Retail Electricity Tariff Design, Distributed Energy Resources, and Emissions

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Abstract

Policymakers across the world are starting to look to residential energy customers and behind-the-meter distributed energy resources (DERs) such as rooftop solar panels, energy storage systems, smart appliances, and heating electrification as part of the solution to combat climate change. However, because the deployment and operation of these technologies are determined by the incentives residential customers face – through retail electricity tariffs – if or how much they reduce emissions is uncertain. In this paper, we use an economics-engineering simulation model to analyze how different types of residential retail tariff designs such as time-of-use, critical-peak pricing, and fully cost-reflective tariffs affect DER deployment and use, and, hence, the resulting emissions of CO_2, SO_2, and NO_x in the Commonwealth Edison service territory in Chicago. Our results show that in the short term retail tariffs can help or hinder environmental goals through their effect on DER deployment and consumption behavior, emphasizing the importance of pairing DER policy initiatives with decarbonization efforts at the wholesale electricity level. Further, we show that the effectiveness of other climate policies such as a carbon tax can vary depending on the granularity of tariff designs, highlighting the importance of considering retail tariff design in climate policy discussions.

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1. Introduction

Many policymakers around the world are starting to look to residential energy customers and behind-the-meter distributed energy resources (DERs) such as rooftop solar panels, energy storage systems, and smart appliances in their efforts to reduce greenhouse gas emissions. In fact, the perceived environmental benefits of these resources are among the major drivers of policies and mandates that aim to increase DER deployment. At the same time, incentivizing consumers to switch to electric heat pumps from gas heating is also considered a crucial element for reaching decarbonization goals. However, because of the manner in which the electric grid operates, if and by how much these technologies bring emissions benefits depends on where they are deployed, and how they are operated. And, because both their deployment and operation depend heavily on the financial incentives their owners face – the potential electricity bill savings that DERs provide as determined by retail electricity rates – it is uncertain whether, or by how much, DERs can reduce emissions.

Economic inefficiencies in current retail tariffs are already well established in the literature. (Borenstein and Bushnell 2018; Revesz and Unel 2020). In the U.S., most residential electricity customers currently face a two-part tariff, with a fixed monthly charge and a flat volumetric per-kWh charge, even though wholesale electricity prices vary significantly throughout the day. Hence, there is a disconnect between the retail electricity tariffs end-users face, which are set through utility rate cases by state regulators for multi-year periods, and the prices in the wholesale energy markets, which are generally determined by grid operators at sub-hourly intervals using auctions. Furthermore, electric generation, transmission and distribution capacity costs are driven by peak demand needs, and thus cannot be reflected accurately by flat volumetric rates. In addition, there is no existing price on pollution that is high enough to fully internalize the damages from the emissions – in particular CO_2, NO_x and SO_2 - associated with electricity generation. In other words, most retail electricity customers do not see the full social marginal cost of electricity, leading to consumers either overpaying or underpaying depending on when and where they consume their electricity (Borenstein and Bushnell 2018). And, because most DER compensation frameworks such as net energy metering (NEM) rely on the retail tariff structure and underlying rates the customers face, a discrepancy between retail electricity prices and the underlying social marginal costs also leads to an inefficient deployment of DERs (Revesz and Unel 2017; Sexton et al. 2018).

In recent decades, there has been slow movement toward more advanced tariff designs (Revesz and Unel 2020). In many states, electric utilities offer various types of voluntary time-variant rates, with for example Commonwealth Edison (ComEd) in Illinois even offering real-time pricing. California has required its three large investor-owned utilities to introduce default time-of-use rates for its residential electricity customers. And some states, like New York, are requiring their utilities to offer more cost-reflective tariff designs to increase the DER deployment in their states. But, though these policy and regulatory initiatives are partially motivated by environmental goals, any discussion about the potential of DERs leading to negative environmental consequences has been lacking in these policy discussions. Similarly, while the policymakers recognize the role that electricity rates play in incentivizing electrification of the building and transportation sectors, they usually focus on keeping the rates low to encourage electrification, ignoring the possibility that emissions could increase if the electricity rates do not reflect the social marginal cost of electricity provision accurately.

Understanding the potential effects of retail tariff design on emissions in the presence of new technologies is complicated by the fact that retail tariff design affects not just the operation of DERs, but also the initial investment and deployment of them. While there are studies that look at the effect of tariff design on either of these dimensions on their own, there are only a few studies that simultaneously look at the effect of retail design on endogenous DER deployment and the operational incentives (Spiller et al. 2020, Boampong and Brown 2018), and the resulting social welfare implications. However, these studies focus on private and system costs, and do not consider emissions.

Our first objective with this paper is to fill this gap in the literature by using a novel techno-economic simulation model to show the potential effects of different types of retail tariff designs on DER deployment and operation, as well as heating electrification, and the resulting emissions of CO_2, SO_2, and NO_x. We adapt a well-established engineering model for optimal DER operation by incorporating utility functions for consumers and calibrating it to smart meter data from ComEd residential customers in Chicago, thereby allowing us to take into account the unobservable intrinsic utility households receive from consuming electricity at an hourly basis. Our approach allows us to show the potential consequences of various tariff designs, including theoretical cost-reflective tariffs, on consumer behavior and social welfare.

We add to the literature on the welfare consequences of tariff design by showing that it can affect emissions through its effect on DER deployment and operation decisions. It might even be the case that increased DER deployment could be detrimental to society when emissions are taken into account – at least in the short term, when the grid is still emission-intensive in some periods. This happens when the highest priced periods do not correspond with the periods with the highest marginal emission rates, in which case load shifting due to DER operation and behavioral change in response to high prices may increase emissions. For example, a recent analysis of California's Self-Generation Incentive Program showed that increased deployment of behind-the-meter storage systems led to an increase in emissions, despite being in a state with a relatively cleaner generation mix, because the time-of-use periods for retail electricity tariffs did not match well with marginal emission rates (Itron 2017). And, even if this load shifting might avoid or defer costs associated with peak capacity, those costs savings might not be high enough to compensate for the social costs due to increases in emissions.

Although several authors have looked at the implications of specific tariff designs on emissions (Allcott 2011; Holland and Mansur 2008; Harding, Kettler, and Lamarche 2019), ours is, to the best of our knowledge, the first that can compare the consequences of multiple tariff designs in a consistent way. Similarly, there is a lengthy literature analyzing the environmental consequences of specific DER technologies that can shift or modify consumer demand, including energy storage (Graff Zivin, Kotchen, and Mansur 2014; Hittinger and Azevedo 2015; Hittinger and Azevedo 2015; Carson and Novan 2013; Linn and Shih 2019; Revesz and Unel 2018; Shrader et al. 2020), demand response (Holladay, Price, and Wanamaker 2015; Gilbraith and Powers 2013), or energy efficiency (Callaway, Fowlie, and McCormick 2018; Fowlie, Greenstone, and Wolfram 2018), as well technologies that can reduce net demand such as solar panels (Siler-Evans et al. 2013; Spiller et al. 2017; Sexton et al. 2018). However, our model allows us to consider all these DER options together, as well as heating electrification, taking into account that the decision to adopt a specific combination of DERs, if any at all, is endogenous to both the tariff design and the availability of other DER investment options. In other words, we can separate out the static effects of a single type of DER adoption and operation, and the dynamic effects of endogenously choosing to invest and operate a portfolio of DERs.

Our second goal also is to highlight the impact tariff design can have on the effectiveness of climate policies, even though retail tariff design is usually an afterthought in climate policy design. Our results show that retail electricity tariffs that do not reflect prices in the wholesale energy markets can reduce the effectiveness of a Pigouvian CO_2 emission tax (such as the one currently being discussed in New York) by eliminating a potential emission reduction channel, i.e. load shifting by consumers. Lack of granular tariff designs also hinder the ability of a carbon tax to align the arbitrage incentives for behind-the-meter batteries with emission reduction opportunities. In other words, inefficiently designed retail tariffs not only hinder economic efficiency by distorting price signals, but also hinder the effectiveness of a potential "first-best" climate policy of an economy-wide carbon tax.

Finally, we show that an "incomplete" carbon tax in electricity markets might hurt social welfare. If there is a carbon price on the bulk power system, but emitting DERs such as gas-fired backup generators are not subject to the same carbon price, more granular tariff designs may lead to higher deployment of such DERs. Similarly, if natural gas for residential heating is not subject to a carbon tax, there might be emission leakage. Consequently, depending on the emission rates of the DERs that consumers end up adopting, the welfare gains achieved by a carbon tax implemented only in the wholesale electricity markets could be reduced. This result particularly highlights the need for careful coordination among policymakers in electricity regulation, where there is a jurisdictional divide between agencies regulating different parts of the sector.

Our results are highly relevant to policymakers focused on environmental objectives. We highlight the importance of retail tariff design, usually an afterthought in environmental policymaking, in achieving environmental goals through DER adoption. How retail tariffs are designed determines whether DERs can actually help or hinder the environmental goals of DER policies. And retail tariff design can even hinder the effectiveness of other, broader climate policies by muting price signals from the wholesale electricity markets.

The rest of the paper is organized as follows. In Section 2, we explain our methodology and model. In Section 3, we describe different tariff design scenarios we test. In Section 4, we describe our results. In Section 5, we discuss the policy implications of our results. Finally, in Section 6 we conclude.

2. Modeling and Calibration Methodology

We use a novel techno-economic simulation model to understand the effects of tariff designs on DER adoption and use, and in turn, their effect on emissions. Here, we briefly explain the main features of our model. Our full modeling framework, and technical assumptions, are explained in more detail in (Spiller et al. 2020; Esparza et al. 2020; Bharatkumar et al. 2019) and Tapia-Ahumada et al. (2020).

In our model, for a given tariff design, a household chooses its electricity consumption, DER investments, and DER operations to minimize its net electricity expenditure, subject to a variety of technical and physical constraints. Our modeling gives us three important advantages that are valuable to current policymaking discussions.

First, our simulation model allows us to test hypothetical tariff design scenarios that are not yet implemented. This exercise is especially important for current policymaking as more jurisdictions are trying to implement more advanced designs, and looking for guidance from the economics literature. Even as there are econometric estimates of consumer response to different tariff designs, those analyses are limited to designs that are currently implemented (e.g. Faruqui and Sergici 2010; Allcott 2011), further hindering policy discussions about more innovative designs. For example, state regulators frequently cite the lack of empirical evidence related to consumer response to residential coincident-peak demand charges as one of the reasons for their hesitance to implement said rates. Further, there is no easy way to compare consumer responses across different designs, as ex-post empirical analyses consider different groups of consumers facing different tariff designs in different settings in different states. As a result, well-calibrated simulation exercises based on smart meter data can provide valuable guidance beyond a theoretical discussion and identify which rates are most promising to test out in a real-world pricing pilot. Similarly, with our methodology, we can test different levels and configurations of a potential carbon tax, which is not currently politically feasible.

Second, our model, which combines economic theory with machine learning techniques, allows us to leverage smart meter data into representative consumer groups, with inferences about the underlying utility function parameters. Identifying unobserved preferences is especially challenging in econometric analysis without a rich enough dataset that can control for a long list of variables ranging from household income to the number and types of appliances in a given household. And, even then, inferring the underlying utility function to be able to predict inter-hour substitution when faced with a different tariff design is difficult. For example, even if consumers have a price elasticity of -0.1 in aggregate, that doesn't mean that they would reduce their consumption consistently by 1% across all hours when faced with a 10% price increase. It may be that they value consumption during a certain hour high enough that they would not change their consumption during that period, instead changing their behavior in other times. Because using AMI data allows us to infer parameters of a utility function that allows for inter-hour substitution, our model can take into account such intrinsic preferences. As a result, we can simulate hourly consumption profiles that are consistent with observed real-life patterns in business-as-usual scenarios, even if we cannot observe many intrinsic characteristics and preferences of households.

In other words, our model allows us to be more confident in our predictions about consumer behavior under different tariff designs, especially the ones that include significant time variation, even when there is not yet a real world example of that design, rather than merely by extrapolating using an aggregate price elasticity estimated ex-post with incomplete controls. This is especially important for an accurate understanding of the emissions consequences of tariff designs when many consumers shift their load patterns as a response to time-variant pricing, or when consumers can endogenously choose a portfolio of DER investments.

Third, our model allows us to take into account forward-looking avoidable costs, rather than relying only on embedded cost data. Economically efficient retail tariffs should reflect forward-looking avoidable costs (Kahn 1988). And, whether a particular DER can improve social welfare depends on whether it can avoid any costs, be it costs related to energy, network, or emissions. However, both the current retail tariffs, as well as the welfare analyses of them, rely on embedded costs of service (Burger et al. 2020). Our model, by using a network model, allows us to incorporate costs that can be avoided in the future based on optimized distribution level network investments.

Consequently, we can discuss the overall social welfare consequences of tariff design changes that include consumer welfare, utility avoided costs, as well as emissions.

Because our model includes multiple modules, each with its own calibration methodology, we only briefly explain the structure and the analytical steps here. At a high level, our modeling involves three different modules that interact: (1) consumer decision-making module, (2) wholesale market module, and (3) distribution network module. The combination of these three modules gives us a model that represents electricity generation and distribution in our area of interest, as well as the behavior of the consumers in that area. As a result, we can test how consumers behave when faced with various tariff designs, in terms of load shifting and DER adoption, and thus estimate the effect on future costs and emissions.

a. Consumer Decision-making Module

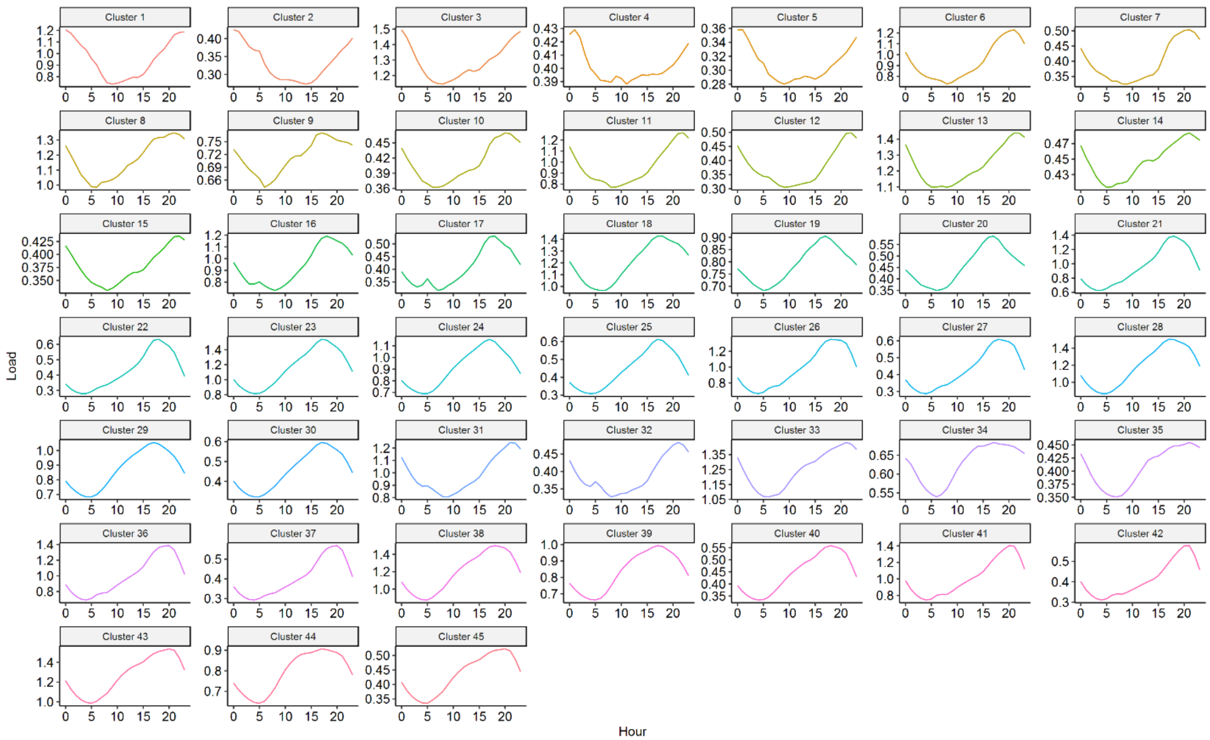
We adapt an engineering simulation model developed by Massachusetts Institute of Technology (MIT) to better represent customers' preferences about electricity consumption. The Demand Response and Distributed Resources Economic Model (DR-DRE) 2.0 simulates households' hourly electricity consumption, DER and electrification investments and operations decisions, based on the household's electricity prices/tariff structure and investment costs. DR-DRE 2.0 can represent a variety of tariff designs, which can include time-varying energy ($/kWh), capacity ($/kW), or fixed charge components. Based on these tariffs, consumers choose a portfolio of DER investments and associated operations, leading to different load shapes under each tariff design. The available DER investment options in DR-DRE 2.0 are rooftop solar panels, energy storage, and natural-gas-fired distributed generation. In addition, this model allows consumers to endogenously switch to electric heating (i.e. air-source heat pumps) from gas heating if that is more beneficial for the consumer given a tariff design. Consistent with most common state policies, rooftop solar panels and energy storage qualify for net metering compensation – consumers receive a bill credit equivalent to the volumetric rate for every kWh of electricity generated in the billing period. However, natural-gas-fired distributed generation can only offset a consumer's load, as this type of DER is not typically subject to net energy metering. DR-DRE 2.0 can also simulate optimal provision of different services from DERs, such as energy and capacity. And, in turn, these different load shapes lead to different emissions outcomes.

In its original form, DR-DRE is a typical engineering cost-minimization problem with an ad-hoc and time-invariant monetary penalty for deviations from a reference temperature. Therefore, it lacks the ability to take into account intrinsic consumer preferences about the timing of electricity use. However, being able to take these preferences into account is especially important when trying to understand how consumers would respond to hypothetical time-variant tariff design scenarios. So, we convert this model into an expenditure minimization problem subject to a utility constraint. To characterize consumer preferences, our utility function has two parts. First, we use a Stone-Geary utility function to represent the utility changes from inter-hour substitutions of non-thermal electricity use, such as running a dishwasher at different hours. Second, we include a quadratic utility function for thermal electricity use to represent consumer preferences related to thermal comfort, such as running an air conditioner to keep indoor temperatures close to their optimal comfort levels (see Bharatkumar et al. 2020). This expenditure minimization problem gives us the compensated demands of our households.

Calibrating DR-DRE 2.0 requires two sets of parameters: those related to consumer preferences and those related to technical and cost properties of technologies. To calibrate consumer preference parameters, we use 30-minute Advanced Metering Infrastructure (AMI) data from the ComEd service territory from 2016 to calibrate consumer preferences and the underlying utility network. The observed individual loads not only allow us to simulate an optimal network that could serve those customers, and hence the cost of serving those customers, but also allow us to infer the parameters of the utility function of each customer. As a result, when we simulate consumer behavior under different tariff designs, our model can take into account both the cost implications of any behavior change and the corresponding change in a consumer's utility. Therefore, our model results in a more realistic depiction of the trade-offs faced by a typical electricity consumer: comfort and convenience vs. electric bills.

Our initial sample includes 55,635 users from three contiguous zip codes in ComEd territory, all of which had high levels of AMI roll out in 2016. We further restrict our sample to single-family users with a full year's of load data, with our final sample including 44,185 consumers. Due to the computing requirements of optimizing investment and operation over all 8,760 hours of the year for each individual user, based on the methodology of (Kwac et al. 2014), we used VISDOM to create a data-dictionary of load shapes, and used a k-means algorithm to cluster households into groups based on the similarity of their usage patterns. We further refined the clustering based on the timing of the summer peaks, ending with 45 different cluster of customers (for more details on our clustering method, see Esparza et al 2020). Figure 1 shows the average hourly load shapes of these clusters.

Figure 1. Annual average hourly load shapes by cluster



Note: To show the variability in the load shapes, we did not restrict the y-axes to be uniform.

Once we cluster the households into 45 groups, we use regression and machine-learning techniques to calibrate the preference parameters of the customers in each group, as described in (Bharatkumar et al. 2020). Using weather data and regression analysis, we separate hourly loads into thermal loads, for space heating and cooling, and non-thermal loads. We then use the resulting non-thermal loads to calibrate the hourly parameters of the utility function so that our model can closely mimic the observed loads under the current tariff they face. Further, we calibrate the HVAC system and building material parameters to get synthetic thermal loads that are similar to our estimated thermal loads. In this way, we are confident that the model's synthetic loads will reflect the preference parameters specific to the cluster's representative household under a baseline tariff scenario with a flat (non-time varying) volumetric rate, and hence can mimic the behaviour of the same households, with the same underlying preferences, under different, time-varying rates. As Table 1 shows, our simulated consumer behaviour under existing ComEd tariff matches the observed loads in the smart meter data closely.

Table 1. Correlation between DR-DRE simulated hourly average loads and observed loads.

Thermal Loads					
Min	1st Q	Median	Mean	3rd Q	Max
0.961	0.9769	0.9846	0.9839	0.9931	0.9987
Non-Thermal Loads					
Min	1st Q	Median	Mean	3rd Q	Max
0.9793	0.9933	0.9951	0.9945	0.9969	0.9997

To calibrate the technological parameters, we rely on data from NREL for solar PV costs, data from Home Advisor for natural-gas-fired distributed generators, and data from Solar Quotes for residential battery costs. For our base cost scenario, we assume 30% federal subsidy for solar PV and batteries to reflect the current tax credits – i.e. we assume 70% of current all-in costs in our simulations. As Spiller et al. 2020 explains, upfront capital costs are a major driver of DER adoption. So, to understand if and how tariff designs can affect emission outcomes under different future cost declines, we pick two additional cost scenarios from the sensitivity analysis in Spiller et al. 2020, based on the cost thresholds that leads to significant solar PV or battery adoption, and analyze outcomes under 50% and 10% of current all-in costs for investment in these DERs. These scenarios can be plausible given the fast decline in technology costs and the increased subsidies policymakers are willing to give to meet their ambitious technology-specific mandates.

b. Wholesale Energy Market Module

We also developed a simple economic dispatch model to understand marginal emissions rates, and to be able to calculate how changes in consumer behavior affects emissions. This exercise might have been unnecessary if we wanted to look at only the effect of current tariff designs in only the current policy environment. In that case, relying on empirical estimates of marginal emission rates would have been sufficient. However, because we are interested in developing different tariff designs that require granular pricing for energy, such as real-time pricing, and because we are interested in analyzing if and how a carbon tax would change our conclusions, a dispatch model is necessary.

We develop a single node, unit commitment and dispatch model, and calibrate it to represent the segment of PJM that serves the ComEd territory. We use 2016 data from SNL, EIA, and NREL to calibrate operational variables such as fuel costs, minimum and maximum generation, as well as the emission rates of generators located within ComEd's service territory. In addition, we model and calibrate imports and exports from other PJM territories using real-time energy data from PJM and the marginal fuel data provided by PJM's Market Monitor. A comparison of our simulated dispatch with actual 2016 generation mix and price data shows that our simple model leads to a realistic representation of PJM's ComEd zone (see Table 2.)

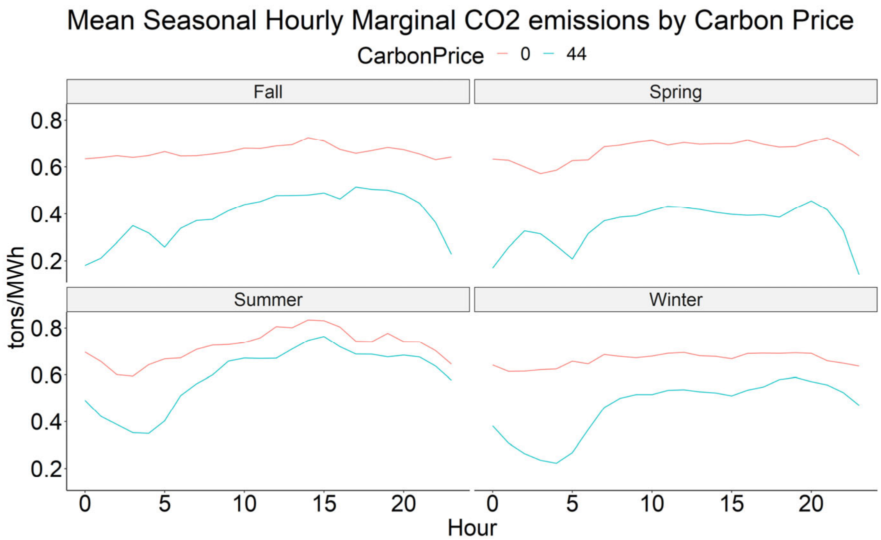
Table 2. Correlation between the hourly prices from the electric dispatch model and real-time PJM prices

Min	1st Q	Median	Mean	3rd Q	Max
0.5988	0.8274	0.8956	0.8824	0.9587	0.9991

We also run the dispatch model with a carbon tax, using the marginal damage estimates based on the U.S. Government's Interagency Working Group's Social Cost of Carbon (SCC) (EPA, 2016). The central estimate of the SCC for emissions in 2016, with a 3% discount rate, using 2016 dollars is $44/ton.[1] As Figure 2 below shows, marginal emissions rates change as predicted, going down with the higher carbon price. Further, the changes are more significant during off-peak hours when transmission constraints are not limiting the resource choices.

[1] We also run our model with a lower carbon price of $25/ton as a sensitivity, to consider the possibility that a lower carbon price might initially more politically palatable. While the quantitative results differ, qualitative results do not change. So, for simplicity, we refer only to the results with a higher carbon price.

Figure 2. Seasonal Marginal CO2 Emission Rates



c. ***Distribution Network Module***

Our third module is the Reference Network Model (RNM), a regulatory tool developed by IIT-Comillas. RNM builds an efficient, least-cost electricity distribution network calibrated to a specific service territory. RNM uses geospatial information of the service territory, such as roads and building footprints, taking into account DER penetration, and then calculates the total costs associated with that network. With input from ComEd engineers, we calibrated RNM to the chosen zip codes within ComEd's service territory to ensure that the system built by RNM was consistent with major indicators of the ComEd system. This exercise allows us to figure out if, and by how much, DER investments can avoid additional network upgrades and thereby future distribution-level network costs.

3. Tariff design Scenarios

Once we calibrate our model, we develop six different tariff designs to understand their effects on emissions: a flat tariff, a time-of-use (TOU) tariff, a critical-peak price (CPP) tariff, a real-time price (RTP) tariff, and two cost-reflective tariff designs. We chose TOU, CPP, and RTP tariffs because these designs are more prevalent in current policy discussions (Revesz and Unel 2020). In addition, we analyze two tariff designs cost-reflective not only of wholesale marginal generation costs but also of generation and network capacity costs to test the potential benefits of such theoretically guided, but not currently implemented, tariff designs. Furthermore, all rates are re-calculated for scenarios with a carbon tax.

The flat tariff is based on the tariff design that ComEd customers faced during 2016. We use this tariff structure as the default tariff, but when calculating the rates, we use energy prices from our own dispatch model instead of the historical PJM energy prices.[2] This flat tariff allows us to test that our simulations can replicate the load patterns we observe in the ComEd smart meter data. We develop a TOU tariff based on the methodology and time-period choices that ComEd used in their most recent time-of-use pilot, but, again, with energy supply charges developed from our own dispatch model.[3] Similarly, we develop our RTP design based on ComEd's existing real-time pricing design.[4] For critical peak pricing, we identify the top 10 hottest days of the year, and implement a peak price with a 10:1 peak to off-peak price ratio during the peak period. We use ComEd's rate case filings to determine the charges related to the distribution network and the recovery of cost for electricity distribution. We assume revenue neutrality when calculating the rates, based on the revenue requirement for ComEd in 2016. These designs, and the specific rates are summarized in Table 3 (for more details on calculations of these rates, see Spiller et al. 2020).

Table 3**.** Tariff designs with No Carbon Price[5]

	Fixed Charge ($/month)	Volumetric Charges ($/kWh)	Demand Charge ($/kW-month)	Peak Periods
Flat	14.89	$0.075	$4.21 (Jan-May) $3.12 (Jun-Dec)	N/A
Time-of-Use	14.89	$0.066 -$0.105	$4.21 (Jan-May) $3.12 (Jun-Dec)	Super Peak: 3pm-7pm Off-Peak:12am-6am Shoulder: 6am-3pm, 7pm-12am
Critical Peak Price	14.89	$0.072-$0.287	$4.21 (Jan-May) $3.12 (Jun-Dec)	3pm-7pm on top 10 hottest days of the year
Real-Time Pricing	15.28	Real-time price	$4.21 (Jan-May) $3.12 (Jun-Dec)	N/A

[2] This allows us to meaningfully compare results when we re-estimate a new flat tariff when we are testing a carbon price. See Spiller et al (2020) for more description on the approach.
[3] Commonwealth Edison Company (2019). "Rate RTOUPP Residential Time of Use Pricing Pilot", ILL C.C. No. 10, Original Sheet NO. 28.5. Effective Date January 3, 2019
[4] See https://www.comed.com/SiteCollectionDocuments/MyAccount/MyBillUsage/CurrentRates/05_RateBESH.pdf. Again, real-time energy prices are from our own dispatch model
[5] See Appendix for rates with carbon prices.

Cost-Reflective, Fixed residual Recovery	33.18	Real-time price	$4.1/kW applied on top 10 peak hours of the year; $0.41/kW applied on top 10 peak monthly hours	Variable peak hours of year/month
Cost-Reflective, Volumetric Residual Recovery	15.24	Real time price + $0.024/kWh	$4.1/kW applied on top 10 peak hours of the year; $0.41/kW applied on top 10 peak monthly hours	Variable peak hours of year/month

Note: The mean real-time price in our model was $0.026/kWh.

For cost-reflective tariffs, we rely on design principles outlined in (Perez-Arriaga and Bharatkumar 2014; Richard L Revesz and Unel 2020). These designs include multiple components, based on underlying cost drivers: 1) a volumetric energy supply charge, 2) coincident-peak demand charges for network and generation capacity costs, and 3) a customer-specific charge. Thus, customer-specific costs (e.g., billing and metering) determine the customer charge, and the hourly real-time rate based on the dispatch model determines the volumetric energy supply charge. In addition, we impose a demand charge on the top 10 demand hours in a month for generation capacity based on PJM's capacity auction. For distribution capacity, we impose a demand charge on the top 10 demand hours of the year, based on the marginal distribution capacity costs calculated by RNM. However, the revenues collected by these cost-reflective tariffs, because they are based on forward-looking costs and not the embedded costs, fall short of meeting ComEd's revenue requirement in 2016. To cover up the shortfall, we test two alternatives: CRRf, in which all the residual costs are recovered through fixed customer charges (such that the marginal incentives are not distorted), and, CRRv, in which all the residual costs are recovered through a volumetric adder.

4. Effects of Tariff design on Emissions

There are three underlying channels through which tariff design can affect emissions.

Changes in Load Profiles: A change in tariff design leads to a change in the load profile of the customer. Depending on how the relative prices change between time periods, consumers can increase or decrease their consumption in a given period. The marginal emission rates in each period then determines the resulting emissions caused by changes in consumption patterns. Therefore, the total emissions in a year could increase or decrease based on the patterns of this load shifting.

DER Adoption: A change in tariff design affects the incentives of end-users to adopt different DER technologies. If, as a result of a tariff design change, consumers adopt electricity-generating DERs and thus reduce their net demand for withdrawals from the grid (or even export excess generation), this would reduce the need for the bulk system generator to operate. Thus, DER adoption can reduce emissions by both offsetting the onsite consumption of the owner and by injecting electricity to the grid to meet the demand of the other customers. With this channel, the amount of emission reductions would depend on how much net load reduction DERs cause at a given hour, and the corresponding marginal emission rate in that hour.

DER operation: tariff design affects how customers operate DERs and electric heat pumps. If a given tariff design leads customers to adopt and operate emitting DERs, then the total emissions impact depends on the relative emissions of the DER compared to the marginal emissions rate of the grid. If a given tariff design leads customers to adopt batteries, then the total emissions impact depends also on the marginal emissions rates during charging and discharging periods, and the total emissions may in fact increase as a result of battery operation. Similarly, emissions from using heat pumps depend on when they operate and the marginal emissions rates. The net emissions effects of this switch would depend on how the increase in emissions from the grid compare to the reduction in gas usage for heating.

To understand all these effects, we run simulations for each design and carbon price combination. Our modeling setup allows us to separately calculate the effect of all these three mechanisms. For each tariff design, we do an initial run in which we do not allow any DER investment to isolate the effect of tariff design on load patterns. Then, we allow investment in DERs to see how tariff design affects emissions via the second and third channels. To calculate the emissions that result from electricity use under each design, we first calculate the marginal emissions rates using our dispatch model, with and without carbon prices. Then, we multiply the predicted hourly loads of each cluster with the marginal emissions rate in that hour for each pollutant for each carbon pricing scenario, and sum over the 8,760 hours of the year. Underlying this approach is an assumption that our sample is small enough compared to the entire ComEd zone that any change in their load, even including the heat pumps, would be only marginal and – in contrast to the carbon price – not affect the order of dispatch in the wholesale market. If there is investment in emitting DERs, we calculate the additional emissions by multiplying its operation profile by its emission rate, and add to the grid emissions to calculate the total emissions.

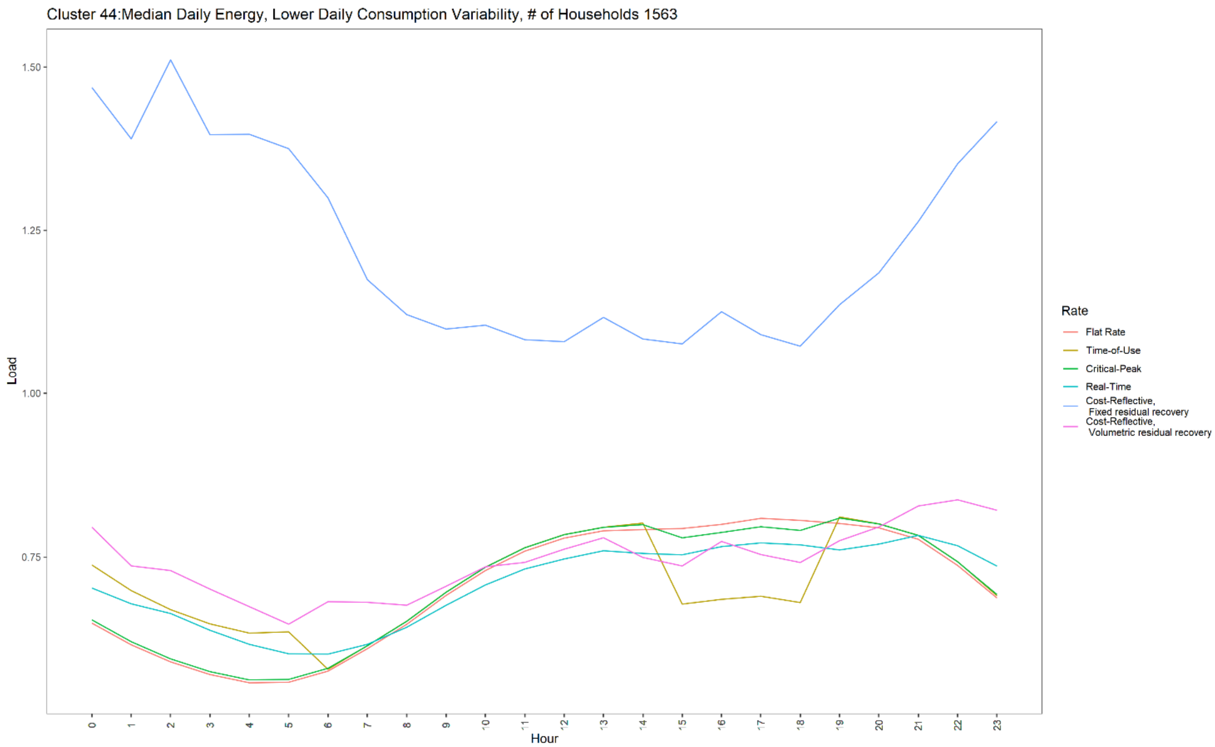
a. The Effects of Tariff designs on Emissions Without a Carbon Tax

First, to test the effect of the load-shifting channel, we run our simulations without allowing investment in DERs. The effect of load shifting under our tariff design scenarios compared to a flat rate is ambiguous. As Figure 3 shows, the changes in consumer load profiles in response to changes in tariff designs without DER investment are as expected: compared to a flat rate, consumers under time-variant rates reduce their electricity usage whenever relative prices are higher, and shift that usage to lower priced periods.

The amount of load shift compared to the flat tariff depends on the relative strength of the price signal for the most expensive time periods. For example, because the relative prices under TOU are consistently higher during the peak time periods, average peak loads under TOU tariffs decline more compared to CPP tariffs, which provide a more intense peak price signal but for a limited number of hours. Therefore, the average magnitude of the change in consumer behavior under CPP is less compared to the other tariff designs.

Further, consistent with previous literature (Holladay, Price, and Wanamaker 2015), our results show that the total annual electricity consumption could increase with different tariff designs, even if by small amounts. In other words, consumers take advantage of lower priced electricity during non-peak hours. This effect is especially significant for cost-reflective tariffs, which have very low volumetric charges during off-peak hours. Consequently, whether the total emissions increase or decrease depends on the differences between the marginal emission rates of higher- and lower-priced time periods.

Figure 3. Annual average hourly net load profiles of an example cluster under different tariff designs when no investment is allowed



The main results on the emissions impacts of tariff design when there is no carbon tax are summarized in Figure 4.[6] Total emissions are the total CO_2 emissions that stem from electricity and gas consumption of our 44,185 households. As a consequence of the relatively limited consumption pattern changes when no DER investment is allowed, the CO_2 emissions under TOU, CPP, and RTP are similar to emissions with flat tariffs, either slightly above or slightly below (see the left bars for each tariff design in Figure 4).[7] Moving to a CRRv increases total emissions slightly because there is a high enough increase in consumption during non-peak hours. There are, however, significant increases in emissions under CRRf. With CRRf, when the residual is recovered with a fixed charge and hence the volumetric electricity charge is low, consumers find it (privately) beneficial to switch to electric heating from gas heating. As a result, their electricity consumption,

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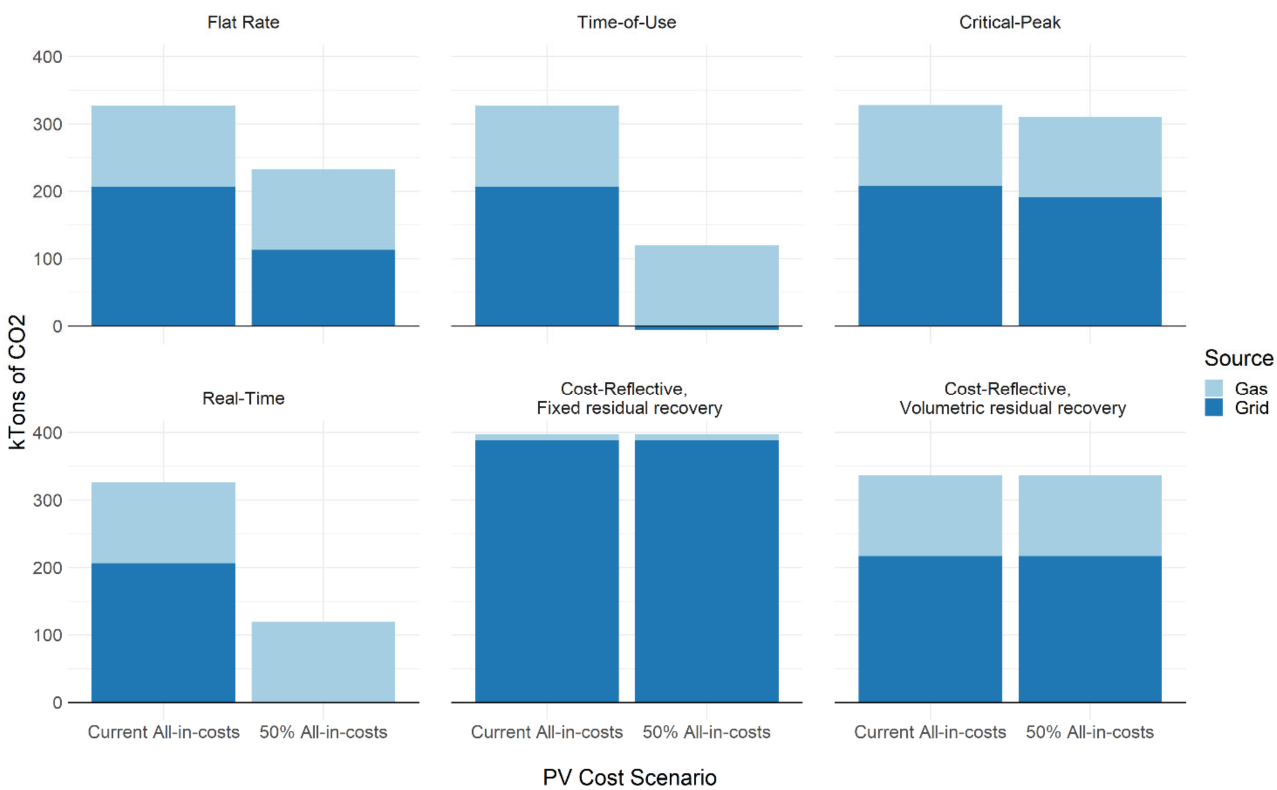
[6] Numerical tables are provided in the appendix.

[7] For brevity, we discuss only the CO_2 emissions in the text. The results for SO_2 and NO_x emissions can be found in the appendix.

and hence the emissions from the grid, increase compared to a flat tariff. Even though the emissions from gas use decrease, the increase in emissions from electricity use is high enough to offset that decrease with the 2016 marginal emission rates on the part of the PJM system we analyze.[8] This dynamic highlights that electrification, due to the existing grid mix and operations, might lead to perverse results in the short run. Notably, however, changes in the future mix of electric generating resources are likely to change this result.

Figure 4. Annual CO_2 emissions in thousand metric tons under different tariff designs without a carbon tax



Notes: The totals are the annual sums of emissions from of each cluster, weighted by the number of households in each cluster. For each tariff design, the left bar reflects the emissions under the base cost scenario with 70% all-in costs, and the right bar reflects the emissions under 50% all-in costs. Dark blue shows emissions from the grid, and light blue shows emissions associated with natural gas use for heating.

When we allow for DER investment in our base cost scenario – current costs with a 30% federal subsidy – our results do not change (so, still can be depicted by the left bars of Figure 4)

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[8] In addition, higher efficiency losses related to electricity transmission and distribution compared to natural gas delivery offset some of the potential gains of air source heat pumps.

because, given this cost structure, none of the tariff designs we study provide enough annual bill savings for the customers to make it profitable to adopt DERs in our sample.[9] Even with net metering using flat rates, in which consumers get compensated the volumetric rate for their injections regardless of when that injection occurs, the financial incentives are not high enough to justify the upfront capital costs.[10] Incentives for solar PV adoption are even worse with other tariff designs, when the highest compensation occurs during peak periods, which are usually in the late afternoon and early evening. Because the peak PV generation is mid-day, this mismatch with peak price periods makes it difficult for residential customers to recover their investment costs under net metering. As a result, and consistent with what ComEd observed during the same period for their existing tariffs, no PV adoption occurs under any tariff structure. Furthermore, our simulation results find no investment in any other DERs under flat, TOU, CPP, or RTP tariffs, eliminating the DER adoption and operation as channels to reduce emissions. Consequently, total emissions do not change under these tariffs compared to the no-investment outcomes, under the base cost scenario. Thus, the only changes in emissions in this base case comes from load shifting and electrification of heating loads.

To understand if and how tariff designs might affect emission outcomes in cost conditions under which consumers find it privately optimal to adopt DERs, we also ran our simulations with a hypothetical reduction in future costs to 50% of the current all-in private costs of DERs (see the right panels for each tariff design in Figure 4).[11] In this scenario, we see that consumers adopt solar PVs under some of the tariff designs, but they still find batteries too expensive to be privately optimal. We see solar PV adoption, and hence reduction in emissions from the grid, under flat, TOU, CPP, and RTP tariffs. With TOU tariffs, consumers adopting PV not only offset their own load, but also displace bulk system generation needed for other customers, leading to "negative" grid electricity emissions for our sample, even if minimal.

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[9] See Spiller et al. (2020) for a discussion of subsidy levels that would enable customer adoption under different tariff designs.

[10] Sensitivity analysis in Spiller et al (2020) show that for higher supply rates, with net metering, we get adoption of solar PVs with flat tariffs.

[11] Note that such reduction might actually be achieved with state subsidies on top of the 30% federal subsidy, or by another 20% reduction in costs on top of the 30% federal subsidy, so could be realized in the near future given the ambitious goals of many U.S. states.

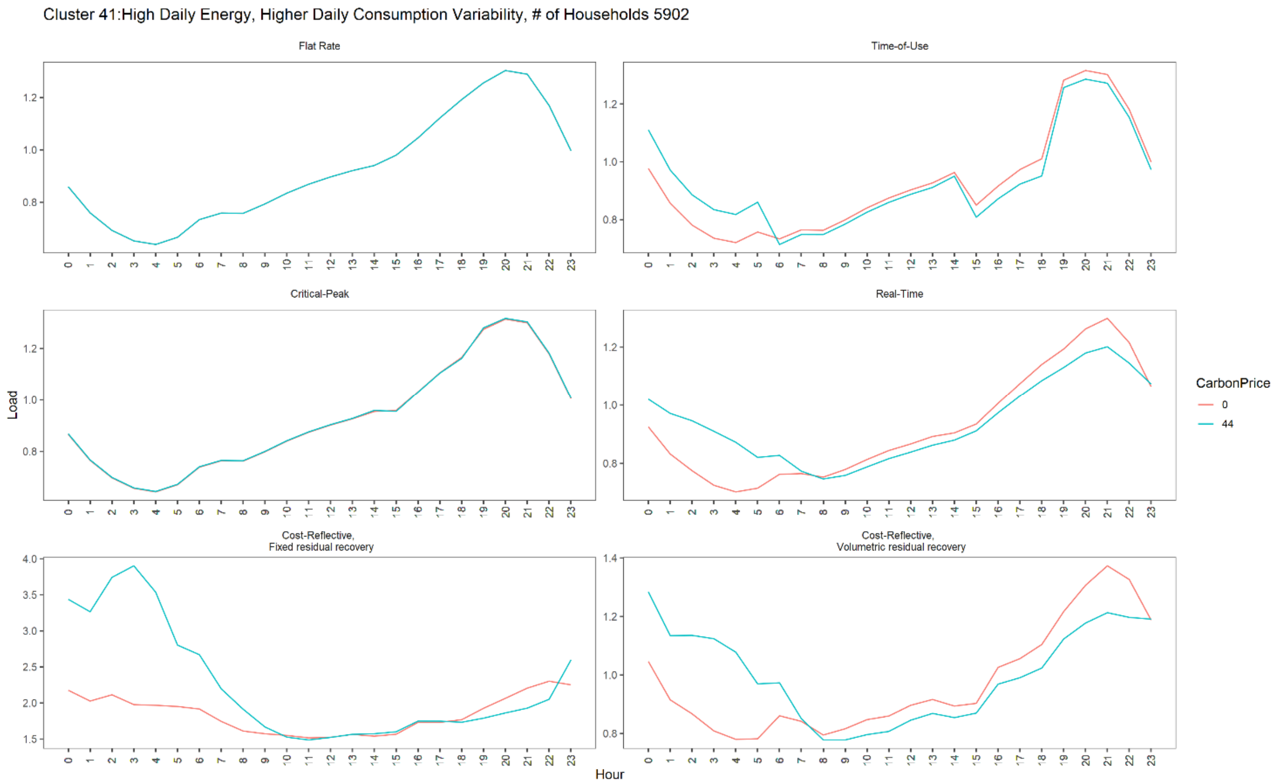
Such investment incentives is most apparent under the TOU and RTP tariffs. The net metering framework allows consumers to get compensated with a higher price, compared to the other tariffs, during a relatively greater number of hours that correspond with solar generation. For example, the CPP and the two CRR rates have high prices for only a small number of hours per year, and the flat rate never has any high prices during the day. As such, households have higher incentives to invest under TOU and RTP tariffs compared to other tariff designs, leading to the highest emission reductions.

b. The Effects of a Pigouvian Carbon Tax

Next, we look at the emissions impacts of tariff design *with* a complete carbon tax – i.e. on both wholesale energy market CO_2 emissions as well as natural gas used for heating. Using the Interagency Working Group's Social Cost of Carbon, we impose a $44/ton Pigouvian tax on all CO_2 emissions, including on natural gas used for heating, recalculate our supply rates, and run our model again.

Incorporating a carbon tax would not only change the dispatch order in the wholesale energy markets, but would also provide better price signals about the social marginal cost of electricity. As a result, to the extent a carbon tax changes the relative prices between time periods, consumers would change their load profiles accordingly. In addition, under more time-varying rates, a carbon tax would increase the value of DER injections when marginal emission rates are high, potentially leading to a higher deployment of DERs. The effect on heating electrification, on the other hand, is ambiguous. On the one hand, it could make electricity more expensive on average, which would discourage electrification. On the other hand, with time-granular tariff designs, prices during cleaner time periods might be low enough to induce switching from gas heating (also subject to the carbon tax in our scenario), especially because heating demand is likely to be higher during the night when electricity prices tend to be lower.

Figure 6. Annual average hourly net load profiles of the largest cluster under different tariff designs with and without a carbon tax when no DER investment is allowed with our base case cost and subsidy assumptions



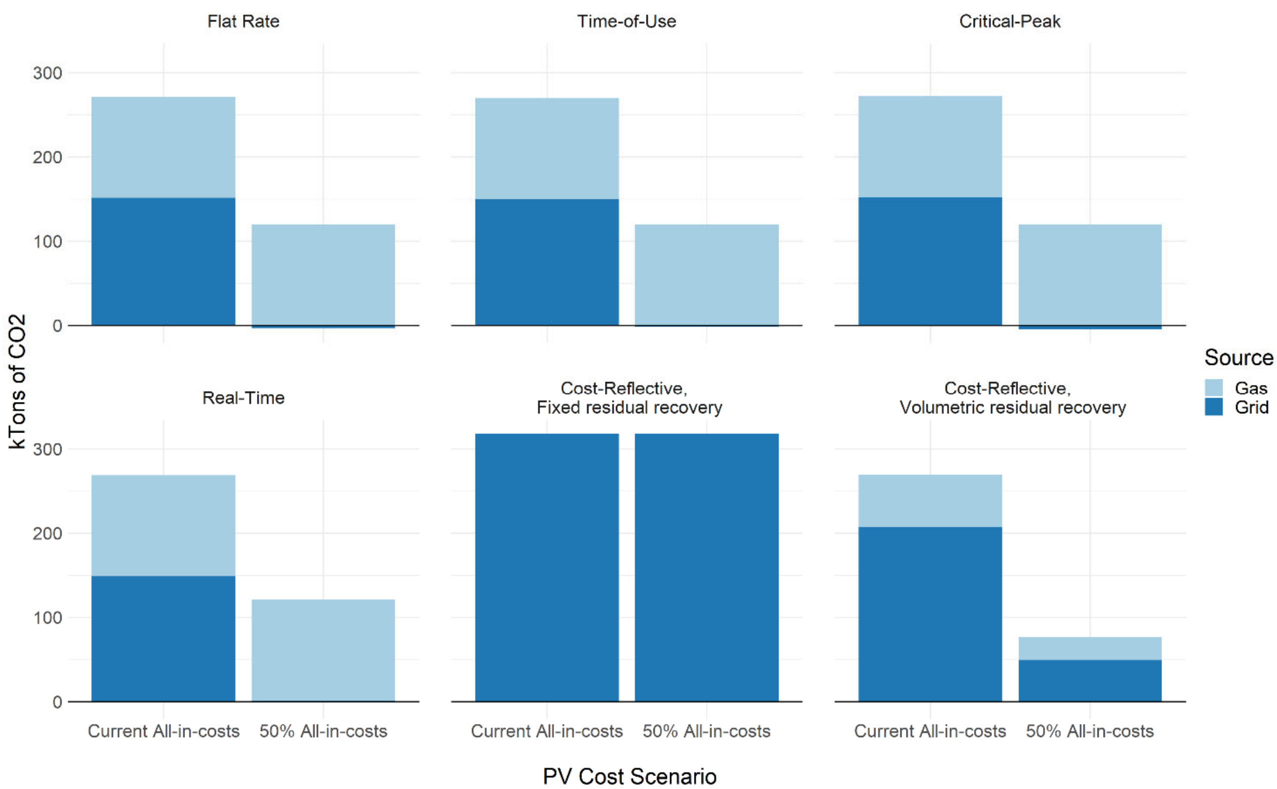
Notes: The y- axes are not uniform. For simplicity, we are showing only the largest cluster. The aggregated load shapes are in Appendix. Load shapes of all clusters for all tariff designs can be found in the online appendix, available here.

Again, to understand the effect of emissions via the load-shifting channel under a carbon tax, we first run our simulations without allowing DER investment. Given that we are using an expenditure minimization, and calculating compensated demands, as Figure 6 shows, a carbon tax changes load profiles only to the extent that it changes relative prices between different hours. For example, because the relative prices between different time periods under flat rates do not change with carbon tax, the compensated demand stays the same, not leading to any changes in the load profiles. However, the load profiles observed under the other tariffs change significantly, reducing consumption during periods with higher marginal emission rates (and, hence, higher prices) and increasing consumption during periods with lower marginal emission rates that are shown in Figure 2. In other words, flat rates dull the price signals that a carbon tax might give by breaking the link between the wholesale price signals and the retail price signals.

Just as in the case above without a carbon tax, we see that there is very little difference in total CO_2 emissions between the flat rate, TOU, CPP and RTP tariff scenarios due to the load shifting channel. CRRf continues to lead to heat pump investment, significantly increasing electricity usage, and hence emissions compared to the flat rate with a carbon tax. CRRv now reduces emissions compared to the flat tariff. Because the volumetric rates under this tariff design are higher compared to those in CRRf, CRRv provides higher incentives for electricity conservation, and therefore the increase in electricity use due to electrification is not as high compared to CRRf.

Because our modeling looks at expenditure minimization and compensated demands, our results are mostly relevant for various carbon tax and dividend policy proposals, in which a carbon tax is coupled with payments that could help reduce the income effect of the tax. If the magnitude of those payments are in line with customers' compensating variations, the resulting demand changes would be more in line with the compensated demands that our model simulate. And our results would imply that, without time-variant rates, consumers would not change their load shapes, and the only emission reductions would come from the changes in the generation mix. Therefore, disregarding the importance of the end-user price signals in designing carbon taxes would leave an important emission reduction channel underutilized.

Figure 5. Annual CO2 emissions in thousand metric tons under different tariff designs, with a $44/ton carbon tax on all emitting power generation and natural gas used for heating.



Notes: The totals are the annual sums of emissions from of each cluster, weighted by the number of households in each cluster. For each tariff design, the left bar reflects the emissions under the base cost scenario with 70% all-in costs, and the right bar reflects the emissions under 50% all-in costs. Dark blue shows emissions from the grid, and light blue shows emissions associated with natural gas use for heating.

Next, we run our simulations allowing DER investment. Even though a carbon tax reduces the magnitude of both grid and DER emissions in all scenarios (compare Figure 4 and

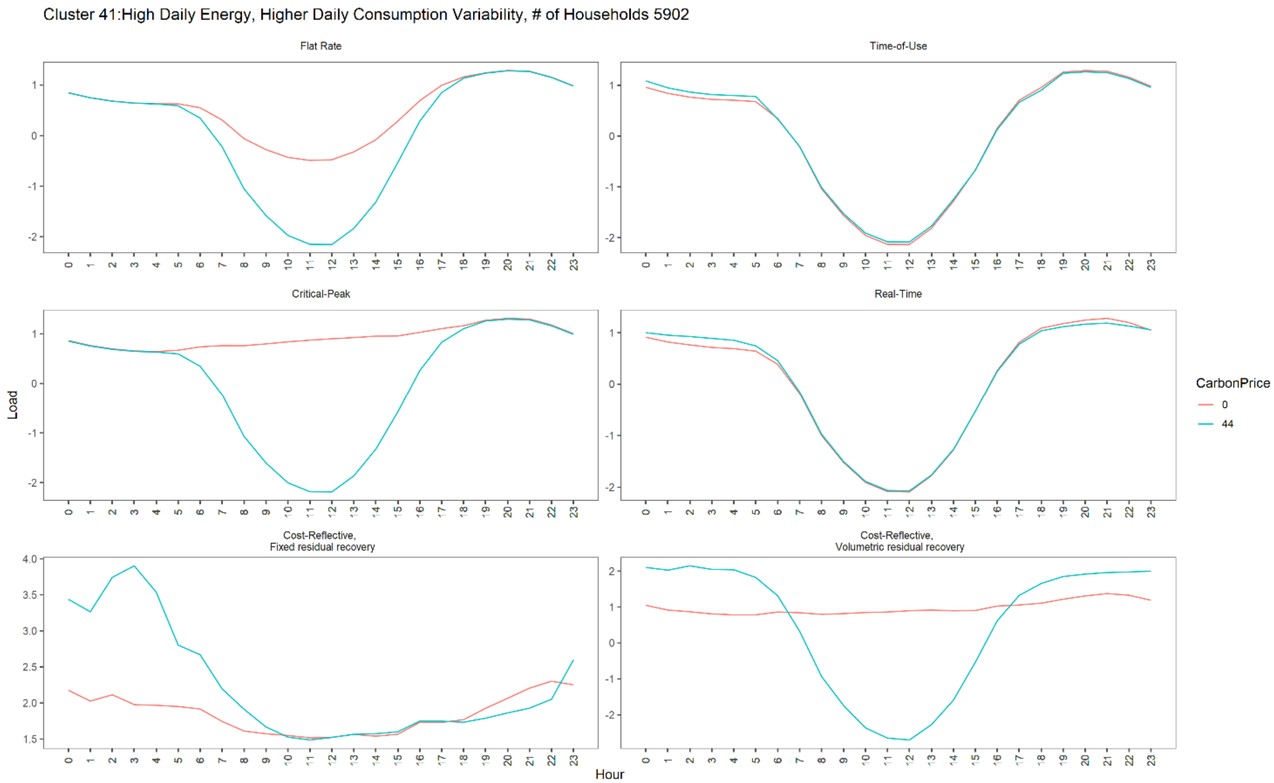
Figure 5), our qualitative results mostly stay the same. Even with a $44 carbon tax, no tariff design leads to PV or battery investment under our base cost scenario (the left bars in Figure 5), again eliminating the DER deployment and operation as potential channels to reduce emissions for most tariff designs. In this scenario, most emission changes come from load shifting.

If DER costs further decline (or receive additional subsidies), the combination of a carbon tax and tariff design leads to different investment patterns. As Figure 6 shows, net load profiles change significantly under a carbon tax if DER costs decline to 50% of current all-in-costs. Now, we observe more investment in solar PVs even under flat tariffs, CPP and CRRv, leading to net injections under these tariff designs as well.

How a carbon tax changes emission outcomes depends on which of the two following countervailing effects dominate. A carbon tax increases the volumetric prices to account for the value of emissions, and hence increasing the compensation a consumer could get for injections and adoption incentives. However, at the same time, a carbon tax changes the grid operations, internalizing emissions as a cost in the dispatch order and making the grid cleaner, hence reducing the amount of emissions DERs can potentially displace.

Comparing the right-side bars of Figure 4 and Figure 5 for each tariff design highlights this dynamic. For tariff designs that were sufficient to incentivize high levels of solar PV adoption even without a carbon tax, such as the TOU and RTP tariffs, the second effect dominates. While the consumers continue to adopt solar PVs, because a carbon tax reduces marginal emission rates, injections from those systems no longer avoid as much emissions from the grid. Therefore, the decrease in grid emissions from DER adoption is much lower under a carbon tax. However, for flat tariffs, CPP and CRRv, the first effect dominates. Because consumers now face higher volumetric rates due to the carbon tax, the increased DER compensation increases enough to drive more solar PV adoption to reduce emissions further.

Figure 6. Annual average hourly net load profiles of the largest cluster under different tariff designs with and without a carbon tax when investment is allowed, 50% All-in Costs



Notes: The y- axes are not uniform. For simplicity, we are showing only the largest cluster. The aggregated load shapes are in Appendix. Load shapes of all clusters for all tariff designs can be found in the online appendix, available here.

Our simulations highlight another important, but not surprising, result. Even though tariff design can affect load shifting and DER adoption incentives, the majority of the emission reductions due to the carbon tax result from the changes in the dispatch order, and hence the changes in marginal emission rates. Therefore, a robust carbon price signal that affects the dispatch order in energy markets and make dirty generation less competitive remains the key component for addressing electricity sector CO2 emissions.

Table 4. Causes of grid emission reductions under each tariff design in thousand metric tons

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
Changes in dispatch order	56	57	56	56	124	59
Load shifting	0	0.5	-0.3	1	-54	-49

Notes: The emission reductions due to the changes in dispatch order is the difference in emissions given different marginal emission rates with and without a carbon price, holding constant the load profile without a carbon tax. The emission reductions due to the changes in load shifting is the difference in emissions between the load profiles with and without a carbon prices, holding constant the marginal emission rates with a carbon price. The net change in grid emissions between Figures 4 and 5 is the sum of the two effects. A negative indicates an increase in emissions.

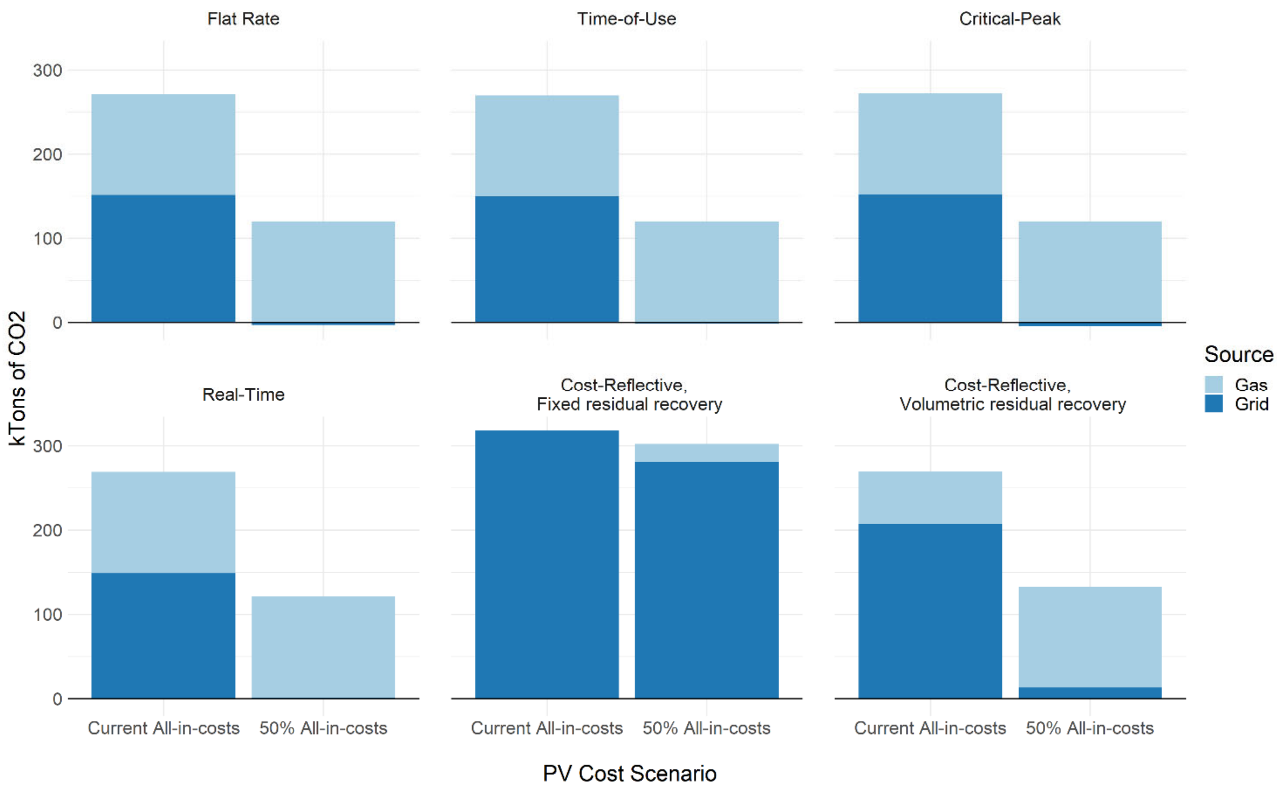
c. The Effects of an Incomplete Carbon Price

In the U.S., states and the federal government share the responsibility for energy and environmental regulation. Wholesale markets are generally subject to the jurisdiction of the Federal Energy Regulatory Commission, and the retail tariffs are regulated by state regulators. As a result, there can be efficiency losses when different agencies do not coordinate their policies. For example, in the case of carbon pricing like the one under discussion in NYISO, a grid operator can impose a carbon price only in the electricity market, but that would leave CO_2 emissions from natural gas combustion for heating or small, behind-the-meter distributed generation unpriced. And, if the state regulators decide not to impose a tax on emissions from all uses of fossil fuels including natural gas for direct residential use, the possibility of carbon leakage arises.

To understand the implications of such leakage potential, we ran simulations in which natural gas for heating and the emitting DERs are not subject to a carbon tax. Our results show that consumers do not invest in emitting distributed generation even in this scenario. However, we get higher emissions from gas heating under this scenario. Comparing the bars for electric and gas emissions in

Figure 5 and Figure 7 for the same tariff designs and cost scenarios, we see that an incomplete carbon tax limited just to the wholesale electricity market reduces emissions from the grid but increases emissions from gas heating for CRRf and CRRv compared to both the economy-wide carbon tax and the scenarios without a carbon tax. This leakage occurs because heat pumps become a less attractive option when the carbon tax is only applied in the wholesale electricity market because electricity prices increase relative to natural gas prices. In the case of the CRRv design this leakage is high enough to offset the emission reductions achieved through a carbon tax changing the dispatch order, and leads to a net increase in emissions compared to CRRv rate with an economy wide carbon tax.

Figure 7 Annual CO2 emissions in metric tons under different emissions in thousand metric tons under different tariff designs with a $44/ton carbon tax applied only on wholesale energy electricity market.



Notes: The totals are the annual sums of emissions from of each cluster, weighted by the number of households in each cluster. For each tariff design, the left bar reflects the emissions under the base cost scenario with 70% all-in costs, and the right bar reflects the emissions under 50% all-in costs. Dark blue shows emissions from the grid, and light blue shows emissions associated with natural gas use for heating.

Such leakage from an incomplete carbon price is especially important for local pollutants and environmental justice considerations. Because any substitution between grid electricity and gas heating would change where local pollutants are emitted and how they are dispersed, the exposed population, and, hence, the external costs in terms of health damages under different tariffs would differ. Importantly, onsite gas heating by consumers will move emissions away from bulk system generators closer to load centers, likely exposing a higher number of people to these pollutants. Further, the demographics of the exposed populations will also be different. However, this type of environmental justice analysis is beyond the scope of this paper.

d. The Effects of Batteries

Different tariff designs can make batteries more attractive and drive more investment, yet might create more emissions due to how they are operated in response to the tariff. As batteries are essential to decarbonization, it is important to understand how tariff design can affect behind-the-meter battery adoption and operation, and, in turn, emissions. However, none of our initial cost scenarios led to battery adoption, highlighting the fact that batteries are still too expensive for a widespread behind-the-meter adoption.

So, as explained in Spiller et al. 2020, we ran additional cost and policy scenarios to understand when it becomes privately optimal for customers to adopt batteries, and analyze the emission implications of batteries for those scenarios. We observe battery adoption when costs fall down to 10% of the current all-in-cost and when net metering policies are modified to compensate residential battery owners for electricity injections back into the grid at a rate lower than the full retail rate. This scenario reduces the compensation a consumer gets for injections, and, hence, strengthens the incentives for battery adoption by increasing the relative value of storing electricity generated by solar panels for later consumption.

Table 5 shows how batteries affect emissions under this cost and policy scenario. To show the effects of battery adoption and operation on emissions, we disaggregate grid emissions into three categories: emissions from consumption, reduction in emissions from solar PV generation, and net emissions from operation of batteries. The first category reflects the emissions that result for consumers' thermal and non-thermal loads. The second category reflects the reductions in emissions that result from solar PV generation. The final term reflects the difference between the emissions at times when a battery is charging and the emissions at times when it is discharging.[12]

[12] It is important to note that, even some might consider that charging batteries do not increase emissions because they are charged "from" the on-site solar PV generation, there is an emissions opportunity cost of charging of

We calculate emissions by multiplying the hourly profiles of consumption and generation, and batteries with the hourly marginal emission rates, and summing over the year.

Table 5. Annual CO_2 emissions from batteries in thousand metric tons under different tariff designs without a carbon tax with 10% of All-In Costs.

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No Battery Investment Allowed						
Total Emissions	199	198	199	199	264	219
Consumption Emissions	315	320	316	314	406	406
Solar PV Generation	-235	-242	-236	-234	-143	-221
Battery Operations	-	-	-	-	-	-
Gas for Heating Emissions	120	120	120	120	1	33
Percentage difference in total emissions compared to flat tariff	-	-0.5%	0.0%	0.0%	32.7%	10.1%
Battery Investment Allowed						
Total Emissions	199	187	199	199	264	219
Consumption Emissions	315	314	316	314	406	406
Solar PV Generation	-235	-248	-236	-234	-143	-221
Battery Operations	-	0.2	-	-	-	-
Gas for Heating Emissions	120	120	120	120	1	33
Percentage difference in total emissions compared to flat tariff	-	-6.0%	0.0%	0.0%	32.7%	10.1%

Notes: The totals are the annual sums of emissions from of each cluster, weighted by the number of households in each cluster. Consumption emissions are calculated by multiplying the load profile for thermal and non-thermal consumption by hourly marginal emission rates. Emissions avoided by solar PVs are calculated by multiplying their generation by

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batteries. Using on-site solar PV generation to charge batteries means that it cannot be injected to the grid or be used for consumption, and hence it foregoes the opportunity to reduce emissions that would have occurred if, all else constant, there were no batteries. Calculating the battery emissions using the hourly marginal emission rates during charging and discharging takes this opportunity cost into account.

hourly marginal emission rates. Emissions from battery operations are the difference between the emissions caused during charging periods and the emissions avoided during discharging periods, calculated by hourly marginal emission rates.

To understand the effect of battery adoption, we first run our simulation without allowing investment in batteries. The first panel of Table 5 shows this baseline. Note that, because we are looking at a case where costs are 10% of all-in-costs for all DER technologies, we also observe solar PV adoption under all tariff designs, unlike our earlier discussion.

When we allow battery investment, as the second panel of Table 5 shows, we get minimal battery investment under the TOU tariff and no adoption under any other tariff. This result is due to the arbitrage opportunities between peak and off-peak time periods that TOU allows continuously throughout the year. As directionally consistent with what California's Self-Generation Incentive Program observed and what the literature suggests (Carson and Novan 2013; Shrader et al. 2020; Revesz and Unel 2018; Hittinger and Azevedo 2015), the charging and discharging of batteries lead to an increase, even if minimal, in emissions. In other words, because the TOU periods are not well aligned with the times when the marginal emission are higher, all else equal, the operation of batteries leads to an increase in emissions.

However, our results also reveal a novel insight. This low battery cost and reduced NEM compensation scenario not only makes it privately optimal to invest in batteries, but the ability to store electricity makes it more attractive to invest in more solar PV. Comparing solar PV generation when no households are allowed to invest in batteries compared to a scenario when we allow battery investment (i.e. comparing the first and second panels of Table 5. Annual CO_2 emissions from batteries in thousand metric tons under different tariff designs without a carbon tax), we see that consumers install bigger solar panels when they also install batteries. Therefore, because incentivizing batteries also incentives more clean generation that can be used to offset grid electricity, the total emissions go down, despite the increase in emissions due to battery operations. Even though the difference in the average installed PV size is modest, 5 kW vs. 4.7 kW, the additional generation reduces emissions by multiple orders of magnitude compared to the emission increases from the operation of the batteries. To the best of our knowledge, our results are the first to show this endogenous technology portfolio effect on emissions.

Next, we test whether these results change when there is a carbon tax.[13] Comparing Table 5 and Table 6 shows that a carbon tax, unsurprisingly, reduces total emissions. Similar to earlier results, the main reason for the changes in emission outcomes is the change in the dispatch order due to the tax. Because the marginal emission rates are lower, emissions from consumption are lower. At the same time, now that the grid is cleaner, solar PV generation can displace less emissions. However, an analysis on the emissions impacts due to the changes in DER adoption and operation shows interesting insights.

Because a carbon tax makes electricity more expensive, it increases incentives to adopt batteries. So, with a carbon tax, we see battery adoption under all tariffs other than CRRf. Comparing cases where we do not allow battery investment to cases where we do (i.e. the first and second panels of Table 6. Annual CO_2 emissions from batteries in metric tons under different tariff designs with a \$44/ton carbon tax on all sources, we see that investment in batteries also increase investment in solar panels. And even though the difference in the average installed sizes are small, 0.2 to 0.3 kWs, the additional solar PV installation leads to a reduction in the total emissions. So, again, there is a reduction in emissions due to the technology portfolio effect

However, we find that operation of batteries do not always lead to an increase in battery driven emissions. Looking at the bottom panel of Table 7, we see that emissions due to battery operations are positive under flat, TOU, and CPP tariffs – when the price signals are coarse. However, emissions from battery operations are negative under RTP and CRRv, where the price signals can granularly reflect the carbon tax. In other words, a carbon tax, by itself, is not sufficient to align the arbitrage incentives for behind-the-meter batteries with emission reduction goals if retail tariffs are not granular enough to transmit that wholesale market price signal inclusive of a carbon tax. This result, again, highlights the importance of considering tariff design as a core element when designing energy and climate policy.

Table 6. Annual CO_2 emissions from batteries in metric tons under different tariff designs with a \$44/ton carbon tax on all sources

[13] For simplicity, we are showing only the scenarios with a complete carbon tax. While the magnitude of the effects change under an incomplete carbon tax, the qualitative results do not change.

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No Battery Investment Allowed						
Total Emissions	174	172	175	173	148	145
Consumption Emissions	245	248	246	243	304	317
Solar PV Generation	-190	-196	-191	-190	-157	-193
Battery Operations	-	-	-	-	-	-
Gas for Heating Emissions	120	120	120	120	0	21
Percentage difference in total emissions compared to flat tariff	-	-1.1%	0.6%	-0.6%	-14.9%	-16.7%
Percentage difference in total emissions compared to same tariff design without a carbon tax (Table 5)	-13%	-13%	-12%	-13%	-44%	-34%
Battery Investment Allowed						
Total Emissions	155	151	157	151	148	124
Consumption Emissions	234	232	233	231	304	314
Solar PV Generation	-203	-201	-198	-198	-157	-198
Battery Operations	4	0.4	4	-2	-	-3
Gas for Heating Emissions	120	120	120	119	0	11
Percentage difference in total emissions compared to flat tariff	-	-2.6%	1.3%	-2.6%	-4.5%	-20.0%
Percentage difference in total emissions compared to same tariff design without a carbon tax (Table 5)	-22%	-19%	-21%	-24%	-44%	-43%

Notes: The totals are the annual sums of emissions from of each cluster, weighted by the number of households in each cluster. Consumption emissions are calculated by multiplying the load profile for thermal and non-thermal consumption by hourly marginal emission rates. Emissions avoided by solar PVs are calculated by multiplying their generation by hourly marginal emission rates. Emissions from battery operations are the difference between the emissions caused during charging periods and the emissions avoided during discharging periods, calculated by hourly marginal emission rates.

5. Discussion

With the emerging focus on the role of DERs and electrification in achieving climate policy goals, there has been a surge of attention on the inefficiencies in residential electricity tariff designs, specifically the discrepancies between the typical flat volumetric rates and the time-varying social marginal cost of electricity. With it there has been a surge in calls for residential rate reforms to ensure socially efficient deployment of DERs. Many states from Hawaii to Illinois to New York are in the various stages of reforming their retail tariffs, with the goal of increasing DER deployment and electrification, and, at the same time, reducing emissions.

In theory, improving the time-granularity of the tariff designs to more accurately reflect social marginal cost should lead to more efficient DER deployment and operation, and, reduce CO_2 emissions. And, with a theoretically ideal cost-reflective tariff, which would include a carbon tax, we should get DER adoption only when they are socially efficient.

Our results show that in our setting in ComEd, given current capital costs of DERs, and associated federal subsidies, adoption of neither solar PVs nor batteries is privately optimal under any type of tariff design scenarios we considered. Even a carbon tax, which should align private incentives for DER adoption more with socially beneficial outcomes, does not lead to adoption of solar PVs or behind-the-meter batteries under any of the tariff designs we tested, given the high upfront cost of the technology and low electricity rates in the study area. As a result, contrary to the common expectation of policymakers, TOU, CPP, and RTP tariffs lead only to load shifting from higher-priced time periods to lower-priced time periods, with minimal net effects on emissions compared to flat tariffs. Given that these three designs are the most commonly discussed reform options, our results highlight the importance of analyzing emission implications of tariff designs for policymakers.

Even under a cost-reflective tariff with a carbon tax, we get minimal solar PV adoption, implying that DERs are not privately optimal under the current cost structures and electricity price levels in the ComEd service territory, even when combined with a $44/ton carbon tax. And, while we get some electrification under the cost-reflective tariffs we test, only those consumers with high enough space heating requirements (and low enough volumetric rates) find it individually rational to switch to electric heating. Furthermore, with CRRf, emissions increase given the extra load from electric heating, leading to significant external damages, potentially offsetting other welfare gains that could be achieved by avoided capacity investment costs achieved under this tariff. Only in CRRv with a carbon tax do some customers find it privately optimal to switch to electric heating and invest in a solar panel at the same time, leading to significantly lower emissions.

Our results imply that, without significant cost declines or larger subsidies, more cost-reflective tariff designs would not likely to lead to higher DER deployment or significant reductions in emissions in the ComEd service territory. On the contrary, implementing cost reflective tariffs could lead to electrification and higher electricity use, and increasing emissions, especially when there is no carbon price signal. When we run our simulations under lower costs, we see that consumers may find it privately optimal to invest in DERs, and DERs might indeed lead to lower emissions. In those scenarios, tariff designs and if and how a carbon tax is imposed significantly affects the emission outcomes. These results highlight the importance of considering the emission implications in tariff design reform discussions. Given that usually only TOU and CPP designs are considered in most tariff reform discussions (Revesz and Unel 2020), and an economy-wide carbon tax is far from reality, tariff design reforms that intend to incentivize DERs and electrification to help decarbonize the grid might lead to unintended consequences if policymakers do not take emissions into account.

An important caveat is that the direction and magnitude of our results depend on the generation mix of a given grid, so they are time- and location-dependent. Our findings are particular to the Chicago area in 2016. The same analysis might lead to different conclusions in other parts of the country. Furthermore, even at a given location, as the generation mix changes over time, the emissions implications will change accordingly. As clean resources such as wind start to meet baseload demand during off-peak hours, reducing marginal emission rates during those hours, even to zero, the load shifted to those hours would not increase emissions. Thus, with a generation mix dominated by large renewable resources, more advanced tariff designs are more likely to reduce net emissions, even with increased demand due to electrification.

In addition, it is important to note that we simulate compensated demands, which is less elastic than ordinary Marshallian demands. Thus, our results are likely to overestimate the demand we would observe if any of our tariffs were to be implemented. Therefore, the increase in system costs and emissions should be treated as an upper bound. Similarly, because we do not simulate the dynamic interaction between the changes in demand and the wholesale energy market prices, we overestimate the system costs.

6. Conclusion

In conclusion, our research provides important insights on how to analyze the effect of tariff design on emission consequences of DER adoption and use. Using an economics-engineering simulation model, we show that DER deployment and use is sensitive to underlying tariff design, and that, depending on the tariff design, more advanced tariff designs might end up increasing emissions – at least in the short term and in places with relatively dirty generation on the margin. These results emphasize the importance of pairing DER policy initiatives with decarbonization efforts at the wholesale electricity level. Complementary to existing results in the literature, our results show that if peak price periods in a given tariff design do not correspond well with periods with higher marginal emission rates, DER operation or load shifting might increase emissions.

Finally, we show that even if there is a carbon price at the wholesale level, the emission consequences of DERs will depend on whether retail customers directly see wholesale level price signals, at what granularity, and whether the same carbon price also applies to natural gas use for heating and distributed generation. This result shows that the effectiveness of other climate policies such as a carbon tax can vary depending on the granularity of tariff designs, highlighting the importance of considering retail tariff design in climate policy discussions.

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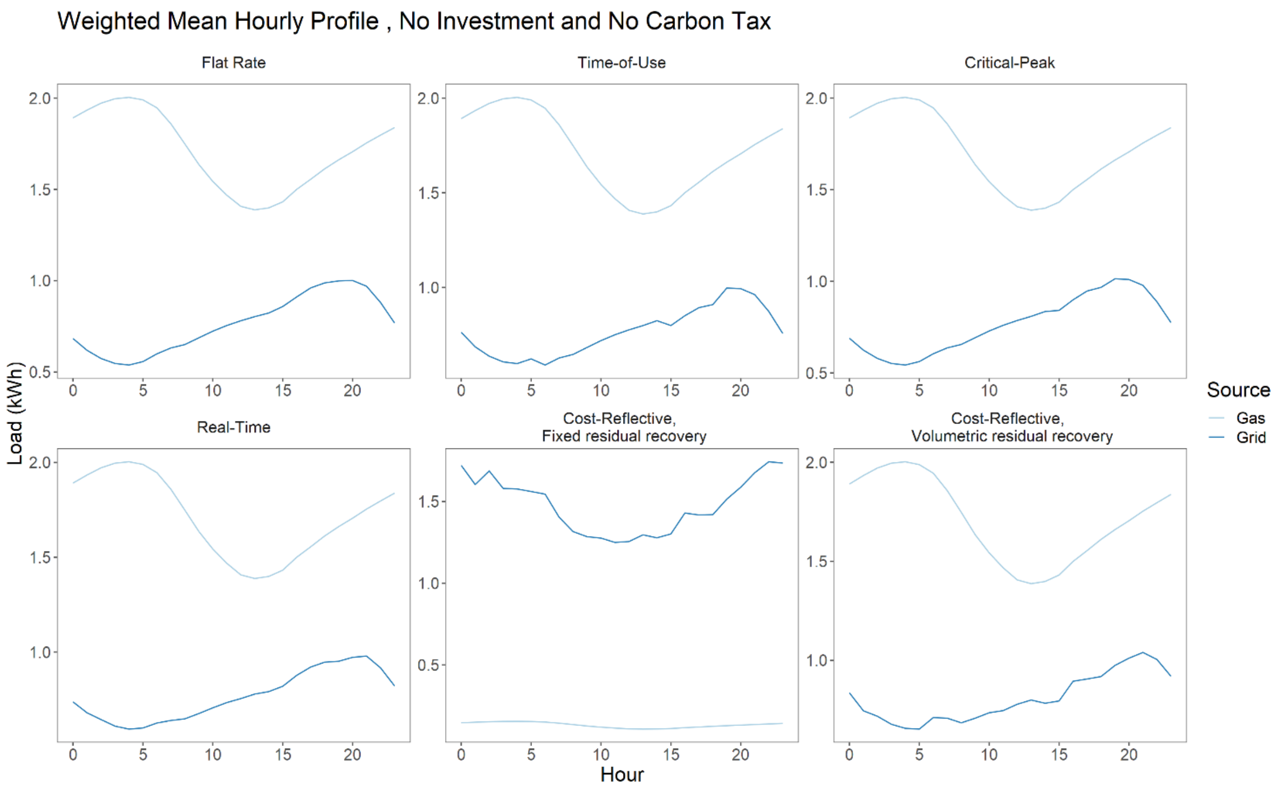
Appendix

Table A1. Tariff designs with \$44 per ton Carbon Price

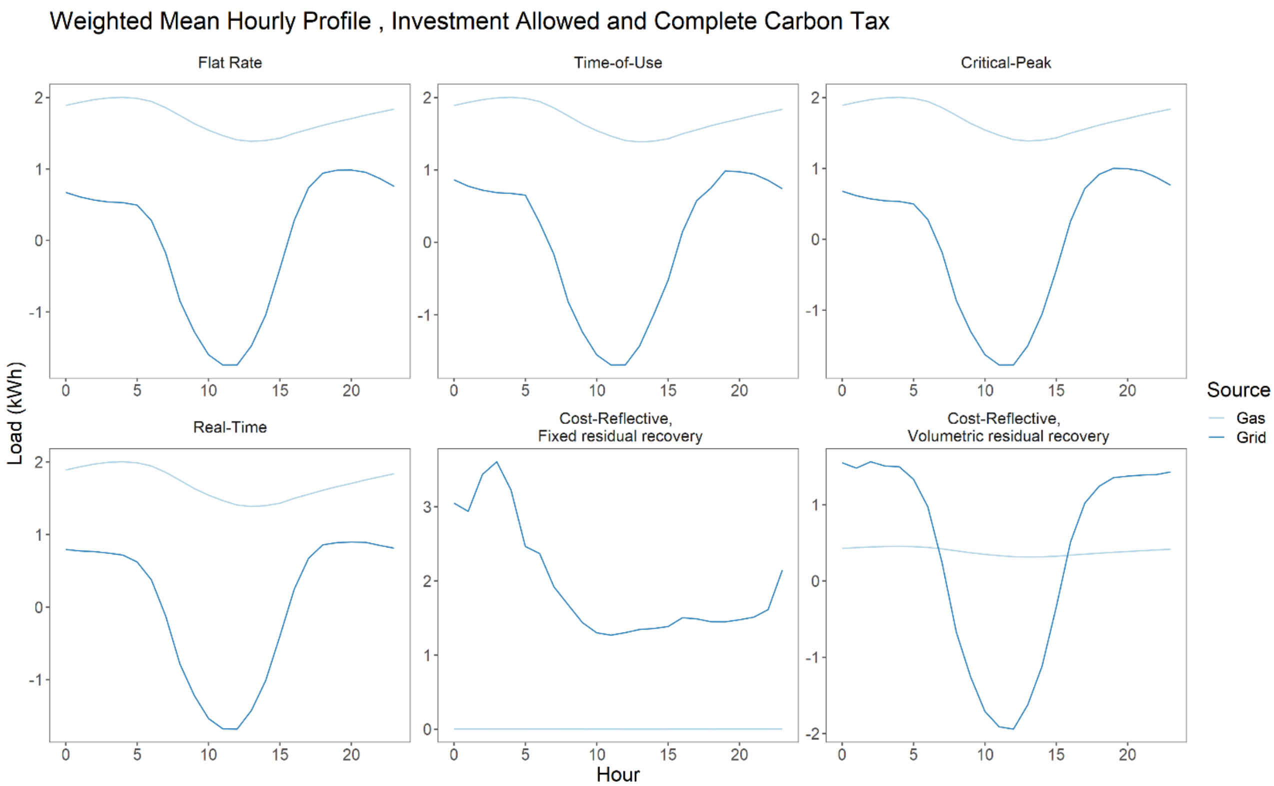
	Fixed Charge (\$/month)	Volumetric Charges (\$/kWh)	Demand Charge (\$/kW)	Peak Periods
Flat Tariff	14.89	\$0.093	\$4.21 (Jan-May) \$3.12 (Jun-Dec)	N/A
Time-of-Use Tariff	14.89	\$0.063 -\$0.143	\$4.21 (Jan-May) \$3.12 (Jun-Dec)	Super Peak: 3pm-7pm Off-Peak:12am-6am Shoulder: 6am-3pm, 7pm-12am
Critical Peak Price Tariff	14.89	\$0.09-\$0.44	\$4.21 (Jan-May) \$3.12 (Jun-Dec)	3 pm-7pm on top 10 hottest days of the year
Real-Time Pricing Tariff	15.28	Real-time price	\$4.21 (Jan-May) \$3.12 (Jun-Dec)	N/A
Cost-Reflective Tariff, Fixed residual Recovery	33.18	Real-time price	\$4.1/kW applied on top 10 peak hours of the year; \$.41/kW applied on top 10 peak monthly hours	Variable peak hours of year/month
Cost-Reflective Tariff, Volumetric Residual Recovery	15.24	Real time price + \$0.024/kWh	\$4.1/kW applied on top 10 peak hours of the year; \$.41/kW applied on top 10 peak monthly hours	Variable peak hours of year/month

Figure A1. Weighted Mean Hourly Profile of Gas and Electricity Use, with 50% All-In Costs, Without a Carbon Tax



Notes: The y-axes are not uniform. The gas use is converted to kWh using 29.3001kWh per therm.

Figure A2. Weighted Mean Hourly Profile of Gas and Electricity Use, with 50% All-In Costs, Under Complete Carbon Tax



Notes: The y-axes are not uniform. The gas use is converted to kWh using 29.3001kWh per therm.

Table A2: Annual CO_2 emissions in thousand metric tons under different tariff designs without a carbon tax

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total CO_2 Emissions	327	327	328	326	398	337
Grid Emissions	207	207	208	207	388	217
Gas for Heating Emissions	120	120	120	120	9	120
Percentage difference in total emissions compared to flat tariff	-	0.0%	0.3%	-0.3%	21.7%	3.1%
DER Investment Allowed, Base Cost Scenario						
Total CO_2 Emissions	327	327	328	326	398	337
Grid Emissions	207	207	208	207	388	217
Gas for Heating Emissions	120	120	120	120	9	120
Percentage difference in total emissions compared to flat tariff	-	0.0%	0.3%	-0.3%	21.7%	3.1%
DER Investment Allowed, 50% All-in Costs						
Total CO_2 Emissions	233	114	311	119	398	337
Grid Emissions	113	-6	191	0	388	217
Gas for Heating Emissions	120	120	120	120	9	120
Percentage difference in total emissions compared to flat tariff	-	-51.1%	33.5%	-48.9%	70.8%	44.6%

Note: The totals are the annual sums of emissions from each cluster, weighted by the number of households in each cluster. The aggregated load profiles for electricity and gas use under each design with 50% all-in cost structure is in the Appendix.

Table A3: Annual CO_2 emissions in thousand metric tons under different tariff designs, with a $44/ton carbon tax on all emitting power generation and natural gas used for heating.

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total Emissions	271	270	272	269	318	269
Grid Emissions	152	150	152	149	318	208
Gas for Heating Emissions	120	120	120	120	0	62
Percentage difference in total emissions compared to flat tariff with carbon tax	-	-0.4%	0.4%	-0.7%	17.3%	-0.7%
Percentage difference in total emissions compared to same tariff design without a carbon tax (Table A2)	-17%	-17%	-17%	-17%	-24%	-18%
DER Investment Allowed, Base Cost Scenario						
Total Emissions	271	270	272	269	318	269
Grid Emissions	152	150	152	149	318	208
Gas for Heating Emissions	120	120	120	120	0	62
Percentage difference in total emissions compared to flat tariff with carbon tax	-	-0.4%	0.4%	-0.7%	17.3%	-0.7%
Percentage difference in total emissions compared to same tariff design without a carbon tax (Table A2)	-17%	-17%	-17%	-17%	-24%	-18%
DER Investment Allowed, 50% All-in-Costs						
Total Emissions	117	118	115	121	318	76
Grid Emissions	-3	-1	-4	1	318	49
Gas for Heating Emissions	120	120	120	120	0	27
Percentage difference in total emissions compared to flat tariff with carbon tax	-	0.9%	-1.7%	3.4%	171.8%	-35.0%
Percentage difference in total emissions compared to same tariff design without a carbon tax (Table A2)	-50%	4%	-63%	2%	-20%	-77%

Note: The totals are the annual sums of emissions from of each cluster, weighted by the number of households in each cluster. The aggregated load profiles for electricity and gas use under each design with 50% all-in cost structure is in the Appendix.

Table A4: Annual CO_2 emissions in thousand metric tons under different tariff designs with a carbon tax applied only on wholesale electricity market

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total Emissions	271	270	272	269	302	276
Grid Emissions	152	150	152	149	281	156
Gas for Heating Emissions	120	120	120	120	22	120
Percentage difference in total emissions compared to flat tariff with incomplete carbon tax	-	-0.4%	0.4%	-0.7%	11.4%	1.8%
Percentage difference in total emissions compared to same tariff design without a carbon tax (Table A2)	-17%	-17%	-17%	-17%	-24%	-18%
DER Investment Allowed, Base Cost Scenario						
Total Emissions	271	270	272	269	302	276
Grid Emissions	152	150	152	149	281	156
Gas for Heating Emissions	120	120	120	120	22	120
Percentage difference in total emissions compared to flat tariff with incomplete carbon tax	-	-0.7%	1.0%	-1.2%	12.4%	-8.7%
Percentage difference in total emissions compared to same tariff design without a carbon tax (Table A2)	-17%	-17%	-17%	-17%	-24%	-18%
DER Investment Allowed, 50% All-in-Costs						
Total Emissions	117	118	116	121	302	133
Grid Emissions	-3	-1	-4	1	281	13
Gas for Heating Emissions	120	120	120	120	22	120
Percentage difference in total emissions compared to flat tariff with incomplete carbon tax	-	0.9%	-0.9%	3.4%	158.1%	13.7%
Percentage difference in total emissions compared to same tariff design without a carbon tax (Table A2)	-50%	4%	-63%	2%	-24%	-61%

Note: The totals are the annual sums of emissions from of each cluster, weighted by the number of households in each cluster.

Table A5. Tons of annual SO_2 emissions under different tariff designs without carbon tax, base case scenario

	Flat Tariff	Time-of-Use Tariff (TOU	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total Emissions	167	168	168	168	321	178
Grid Emissions	166	167	167	168	321	178
Gas for Heating Emissions	1	1	1	1	0	1
DER Investment Allowed, Base Cost Scenario						
Total Emissions	167	168	168	168	321	178
Grid Emissions	166	167	167	168	321	178
Gas for Heating Emissions	1	1	1	1	0	1
DER Investment Allowed, 50% All-in Costs						
Total Emissions	91	-4	154	1	321	178
Grid Emissions	90	-5	153	0	321	178
Gas for Heating Emissions	1	1	1	1	0	1

Notes: The totals are the annual sums of emissions from each cluster, weighted by the number of households in each cluster.

*Table A6***.** Tons of annual SO_2 emissions under different tariff designs with complete carbon tax

	Flat Tariff	Time-of-Use Tariff (TOU	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total Emissions	81	80	81	81	151	88
Grid Emissions	80	79	81	81	151	87
Gas for Heating Emissions	1	1	1	1	0	1
DER Investment Allowed, Base Cost Scenario						
Total Emissions	81	80	81	81	173	106
Grid Emissions	80	79	81	81	173	106
Gas for Heating Emissions	1	1	1	1	0	0
DER Investment Allowed, 50% All-in Costs						
Total Emissions	7	7	6	10	173	27
Grid Emissions	6	7	6	10	173	27
Gas for Heating Emissions	1	1	1	1	0	0

Notes: The totals are the annual sums of emissions from each cluster, weighted by the number of households in each cluster.

Table A7. Tons of annual SO_2 emissions under different tariff designs with *incomplete* carbon tax

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total Emissions	81	80	81	81	151	88
Grid Emissions	80	79	81	81	151	87
Gas for Heating Emissions	1	1	1	1	0	1
DER Investment Allowed, Base Cost Scenario						
Total Emissions	81	80	81	81	151	88
Grid Emissions	80	79	81	81	151	87
Gas for Heating Emissions	1	1	1	1	0	1
DER Investment Allowed, 50% All-in Costs						
Total Emissions	7	7	6	10	151	19
Grid Emissions	6	7	6	10	151	18
Gas for Heating Emissions	1	1	1	1	0	1

Notes: The totals are the annual sums of emissions from each cluster, weighted by the number of households in each cluster.

Table A8 Tons of annual NOx emissions under different tariff designs without a carbon tax

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total Emissions	260	260	260	258	260	265
Grid Emissions	138	138	139	137	251	143
Gas for Heating Emissions	122	122	122	122	9	122
DER Investment Allowed, Base Cost Scenario						
Total Emissions	260	260	260	258	260	265
Grid Emissions	138	138	139	137	251	143
Gas for Heating Emissions	122	122	122	122	9	122
DER Investment Allowed, 50% All-in Costs						
Total Emissions	196	115	249	118	260	265
Grid Emissions	74	-7	127	(4)	251	143
Gas for Heating Emissions	122	122	122	122	9	122

Notes: The totals are the annual sums of emissions from each cluster, weighted by the number of households in each cluster.

*Table A9***.** Tons of annual NOx emissions under different tariff designs with complete carbon tax

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total Emissions	271	274	272	266	272	256
Grid Emissions	149	152	150	144	272	194
Gas for Heating Emissions	122	122	122	122	0	63
DER Investment Allowed, Base Cost Scenario						
Total Emissions	271	274	272	266	272	256
Grid Emissions	149	152	150	144	272	194
Gas for Heating Emissions	122	122	122	122	0	63
DER Investment Allowed, 50% All-in Costs						
Total Emissions	42	49	39	47	272	(30)
Grid Emissions	(80)	(72)	(83)	(74)	272	(57)
Gas for Heating Emissions	122	122	122	122	0	28

Notes: The totals are the annual sums of emissions from each cluster, weighted by the number of households in each cluster.

*Table A10***.** Tons of annual NOx emissions under different tariff designs with an *incomplete* carbon tax

	Flat Tariff	Time-of-Use Tariff (TOU)	Critical-Peak Pricing Tariff (CPP)	Real-Time Pricing Tariff (RTP)	Cost-Reflective Tariff, Fixed residual recovery (CRRf)	Cost-Reflective Tariff, Volumetric residual recovery (CRRv)
No DER Investment Allowed						
Total Emissions	271	272	272	266	265	268
Grid Emissions	149	150	150	144	243	147
Gas for Heating Emissions	122	122	122	122	22	122
DER Investment Allowed, Base Cost Scenario						
Total Emissions	271	272	272	266	265	268
Grid Emissions	149	150	150	144	243	147
Gas for Heating Emissions	122	122	122	122	22	122
DER Investment Allowed, 50% All-in Costs						
Total Emissions	42	49	39	47	265	57
Grid Emissions	(80)	(72)	(83)	(74)	243	(65)
Gas for Heating Emissions	122	122	122	122	22	122

Notes: The totals are the annual sums of emissions from each cluster, weighted by the number of households in each cluster.