only. This allows us to simplify Equation 9 to the form shown in Equation 10.

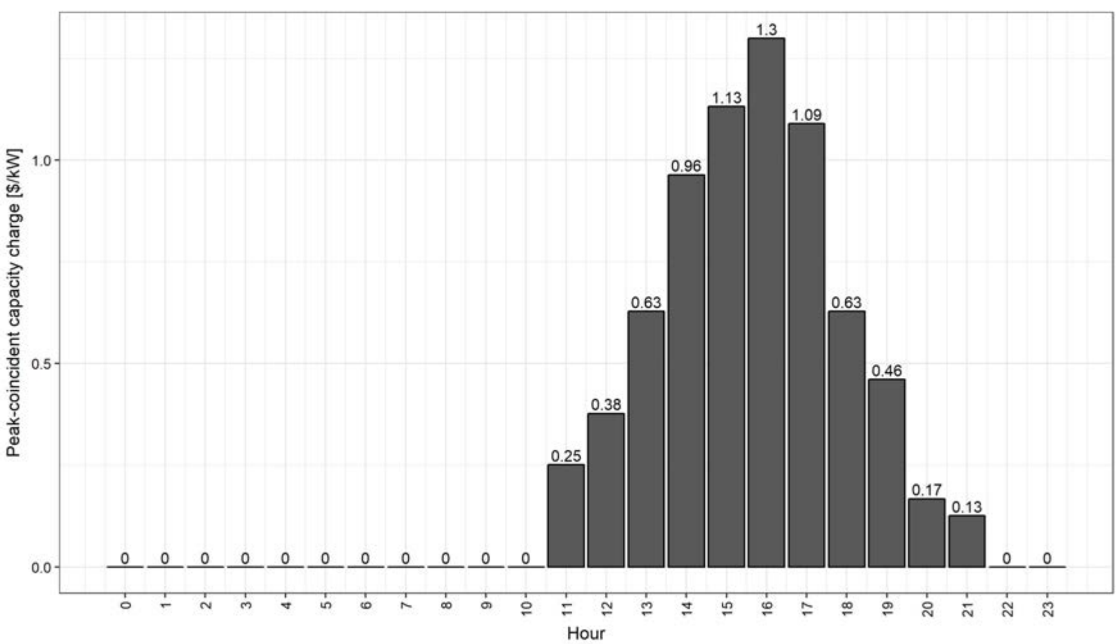
$$E\left[\frac{\partial C}{\partial x_t}\right] = E\left[\frac{\partial D(P^*)}{\partial x_t}\right]E[P^*] \tag{10}$$

We calculate the expected capacity market clearing price as the average of the 2013, 2014, and 2015 capacity market clearing prices for the ComEd load zone. We calculate the expected change in the capacity market demand as the probability weighted change in the demand of the customers in our sample. We use 2005-2015 PJM system-wide data to calculate the probability that any given hour will be one of the five PJM-wide peak demand hours.[33] The resulting prices are represented in Figure 12. We add these peak-coincident capacity charges to the real-time price of energy during the five days of highest PJM-wide demand in 2016.[34] On all other days, the marginal energy price is the hourly locational marginal price at the ComEd load zone. In practice, this might look very similar to a critical peak price added on top of a real-time price, in which event days are announced in anticipation of peak demand.

[33]This mirrors the method used by Newell and Faruqui (2009). Mays and Klabjan (2017) use an optimization model to compute the optimal pass through of capacity market costs. The focus of our paper is on the distributional impacts rather than on estimating a precise measure of welfare gain, and thus believe our simplified approach to be adequate.

[34]These days were, in order of highest demand, 8/11/16, 7/25/16, 8/12/16, 7/27/16, 8/10/16 (PJM Interconnection, 2017)

Figure 12: Coincident capacity charges



6.4 Drivers of bill changes

To understand the primary drivers of the bill changes seen in Figure 4, we run a series of simple linear regressions on various customer-level characteristics. We model annual expenditure changes for tariff r and customer i as $\Delta_{i,r} = \Gamma_r C_i + \epsilon_{i,r}$, where, ϵ_{ir} represents the residual, and C_i represents the customer characteristic of interest. We assess customer service class and six energy consumption-based characteristics, outlined below:

1. Annual consumption: $AC_i = \sum_t x_{i,t}$, where $x_{i,t}$ is customer i's demand at time t
2. Monthly consumption: $MC_{i,m} = \sum_{t \in m} x_{i,t}, \quad \forall m \in \{1, ..., 12\}$
3. Monthly peak demand: $\hat{x}_{i,m} = max(x_{i,t}), \quad \forall t \in m, \quad \forall m \in \{1, ..., 12\}$
4. Price quantiles: $PQ_{i,q,r} = \sum_{t \in q} x_{i,t}, \quad \forall q \in \{1, ..., Q\}, \quad \forall r$[35]
5. Hourly consumption: $HC_{i,h} = \sum_{t \in h} x_{i,t}, \quad \forall h \in \{1, ..., 24\}$
6. Standard deviation of daily consumption: $\sigma_i^d = \sqrt{\frac{\sum_d (x_{i,d} - \bar{x}_{i,d})}{365}}$

Table 7 presents the adjusted R^2 values from 8 sets of customer characteristics. We observe that, as expected, the primary driver of bill changes in a transition towards time varying rates is aggregate consumption during high price periods. We also note that annual consumption is a strong predictor of bill changes under the RTP-CCC tariff, stemming primarily from the fact that the RTP-CCC tariff includes a substantially lower volumetric rate and substantially higher fixed charge.

[35]We sort each marginal price vector into quantiles, and sum each customer's energy consumption during the times corresponding to that price quantile. For example, if $q = 10$, $PQ_{i,10,r}$ is the sum of consumer i's energy consumption during the hours corresponding to the 10% highest energy prices for tariff r. For the RTP-Volumetric and RTP-CCC tariffs, $Q = 10$. For the CPP-10 tariff, $q = 2$. Given that the flat default and Flat-NCDC tariffs have no price variation over time, $Q = 0$.

Table 7: Adjusted R^2 values for regressions of aggregate changes in annual expenditures on profile characteristics

Profile Characteristic	Flat-NCDC	CPP-10	RTP-Volumetric	RTP-CCC
Annual Consumption	0.027	0.020	0.003	0.928
Monthly Consumption	0.414	0.328	0.578	0.959
Monthly Peaks	0.215	0.210	0.419	0.499
Price Quantiles	0.000	0.583	0.978	0.977
Price Quantiles and Class	0.000	0.891	0.978	0.989
Hourly Consumption	0.078	0.434	0.693	0.957
Service Class	0.370	0.106	0.112	0.216
Std. Dev. Of Daily Consumption	0.046	0.134	0.025	0.547

6.5 Consumer surplus calculations

In this paper, we adopt assume customer demand for each customer i in each time period t follows the following equation:

$$x_{i,t} = A_{i,t} p_t^{\epsilon} \tag{11}$$

Equation 11 follows from Borenstein (2013). The parameter $A_{i,h}$ is a customer-specific scaling factor that is calculated using the customer's consumption under the default rate and the default volumetric rate. The parameter ϵ is the own price elasticity of demand. Following from from Equation 11, the consumer surplus in each time period is calculated as follows:

$$CS_{i,t} = \int_{x_{i,t}(p_{max})}^{x_{i,t}(p_t)} \left(\frac{x_{i,t}}{A_{i,t}}\right)^{1/\epsilon} dx - F_{i,t} \tag{12}$$

The parameter p_{max} is the maximum price the customer is willing to pay for the first unit of electricity consumed. We detail how this parameter is calculated below. The parameter $F_{i,t}$ is the fixed charge that customer i faces, scaled to time period t. The aggregated consumer surplus over the entire year is calculated by summing Equation 12 over all t:

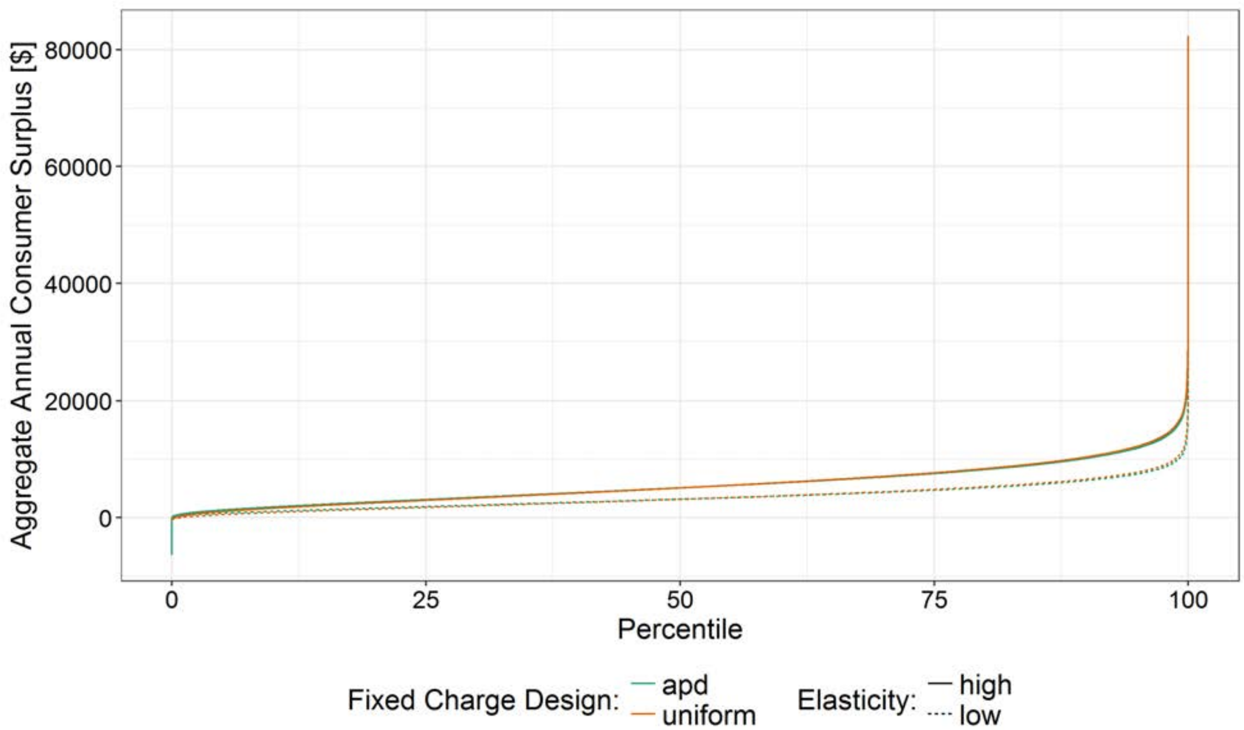
$$CS_i = \frac{\epsilon}{1+\epsilon} \sum_t \Big(A_{i,t}\big(p_t^{\epsilon+1} - p_{max}^{\epsilon+1}\big)\Big) - \sum_t F_{i,t} \tag{13}$$

To calculate the maximum price that consumers are willing to pay, we calculate p_{max} such that all customers have non-negative consumer surplus under the default flat tariff. That is, for every consumer, the surplus from consumption is greater than or equal to the fixed charge under the default tariff. In order to find this value, we first solve the consumer surplus calculations for the flat tariff using a placeholder p_{max} value. We then find the consumer with the lowest total surplus. Finally, using a low estimate of price elasticity ($\epsilon = -0.1$), we solve the following equation for the p_{max} that yields zero surplus:

$$p_{max} = \left(\frac{\sum_t \left(A_t p_t^{\epsilon+1}\right) - \left(\frac{1+\epsilon}{\epsilon}\right)F}{\sum_t A_t}\right)^{\frac{1}{\epsilon+1}} \tag{14}$$

The resulting p_{max} is \$9.012/kWh, which is roughly in line with measures of the cost of interruptions of electricity service for residential customers. Using this p_{max}, we see that, with low elasticity, more than 99% of customers have positive surplus under the RTP-CCC tariff (in which all customers have a uniform fixed charge of roughly \$39 per customer per month). With high elasticity, more than 99.7% of customers have positive surplus under the RTP-CCC tariff. Under the RTP-CCC-APD tariff (in which fixed charges are allocated based on customer peak demand), more than 99.7% of customers have positive surplus with low elasticity. With high elasticity, more than 99.9% of customers have positive elasticity under the RTP-CCC-APD tariff. This is likely a conservative estimate, as the value of connecting to the network is likely to be higher than the short term cost of curtailing consumption. Figure 13 displays the aggregate consumer surplus under the RTP-CCC and RTP-CCC-APD tariffs.

Figure 13: Distribution of annual consumer surplus under the RTP-CCC and RTP-CCC-APD tariffs



6.6 Change in consumer surplus in the transition from the flat to the RTP-CCC tariff

Table 8: Change in consumer surplus relative to the flat default tariff by socioeconomic group, high elasticity case

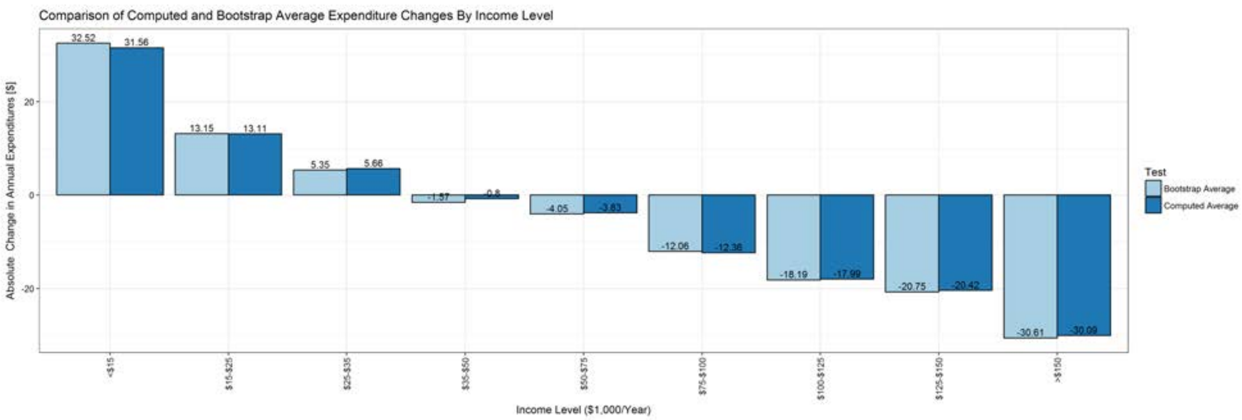
	Demographic variable	Flat NCDC			CPP 10			RTP Volumetric			RTP CCC		
		Mean	2.5%	97.5%	Mean	2.5%	97.5%	Mean	2.5%	97.5%	Mean	2.5%	97.5%
Income	Less than $15,000	31.88	18.53	44.72	15.48	12.75	18.42	5.58	4.27	6.78	228.94	190.27	270.81
	$15,000 - $24,999	40.73	24.37	56.80	15.59	12.20	19.07	4.80	3.43	6.22	265.28	222.76	306.27
	$25,000 - $34,999	38.68	22.07	55.53	15.23	11.84	19.31	4.50	2.96	5.92	279.60	234.92	320.89
	$35,000 - $49,999	39.21	24.64	53.52	15.24	12.15	18.66	3.98	2.54	5.29	292.62	257.73	331.29
	$50,000 - $74,999	32.11	18.66	45.02	14.06	11.18	16.98	3.60	2.55	4.95	299.70	266.72	336.54
	$75,000 - $99,999	30.61	13.98	46.17	14.13	10.64	17.67	3.06	1.60	4.42	317.27	277.75	357.79
	$100,000 - $124,999	27.59	5.10	45.05	14.19	9.44	18.82	2.72	0.93	4.63	327.65	276.61	381.56
	$125,000 - $149,999	24.54	-1.60	49.29	14.31	8.94	20.07	2.55	0.44	5.20	332.39	266.74	404.36
	More than $150,000	7.42	-13.03	26.27	14.44	10.80	18.64	2.75	1.04	4.35	346.70	296.51	407.12
Age	0-17	41.78	30.84	54.18	15.49	13.05	17.99	3.66	2.65	4.70	311.20	282.50	338.88
	18-24	36.96	19.17	55.41	15.62	11.87	19.05	4.11	2.54	5.75	283.20	238.49	328.52
	25-64	28.74	20.99	35.55	14.61	13.06	16.13	3.87	3.20	4.53	290.32	270.56	308.96
	65+	20.22	5.27	33.90	13.60	10.48	16.87	4.09	2.73	5.41	286.86	247.60	328.13
Race	White alone	21.51	14.01	29.26	12.00	10.50	13.41	2.57	1.99	3.20	303.12	285.25	324.50
	Black or African Amer. alone	44.84	33.89	54.91	22.28	19.81	25.01	7.70	6.76	8.80	264.36	234.15	292.85
	Amer. Indian & Alaska native alone	47.68	-76.77	118.24	13.81	-4.85	32.63	3.54	-5.01	12.61	282.75	61.91	523.43
	Asian alone	-3.36	-24.74	20.27	9.81	5.30	14.21	3.11	1.18	5.40	263.62	206.29	331.77
	Native Hawaiian & other Pac. Isl. alone	14.01	-176.18	156.42	14.47	-18.15	52.53	4.18	-9.98	14.32	208.51	-171.25	843.89
	Other racial designations	61.67	48.93	72.73	16.11	13.23	19.23	3.43	2.19	4.62	315.93	279.96	348.22
Educational Attainment	Less than 9th Grade	60.02	42.49	74.70	15.87	12.33	19.50	3.77	2.36	5.34	290.22	252.14	331.34
	Some High School, no diploma	52.18	33.93	70.07	16.65	12.85	20.97	4.51	2.78	6.31	282.92	234.82	332.37
	High School Graduate (or GED)	43.62	33.39	54.39	14.89	12.37	17.18	3.66	2.63	4.74	309.08	282.16	335.76
	Some College, no degree	33.41	20.57	46.02	15.15	12.85	18.16	4.03	2.95	5.01	301.92	264.63	336.56
	Associate Degree	31.23	8.01	50.50	13.86	8.92	18.23	3.48	1.76	5.57	307.63	251.03	362.37
	Bachelor's Degree	8.62	-4.45	22.44	13.48	11.00	16.00	3.73	2.67	4.80	280.21	243.79	322.39
	Master's Degree	3.95	-15.78	21.41	14.08	10.15	17.95	4.04	2.62	5.94	276.94	226.89	329.35
	Professional School Degree	-7.78	-48.70	31.86	15.12	7.09	24.15	4.69	1.53	8.73	275.25	165.86	387.75
	Doctorate Degree	-4.71	-53.87	50.78	14.23	5.41	27.54	4.50	0.27	9.53	250.45	99.44	458.57
Employ.	Civilian employed	28.18	20.00	36.04	14.32	12.68	15.82	3.61	3.00	4.28	295.24	275.84	313.42
	Civilian unemployed	45.68	25.87	65.80	17.16	12.65	21.16	4.70	3.05	6.85	295.25	238.98	347.20
	Armed forces	50.10	-119.01	207.51	9.48	-19.85	68.11	0.31	-19.88	18.21	241.40	-135.92	949.08
	Not in labor force	33.82	24.73	43.63	15.09	13.15	17.28	4.18	3.38	5.04	291.05	265.81	316.27

Note: All values in 2016 USD.

6.7 Bootstrap

Figure 14 demonstrates that the bootstrap method and the method described in Equation 1 provide the same result. The slight differences in the computed and bootstrapped means result from the size of the bootstrap. This confirms that the method provides the results as expected.

Figure 14: Comparison of bootstrap and computed results for the RTP-CCC tariff



6.8 Progressive pricing

Table 9 contains the average values for several consumption characteristics for different income levels. This is presented in a normalized fashion and described in greater detail in Table 5 in Section 4.1.

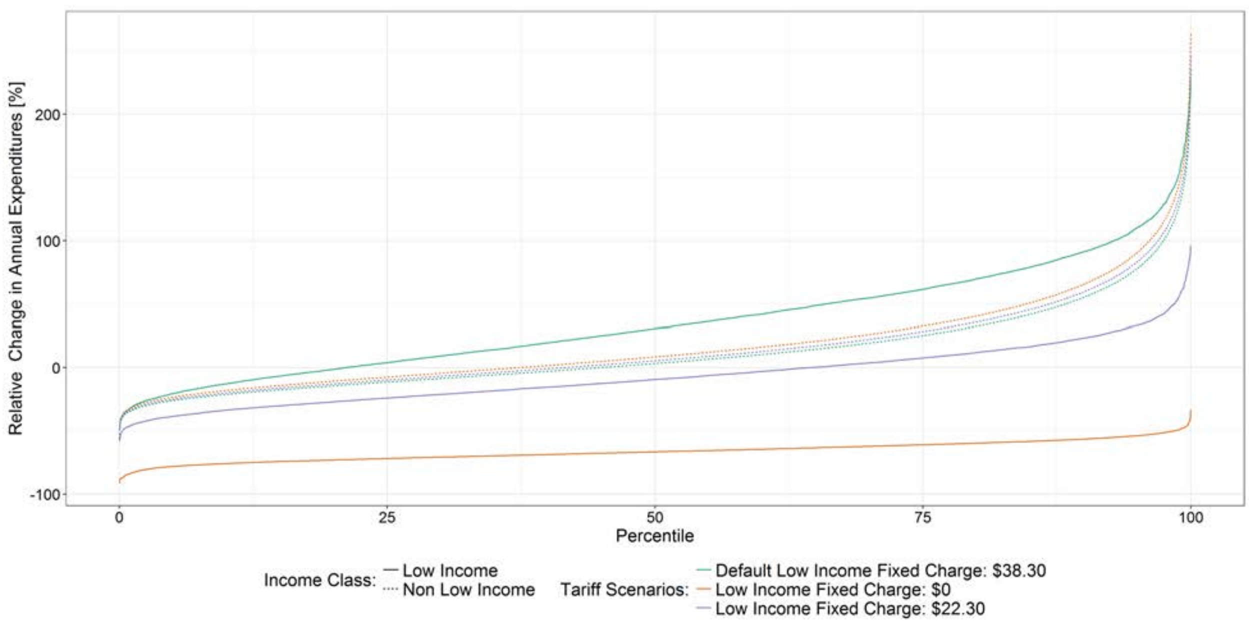
Table 9: Average Profile Variables by Income

Income ($1,000 USD)	Average Monthly Consumption	Annual Peak Demand	Peak-To-Off-Peak Ratio	May Peak Demand	June Peak Demand	July Peak Demand	August Peak Demand	Consumption: 5:30PM-6:00PM	Consumption: 6:00PM-6:30PM	Consumption: 6:30PM-7:00PM
<$15	464.53	3.98	15.01	2.81	3.13	3.25	3.24	141.83	144.77	146.26
$15 – $25	496.02	4.11	14.31	2.94	3.30	3.42	3.40	153.56	156.47	157.87
$25 – $35	509.26	4.23	14.22	3.04	3.42	3.53	3.52	158.59	161.60	163.04
$35 – $50	521.05	4.33	14.22	3.13	3.54	3.65	3.63	163.53	166.58	167.96
$50 – $75	530.48	4.49	14.49	3.27	3.67	3.79	3.76	167.72	170.97	172.34
$75 – $100	546.66	4.63	14.51	3.41	3.83	3.94	3.92	174.55	177.91	179.21
$100 – $125	556.69	4.74	14.56	3.52	3.94	4.06	4.03	179.03	182.63	183.94
$125 – $150	561.76	4.82	14.73	3.58	4.01	4.12	4.10	181.42	185.09	186.39
>$150	578.45	5.14	15.34	3.82	4.23	4.35	4.32	187.63	192.09	193.67

Figure 15 shows the impact of progressive fixed charges on low-income and non-low-income customer bills for three different fixed charge scenarios in the RTP-CCC tariff. The first—the default case—all customers have the same fixed charge, regardless of income ($38.30 per-customer per-month). In this case, roughly 80% of low-income customers see a bill increase, and roughly 56% of non-low-income customers see bill increases.[36] In the second case, low-income customers face a $22.30 per-customer per-month fixed charge, and non-low-income customers face a $39.64 monthly fixed charge. In this case, only roughly 35% of low-income customers face bill increases, and the percent of non-low-income customers facing positive bill changes increases slightly to roughly 58%. Finally, in the third case, low-income customers face zero fixed charges, and non-low-income customers pay a monthly fixed charge of $41.51. In this case, all low-income customers see bill decreases, while the fraction of non-low-income customers facing positive bill changes increases to 62.5%. It is worth stating that charging zero residual costs to low-income customers would entail a cross-subsidy from non-low-income to low-income customers, as low-income customers would no longer be paying more than their incremental cost of service (Faulhaber, 1975).

[36]Note that these numbers differ from those seen in Figure 7 due to the different method of identifying low-income customers. In Figure 7, we directly identify the impacts on low-income customers using the method defined in Section 2.2. Here, we identify low-income customers as customers living in Census Block Groups with median incomes below $25,000.

Figure 15: Impact of progressive fixed charges on low- and non-low-income bill changes for three charge scenarios



Note: Zero-elasticity case.