MIT CEEPR

MIT Center for Energy and Environmental Policy Research

Working Paper Series

Quantifying the Distributional Impacts of Rooftop Solar PV Adoption Under Net Energy Metering

SCOTT P. BURGER, CHRISTOPHER R. KNITTEL, AND IGNACIO J. PÉREZ-ARRIAGA

SEPTEMBER 2020

CEEPR WP 2020-017

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

Quantifying The Distributional Impacts of Rooftop Solar PV Adoption Under Net Energy Metering

Scott P. Burger   Christopher R. Knittel   Ignacio J. Pérez-Arriaga *

Abstract

We show that residential rooftop solar photovoltaics (PV) adoption under typical electricity tariffs that inefficiently recover residual costs through volumetric charges creates substantial income distributional effects. Specifically, rooftop solar PV adoption under such tariffs increases average expenditures substantially for non-adopters, which tend to be predominately lower income customers. At high penetrations of rooftop solar PV inefficient rates can increase average expenditures for non-adopting customers by as much as 80%. Efficient tariffs prevent this regressive cost shifting. Further, we find that under moderate PV adoption low-income consumers may be better off under a tariff that recovers residual costs through fixed charges—a rate design often criticized for being regressive in nature. In short, failing to reform residential electricity rates may lead to worse distributional outcomes than reforming rates, even if reforms are implemented naively.

Keywords: Electricity tariff design, socioeconomic status, pricing, rooftop solar photovoltaics, regulation.

*Burger: Institute for Data, Systems, and Society, MIT sburger@mit.edu. Knittel: Shultz Professor of Applied Economics, Sloan School of Management, Director of the Center for Energy and Environmental Policy Research, Co-Director, Electric Power Systems Low Carbon Energy Center, MIT and NBER, knittel@mit.edu. Pérez-Arriaga: Visiting Professor, Sloan School of Management, MIT. Professor and Director of the BP Chair on Sustainable Development, Comillas University. Director of Energy Training, Florence School of Regulation, ipa@mit.edu. We thank, without implicating, Ian Schneider, Carlos Batlle, Richard Schmalensee, and Paul Joskow for their thoughtful feedback on the content and theme of this paper. We thank Dave Kolata and Jeff Zethmayr for their support in accessing the data used in this study. The usual disclaimer applies.

1 Introduction and Background

Improving electricity rate design is one of the most important tasks facing regulators in the 21st century. Electricity prices are the nervous system of the power sector, helping coordinate the diverse interests of the producers and consumers that rely on the power grid. Efficient prices are one of the keys to ensuring that the trends of decentralization, decarbonization, and digitization benefit, rather than harm, customers (Pérez-Arriaga et al., 2016). As a result, regulators globally are searching for ways to modernize electricity rates.

While the basic tenants of economically efficient rate design have been known for nearly a century, rates today remain inefficient for the vast majority residential and commercial consumers. Many factors contribute to this gap between theory and practice. One key factor is that electricity is essential to modern life and is regulated as such. The result is that economic efficiency is often not the primary—and almost never the sole—goal for regulators when setting prices. Rather, regulators often prioritize goals of fairness and distributional equity[1] when setting prices. For example, of the California Public Utility Commission's (CPUC) rate design principles, the first relates to access and affordability to electricity for vulnerable populations (California Public Utilities Commission, 2018).[2] The CPUC is not alone—regulators across the U.S. are broadly concerned with the distributional impacts of tariffs (Levinson and Silva, 2019).

The emergence of distributed energy resources (DER) adds a new dimension to the challenge of assessing the distributional impacts of rate design. A full accounting of the distributional impacts of rate design must now consider not only how any given rate will impact different customer types, but also how the rate will influence DER adoption, how rates change as customers install DERs, and how these changes impact customers of different socioeconomic groups. While some literature analyzes the distributional impacts of transitioning to time varying energy charges (see, e.g., Horowitz and Lave (2014)) or to alternative network charges (see, e.g., Borenstein (2011), Borenstein and Davis (2012), and Azarova et al. (2018)), there is a dearth of research analyzing how efficient or inefficient rates perform as DER adoption increases.

[1]Distributional equity refers to any relevant standards for the distribution of goods between different various members of society, particularly between vulnerable and non-vulnerable customers (Burger et al., 2018).

[2]Vulnerable customers in the context of the California Public Utilities Commission (2018)'s rate design principles refers to "low-income and medical baseline customers." This paper defines "vulnerable customers" broadly as any customer group that has been defined as needing electricity price and/ or bill protections in a given location. Low-income, fixed-income, and rural customers are the most common types of vulnerable customers.

DER adoption and retail electricity rates are intertwined in two ways. First, in many markets, including the vast majority of U.S. markets, DERs are remunerated according to the retail tariff.[3] Second, the costs of DER adoption and support programs are often recovered through the retail tariff.[4]

This paper analyzes the rate impacts of the installation of rooftop solar photovoltaics (PV) by homeowners in the Chicago, Illinois region under alternative electricity rate designs. Specifically, we analyze the impacts of inefficient and efficient methods for recovering residual network costs as DER penetration increases. While the data used to parameterize the models used herein are from Chicago, the lessons gleaned about the potential impacts of inefficient rates are universal.

This paper uses three primary data sources and tools. First, we develop simple models that captures a utility's costs, the structure of the tariffs used to recover these costs, and the changes in the utility's costs and rates as the penetration of rooftop solar PV among residential customers increases. We parameterize these models with half-hourly energy consumption data for 100,170 customers in the Chicago, Illinois region, and with U.S. census (American Community Survey) data on the socioeconomic characteristics of these customers. Finally, we leverage data from the Lawrence Berkeley National Laboratory on the income trends of rooftop solar PV adopters to simulate the demographics of PV adoption (see Barbose et al. (2018)).

The research presented here leads to several novel results. First, we find that annual expenditures for non-solar adopting customers in the bottom income quintile[5] may increase substantially—by as much as 80%—at high solar penetrations under the default electricity tariff in ComEd. The default ComEd tariff does not vary with time and recovers a substan-

[3] The retail tariff directly determines the value of energy production from behind-the-meter DERs, when that energy production offsets consumption. For example, if a customer pays \$0.10 per kilowatt-hour (kWh), then the value of DER production (when that production offsets local consumption) is \$0.10/kWh. In many places, the retail tariff also determines the value of energy production from DERs that is exported to the grid. In the most generous case, exported energy from DERs receives a price equal to the cost of consumption, i.e. \$0.10/kWh if the retail rate is also \$0.10/kWh; this is called net-metering. The retail tariff might also determine if there are other applicable rates for DERs. In some locations, DER owners pay additional fixed monthly charges, or are placed on a different tariff type (e.g., time-of-use).

[4] In many cases, for example in the European Union, the aggregate costs of explicit subsidies for DERs are recovered through retail tariffs. This paper focuses on a more subtle type of DER support cost. As this paper discusses in much more detail, if DER adoption reduces a customer's payments more than it reduces system costs, the resulting revenue shortfall may require increasing rates. Where rates allow customers to avoid paying for residual costs by reducing net demand, a DER-driven decrease in net demand increases the effective per kWh charge for residual cost recovery.

[5] That is, the customers with the lowest 20% of incomes. Throughout this paper we refer to the customers with the lowest 20 percent of incomes as the 1st income quintile, or Q1. Likewise, we refer to customers with the highest 20% of incomes as the fifth income quintile, or Q5.

tial portion of total residual network and policy costs through volumetric charges ($/kWh). Under this tariff, as customers adopt solar they decrease their net demand, requiring an increase in charges for residual cost recovery and increasing bills for non-solar adopters. Given that the majority of solar adopters tend to be affluent, this drives a net increase in expenditures for less affluent customers. Average expenditures for all customers in the bottom income quintile—including both adopting and non-adopting customers—could increase as much as 35%.

Second, we find that tariffs with efficient cost recovery mechanisms—that is, fixed charges—do not create such cost shifts; solar PV adoption under efficient tariffs leads to average bill savings across all income quintiles.

Third, we find that average expenditures for low-income customers under a tariff with volumetric residual cost recovery *exceed* average expenditures for low-income customers under a tariff with uniform fixed charges for residual cost recovery at moderate levels of solar PV penetration (less than 25% of single-family homes). This finding dispels the common belief that volumetric rates are inherently progressive relative to fixed charges.

Finally, we find that net metering under the default tariff likely overcompensates rooftop PV for the network loss and capacity cost reductions that it may create, even under very aggressive assumptions about the magnitudes of these cost reductions. More specifically, the marginal revenue per-kilowatt (kW) of solar PV under tariffs that accurately value the impact of solar PV adoption on future network costs is *less* than the marginal revenue per-kW of solar PV under the default (flat) tariff. This reinforces the idea that time invariant rates with volumetric residual cost recovery mechanisms are crude and imperfect subsidies for distributed solar PV.

This paper proceeds as follows. Section 1.1 introduces the literature covering issues related to rate design and the distributional impacts of rooftop PV adoption. Section 2 reviews the methods used to assess the potential distributional impacts of DER adoption in this paper. The data used in this study are extensive, and are thus detailed separately in Appendix 6.1. Section 3 assesses the distributional impacts of efficient and inefficient rates as distributed PV penetration among residential customers increases. Given the lack of data regarding the topology and investment needs in the distribution system in the ComEd service territory, Section 3 assumes that the distribution network is sufficiently sized such that no new distribution investments are needed, meaning that solar PV penetration does not reduce network costs. Section 4, on the other hand, assumes that all distribution network costs are marginal with respect to consumption and production, and designs a tariff that accounts for these marginal distribution network costs. Section 4 then analyzes the distributional impacts of increasing rooftop solar PV adoption under this tariff. Together, the results in Section 3 and Section 4 provide a useful bound on the potential distributional impacts of efficient and inefficient electricity rates. Finally, Section 5 discusses and concludes. Extensive sensitivities of the results to assumptions are detailed in the Appendices.

1.1 Background Literature

The literature on electricity tariff design is large, with theoretical work on efficient rate design beginning in the early 20th century (Coase, 1946; Houthakker, 1951; Vickrey, 1971; Borenstein, 2005). More recently, the theoretical benefits of efficient rate design have been demonstrated in empirical research (Jessoe and Rapson, 2014; Wolak, 2011; Allcott, 2011; Savolainen and Svento, 2012). The overarching message of this theoretical and empirical research is that the societal benefits of electricity consumption are maximized when the marginal price that customers pay for consuming (and are paid for producing) energy is equal to the social marginal cost of producing that energy. This implies that any electricity-related costs that do not vary with short run production and consumption decisions and that are not recovered by short run social marginal costs[6] are most efficiently recovered through non-marginal charges.

Economic efficiency is not the only consideration in rate design. For example, many considerations exist alongside economic efficiency in the widely used rate design principles outlined in Bonbright (1961) and Chapter 8 of Pérez-Arriaga (2014). Among these considerations, equity—and, in particular, the distributional effects of rate design—loom large. Indeed, regulation has long been used as a means of distributing benefits (Posner, 1971). As evidence of this fact, Levinson and Silva (2019) found that utilities in regions with higher levels of income inequality had more income redistributive electricity rates. Most commonly this entails recovering residual costs[7] through volumetric, rather than fixed, charges. Transitioning from volumetric to fixed charges that are uniform for all customers would be regressive with respect ot income (Borenstein, 2012b; Burger et al., 2020). However, non-uniform fixed charges can be designed to recover residual costs in an income neutral or even progressive way (Burger et al., 2020).

[6]The economics literature refers to these costs as "residual" costs. In short, these are the costs left over (residual) after efficient prices have been charged. Given non-convexities in the long-run supply function for electricity and many other factors, efficient marginal prices rarely recover all network and regulatory costs, meaning that residual costs make up a substantial portion of total electricity costs Rubio-Odériz and Perez-Arriaga (2000).

[7]A portion of the costs associated with electricity transmission and distribution networks as well as costs associated with regulations and policies that are recovered through tariffs.

In recent years, regulators and the academic literature have begun to focus on the interaction between DER adoption and retail rates, with a focus on the distributional impacts of DER adoption. Given the scale of the distributed solar industry relative to other distributed resources, the bulk of the literature on the net social benefits of DERs and the distributional impacts of DER support schemes has focused on solar PV. Vaishnav et al. (2017) analyzes the costs of support programs for rooftop solar PV and the benefits of the associated climate and air pollution reductions, and finds that, between 2011 and 2015, private benefits exceeded public benefits by roughly $13.5 billion in the U.S.[8] Vaishnav et al. (2017) also find that these benefits have accrued predominately to more affluent households. Similarly, Borenstein (2017) analyzes the private benefits of solar PV adoption in California, and finds that these benefits have disproportionately accrued to affluent households. Borenstein and Davis (2016) analyze support programs beyond solar PV, including tax credits for home weatherization, hybrid and electric vehicles, and other types of "clean energy;" the authors again find that the top income quintiles receive the lion's share of the benefits of these programs.

Outside of federal tax credits, the costs of which are recovered through general taxation measures, the bulk of the costs of support programs for DERs are recovered through charges levied on electricity consumers in electricity tariffs. Rates also must recover residual network costs. The second relevant stream of literature analyzes how the structure of the mechanisms used to recover DER support costs, more generic policy costs, and residual network costs impacts customers of different socioeconomic groups.

One challenge associated with measuring the distributional impacts of rate designs is that determining the structure and magnitude of an economically efficient tariff is not straightforward. The ideal short run marginal price—i.e. the variable price in the tariff at any given point in time—would convey the full societal marginal cost of consumption or production. This marginal price should include the cost of any externalities (e.g., emissions), the cost of energy, and, critically, the marginal cost of short run production and consumption decisions on future network and generation capacity costs.

If the electricity tariff enables a DER adopter to save money in excess of society's cost savings from that DER adoption, the excess savings are both a transfer from non-adopters to adopters and a wedge between efficient and a source of inefficient DER adoption. Given the complexities of the issue and a general dearth of useful data, there is substantial uncertainty over the optimal design and magnitude of price signals to reflect the marginal impacts of

[8] Note that this analysis does not include two important factors. First, the potential network cost impacts (either cost reductions or increases) of DER adoption. Second, the potential spillover benefits of solar PV subsidies on cost reduction and deployment in other markets. For a discussion of these benefits, see Gerarden (2017) and Borenstein (2012a).

consumption and production decisions on network costs. While the magnitude and design of the optimal marginal network tariff is uncertain, one thing is clear: the magnitude of the optimal marginal network tariff will vary widely depending on location and time (Burger et al., 2019; Pérez-Arriaga et al., 2016).

Some initial evidence suggests that DERs—in particular, rooftop solar PV—enable greater private savings than system cost reductions on average. For example, Schmalensee et al. (2015) finds that solar PV adoption likely increases rather than decreases network costs under a variety of conditions. Using a simulation model, Satchwell et al. (2015) finds that solar PV adoption generally reduces private costs in excess of utility costs using two model utilities in the U.S.

This observation, combined with the fact that the benefits of DER support schemes have flown predominately to the affluent, has led to a review of the role of tariffs in the distributional impacts of DER adoption. Nelson et al. (2011) argues that the mechanism for supporting rooftop solar PV in Australia is regressive, benefiting high-income customers at the expense of lower income customers. Simshauser (2016) concurs, finding that, as rooftop solar PV penetration increases, flat, volumetric rates cause a net cost shift from low-income to higher-income customers in Australia, and argues for coincident-peak demand-based tariffs as a potential remedy. Simshauser (2016) extrapolates from a small set of customers intended to represent typical Queensland Australia customers. Using a model of nine customers intended to be representative of customers in New Jersey in the United States, Johnson et al. (2017) similarly finds that DER adopters tend to benefit at the expense of non-adopters. Leveraging a data set of 199 customers in the United Kingdom, Strielkowski et al. (2017) duplicates Simshauser (2016)'s model and, logically, find similar results. Using a robust data set of annual consumption[9] from roughly 135,000 customers in Switzerland, Feger et al. (2017) calculates tariffs that equalize bill increases across income classes while meeting a specified distributed solar adoption target.

The findings from this literature are relatively consistent: DER adoption has the potential to create distributional impacts across adopters and non-adopters, and across customers of different socioeconomic backgrounds. This paper builds upon this literature by expanding the scope of analysis (no paper to date has analyzed these issues in the U.S. context), leveraging a large and granular data set, and simulating potential futures with very high penetrations of rooftop solar PV.

[9] The authors partner with a Swiss startup to simulate hourly consumption profiles based on household characteristics.

2 Methods

We first detail the method used to simulate solar PV adoption. We then detail how this adoption information is used to estimate the distributional impacts of different tariffs.

2.1 Solar Adoption and Production Simulation

Holding the adoption probabilities introduced in Section 6.1.2 constant, we calculate the probability that any given customer will adopt solar at each penetration level, allowing this probability to differ across income quintiles. Specifically, we calculate:

$$\alpha_{Q,\phi} = \frac{\phi \sum_Q (N_Q) P_Q}{N_Q}, \tag{1}$$

ϕ is the percentage of single-family homes that have solar (e.g., 0%, 1%,...,75%), N_Q is the number of customers in each income quintile Q in our sample (see Table 4), and P_Q is the fraction of total solar adoption that happens in income quintile Q (see Table 5). A sample output from this equation is provided in Table 1.

Table 1: Customer-level PV adoption probabilities at different penetrations, 2016 Distribution case

All Single-Family Homes PV Penetration Level ϕ	Customer Adoption Probability				
	1^{st} Quintile α_1	2^{nd} Quintile α_2	3^{rd} Quintile α_3	4^{th} Quintile α_4	5^{th} Quintile α_5
0.5%	0.3%	0.3%	0.6%	0.7%	0.6%
1.0%	0.6%	0.6%	1.2%	1.3%	1.3%
1.5%	0.9%	0.8%	1.7%	2.0%	1.9%
2.0%	1.2%	1.1%	2.3%	2.7%	2.5%
⋮	⋮	⋮	⋮	⋮	⋮
73.0%	42.6%	41.0%	84.8%	97.7%	92.0%
73.5%	42.9%	41.2%	85.3%	98.3%	92.7%
74.0%	43.2%	41.5%	85.9%	99.0%	93.3%
74.5%	43.4%	41.8%	86.5%	99.7%	93.9%
75.0%	43.7%	42.1%	87.1%	100.0%	94.6%

In order to simulate which customers adopt solar at any given penetration level, we first draw a random number between zero and one, $rand_i$. If $rand_i$ is less than $\alpha_{Q,\phi}$, we assume that the customer has adopted solar (we denote this with $\lambda_{i,\phi} = 1$).

Thus, at any given point in time, solar generation for customer i is as follows:

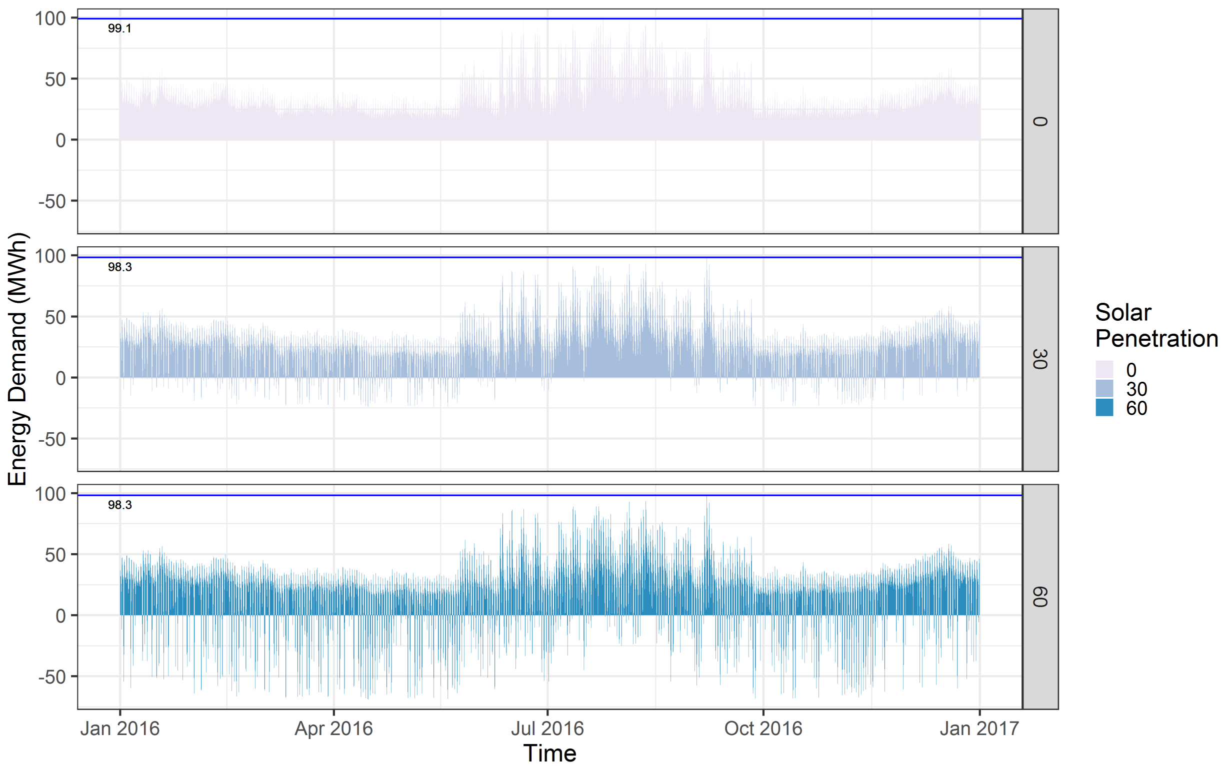
$$g_{i,t,\phi} = \lambda_{i,\phi}\kappa_i\tilde{g}_t \tag{2}$$

$\tilde{g}_t$ is the normalized solar generation per kW (AC) of solar PV (in units of kWh per kW), and κ_i is the size of the solar PV array adopted by customer i. We explore two different models for κ_i. First, we size each adopting customer's solar PV system according to that customer's annual peak demand ($\kappa_i = \hat{x}_{i,t}$). We refer to this as the "Peak Demand PV Case." Second, we size each customer's solar PV system such that it meets 80% of the customer's energy demand for the year ($\kappa_i = \frac{0.8\sum_t(x_{i,t})}{\sum_t(\tilde{g}_t)}$). we refer to this as the "Annual Consumption PV Case." In the Annual Consumption PV Case, the average PV unit size in our sample is 3.6 kW. In the Peak Demand PV Case, the average PV unit size is 5 kW. The average rooftop PV unit size in the U.S. is 5 kW according to the Solar Energy Industries Association, the trade association representing the U.S. PV industry (Solar Energy Industries Association, N.D.). We discuss the impact of sizing assumptions in Section 3.

Figure 1 displays the peak demand and net demand for three solar PV penetration cases under the Annual Consumption PV Case and with a PV azimuth of 180. The blue line on each plot is the peak demand at that penetration level. Two observations are particularly relevant. First, the aggregate peak demand of all of the customers in our sample decreases by only 0.8% as the penetration of rooftop PV increases. This is particularly relevant for assumptions about the recovery of residual costs, discussed in Section 3. Second, large injections of power become fairly common in the winter and shoulder seasons. We discuss these trends in more detail in Section 4.

One of the primary impacts of solar adoption is to shift the period of peak net demand on the system. However, this effect is not uniform. Due to low or no solar production during winter and shoulder month peak demand periods, solar PV production does not impact the period of coincident peak demand during winter and shoulder months. However, solar PV does produce during periods of coincident peak during the summer months, shifting peak net demand later in the day. This phenomenon is depicted in Figure 2. Figure 2 shows the marginal impact on net demand of a one percent increase in penetration of solar PV during a week in January (left panel) and a week in July (right panel) for three levels of solar penetration: 0% on top, 30% in the middle, and 60% on the bottom. The vertical blue lines represent the hour of peak net demand on each day. We see clearly that solar PV has little impact on winter peak demand, but shifts summer peak demand by several hours as penetration increases.

Figure 1: Net Demand Profiles for $\phi = 0, 30$, and 60



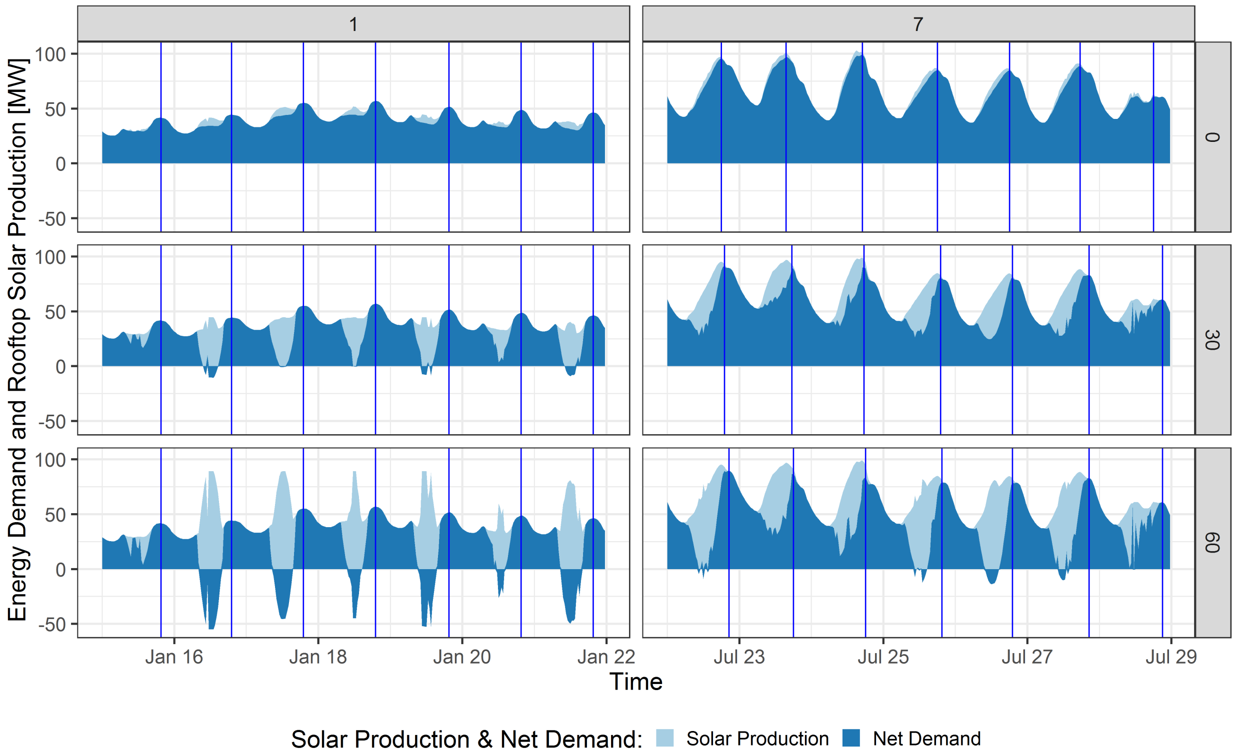
κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

2.2 Modeling the Distributional Impacts of Rate Designs

The primary goal of this paper is to understand the potential distributional impacts of PV adoption under different tariff designs. The optimal tariff contains price signals for marginal energy, generation capacity, and network capacity costs, and recovers all remaining residual costs through a fixed charge. While fixed charges are the most efficient mechanisms for recovering residual costs, most U.S. and European utilities also recover some portion of residual costs through volumetric charges. Further, the vast majority of tariffs charge a constant, time invariant price for energy and do not contain marginal price signals for network and generation capacity.

We now define a customer's electricity bill as a function of a generalized framework, the values of which depend on the solar penetration level (ϕ). This is represented in Equation 3. We represent a customer i's demand at time t as $x_{i,t}$, and the customer's solar generation at time t as $g_{i,t,\phi}$. Given this, the expenditure for customer i over a given time period can be represented as the sum the fixed charge, $F_{i,\phi}$, and the sum of customer's net demand at a

Figure 2: Net Demand Profiles for Two Selected Weeks for $\phi = 0, 30,$ and 60



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

particular point in time (e.g., hour), $x_{i,t} - g_{i,t,\phi}$, times the marginal price (for consumption and/or production) that customer i faces at time t, $p_{i,t,\phi}$.[10] Depending on the tariff structure, $p_{i,t,\phi}$ may include the following components:

1. $p^{e}_{i,t}$: The volumetric charge for energy
2. $p^{ccc}_{i,t}$: The volumetric charge for marginal generation capacity ("CCC" stands for coincident capacity charge)
3. $p^{cp}_{t,z,\phi}$: The volumetric charge for marginal network capacity ("CP" stands for coincident peak)
4. $p^{r}_{i,t,\phi}$: The volumetric charge for residual cost recovery

[10] The consumption data used in this study are reported as kWh used over a half-hourly period. Demand-based charges (dollar per kW) can be represented as energy charges by multiplying the energy consumed by two. For example, if a consumer was reported to have consumed 1/2 kWh in a given 30-minute period, this is equivalent to consuming 1 kW for 30 minutes.

As noted, many of the components of $p_{i,t,\phi}$ will be zero for many tariffs. For example, ComEd's default tariff is comprised of only a volumetric energy price, a volumetric charge for residual cost recovery, and a fixed charge for residual cost recovery. Under ComEd's default tariff, the energy charge is constant throughout each day—that is, the private marginal price paid by each customer does not change depending on when the customer consumes.

In the other rate designs studies in this paper—designs beginning with the letter "RTP"—the volumetric charge for energy—$p^e_{i,t}$—reflects the short-run marginal price of energy at the ComEd trading hub of the electricity market operated by the Regional Transmission Operator, PJM.[11] As a result, for the RTP tariffs studies here, $p^e_{i,t}$ changes on an hourly basis throughout the year.

Following this logic, the tariff titled "RTP-CCC" is a real-time price tariff with a critical capacity charge; the RTP-CCC tariff recovers all residual costs through a fixed charge. The "RTP-CCC-CP" charge is a real-time price tariff with a critical capacity charge and a coincident peak charge.

Consumer expenditures are calculated as follows:

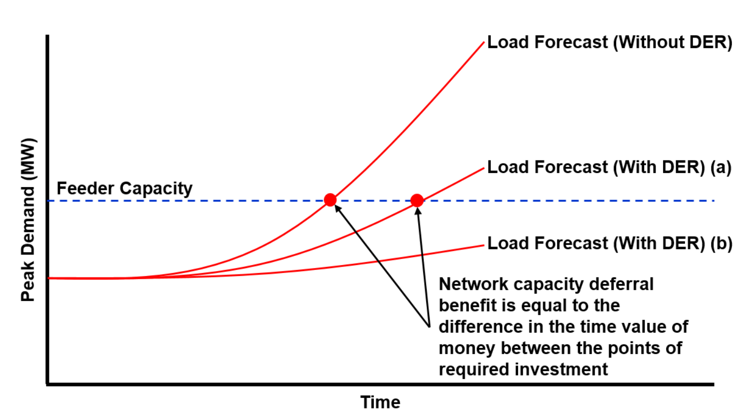
$$E_{i,\phi} = F_{i,\phi} + \sum_t \big(p_{i,t,\phi}(x_{i,t} - g_{i,t,\phi})\big). \tag{3}$$

The charge for marginal network capacity should only be non-zero when and where marginal consumption or production decisions will drive investments in new network capacity (Pérez-Arriaga et al., 2016; Abdelmotteleb et al., 2018). Ideally this charge would vary on a feeder-by-feeder basis, and the magnitude of the charge would be determined using measured load, network topology, and accurate forecast data. In the case of a congested feeder with necessary upgrades, the charge should equal the marginal change in the time value of money between the point at which a network investment would have been required in the absence of a DER and the point at which the network investment is required given the DER. This is depicted in Figure 3. Likewise, if a feeder were congested due to DER-driven injections of power, the charge should convey the marginal time discounted cost of the investments necessary to accommodate increased peak injections.

Given the lack of distribution network topology and technical data and the lack of load

[11] PJM operates the transmission system in many mid-Atlantic states in the U.S. In addition to operating the transmission system, PJM operates wholesale electricity markets. One of the outcomes of these markets are a set of locational prices that represent the marginal cost of consuming or the marginal value of producing electricity at the various nodes or trading hubs in the PJM market (these prices do not necessarily represent the short-run social marginal cost, as they often fail to internalize climate and health externalities). See http://pjm.com/.

Figure 3: Measurement of Network Capacity Value



Adapted from Cohen et al. (2016).

forecast and investment plan data, we simulate the distributional impact of rates under two extreme cases. First, a case in which we assume that no distribution feeders are congested, and thus that there are no marginal distribution network costs. This case will tend to show large distributional impacts of PV adoption, as a greater share of network costs are assumed to be residual, enabling larger cost shifts as PV adoption increases. Second, we model a case in which we assume that all distribution feeders are congested, and thus that all distribution network costs are marginal. This case will tend to show smaller distributional impacts of PV adoption, as a smaller share of network costs are assumed to be residual, decreasing cost shifts as PV adoption increases. We detail the methods for estimating the price signal for marginal network costs in Section 2.3. Together, these two cases provide a range of possible distributional impacts of efficient and inefficient rates as PV adoption increases.

Given the lack of distribution network data, the purpose of the modeling of marginal distribution network costs is not to estimate with precision the exact magnitude of distributional impacts. Rather, we try to: 1) estimate the potential order of magnitude of the cost shift, 2) develop an intuition for the potential distribution of the cost shift, and 3) understand the dynamics of the cost shift as distributed PV penetration increases.

A key component of our analysis of the distributional impacts of rate design is ComEd's total residual costs. We estimate ComEd's total residual costs as $R^r = \sum_{i,t} \left(F_{i,\phi=0} + x_{i,t} p^r_{i,t,\phi=0} \right)$, where $x_{i,t}$ is the demand of customer i in time t, and R^r is the total set of residual costs that the utility must recover. In zero marginal network costs case, R^r includes all distribution facilities, metering and customer, policy, and transmission costs. In the marginal network costs case, R^r includes all metering and customer, policy, and transmission costs, as we assume that the distribution facilities costs are marginal (and thus not residual). As solar PV generation increases, residual costs must be recovered across net demand:

$$R^r = F_{i,\phi} + \sum_{i,t} \Big((x_{i,t} - g_{i,t,\phi}) p^r_{i,t,\phi} \Big) \forall \phi = 0, ..., 75 \tag{4}$$

As solar penetration (ϕ) increases, total solar generation increases and net demand (demand minus solar generation) decreases. For an efficient tariff, $p^r_{i,t,\phi} = 0 \forall \phi$. However, in practice, $p^r_{i,t,\phi}$ is typically greater than zero (as it is under ComEd's default rate). Since $p^r_{i,t,\phi}$ is greater than zero at $\phi = 0$, $p^r_{i,t,\phi}$ or $F_{i,\phi}$ must increase as ϕ increases for all residual costs to be recovered (i.e. to meet the constraint in Equation 4).

There are three key assumptions embedded in this method. First, $x_{i,t}$ does not change with ϕ; that is, solar adopters do not modify their consumption behavior after adopting solar. Note that under a net-metering scheme as modeled here, the temporal profile of the customer does not affect the change in $p^r_{i,t,\phi}$—only the sum of the net demand. Second, R^r remains constant as ϕ increases. This assumption likely overstates the potential distributional impacts at low penetrations, and understates the distributional impacts at high penetration. Modeling results indicate that distributed PV adoption can reduce distribution system costs at low penetration, and increases these costs at higher penetrations (Schmalensee et al., 2015; Cohen et al., 2016). While empirical work on this issue is limited, there is initial evidence that distributed PV may increase network costs (and thus residual costs) even at low penetrations (Wolak, 2018). The third core assumption in Equation 4 is that all residual costs must be recovered. There is legal precedent for writing off assets that are not longer valuable. However, this is not common in practice. Further, as we show in Figure 1, peak demand remains fairly consistent as PV penetration grows, indicating that the assets in this case study are likely still useful.

2.3 Estimating marginal distribution network costs

In order to estimate marginal distribution network costs, we approximate feeder level demand by clustering demand at every five-digit zip code, $z \in \mathbb{R}^{153}$. In short, we assume that all customers in a given zip code belong to one feeder. The average peak demand across each zip code in this sample is roughly three megawatts (MW), which is in line with peak demands on average four kilovolt-amp feeders in the U.S.

To find the marginal cost of reducing (or of driving) coincident network loading, we perform the calculations depicted in Equations 5. We begin by identifying the times of the maximum

200 half hours of the absolute value of net demand (demand minus generation) in each z. Note that peak network loading may occur during times of PV injection and thus negative net demand. We sum the net demand across all customers i in each time period t and identify the top 200[12] half-hourly network loading periods in each z. Note that the demand in this case is the demand across all 100,170 customers in the sample, not the subset of single-family homes. This follows from the fact that networks are built to meet the demand of *all* customers. We refer to the times of these coincident peak periods as $\hat{t}_{z,\phi}$. We then calculate a per-kWh coincident-peak charge, referred to as $p^{cp}_{t,z,\phi}$, that recovers all distribution facilities costs from expected net demand in these coincident peak hours. We do this by dividing all distribution facilities costs[13] by the sum of the absolute value of net demand in these 200 half hours. This charge is symmetric—that is, a marginal increase in demand during a coincident peak demand period will increase customer expenditures, and a marginal increase in injection during a coincident peak injection period will also increase expenditures.

$$p^{cp}_{t,z,\phi} = \begin{cases} \frac{R^{dfc}}{\sum_{t,z}|x_{t,z,\phi} - g_{t,z,\phi}|} & \text{if } t \in \hat{t}_{z,\phi} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The calculations depicted in Equations 5 and 8 assume that all distribution facilities costs are marginal (that is, that no distribution facilities costs are residual), and that marginal costs are driven by demand during coincident peak hours. Given that not all areas within a distribution network will require investments at any given point in time, this likely overstates the potential magnitude and pervasiveness of marginal network costs. By holding R^{dfc} constant, we're making the assumption that total costs remain constant even as marginal costs change.

2.4 Estimating the value of avoided distribution network technical losses

In addition to estimating marginal distribution network costs, we estimate marginal distribution network losses. These marginal losses augment the marginal price of electricity. Electrical losses emerge in power systems due to a variety of factors, including ohmic (resistive) heating of electrical equipment (e.g., lines) as power flows through these lines. While

[12] We discuss the sensitivity to this peak period assumption in the appendices to this paper.

[13] This is referred to as R^{dfc}, with $R^{dfc} \approx \$19M$. This excludes metering and customer related charges (e.g., billing) as well as transmission costs. We assume that distributed PV will not reduce these costs.

some electrical losses are "no load" losses,[14] ohmic losses are related to the square of the current flowing through the network. That is, $l_{t,z,\phi} \propto I^2_{t,z,\phi} R_z$. Where $l_{t,z,\phi}$ is ohmic losses at time t in location z and solar penetration ϕ; $I^2_{t,z,\phi}$ is the square of the current; and R_z is the ohmic resistance. Marginal losses with respect to a change in load at any given point in time are equal to the derivative of the loss function with respect to the current: $\frac{\partial l_{t,z,\phi}}{\partial I_{t,z,\phi}} \propto 2 I_{t,z,\phi} R_z$. While distributed solar cannot reduce no load losses, it may reduce ohmic losses by reducing power flows over the distribution network.

We cluster demand by zip code as in Section 2.3. We then find the effective resistance, denoted $R_{z,\bar{l}}$, at an assumed average total loss value across the entire distribution system, denoted $\bar{l}$. We assume a constant voltage at the distribution level, and directly relate current and demand. We calculate marginal losses in every time period assuming a constant $R_{z,\bar{l}}$, and measure the value of solar PV in reducing these losses, denoted $s^l_{z,\phi,\bar{l}}$. We calculate marginal losses and loss avoidance values for two values of $\bar{l}$: 4% and 7%. This process is depicted in Equation 6:

$$
\begin{aligned}
R_{z,\bar{l}} &= \bar{l} \frac{\sum_t (x_{t,z,\phi=0})}{\sum_t (x^2_{t,z,\phi=0})}, \\
\frac{\partial l_{t,z,\phi,\bar{l}}}{\partial I_{t,z,\phi}} &= 2(x_{t,z,\phi} - g_{t,z,\phi}) R_{z,\bar{l}}, \\
p^{e'}_{i,t} &= p^e_{i,t} \Big(1 + \frac{\partial l_{t,z,\phi,\bar{l}}}{\partial I_{t,z,\phi}} \Big).
\end{aligned} \tag{6}
$$

Considering all volumetric energy, marginal network and generation, and marginal losses values, the revenue of customer i's PV unit is modeled as $s_{i,t,\phi} = \lambda_{i,\phi} \kappa_i \tilde{g}_t (p_{i,t,\phi})$ for any given tariff. $p_{i,t,\phi}$ is the total variable (dollar per kilowatt-hour) charge and contains several components (e.g., $p^r_{i,t,\phi}$ and $p^e_{i,t,\phi}$).

[14] That is, they are technical losses (i.e. not the result of electrical theft) but do not depend on the flow of power through the system. No load losses emerge from the need to energize the cores of electrical transformers, for example.

3 The Distributional Impacts of Rate Design with Solar PV Adoption: Zero Marginal Network Costs

In this section, we explore the potential distributional impacts of DER adoption under ComEd's default flat tariff and under the RTP-CCC and RTP-CCC-APD (defined below) tariffs under the assumption that zero percent of network costs are marginal. That is, in this section, $p^{cp}_{t,z,\phi} = 0$. In Section 4 we explore the possibility of non-zero values for $p^{cp}_{t,z,\phi}$. The RTP-CCC and RTP-CCC-APD tariffs recover all residual costs through fixed charges. As a result, $p^{r}_{i,t,\phi} = 0$ for all i, t, and ϕ. This provides a useful contrast to the default tariff, in which $p^{r}_{i,t,\phi} \approx 0.05$ \$/kWh for $\phi = 0$. Customer expenditures under the default tariff and the RTP-CCC tariffs are calculated as in Equation 7. Note that the RTP-CCC and RTP-CCC-APD tariffs are identical except for the fixed charge design.

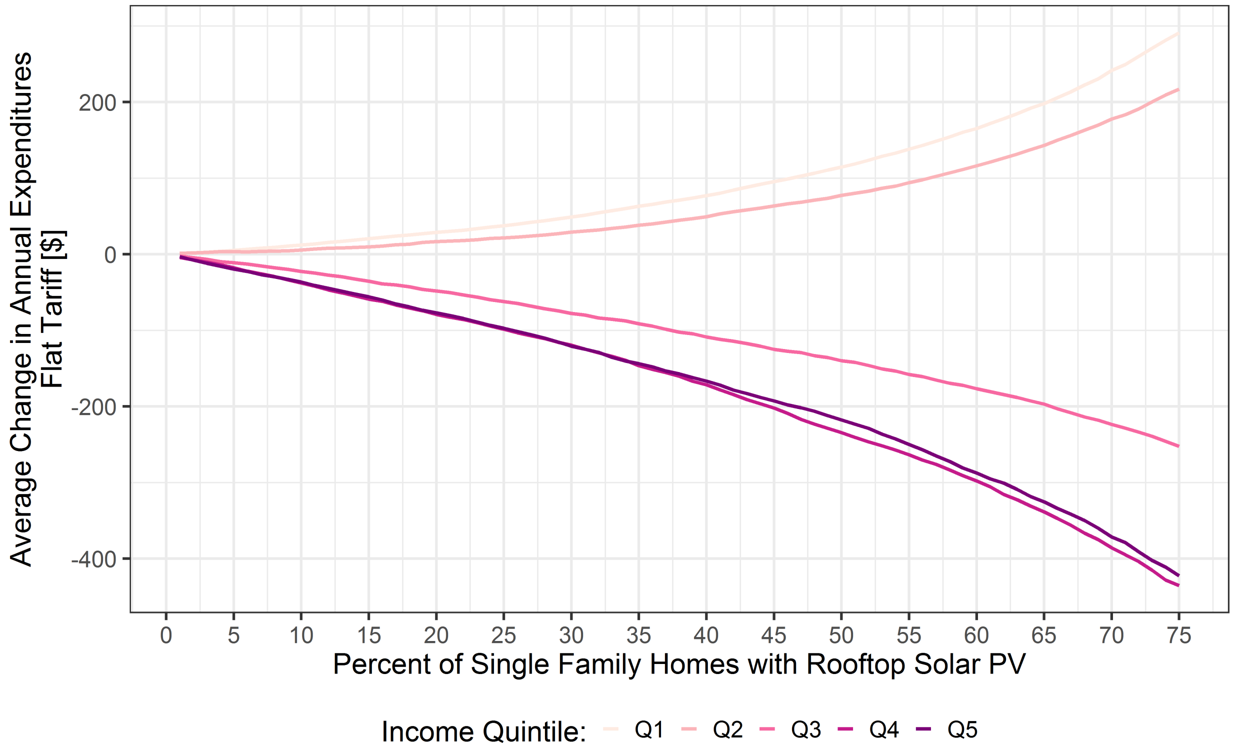
Under the RTP-CCC tariff, fixed charges recover all residual costs—that is, $p^{r}_{i,t,\phi} = 0 \forall i, t$—and are equal for all customers—that is, $F_{i,\phi} = F_{j,\phi} \forall i, j$. However, under the RTP-CCC-APD tariff, fixed charges are scaled by a customer's peak demand. That is, $F_{i,\phi} = \hat{x}_i * \frac{R^r}{\sum_i \hat{x}_i}$, where $\hat{x}_i$ is customer i's peak demand throughout the year, given by:

$$\begin{aligned} E^{default}_{i,\phi} &= F_{i,\phi} + \sum_t \big((p^e_{i,t} + p^r_{i,t,\phi})(x_{i,t} - g_{i,t,\phi})\big), \\ E^{RTP-CCC}_{i,\phi} \& E^{RTP-CCC-APD}_{i,\phi} &= F_{i,\phi} + \sum_t \big((p^e_{i,t} + p^{ccc}_{i,t})(x_{i,t} - g_{i,t,\phi})\big). \end{aligned} \tag{7}$$

Figure 4 shows the change in average expenditures for each income quintile as the penetration of solar PV increases under ComEd's default (flat) tariff. The results demonstrate a clear trend: as solar PV adoption increases, bills increase on average for low-income customers and decrease on average for high income customers. Appendix 6.2 contains the sensitivity results for the various parameters discussed herein. In all of the sensitivity cases explored, average expenditures for the bottom income quintile increase.

In this case, we update only $p^{r}_{i,t,\phi}$ as ϕ increases, holding $F_{i,\phi}$ constant. The results in Figure 4 are driven in part by an increase in $p^{r}_{i,t,\phi}$ as net demand falls, and in part by the fact that low-income customers represent a small fraction of PV adopters. Figure 5 highlights the increase in the volumetric charge for residual cost recovery as PV penetration increases. The per-kWh charge increases by over 200% at 75% solar penetration.

Figure 4: Average Change in Annual Expenditures By Income Quintile
Default (Flat) Tariff



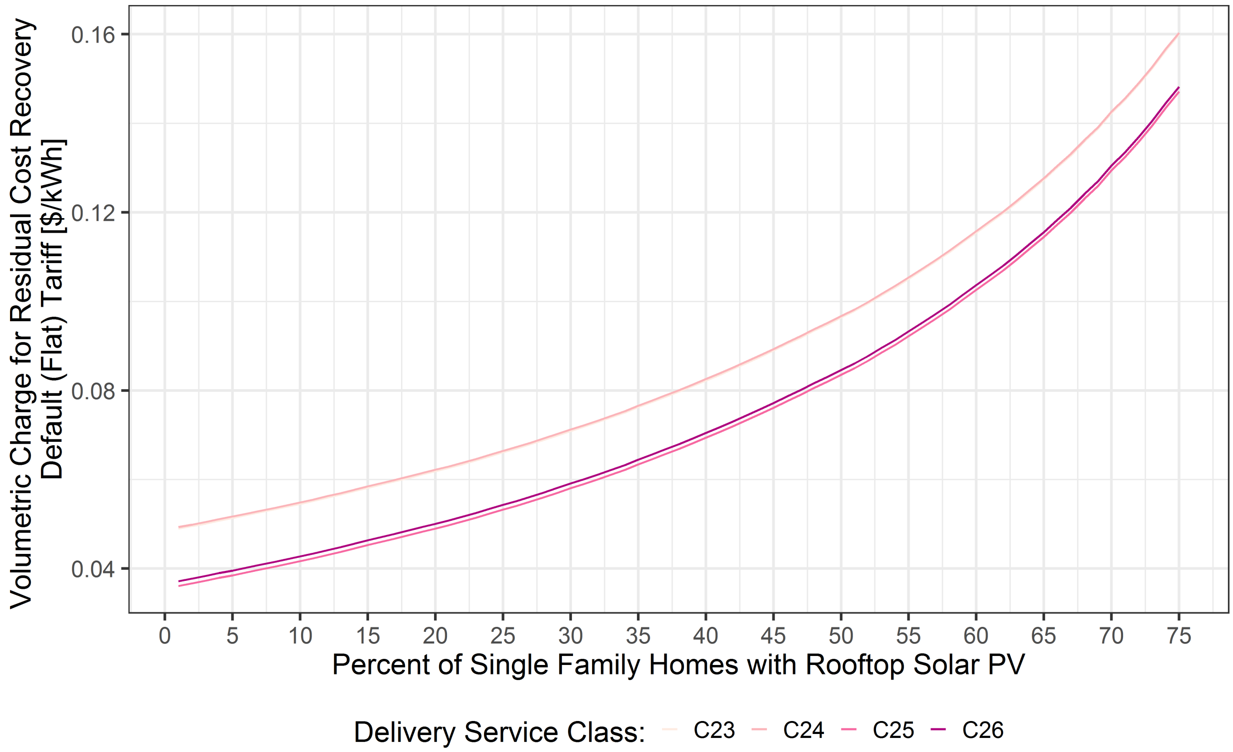
κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

Figure 4 masks two trends: first, that there is a cost shift between adopters and non-adopters within each income quintile. Second, that higher-income customers tend to consume more energy and thus offset a larger share of revenues as adoption increases. Figure 6 displays the average bill impact by income quintile for adopters (dashed lines) and non-adopters (solid lines). Given the assumption about κ and the fact that higher-income customers consume more power on average, we see larger per-customer savings for high income customers than low-income customers.[15]

The impact of changing the formula for κ (the size of the PV unit adopted by each customer) is relatively straightforward: as the average κ increases, the trends depicted in Figures 4 and 6 should accelerate. That is, net demand will fall faster as a function of solar penetration (ϕ). In other words, the bills for non-adopters will increase and the bills for adopters will fall more as κ increases.

[15]This is likely a reasonable assumption given the tendency for high income customers to live in larger houses, use more appliances like air conditioning, etc.

Figure 5: Change in The Volumetric Charge for Residual Cost Recovery
Default (Flat) Tariff



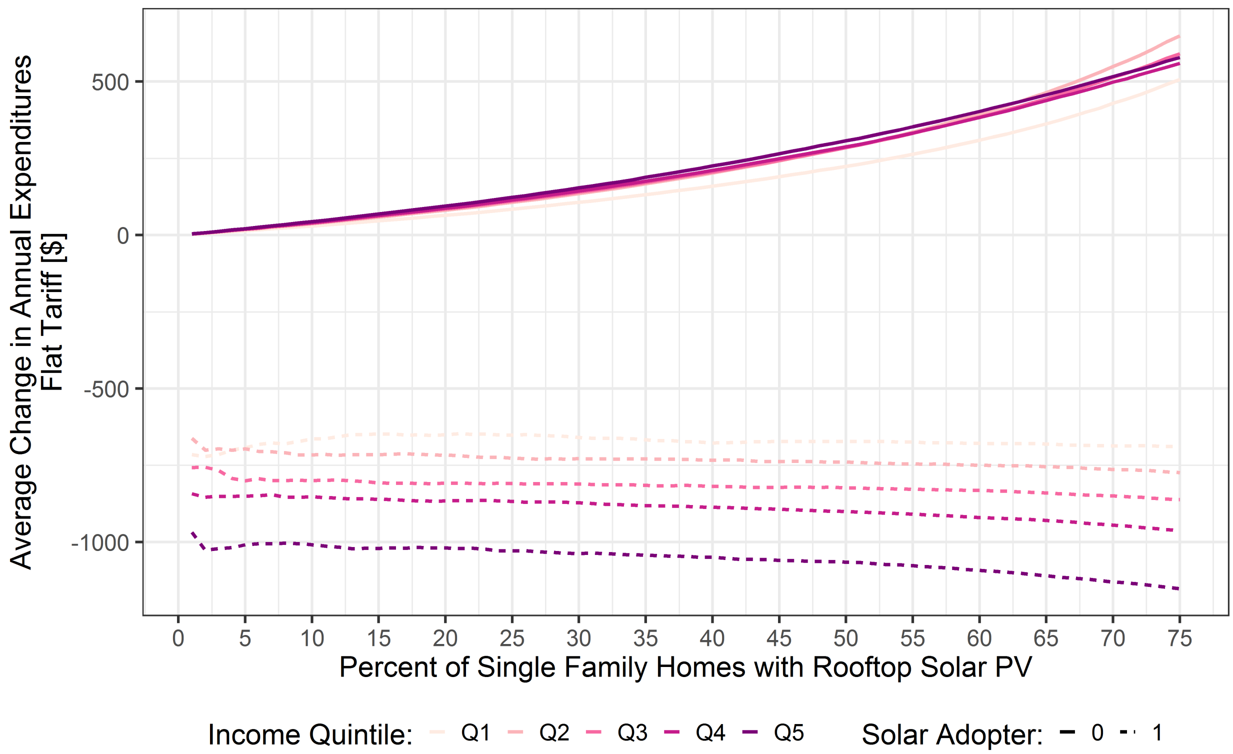
κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

These same trends do not hold for efficient tariffs—that is, for the RTP-CCC and RTP-CCC-APD tariffs. Figure 7 demonstrates the average change in expenditures by income quintile for the tariffs with efficient residual cost recovery: RTP-CCC and RTP-CCC-APD. All income quintiles benefit on average as solar PV penetration increases, as there is no change in $F_{i,\phi}$ or $p^r_{i,t,\phi}$. Solar adopters save money by decreasing their energy costs and non-adopters are not impacted.

Transitioning rate design is not without its impact. The RTP-CCC tariff recovers all residual costs through uniform fixed charges (i.e. every customer faces the same fixed charge). The RTP-CCC-APD tariff recovers all residual costs through fixed charges that scale according to a customer's annual peak demand. The result is that low-income customers would face a bill increase under the RTP-CCC tariff and a decrease under the RTP-CCC-APD tariff.

Figure 8 and 9 compares the average total annual expenditures as solar penetration (ϕ) increases under the default (flat) tariff and the RTP-CCC and RTP-CCC-APD tariffs. In each Figure, the solid line represents expenditures under the default tariff, while the dashed

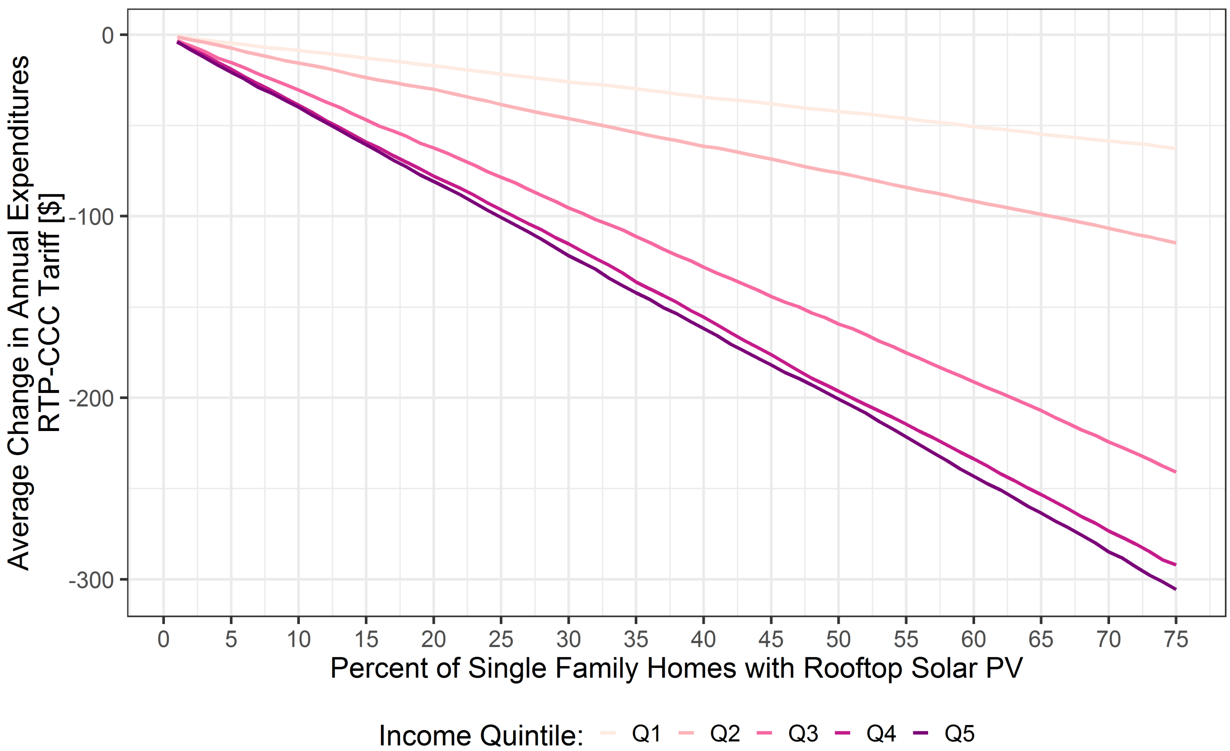
Figure 6: Average Change in Annual Expenditures By Income Quintile: Adopters vs. Non-Adopters
Default (Flat) Tariff



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

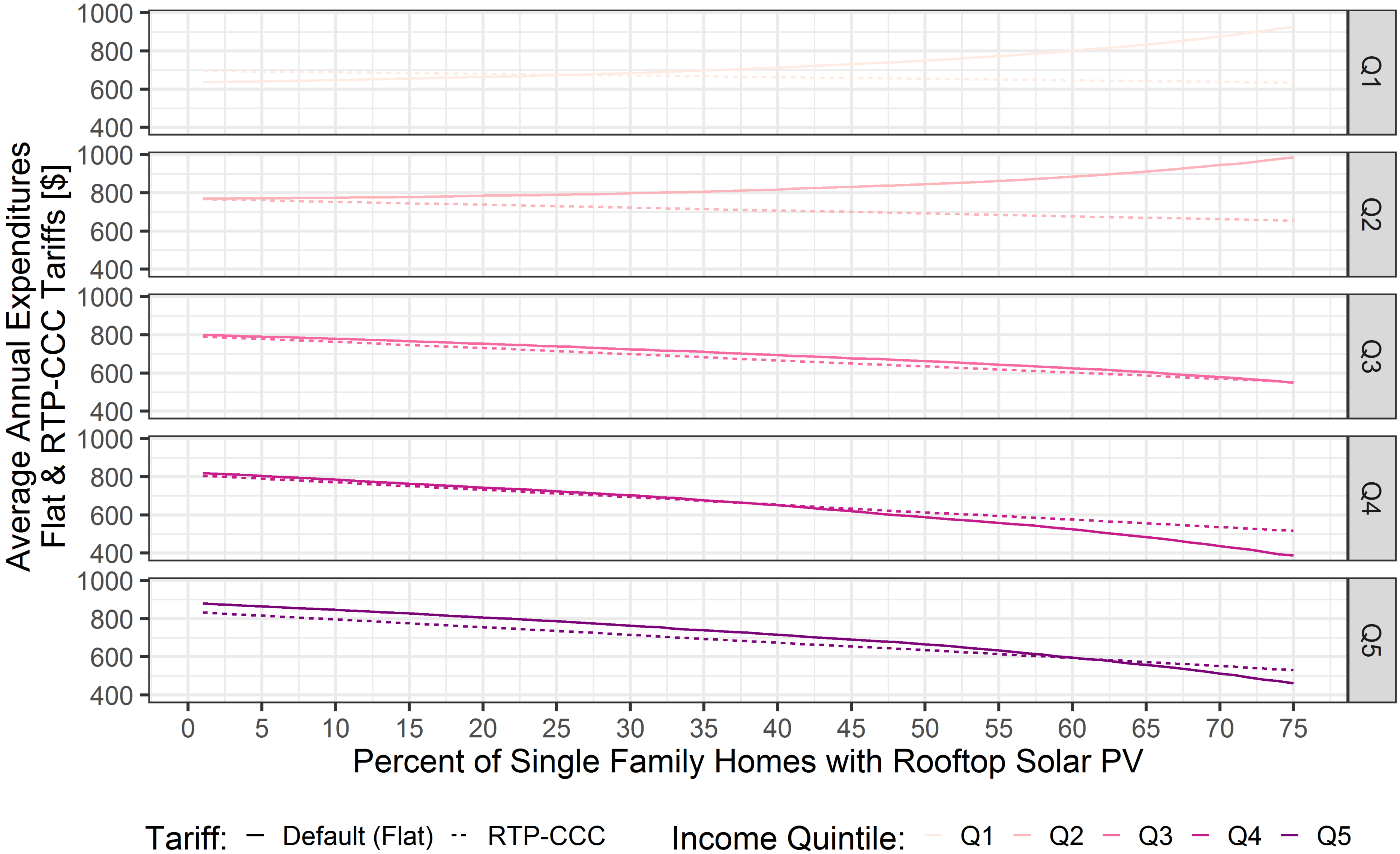
line represents expenditures under the RTP-CCC and RTP-CCC-APD tariffs respectively. At low solar penetrations, expenditures for low-income customers are higher under the RTP-CCC tariff than under the default tariff. However, as penetration increases, we see that low-income expenditures are lower under the RTP-CCC tariff than under the default tariff. Under the RTP-CCC-APD tariff, low-income customer expenditures are lower in all cases.

Figure 7: Average Change in Annual Expenditures By Income Quintile
RTP-CCC and RTP-CCC-APD Tariffs



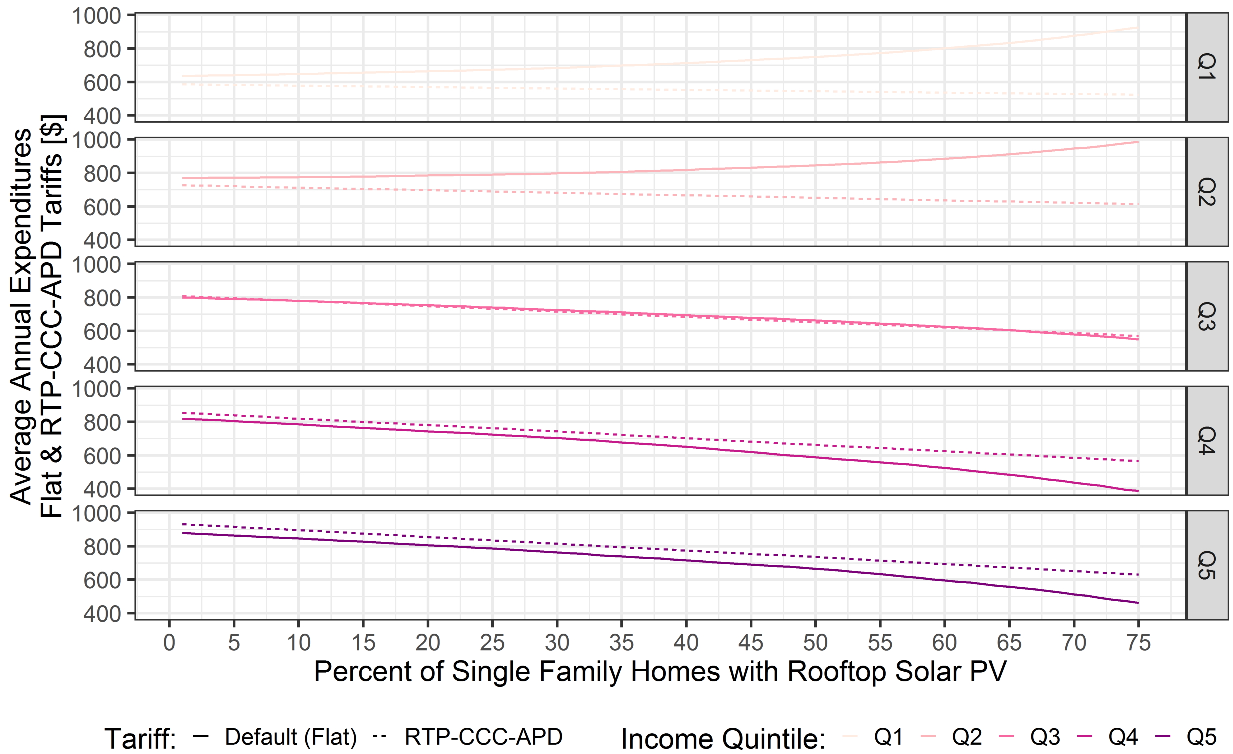
κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

Figure 8: Total Expenditures vs. ϕ: Flat and RTP-CCC Tariffs



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

Figure 9: Total Expenditures vs. ϕ: Flat and RTP-CCC-APD Tariffs



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

One of the core arguments for maintaining time invariant, volumetric tariffs like the default (flat) tariff studied here is that such tariffs are believed to protect low-income and other vulnerable customers. For example, the National Consumer Law Center, a non-profit dedicated to "advancing fairness in the marketplace for all," states plainly that "high utility fixed charges harm low-income, elders and households of color" (National Consumer Law Center, 2016). It is possible to design progressive fixed charges that do not harm vulnerable customers. Further, what this section demonstrates is that, as rooftop solar PV penetration increases, rates with volumetric residual cost recovery do not necessarily protect low-income customers. In fact, low-income customer expenditures may be higher under tariffs with volumetric charges for residual cost recovery than under tariffs that recover residual costs through fixed charges as PV penetration increases.

4 The Distributional Impacts of Rate Design with Solar PV Adpotion: Marginal Network Cost Cases

The previous section demonstrated the potential distributional impacts of distributed solar PV adoption under the assumption that zero percent of network costs are marginal. However, in practice, some portion of distribution network costs may be marginal in the long run, as highlighted in Section 2.2. In fact, some analysts have argued that distributed solar PV does not in fact create any cost shifts, as distributed solar is reducing system costs.[16] In this section, we explore the potential distributional impacts of a tariff that includes a charge for marginal network capacity and model the potential for distributed solar to impact the costs of distribution network capacity and losses.

We begin by exploring the potential impact of solar deployment on distribution network capacity costs and losses. We then explore the results of a tariff that incorporates these potential impacts. We then model the climate and health values of avoided emissions. We conclude with a discussion of how these potential benefits should be considered in light of the findings in Section 3

4.1 Distribution Network Capacity Cost Impacts

If solar PV reduces demand during coincident peaks, this implies that future network costs are reduced. If solar PV increases network loading during coincident peaks, solar PV drives costs. We calculate the impact of solar PV in reducing or driving network peaks per-kW, referred to as $s^{cp}_{\phi,z}$, by multiplying the marginal network value by solar production. In cases where solar PV injections are driving peak loading, the marginal cost is negative (i.e. PV is driving costs). This is depicted in Equation 8:

$$s^{cp}_{\phi,z} = \sum_t (s^{cp}_{t,\phi,z}), \text{ where } s^{cp}_{t,\phi,z} = \begin{cases} \tilde{g}_t p^{cp}_{t,z,\phi} & \text{if } \sum_i (x_{i,t,z} - g_{i,t,z,\phi}) \geq 0 \\ -\tilde{g}_t p^{cp}_{t,z,\phi} & \text{if } \sum_i (x_{i,t,z} - g_{i,t,z,\phi}) < 0. \end{cases} \tag{8}$$

Figure 10 shows the distribution of network capacity values per kW of rooftop solar ($s^{cp}_{\phi,z}$) across the various zip codes in our sample. The black "violins" in the plot show the distribution of values over the zip codes, the red dots show the mean value, and the red bars show

[16] See, for example, Whited et al. (2017) pages 156-164.

the standard deviation of the values. Several trends are immediately clear.

1. There is wide variance in the distribution of network values, due in large part to the alignment of the solar PV production profile with the hours of peak net demand.

2. The marginal network capacity benefit decreases as solar PV penetration increases due to the shift in coincident peaks (see Figure 2).

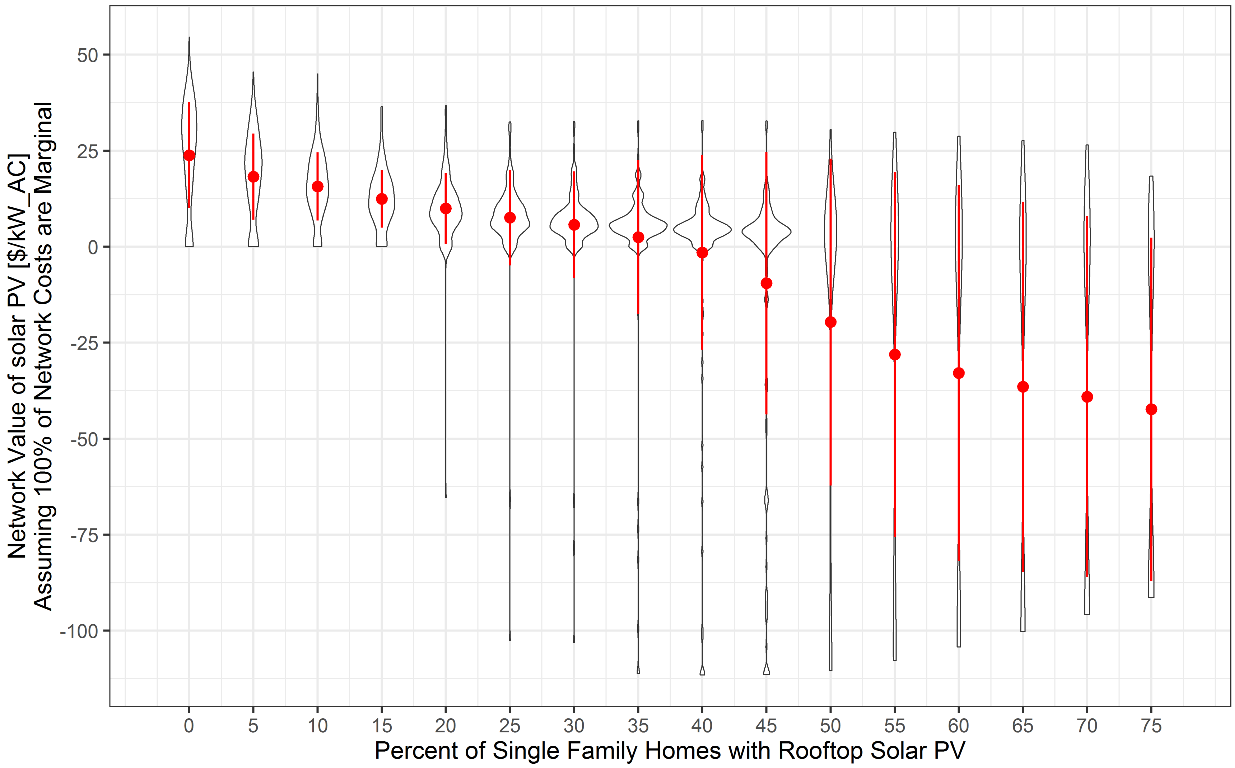
3. As solar penetration increases, peak network loading periods in some regions begin being driven by solar PV injections, rather than demand withdrawals. This implies that solar PV is increasing network costs at these penetrations.

At low solar penetrations, solar PV in some areas exhibits very high network capacity value, while in others it exhibits no or very low value. This is consistent with other estimates of network capacity cost impacts of rooftop solar PV (Cohen et al., 2016). The reason for the non-linearity exhibited in Figure 10 is that, in some areas, once the number of households in that area with solar PV passes a certain threshold, nearly all of the peak loading periods begin being driven by peak injections. Thus, solar may go from driving marginal network cost reductions to driving large marginal network cost increases with small changes in solar penetration.

Figure 11, along with Figure 2, provides intuition as to why we see a large distribution of potential network values of rooftop solar. Figure 11 plots the capacity factor[17] of the solar PV in three areas during the areas coincident peak periods. We see first that the capacity factor is not the same across all areas—that solar PV in some areas is producing a larger portion of its rated capacity during the peak demand periods at low penetrations in some areas than in others. Further, we see that as penetration increases to moderate penetrations, the capacity factor falls across the board. This is due to the fact that solar PV shifts the peak net demand period away from peak solar production periods (i.e. earlier in the morning or later in the day). Finally, in some areas, in this case zip 60053, capacity factor increases dramatically at high penetrations. This is due to the fact that solar PV is now driving peak network loading, and is producing at 50% of its rated capacity during these injection periods.

[17]The U.S. Nuclear Regulatory Commission provides a succinct definition of capacity factor: "The ratio of the available capacity (the amount of electrical power actually produced by a generating unit) to the theoretical capacity (the amount of electrical power that could theoretically have been produced if the generating unit had operated continuously at full power) during a given time period." (U.S. Nuclear Regulatory Commission, 2019).

Figure 10: Estimation of network capacity value of distributed solar PV



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

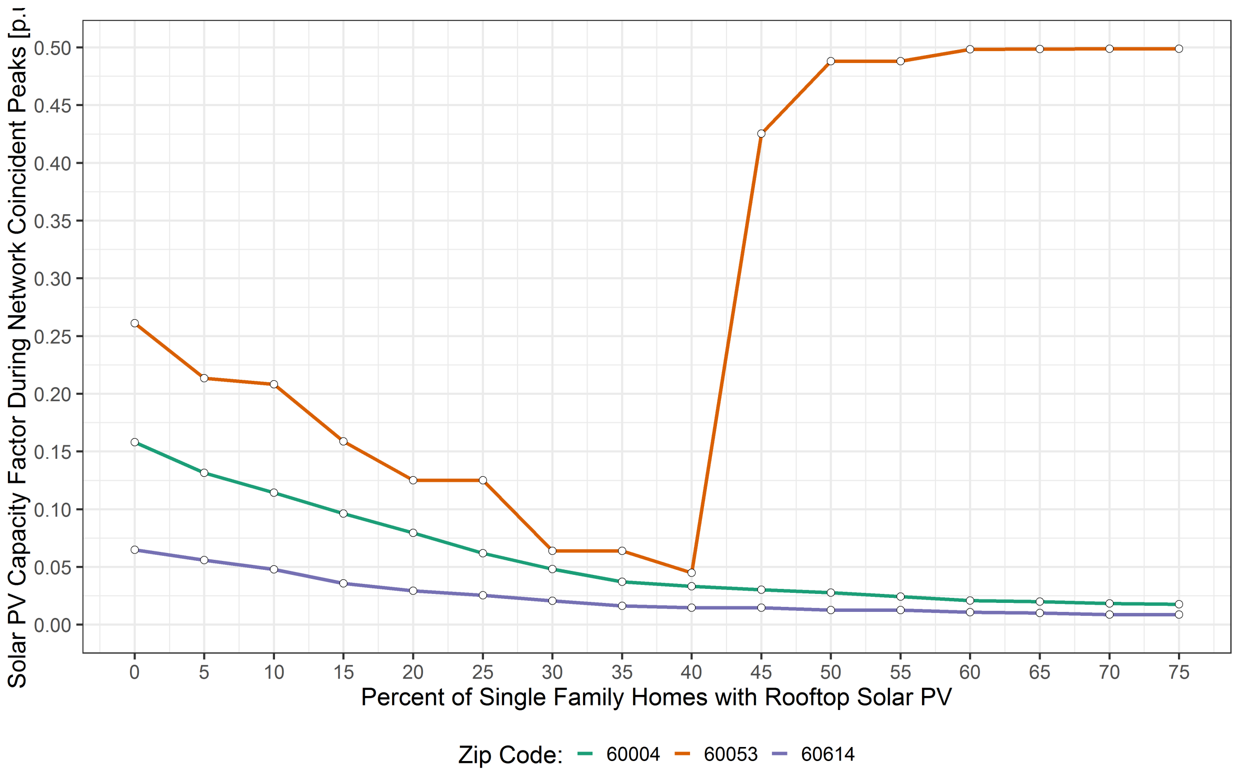
4.2 Distribution Network Ohmic Losses Impacts

In this section we calculate the impact of solar PV in reducing or driving ohmic losses in the distribution network on per-kW basis, referred to as $s^l_{\phi,z}$. We multiply the marginal loss value by solar production. In cases where solar PV injections are driving peak loading, the marginal cost is negative (i.e. PV is driving losses). This is depicted in Equation 9:

$$s^l_{z,\phi,\bar{l}} = \sum_t \left(\tilde{g}_t p^e_{i,t} \frac{\partial l_{t,z,\phi,\bar{l}}}{\partial I_{t,z,\phi}} \right). \tag{9}$$

Figure 12 shows the magnitude of cost reductions from avoided ohmic losses in the distribution network as the penetration of solar PV increases for both the 4% and 7% average losses cases. In the plot, the dots are the mean values and the bars are the standard deviations. The results follow the logic of the results shown in Section 4.1. At low penetrations, rooftop solar PV reduces total flows over the distribution network, reducing costs by avoiding distribution losses. However, at high penetrations, PV injections begin driving increased losses

Figure 11: Capacity factor of rooftop solar PV during peak network loading periods for three selected zip codes



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

and costs.

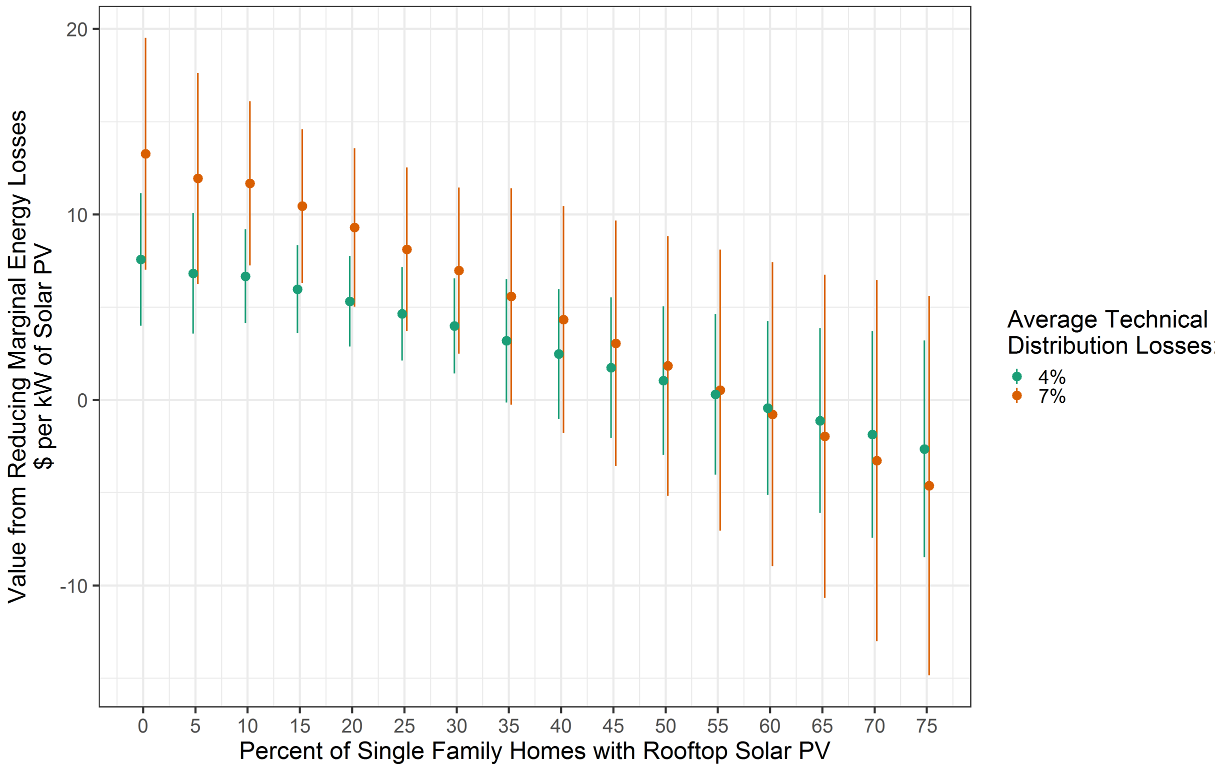
4.3 Distributional Impacts with Marginal Network Costs

In order to analyze the potential distributional impacts of a tariff with a marginal network capacity charge, we create a tariff combining the marginal energy and losses, network capacity, and generation capacity charges. We then recover all residual costs through a uniform fixed charge. We calculate expenditures for each customer according to Equation 10, given by:

$$E_{i,z,\phi}^{RTP-CCC-CP} = F_{i,\phi} + \sum_{t} \left((p_{i,t}^{e} \left(1 + \frac{\partial l_{t,z,\phi,\bar{l}}}{\partial I_{t,z,\phi}}\right) + p_{t,z,\phi}^{cp} + p_{i,t}^{ccc})(x_{i,t} - g_{i,t,\phi}) \right). \tag{10}$$

Figure 13 displays the average change in annual expenditures by income quintile under the

Figure 12: Estimation of cost impact distribution loss avoidance value of distributed solar PV

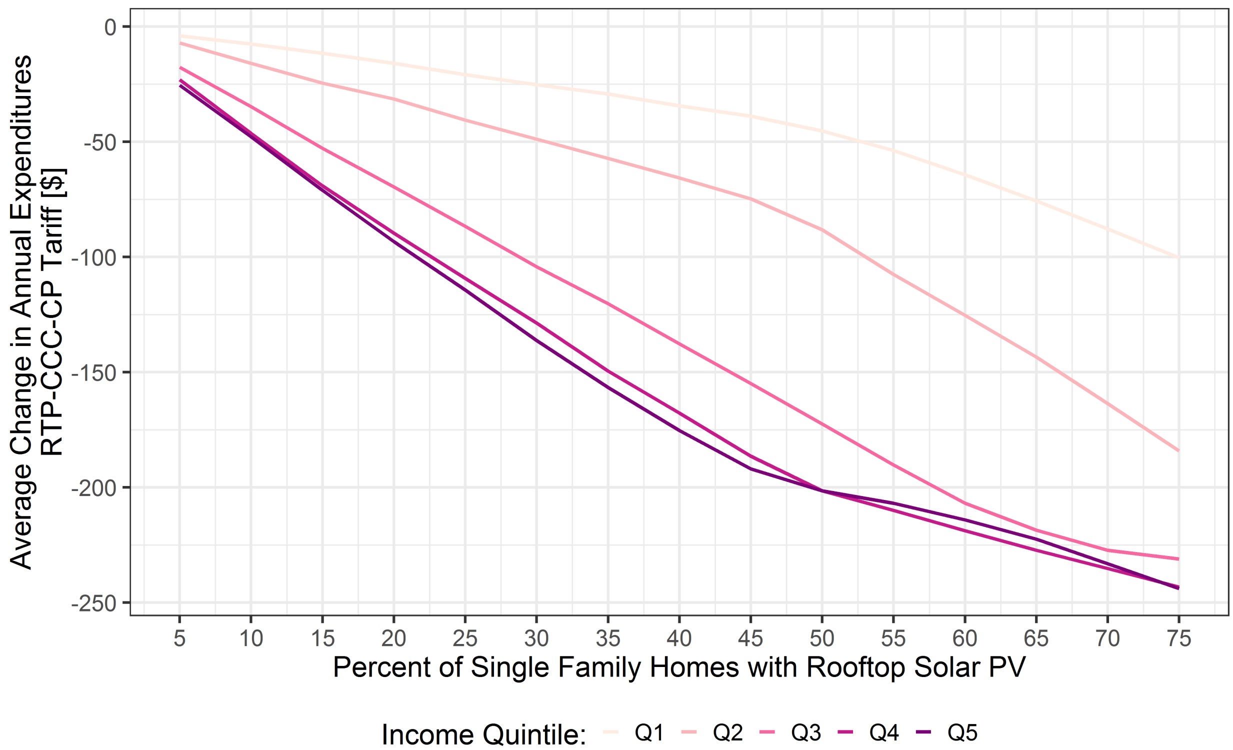


κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

RTP-CCC tariff with a coincident peak network capacity charge (i.e. the RTP-CCC-CP tariff). We see again that an efficient tariff prevents cost shifts, thus decreasing average expenditures for each income quintile. The change in slope of savings at high penetrations highlights the fact that solar PV begins to drive costs at high penetrations.

Figure 14 shows the changes in average expenditures by income quintile for adopters and non-adopters of PV. We see again that efficient tariffs, at low penetrations, do not shift costs between adopters and non-adopters as PV penetration increases. We also see that the average cost savings for adopters falls as PV penetration increases, highlighting the declining marginal value of solar PV. As PV adopters begin increasing peak network loading, costs fall for non-adopters. This is due to the fact that marginal increases in consumption during periods of peak network injections decreases costs. Note that PV adopters still reduce their energy bills on average at high PV penetrations due to the energy and generation capacity value of the PV installations. This implies that efficient tariffs do not fully eliminate the economic case for PV adoption, even at high penetrations (that is, solar adopters still save

Figure 13: Average Change in Annual Expenditures By Income Quintile
RTP-CCC-CP Tariff



κ: Peak Demand. Azimuth: 180. Adoption Probabilities: 2016 Distribution. $\bar{l} = 4\%$.

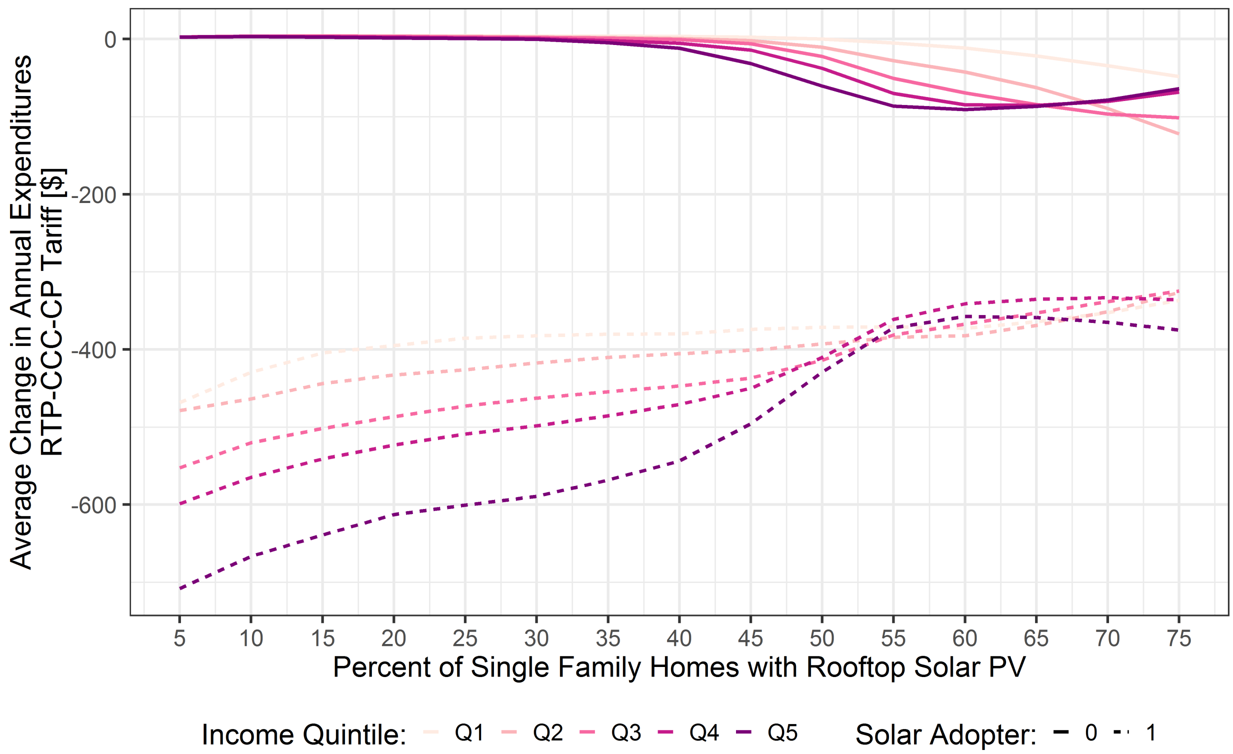
money on average at very high penetrations).

Finally, Figure 15 shows the change in expenditures relative to the flat tariff. We see that average expenditures under an efficient tariff with a coincident peak network capacity charge are roughly equivalent to expenditures under the default tariff. Further, as with the RTP-CCC and RTP-CCC-APD tariffs, RTP-CCC-CP tariff leads to lower costs for lower income customers as PV penetration increases.

4.4 Estimating avoided emissions values

Sections 4.1 and 4.2 explored rooftop solar PV's potential impact on network capacity and losses costs. In addition, rooftop solar PV (and other zero-emissions resources) can offset emissions of greenhouse gas and other pollutants. In this section we estimate the dollar value of avoiding emissions using the marginal emissions data introduced in Appendix 6.1.4. The dollar value of emissions avoided per kW of solar PV adopted, denoted s^{em}, is calculated as:

Figure 14: Average Change in Annual Expenditures By Income Quintile: Adopters vs. Non-Adopters
RTP-CCC-CP Tariff



κ: Peak Demand. Azimuth: 180. Adoption Probabilities: 2016 Distribution. $\bar{l} = 4\%$.

$s^{em} = \sum_t (\tilde{g}_t p_t^{em})$.

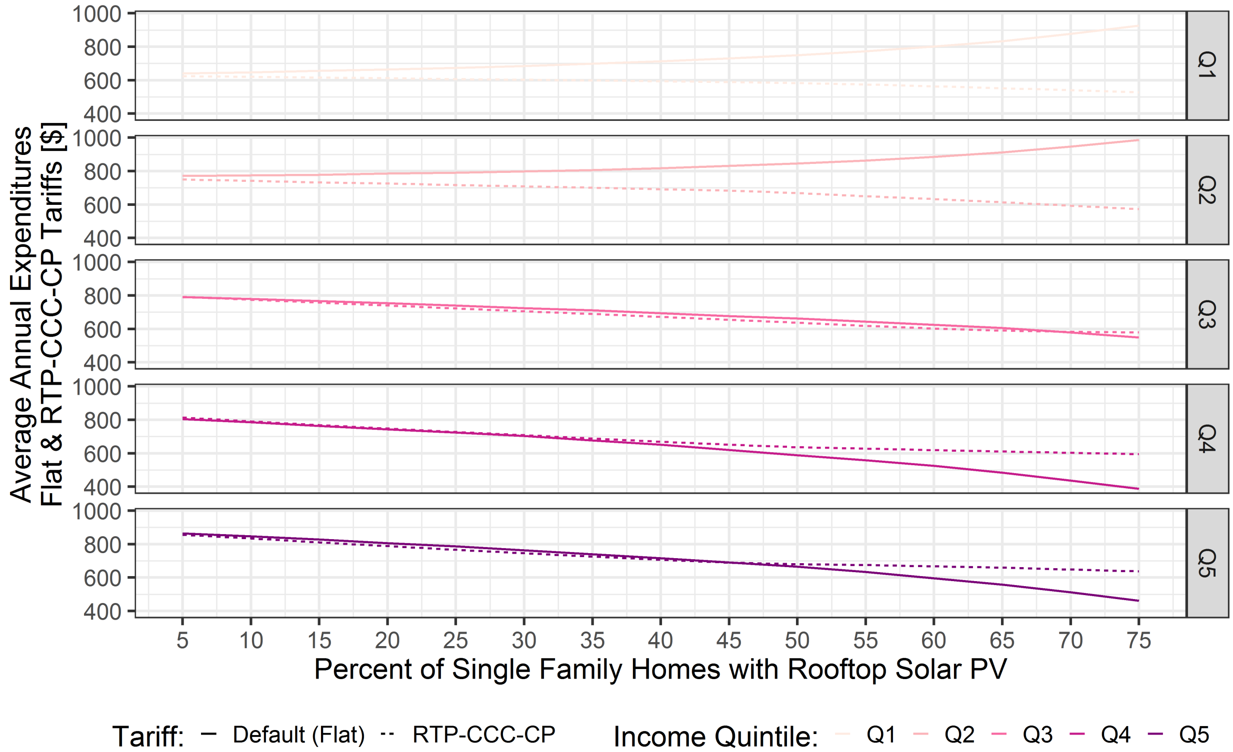
Figure 16 displays the marginal value of avoided emissions per kW of solar PV added, broken out by the damages model used. The black lines on each bar represent the residual cost shift for the zero-solar penetration case ($\phi = 0, p^{cp}_{t,z,\phi} = 0$), as discussed in Section 3.[18] We see that the value of avoided emissions is greater than the value of the cost shift in every case.[19]

There are many programs federally and within Illinois intended to spur the deployment of low-carbon technologies like solar PV. For example, the U.S. federal government provides an investment tax credit and accelerated depreciation for solar PV. Illinois also has a renewable portfolio standard intended to spur solar and wind deployment and remunerate these resources for their emissions avoidance values. Thus, the fact that the emissions avoidance

[18] The cost shift does not depend on the damages model used.

[19] This confirms the findings from Borenstein and Bushnell (2018). Using a different approach than that discussed herein, Borenstein and Bushnell (2018) finds that the average value of the cost of marginal emissions exceeds the average volumetric residual cost recovery charge in the Chicago, IL area.

Figure 15: Total Expenditures vs. ϕ: Flat and RTP-CCC-CP Tariffs

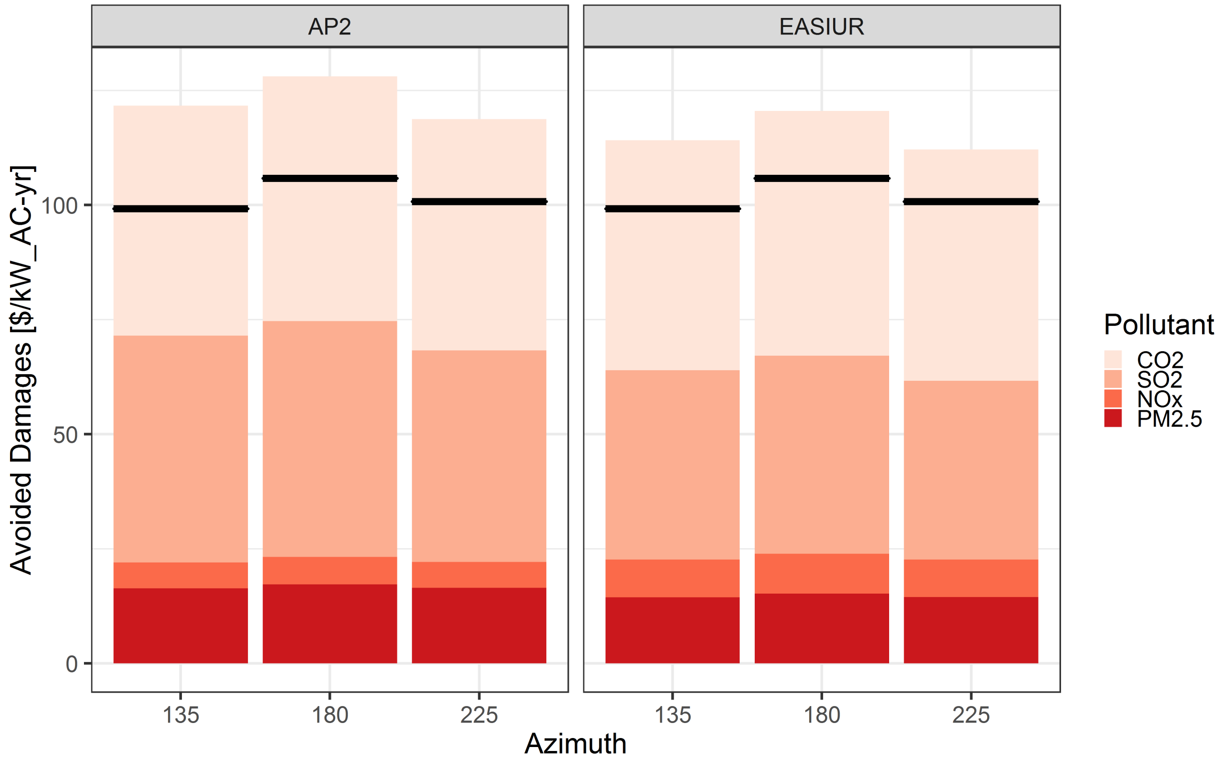


κ: Peak Demand. Azimuth: 180. Adoption Probabilities: 2016 Distribution. $\bar{l} = 4\%$.

value exceeds the residual cost shift does not imply that solar PV is under-valued in Chicago. Answering this question would require a more holistic review of the magnitudes of the various support programs for solar PV.

The data presented in Figure 16 provide a cautionary note. First, that PV adoption in Chicago under net metering may drive cost shifts, but may not necessarily be *economically inefficient* on average. That is, the average private marginal cost of energy may not exceed the average social marginal cost of energy. However, net metering schemes may still drive cost shifts between adopters and non-adopters as the utility changes rates to recover its residual costs. Second, improving the efficiency of residual cost recovery mechanisms could reduce welfare if the cost of energy does not fully internalize the cost of externalities. This implies that in a second best world without carbon pricing, regulators may face tradeoffs between economic efficiency and distributional equity.

Figure 16: Estimation of avoided emissions value of distributed solar PV

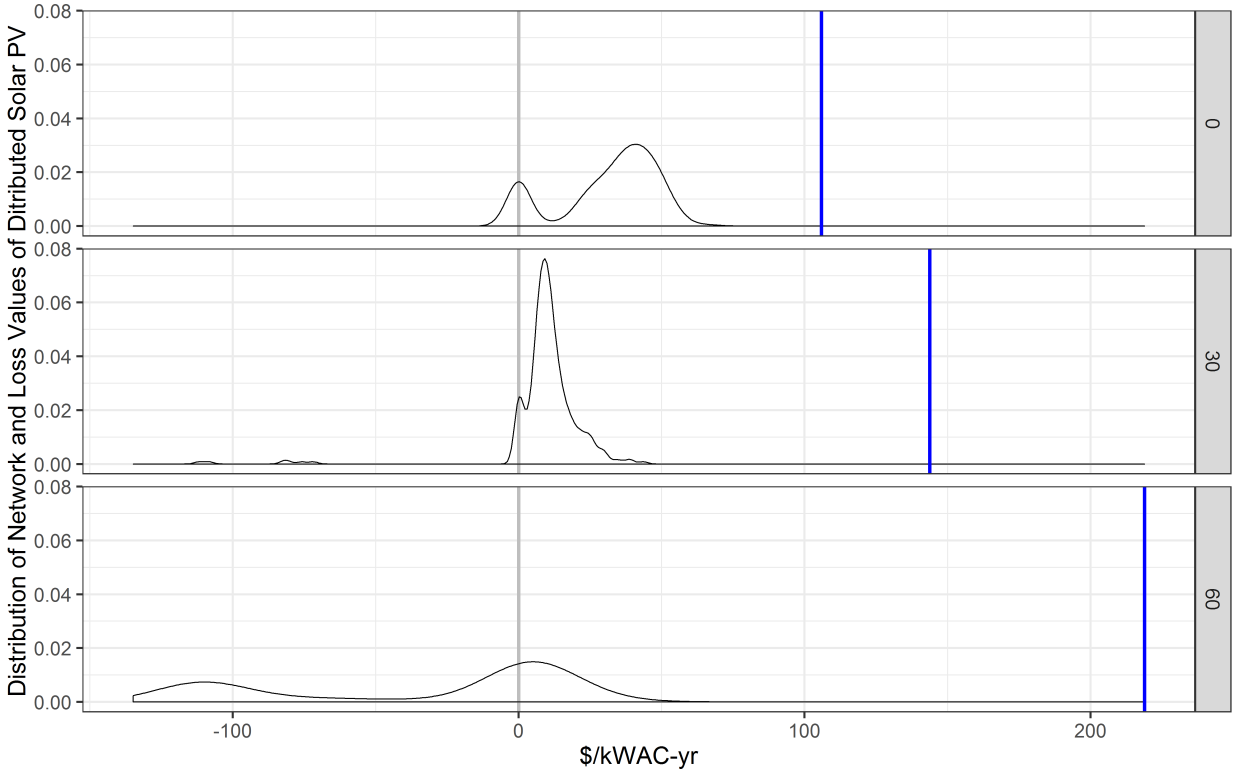


κ: Peak Demand PV Case. $\phi = 0$.

4.5 Interpreting the cost impacts of rooftop solar PV in the context of residual cost shifts

Given the prevalence of net metering programs in the U.S., it is worthwhile to ask how well PV remuneration under net metering programs matches PV remuneration under an optimal tariff. Figure 17 compares the sum of $s^{cp}_{z,\phi}$ and $s^{l}_{z,\phi,\bar{l}}$—the network capacity and losses cost reductions per kW of solar—with the total residual cost shifts under the assumption that $p^{cp}_{t,z,\phi} = 0$. In Figure 17, the black lines show the distribution of network capacity and losses cost impacts across "feeders" (zip codes), while the blue vertical lines show the residual cost shifts at 0%, 30%, and 60% solar penetration. We see that, as PV's network cost impacts shrink, the potential cost shift rises. We also see that even at low penetrations, a net metering program in Chicago likely over-remunerates rooftop solar PV for network cost reductions. This latter point implies that, even under aggressive assumptions about the potential network cost reductions of solar PV—that is, even under the assumption that 100% of distribution network costs are marginal—solar PV adoption under net metering schemes will lead to cost shifts.

Figure 17: Residual cost shift vs. distribution network value



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case. $\bar{l} = 7\%$.

The relationship between network cost reductions and PV cost shifts under net metering will vary by region and utility. However, in general, unless the magnitude of PV cost reductions perfectly matches the volumetric price for residual cost reduction by random chance, net metering schemes are likely to create cost shifts between PV adopters and non-adopters.

5 Conclusions

This paper analyzes the potential distributional impacts of solar PV adoption in the presence of inefficient and efficient rate designs. We leverage a data set of electricity consumption for 100,170 consumers, roughly 60,000 of which live in single-family homes, and data on the income trends of distributed solar PV adoption. We simulate PV adoption among single-family homes, accounting for the propensities of customers in different income quintiles to adopt solar. We build a simple model of utility costs to analyze the changes in customer expenditures by income quintile as rooftop solar PV adoption increases. We first model the distributional impacts of PV adoption assuming that distributed PV cannot reduce network costs before modeling the distributional impacts assuming that all distribution network costs are marginal in the long run according to coincident peak demand.

We find that rooftop solar PV has the potential to create substantial distributional impacts in the presence of tariffs that inefficiently recover residual costs through volumetric (i.e. per-kWh) charges. Rooftop solar PV adoption reduces net demand (demand minus generation). When residual network and policy costs are recovered through volumetric charges, this reduction in net demand creates an under recovery of costs; charges for residual cost recovery must increase to ensure cost recovery. This implies that, in the standard electricity tariff, the bills of non-adopters must increase. Given that solar PV adopters tend to be affluent (see Figure 18), average expenditures across all customers in the top three income quintiles decrease, while average expenditures across all customers in the bottom two income quintiles increase under rates with volumetric residual cost recovery. Average annual expenditures across the entire income quintile[20] for the lowest 20% of incomes increase by 6%, 18%, and 46% at 25%, 50%, and 75% rooftop solar penetrations, respectively. Average annual expenditures for non-adopters in the lowest 20% of incomes increase by 13%, 35%, and 80% at 25%, 50%, and 75% rooftop solar penetrations, respectively. Meanwhile, customers in the top income quintile that adopt solar nearly entirely eliminate their contributions to residual cost recovery. This very substantial impact may be occurring in some locations today, as rooftop solar penetration has already reached 25+% in some markets, including Hawaii and parts of Australia.

This cost shift does not occur under tariffs with efficient network cost allocation and residual cost recovery. When residual costs are recovered through fixed charges, solar PV adopters reduce their expenditures on energy and marginal generation costs, but do not shift residual costs to other customers. As a result, average expenditures across each income quintile decrease as penetration increases. This is the result of a decrease in expenditures for PV adopters and no change in expenditures for non-adopters. This holds true under both the zero marginal network costs and the 100% marginal network costs cases.

This paper demonstrates that at moderate to high penetrations of rooftop solar PV, expenditures may be higher for low-income customers under rates with volumetric residual cost recovery than under rates with uniform fixed charges for residual cost recovery. One of the primary arguments against increasing fixed charges for residual cost recovery has been the potential distributional impacts of the increased fixed charge. The results in this paper challenge this narrative.

[20] That is, including both adopters and non-adopters in the bottom income quintile.

The final issue analyzed in this paper—the potential impacts of a coincident peak demand charge for marginal network capacity and an energy charge adder for marginal distribution network losses—further highlights the potential benefits of efficient rate design. We first design marginal network capacity and distribution loss charges. We then calculate: 1) the potential network capacity and losses impacts of solar PV under such charges, and 2) the distributional impacts of a tariff incorporating these charges as PV penetration increases. We find that distributed PV can substantially reduce the costs of network capacity and losses in some areas at low to modest penetrations. However, we find large variance in the distribution of these cost reductions, and find that rooftop solar PV at high penetrations may increase rather than reduce costs. We then show that an efficient rate design that incorporates these marginal charges results in significantly lower expenditures for low-income customers at high PV penetrations than does ComEd's default tariff. Additionally, at low PV penetrations, there is almost no change in the average expenditures of the bottom income quintile under these charges.

These findings have important implications for rate design. First, that the potential for PV adoption threatens to reverse the redistributional effects of volumetric rates for residual cost recovery. New solutions are needed. Second, that rates that better reflect the time- and location-varying value of energy may be more distributionally equitable than alternatives as the power system incorporates higher penetrations of DERs. Finally, rates that better reflect system costs create opportunities for adopters of DERs like rooftop PV to save money by lowering system costs. These efficient rates avoid the potentially undesirable distributional impacts of net metering under today's time invariant, predominately volumetric rates.

References

Abdelmotteleb, I., T. Gómez, J. P. C. Ávila, and J. Reneses (2018): "Designing efficient distribution network charges in the context of active customers," *Applied energy*, 210, 815–826.

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

Azarova, V., D. Engel, C. Ferner, A. Kollmann, and J. Reichl (2018): "Exploring the impact of network tariffs on household electricity expenditures using load profiles and socio-economic characteristics," *Nature Energy*, 3, 317.

Azevedo, I., N. Horner, K. Siler-Evans, and P. Vaishnav (2017): "Electricity Marginal Factor Estimates," http://cedmcenter.org, accessed: 2019-01-10.

Baker, P. and R. Blundell (1991): "The microeconometric approach to modelling energy demand: some results for UK households," *Oxford Review of Economic Policy*, 7, 54–76.

Baker, P., R. Blundell, and J. Micklewright (1989): "Modelling household energy expenditures using micro-data," *The Economic Journal*, 99, 720–738.

Barbose, G., N. Darghouth, B. Hoen, and R. Wiser (2018): "Income Trends of Residential PV Adopters: An analysis of household-level income estimates," Working paper, Lawrence Berkeley National Laboratory.

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

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

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

——— (2012a): "The private and public economics of renewable electricity generation," *Journal of Economic Perspectives*, 26, 67–92.

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

——— (2017): "Private net benefits of residential solar PV: The role of electricity tariffs, tax incentives, and rebates," *Journal of the Association of Environmental and Resource Economists*, 4, S85–S122.

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.

——— (2016): "The distributional effects of US clean energy tax credits," *Tax Policy and the Economy*, 30, 191–234.

Brown, P. R. and F. M. O'Sullivan (2019): "Spatial and Temporal Variation in the Value of Solar Power Across United States Electricity Markets," Working paper, MIT Center for Energy and Environmental Policy Research.

Burger, S. P., J. D. Jenkins, S. C. Huntington, and I. J. Perez-Arriaga (2019): "Why Distributed?: A Critical Review of the Tradeoffs Between Centralized and Decentralized Resources," *IEEE Power and Energy Magazine*, 17, 16–24.

Burger, S. P., C. R. Knittel, I. J. Pérez-Arriaga, I. Schneider, and F. Vom Scheidt (2020): "The efficiency and distributional effects of alternative residential electricity rate designs," *The Energy Journal*, 41.

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.

California Public Utilities Commission (2018): "Residential Rate Reform / R.12-06-013," http://www.cpuc.ca.gov/General.aspx?id=12154, accessed: 2019-05-12.

Chawla, M. and M. G. Pollitt (2013): "Energy-efficiency and environmental policies & income supplements in the UK: evolution and distributional impacts on domestic energy bills," *Economics of Energy & Environmental Policy*, 2, 21–40.

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.

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.

Feger, F., N. Pavanini, and D. Radulescu (2017): "Welfare and redistribution in residential electricity markets with solar power," Working paper, CEPR Discussion Paper No. DP12517.

Gerarden, T. (2017): "Demanding innovation: The impact of consumer subsidies on solar panel production costs," Working paper, Technical report, Working paper, Harvard University.

Heo, J., P. J. Adams, and H. O. Gao (2016a): "Public health costs of primary PM2. 5 and inorganic PM2. 5 precursor emissions in the United States," *Environmental science & technology*, 50, 6061–6070.

——— (2016b): "Reduced-form modeling of public health impacts of inorganic PM2. 5 and precursor emissions," *Atmospheric environment*, 137, 80–89.

Holmgren, W. F., C. W. Hansen, and M. A. Mikofski (2018): "pvlib python: a python package for modeling solar energy systems," *Journal of Open Source Software*, 3.

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.

Hummon, M., P. Denholm, and R. Margolis (2013): "Impact of photovoltaic orientation on its relative economic value in wholesale energy markets," *Progress in Photovoltaics: Research and Applications*, 21, 1531–1540.

Illinois Commerce Commission (2014): "ICC Docket No. 13-0506, Final Order at 17," https://www.icc.illinois.gov/downloads/public/edocket/367604.pdf, accessed: 2019-12-09.

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

Johnson, E., R. Beppler, C. Blackburn, B. Staver, M. Brown, and D. Matisoff (2017): "Peak shifting and cross-class subsidization: the impacts of solar PV on changes in electricity costs," *Energy Policy*, 106, 436–444.

LEVINSON, A. AND E. SILVA (2019): "The Electric Gini: Income Redistribution through Energy Prices," Working paper, Georgetown University.

MULLER, N. Z. (2014): "Boosting GDP growth by accounting for the environment," *Science*, 345, 873–874.

NATIONAL CONSUMER LAW CENTER (2016): "Utility Rate Design," https://www.nclc.org/issues/energy-utilities-a-communications/utility-rate-design.html, accessed: 2019-04-13.

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 (2019): "CASE 15-E-0751 - In the Matter of the Value of Distributed Energy Resources. Order Regarding Value Stack Compensation." https://www.nyserda.ny.gov/-/media/NYSun/files/Updated-Value-Stack-Order-2019-04-18.pdf.

PÉREZ-ARRIAGA, I. J. (2014): *Regulation of the power sector*, Springer.

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.

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

RUBIO-ODÉRIZ, F. J. AND I. J. PEREZ-ARRIAGA (2000): "Marginal pricing of transmission services: A comparative analysis of network cost allocation methods," *IEEE Transactions on Power systems*, 15, 448–454.

SATCHWELL, A., A. MILLS, AND G. BARBOSE (2015): "Quantifying the financial impacts of net-metered PV on utilities and ratepayers," *Energy Policy*, 80, 133–144.

SAVOLAINEN, M. K. AND R. SVENTO (2012): "Real-time pricing in the nordic power markets," *Energy economics*, 34, 1131–1142.

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.

Simshauser, P. (2016): "Distribution network prices and solar PV: Resolving rate instability and wealth transfers through demand tariffs," *Energy Economics*, 54, 108–122.

Solar Energy Industries Association (N.D.): "Solar Photovoltaic Technology," https://www.seia.org/research-resources/solar-photovoltaic-technology, accessed: 2019-04-13.

Strielkowski, W., D. Štreimikienė, and Y. Bilan (2017): "Network charging and residential tariffs: A case of household photovoltaics in the United Kingdom," *Renewable and Sustainable Energy Reviews*, 77, 461–473.

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

U.S. Nuclear Regulatory Commission (2019): "NRC Glossary: Capacity factor," https://www.nrc.gov/reading-rm/basic-ref/glossary/capacity-factor.html, accessed: 2019-04-15.

Vaishnav, P., N. Horner, and I. L. Azevedo (2017): "Was it worthwhile? Where have the benefits of rooftop solar photovoltaic generation exceeded the cost?" *Environmental Research Letters*, 12, 094015.

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

Whited, M., A. Horowitz, T. Vitolo, W. Ong, and T. Woolf (2017): "Distributed Solar in the District of Columbia: Policy Options, Potential, Value of Solar, and Cost-Shifting," Report, Synapse Energy Economics, Prepared for the Office of the People's Counsel for the District of Columbia, accessed: 2019-04-15.

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

——— (2018): "The Evidence from California on the Economic Impact of Inefficient Distribution Network Pricing," Working paper, National Bureau of Economic Research.

6 Appendices

6.1 Data

6.1.1 Half-Hourly Household Electricity Metering Data

The residential electricity consumption data used in this work come from Commonwealth Edison (hereafter: ComEd).[21] The data contain one full year of anonymous electricity consumption data measured half-hourly for 100,170 residential customers for 2016. The data state each customer's housing type (single-family or multi-family), heating type (electric or non-electric), and 9-digit zip code, indicating the customer's geography. To avoid providing identifying information about any given customer, ComEd applies a "15/15" rule[22] that removes any customers or zip code areas that:

1. contain fewer than 15 customers per customer type, or
2. contain one customer that represents more than 15% of the total consumption of the customers of that type.

This removes very large consumers from our sample. Given that the data are primarily urban and residential, should have limited overall impact on our findings. In addition to ComEd's data cleaning for anonymity, we perform our own data cleaning to ensure the integrity of our sample. The data obtained from ComEd contained data on 344,717 customers. However, consumption observations for many of these customers was missing or potentially flawed. Only 278,821 customer have a complete time series of observations. We removed all customers without complete time series. The sum of the half-hourly consumption observations did not match the reported sum of daily consumption for some customers. We removed all customers with at least one case of a deviation of 5% or more between the reported daily energy consumed and the sum of the half-hourly consumption observations. The demographics of the final sample roughly matched that of the original sample, implying that the data cleaning effort did not meaningfully skew the data.

Table 2 summarizes the breakdown of customer types in the sample. The distribution of housing types in our sample is consistent with the distribution within the broader ComEd service territory: 61.2% of the customers in our sample live in single-family homes compared

[21]Note that this is the same dataset that underpins Burger et al. (2020).
[22]See Illinois Commerce Commission (2014).

to 58.7% in the ComEd service territory, and 38.7% of our sample live in multi family homes compared to 40.2% in the ComEd service territory (Commonwealth Edison, 2011).

Table 2: Breakdown of customer types

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%

We combine the consumption data with socioeconomic data from the 2016 American Community Survey (U.S. Census Bureau, 2018). The most detailed geography for which the American Community Survey publishes public data are the Census Block Group (CBG). In total, our sample contains customers in 2,315 CBGs. The geographic boundaries of CBGs are not the same as those of 9-digit zip-code areas. Thus, to match census data to our household-level consumption data, we have to match CBGs to zip codes. We use a data set from Melissa Data for the matching.[23] 1,975 customers are removed from the sample while merging the two geographic data sets because the zip codes do not have corresponding CBGs.

Table 3 compares the demographics of the customers in our sample with that of the full ComEd service territory. Our sample contains a disproportionate amount of high- and low-income customers relative to the full ComEd service territory. The demographics of the customers in our sample are otherwise roughly consistent with the broader ComEd service territory.

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

A common method in analyzing distributional impacts is to analyze household budget data rather than income data (Baker et al., 1989; Baker and Blundell, 1991; Chawla and Pollitt, 2013). In many cases, low-income households may have high wealth or temporary lapses in income.[24] Budget or expenditure data often capture these facts with more fidelity. While we focus on income data, incorporating expenditure or budget data is a promising direction for future research.

This paper uses three additional sources of data. First, aggregate data on the income trends of solar PV adopters. Second, solar insolation data and a solar PV production model used to produce PV generation profiles. Finally, estimates of the marginal emissions and social damages of these emissions for the Chicago area.

Each customer is assigned the median income of the census block group within which that customer lives. This likely understates the distributional impacts analyzed herein; within each census block group, wealthy customers are more likely to adopt solar.[25]

Within the consumption data, we focus primarily on single-family homes. The vast majority (more than 99%) of rooftop solar PV adopters live in single-family dwelling, most often owner occupied dwellings (Barbose et al., 2018). We assign customers to income quintiles according to the median income of the census block group within which they live. Table 4 contains the breakdown of the number of single-family homes in our sample by income quintile. In Table 4, the 1^{st} Quintile represents the bottom 20% of incomes, and the 5^{th} Quintile represents the top 20% of incomes. The income quintiles are established based on the entire 100,170 customer sample, not on the subset of single-family homes; this explains why the number of customers in each income quintile (N_Q) are not equal.

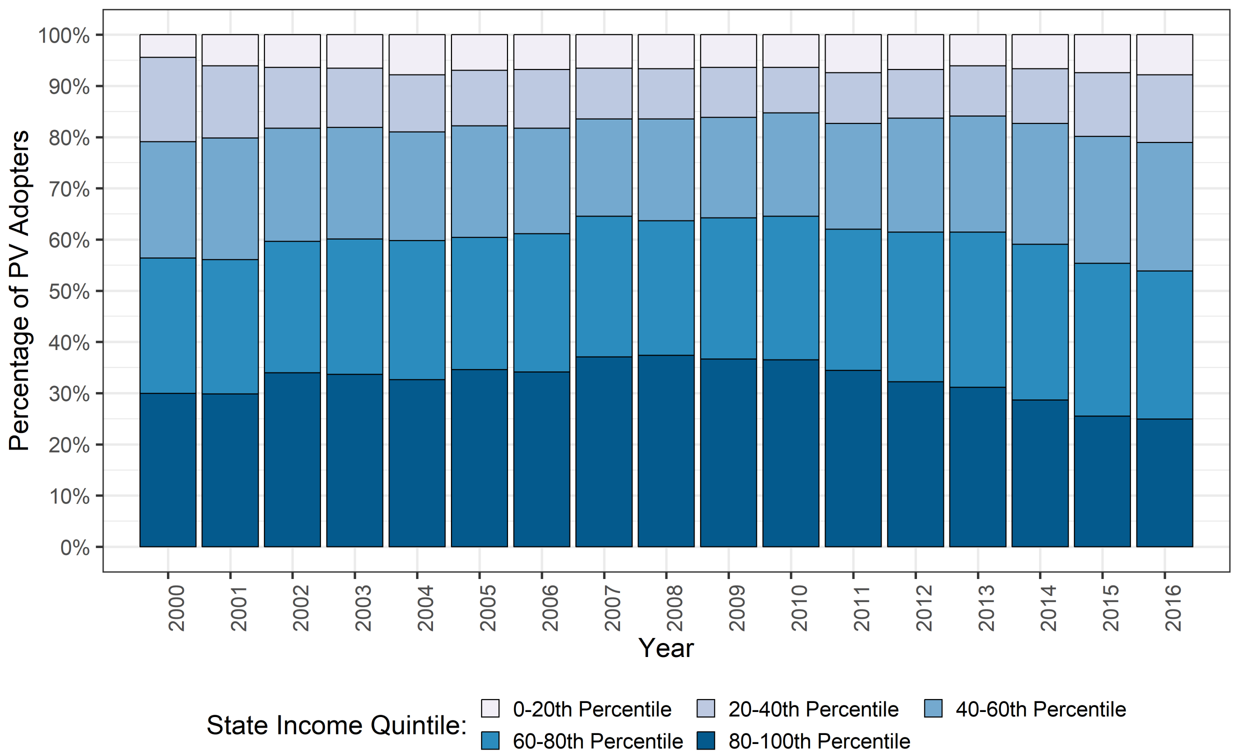
6.1.2 PV Adoption Income Trend Data

The Lawrence Berkeley National Laboratory collected household-level income data for more than 781,000 solar PV adopters across 13 U.S. states between the years 2000 and 2016 (Barbose et al., 2018). These data are summarized in Figure 18. In Figure 18, the 0 to 20th Percentile represents the bottom 20% of incomes, and the 80 to 100th Percentile represents the top 20% of incomes. The income distribution data are relatively consistent across time *and* states. Through 2016, the largest share of PV adoption in the bottom income quintile was 8% (in Nevada), while the lowest share was 5% (in Washington D.C.). The average share of adoption in the bottom two income quintiles across all states through 2016 was

[24] For example, high earners may spend time in graduate school.
[25] See Barbose et al. (2018) page 20 for a discussion of this fact.

roughly 19%. In 2016 the average share of adoption in the bottom two income quintiles across states was 21%. Phrased differently, a customer in the top three income quintiles was roughly four times more likely to adopt solar than a customer in the bottom two income quintiles. While there is greater variation across states in the share of adoption in the top three income quintiles, capturing this variation is less critical for assessing the distributional impacts between higher and lower income quintiles. The distribution of PV adoption between the top three income quintiles has remained nearly constant since 2000, while the distribution between quintiles has changed slightly. Due to the relatively consistent income distributions across time and location, we feel the national average income trends are appropriate for the analysis in this paper.

Figure 18: Income Distribution of Rooftop Solar Adopters by Installation Year



Data source: Barbose et al. (2018)

While the share of adoption in the top three income quintiles has remained relatively constant since 2000, we do see two distinct temporal trends in Figure 18. First, between the year 2000 and 2008, the share of PV adoption in the top three income quintiles grew from 79% to 84%. Second, between 2008 and 2016, the share of PV adoption in the top three income quintiles fell back to 79%. In the base case analysis in Section 3 (the 2016 Distribution case), we use the 2016 distribution of PV adoption. We then perform two sensitivities. In the "2008 to 2016 Trend" sensitivity, we linearly extrapolate the 2008 to 2016 changes in the adoption rates in the bottom two income quintiles to 2040, and assume that the top three income quintiles are all equally likely to install solar.[26] In the "2000 to 2016 Trend" sensitivity, we linearly extrapolate the 2000 to 2016 changes in the adoption rates across all income quintiles to 2040. These data are represented in Table 5. The interpretation of these data are as follows: in the 2016 Distribution case, for every 100 solar adopters in 2016, we would expect roughly 25 to be in the top income quintile, 8 to be in the bottom income quintile, and so on. We describe the use of these data in more detail in Section 2.

6.1.3 Solar PV Simulation and Production Data

The second primary source of data used in this analysis are solar insolation and weather data and a solar PV production model. The design and specifications of the model used to translate solar insolation and weather data into solar PV production is outside of the scope of this thesis. The model used, pvlib python, is a Python-based tool developed and extensively vetted by Sandia National Laboratories (Holmgren et al., 2018).[27] The model uses solar insolation data and weather (e.g., temperature, wind speed, etc.) data and PV system parameters (e.g., module efficiency, azimuth, inverter sizing, etc.) and estimates the output of the specified solar PV system. We modeled three systems with different azimuths (degree to which the panels are facing south). The output of the model with an azimuth of 180 degrees is shown in Figure 19.

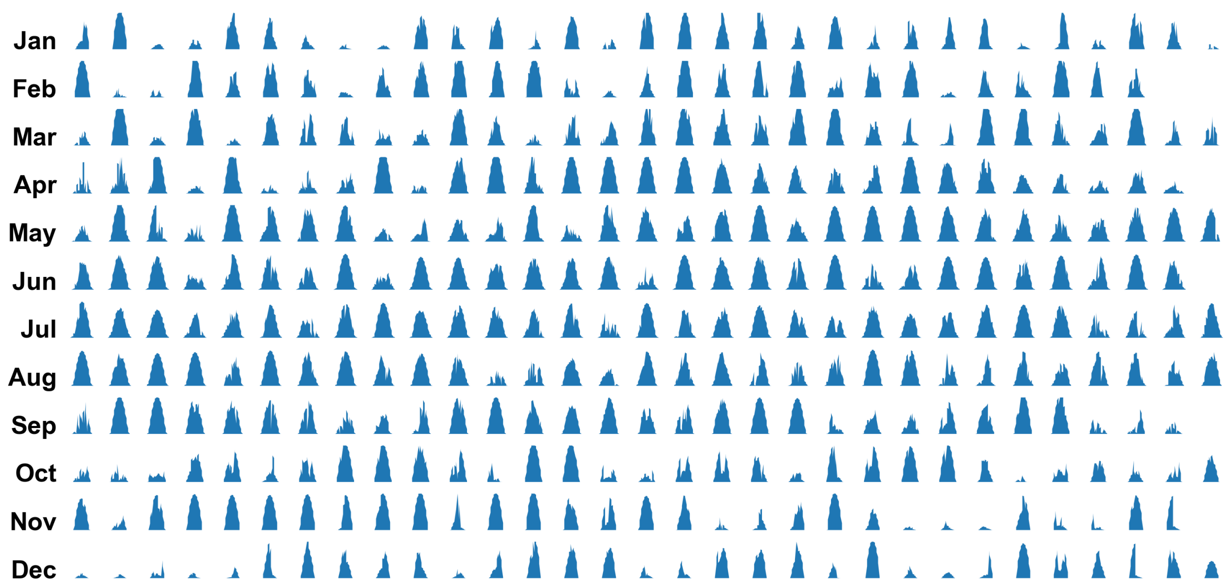
The PV model requires parameters about system performance. We use default values for a typical residential installation, while specifying the azimuth and tilt. The major parameters of the system are documented in Table 6.[28]

[26]If you extend the '08 to '16 trend through 2040 for the top income quintile, the probability of adoption becomes negative. This is obviously not a useful result, so we modify the probabilities.

[27]pvlib python is a project of the Sandia National Laboratories PV Performance Modeling Collaborative. The formulation of pvlib has been vetted over decades by researchers at Sandia and elsewhere, as well as by practitioners. Holmgren et al. (2018) contains information about the model as well as links to further documentation. More model detail can be found at `https://pvlib-python.readthedocs.io/en/latest/` and `https://github.com/pvlib/pvlib-python`. Patrick Brown provided the IPython notebook containing the pvlib model that we used in this paper. The documentation of Patrick's version of the pvlib model can be found in the forthcoming paper, Brown and O'Sullivan (2019).

[28]The model contains many other default parameters, a detailed accounting of which is outside the scope of this paper.

Figure 19: Solar PV Production for Chicago, IL in 2016



Chicago, IL. 2016. Azimuth = 180, Tilt = Latitude.

6.1.4 Emissions Factor Data

The final source of data used in this paper is marginal emissions and health damages data. Most power system operators do not provide data on the fuel type and plant information of the marginal plant in each hour. Ex-post estimation of the marginal emissions of a system at any given point in time is therefore challenging. We use marginal emissions data provided by the Center For Climate and Energy Decision Making at Carnegie Mellon University (Azevedo et al., 2017). We use this marginal emissions data to calculate the potential climate and health benefits of the solar PV adoption simulated herein.

The data set includes marginal emissions factors by time of day and season of year[29] for SO_2, NO_x, $PM_{2.5}$, and CO_2. The data is provided at the North American Electric Reliability Corporation region level. Chicago, IL is in the RFC region, an area that covers parts of Illinois and Wisconsin and all of Michigan, Indiana, Ohio, Pennsylvania, West Virginia, Delaware, and Maryland. In addition to marginal emissions data, the data set includes marginal damages data derived using two models and an assumed $40 per ton price on CO_2. The damages models used are the AP2 model[30] and the EASIUR model[31]. The two models

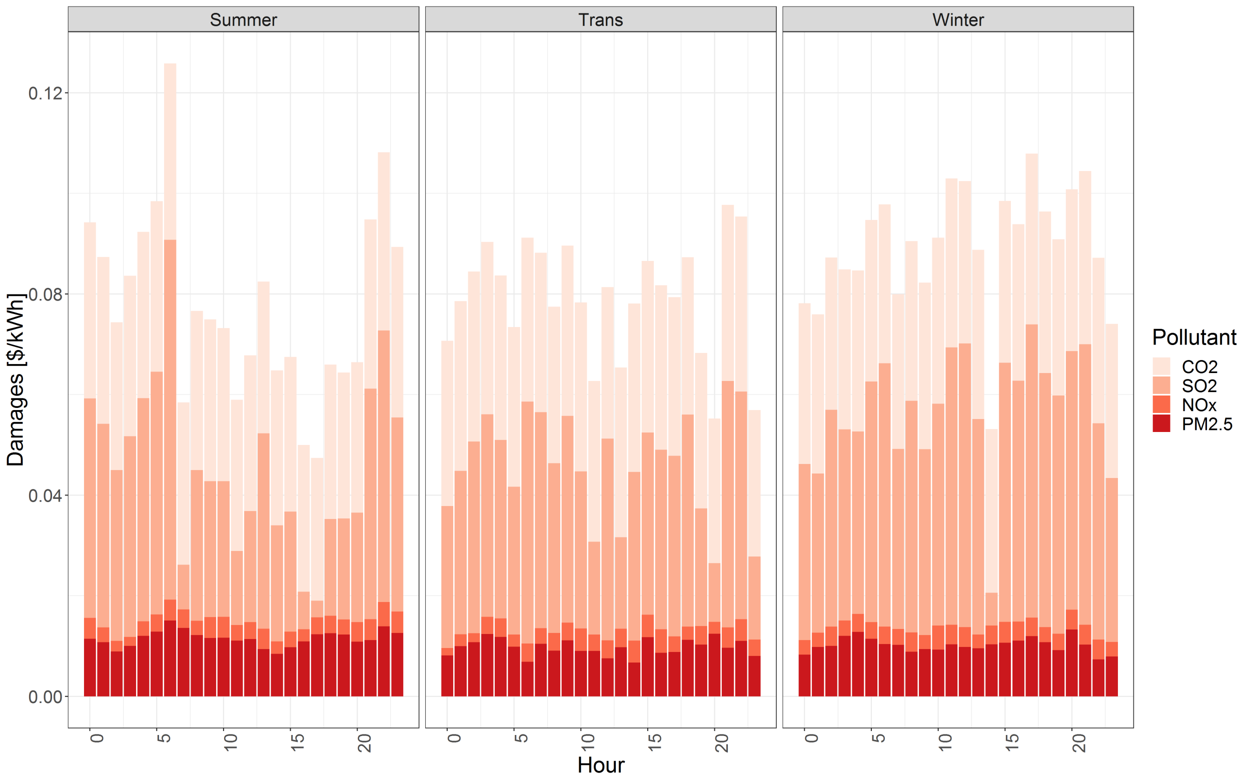
[29] The breakdown for seasonal factors is: Winter (November through March), Summer (May through September), and Transition (April and October).

[30] See Muller (2014)

[31] See Heo et al. (2016b) or Heo et al. (2016a)

provide nearly identical results, so this paper uses only the AP2 model. The damages data from the AP2 model are visualized in Figure 20. We denote the total marginal cost of emissions (including SO_2, NO_x, $PM_{2.5}$, and CO_2) at any given time as p_t^{em}.

Figure 20: Marginal Damages for the RFC Region in 2016



Data source: Azevedo et al. (2017)

6.2 Sensitivities

The simulations in this paper required the use of several assumptions. The logic behind these assumptions is explained in the main text of the paper. This Appendix demonstrates the impacts of the key assumptions on the results. Broadly speaking, the assumptions do not impact the key results. That is, under all sets of assumptions, rooftop PV adoption under inefficient rates increases average expenditures for the lowest income quintile, while efficient rates do not. Nonetheless, the sensitivities in this Appendix provide additional color and robustness to the results presented in the main text of the paper.

This Appendix includes sensitivities on the following assumptions:

1. The solar adoption probabilities—that is, the likelihood that a customer in each income

quintile will adopt solar PV at each penetration level.

2. *kappa*: the size of PV systems adopted by each individual.
3. The azimuth of the solar PV system adopted by each customer—that is, whether the systems are facing due south, southeast, or southwest.
4. The number of critical peak hours that drive network costs used in the RTP-CCC-CP tariff.

6.2.1 Sensitivities to solar adoption probabilities

One of the major factors underpinning the distributional impacts of inefficient rates and rooftop solar PV adoption is the distribution of incomes of solar PV adopters. As shown in Figure 18, the lions share of PV adoption happens in the top three income quintiles. However, the exact breakdown of adoption between income quintiles has not been constant over time. The results in the main text of this paper assume that the 2016 distribution of solar PV adoption remains constant over time. The sensitivities presented here change that assumption.

In the base case analysis in Section 3 (the 2016 Distribution case), we use the 2016 distribution of PV adoption. We then perform two sensitivities. In the "2008 to 2016 Trend" sensitivity, we linearly extrapolate the 2008 to 2016 changes in the adoption rates in the bottom two income quintiles to 2040, and assume that the top three income quintiles are all equally likely to install solar.[32] In the "2000 to 2016 Trend" sensitivity, we linearly extrapolate the 2000 to 2016 changes in the adoption rates across all income quintiles to 2040. This data is represented in Table 5.

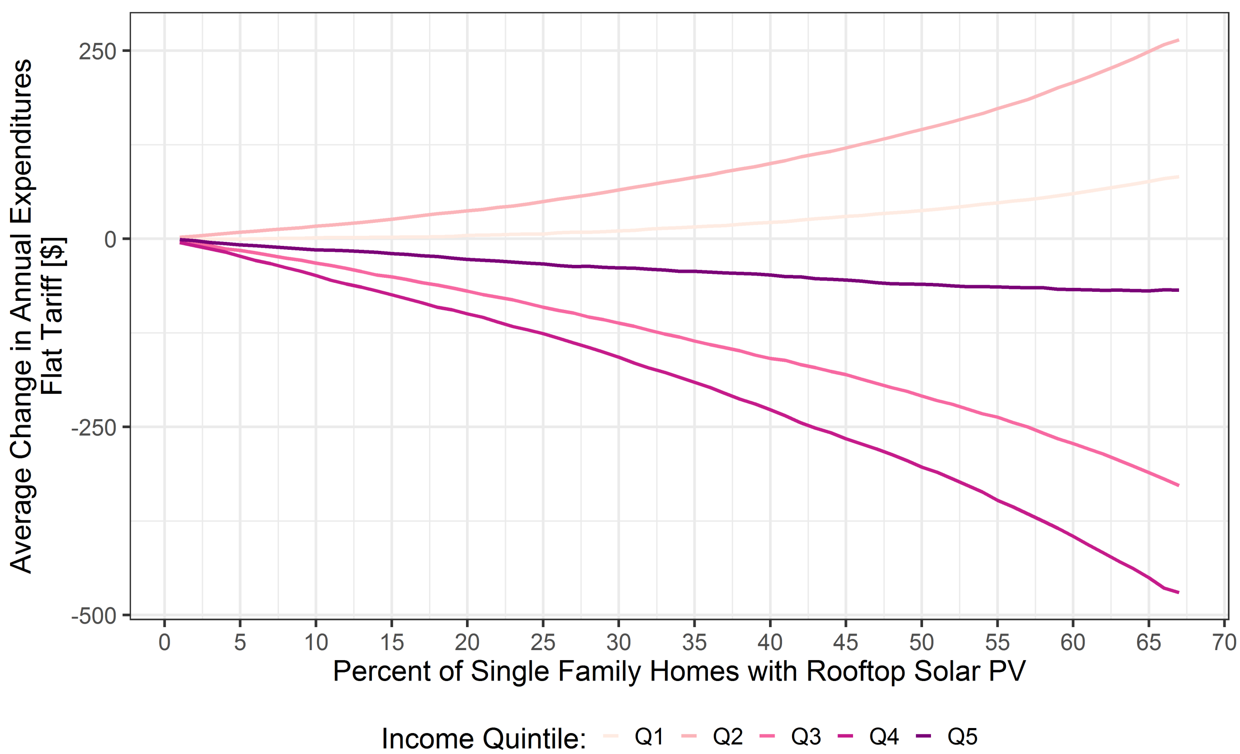
There are of course infinite possible distributions of adoptions across income quintiles. A revolution in financing or business models or a concerted policy effort may increase the likelihood of rooftop PV adoption in the bottom income quintile beyond what is modeled here. However, the distributions shown here cover reasonable linear extrapolations of temporal trends and likely cover a reasonable range of likely outcomes.

Figure 21 shows the change in average expenditures for each income quintile as the penetration of solar PV increases under ComEd's default (flat) tariff. In this case, average expenditures for the lowest income quintile increase, but not as substantially as they do un-

[32] If you extend the '08 to '16 trend through 2040 for the top income quintile, the probability of adoption becomes negative. This is obviously not a useful result, so we modify the probabilities.

der the 2016 Distribution Case. However, average expenditures for the second lowest income quintile increase far more than under the 2016 Distribution Case.

Figure 21: Average Change in Annual Expenditures By Income Quintile
Default (Flat) Tariff, Income Trend Sensitivity

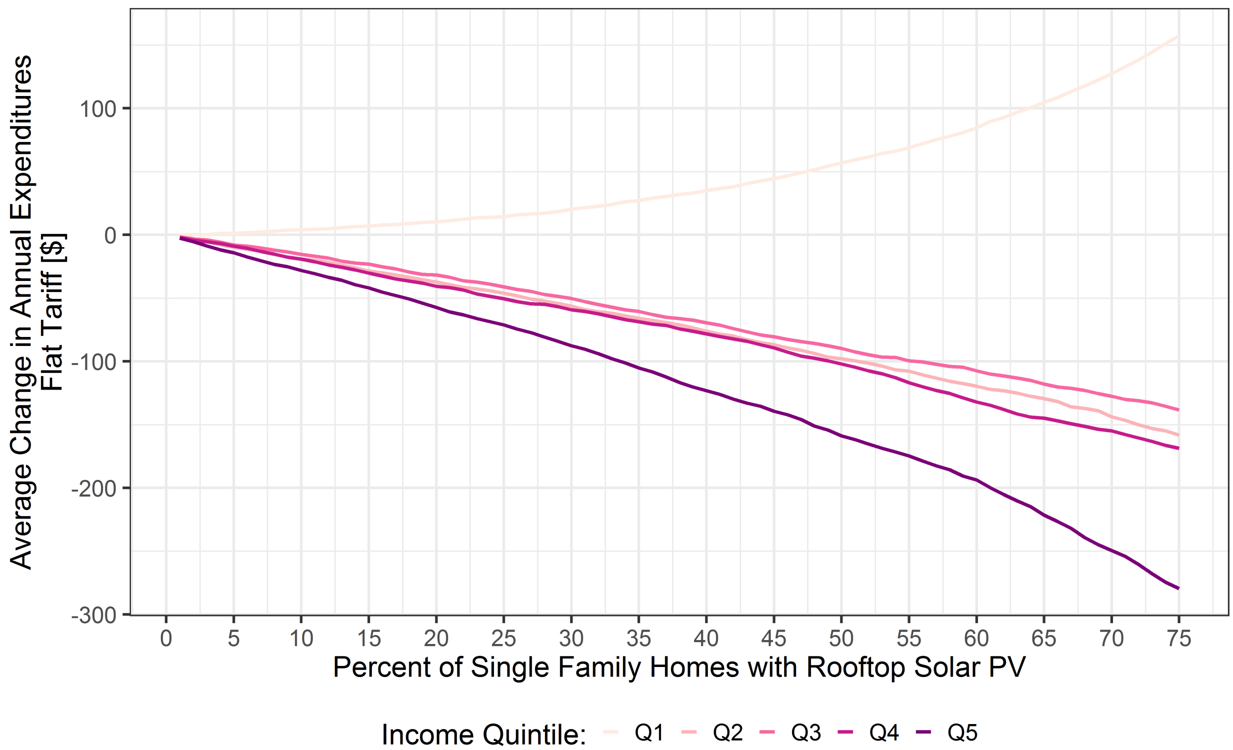


κ: Peak Demand PV Case. Azimuth: 180. **Adoption Probabilities: 2000 to 2016 Trend Case.**

Figure 22 shows the change in average expenditures for each income quintile as the penetration of solar PV increases under ComEd's default (flat) tariff. In this case, average expenditures for the lowest income quintile increase more than under the 2000 to 2016 Trend Case, but not as substantially as they do under the 2016 Distribution Case. Average expenditures for the second lowest income quintile fall, as this income quintile adopts a substantial share of total rooftop solar PV.

There is a crossover point in each income distribution case in which expenditures for low-income customers are lower under a tariff with substantial and uniform fixed charges than under the default, predominately volumetric tariff. In the 2016 Distribution Case this occurred at roughly 25% solar PV adoption (see Figure 8). This crossover point occurs at roughly 34% in the 2000 to 2016 Trend Case and at roughly 31% in the 2008 to 2016 Trend Case. The fact that this occurs in all cases indicates that efforts to increase access to rooftop

Figure 22: Average Change in Annual Expenditures By Income Quintile
Default (Flat) Tariff, Income Trend Sensitivity



κ: Peak Demand PV Case. Azimuth: 180. **Adoption Probabilities: 2008 to 2016 Trend Case.**

solar PV for lower-income groups may not be able to fully counteract the cost shifting impacts of rooftop PV adoption under inefficient rates. This is depicted in Figures 23 and 24.

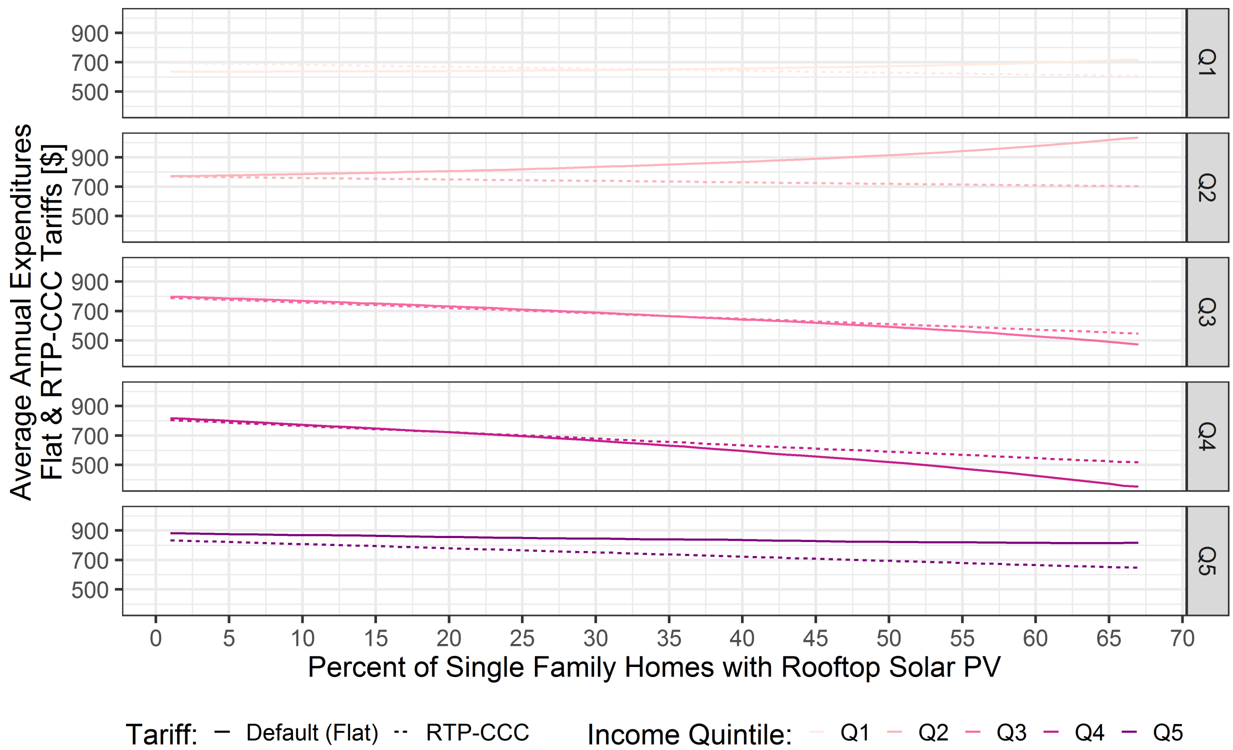
Given that efficient rates do not shift costs from solar adopters to non-adopters, the results for the efficient rates are not interesting, and We do not include them here.

6.2.2 Sensitivities to solar PV installation size

The results in the main text of the paper assume that each customer adopts a solar PV system sized to equal their peak demand. That is, if a customer's peak demand throughout the year is five kilowatts, the customer would adopt a five kilowatt[33] PV system. The larger the PV system, the more kWh the system produces. The more kWh the system produces, the larger the cost shift under inefficient rates. The impact of the sizing assumption is

[33]Sized according to the peak alternating current (AC) output.

Figure 23: Total Expenditures vs. ϕ: Flat and RTP-CCC Tariffs
Income Trend Sensitivity



κ: Peak Demand PV Case. Azimuth: 180. **Adoption Probabilities: 2000 to 2016 Trend Case.**

therefore relatively straightforward. If average PV system sizes are smaller, the impact of PV adoption under inefficient rates is also smaller. This is depicted in Figure 25.

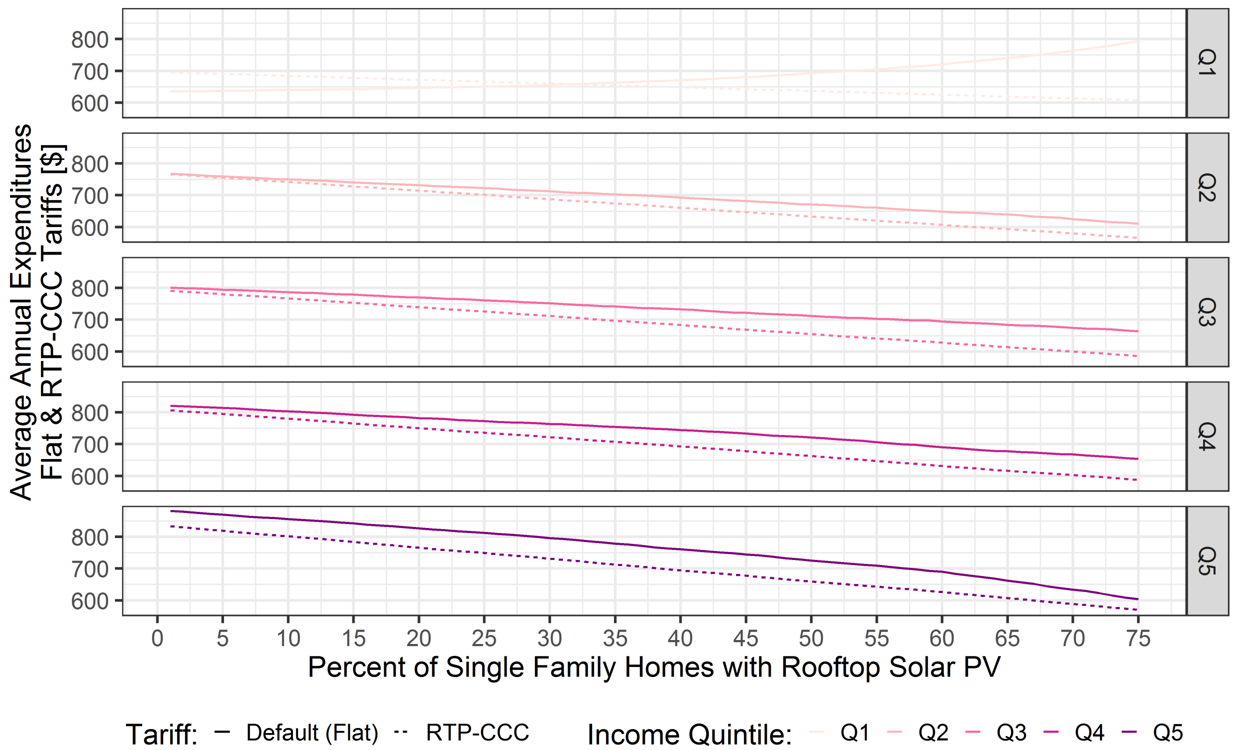
Smaller PV system sizes also increases the PV penetration (ϕ) at which uniform fixed charges for residual cost recovery result in lower expenditures for low-income customers than do volumetric charges for residual cost recovery. This is depicted in Figure 26.

Smaller PV system sizes would also increase the PV penetration at which rooftop PV begins to increase rather than decrease costs.

6.2.3 Sensitivities to solar PV systems' azimuths

Solar PV system production is maximized when facing true south (roughly a PV system azimuth of 180 degrees). The energy output of a PV system with an azimuth of 180° will peak around solar noon, which is roughly equal to true noon in most locations. The annual

Figure 24: Total Expenditures vs. ϕ: Flat and RTP-CCC Tariffs
Income Trend Sensitivity



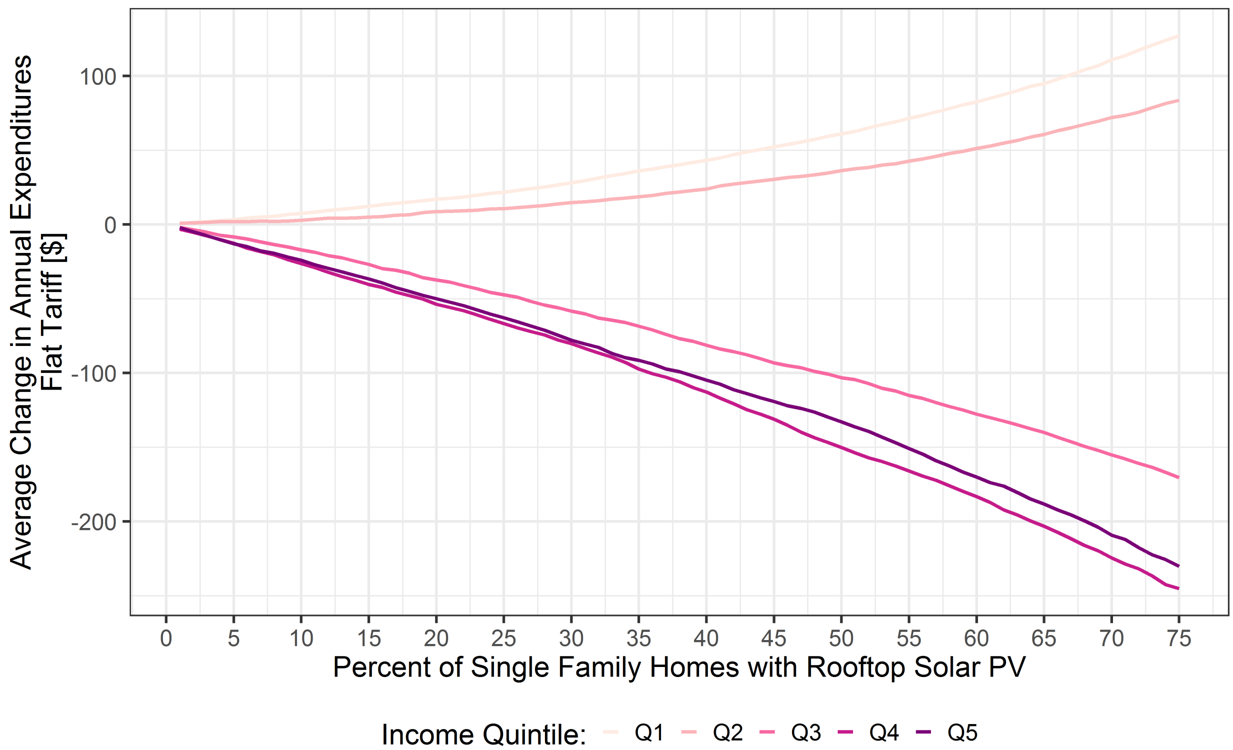
κ: Peak Demand PV Case. Azimuth: 180. **Adoption Probabilities: 2008 to 2016 Trend Case.**

energy output of PV systems facing southeast (azimuth of 135°) or southwest (azimuth of 225°) will be less than that of systems facing 180°. The energy output of a PV system facing southeast (azimuth of 135°) will peak before solar noon, while the energy output of a PV system facing southwest (azimuth of 225°) will peak after solar noon.

The impact of alternative azimuths on total cost shifting is relatively straightforward. Just as in the PV sizing sensitivities, lower aggregate production leads to lower overall cost shifting. However, because peak demand and prices change throughout the day, the impact of azimuth on losses and marginal network capacity costs is less straightforward. This Appendix Section focuses on these latter impacts, as these are the more interesting impacts.

Figures 27 and 28 show the distributions of network capacity values per kW of rooftop solar ($s^{cp}_{\phi,z}$) across the various zip codes in our sample. The black "violins" in the plot show the distribution of values, the red dots show the mean value, and the red bars show the standard deviation of the values. Comparing the results in these Figures to the results in Figure 10,

Figure 25: Average Change in Annual Expenditures By Income Quintile
Default (Flat) Tariff, PV Size Sensitivity

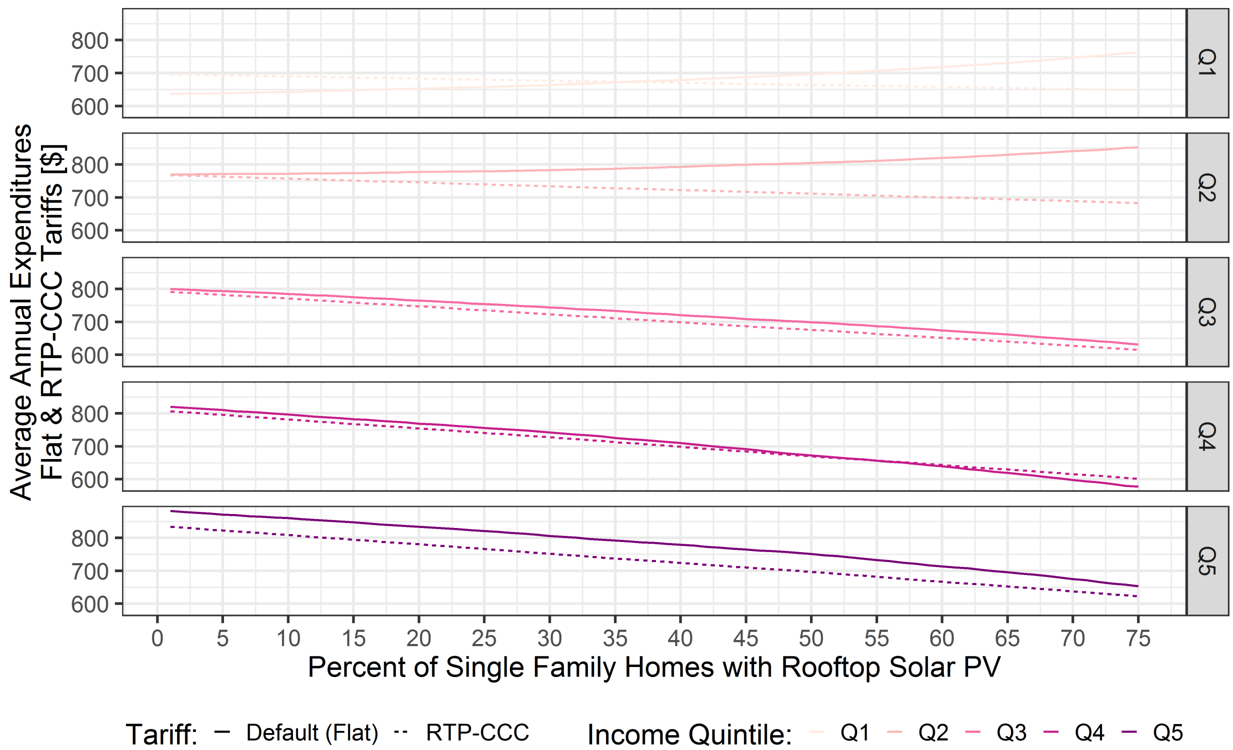


κ**: Annual Consumption PV Case.** Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

the impact of azimuth on the potential network cost reduction of rooftop PV becomes clear. The average cost reduction under azimuths of 135° is substantially lower (nearly 66% lower) than the average cost reduction under azimuths of 225°. This is due largely to the fact that residential demand tends to peak well after 12:00PM in Chicago, and thus the maximum coincident demand peaks are more concentrated in these later afternoon hours. This indicates that if planners or developers were interested in maximizing the network cost reduction value of rooftop PV, they would favor west-facing roofs or sites. This is consistent with the existing literature on the value of PV (see, for example, Hummon et al. (2013)).

Figures 29 and 30 show the magnitude of cost reductions from avoided ohmic losses in the distribution network as the penetration of solar PV increases for both the 4% and 7% average losses cases. In the plot, the dots are the mean values and the bars are the standard deviations. Comparing the results in these Figures to the results in Figure 12 provides insight into the role of PV system azimuth in distribution-level ohmic losses reduction. We see that southwest facing systems provide greater loss reduction value than do southeast or south

Figure 26: Total Expenditures vs. ϕ: Flat and RTP-CCC Tariffs
PV Size Sensitivity



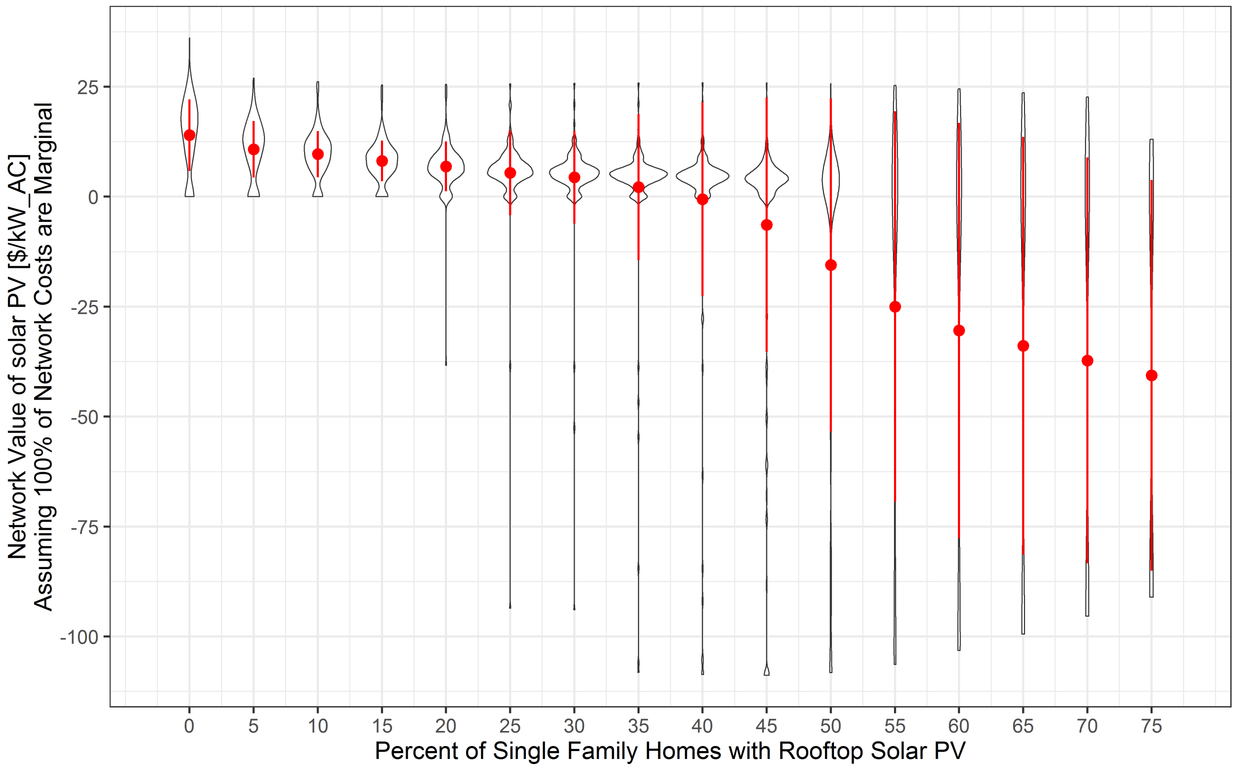
κ**: Annual Consumption PV Case.** Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

facing systems. The logic follows the logic outlined above for the network capacity cost reductions. Residential demand peaks in the afternoon, so reducing afternoon flows reduces losses to a greater degree than reducing flows at other times of the day.

6.2.4 Sensitivities to the number of critical peak hours

The last key sensitivity is the number of critical peak hours that are assumed to drive distribution network costs. In Section 2.3, We calculate the network cost impact of a marginal kWh of consumption or production, assuming that the top **200 half-hourly periods** of demand drive distribution system capacity costs. Today, distribution systems are typically sized to meet demand in the single highest demand hour, plus some margin. Should network costs be considered marginal according to the single peak demand hour? Networks must also be able to operate in all hours—should network costs be considered to be marginal across all hours of demand? The answer to these questions is outside the scope of this dissertation.

Figure 27: Estimation of network capacity value of distributed solar PV
Azimuth Sensitivity

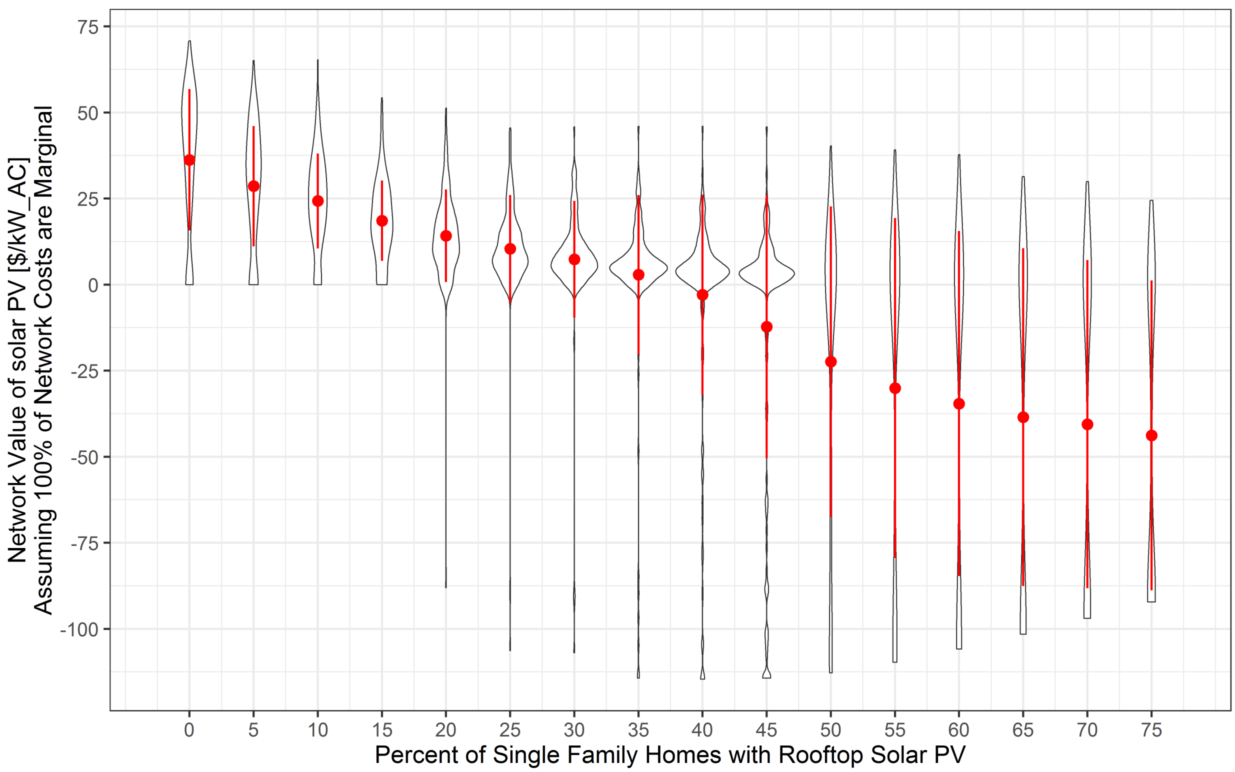


κ: Peak Demand PV Case. **Azimuth: 135.** Adoption Probabilities: 2016 Distribution Case.

Nonetheless, this Section highlights the impact of changing the assumed number of coincident peak hours that drive distribution network costs.

Figures 31 and 32 show the distribution of network capacity cost reduction values of rooftop PV assuming that distribution network costs are marginal across the top 100 half-hourly periods (50 hours) and 400 half-hourly periods (200 hours) respectively. For context, the New York Department of Public Service compensates distributed solar PV units for potential distribution network cost reductions based on their production during roughly the top 240 hours of peak demand throughout the year (See New York Department of Public Service (2019)). Comparing with Figure 10 provides interesting insight into the impact of increasing the number of coincident peak hours. We see that, in this case study, increasing the number of peak demand hours in which network costs are considered to be marginal slightly increases the average network capacity cost reduction impact of rooftop solar PV. Likewise, decreasing the number of peak demand hours slightly decreases the cost reduction impact. While the impacts are relatively limited, they are noteworthy.

Figure 28: Estimation of network capacity value of distributed solar PV
Azimuth Sensitivity



κ: Peak Demand PV Case. **Azimuth: 225.** Adoption Probabilities: 2016 Distribution Case.

Table 3: 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).

Table 4: Number of single-family homes by income quintile

1^{st} Quintile	2^{nd} Quintile	3^{rd} Quintile	4^{th} Quintile	5^{th} Quintile	Total
8,076	13,885	12,831	12,799	11,751	59,342

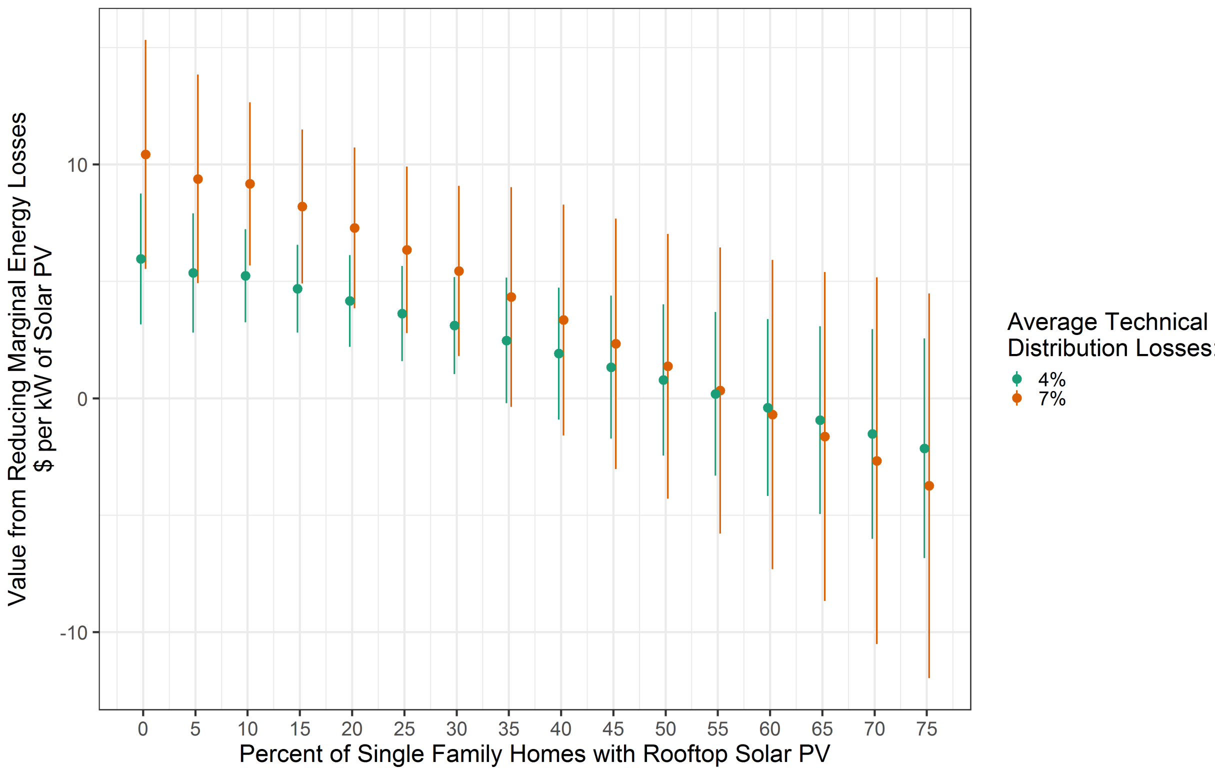
Table 5: Income distribution of PV adopters under the three adoption cases studied

Income Quintiles	2016 Distribution	2008 to 2016 Trend	2000 to 2016 Trend
0 to 20th Percentile	7.9%	11.4%	12.9%
20 to 40th Percentile	13.1%	23.2%	8.4%
40 to 60th Percentile	25.1%	21.8%	28.7%
60 to 80th Percentile	28.9%	21.8%	32.4%
80 to 100th Percentile	25.0%	21.8%	17.6%

Table 6: PV Production Simulation Parameters

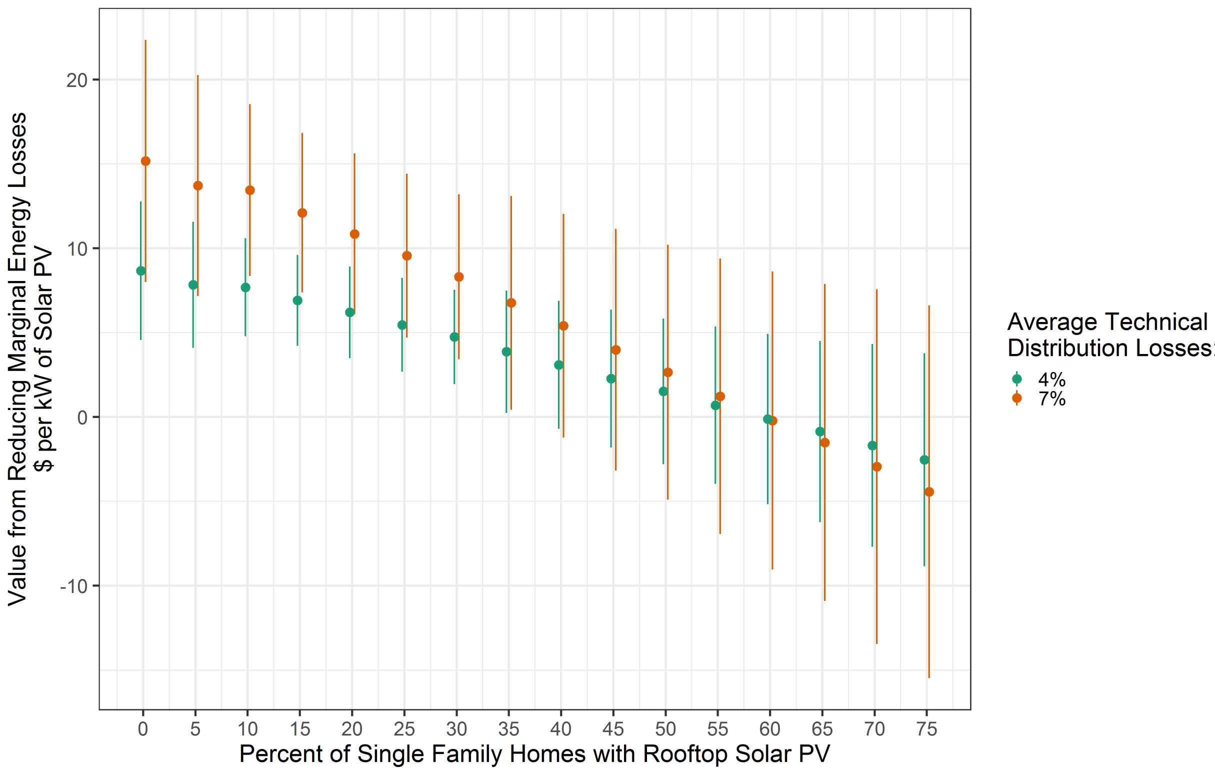
Parameter	Value
System Type	Fixed Tilt
Azimuth	135, 180, or 225
Tilt	41.9
DC-to-AC Derating	1.3
System Losses	14%
Inverter Losses	4%
Temperature Coefficient	-0.004
Albedo	0.2

Figure 29: Estimation of cost impact distribution loss avoidance value of distributed solar PV
Azimuth Sensitivity



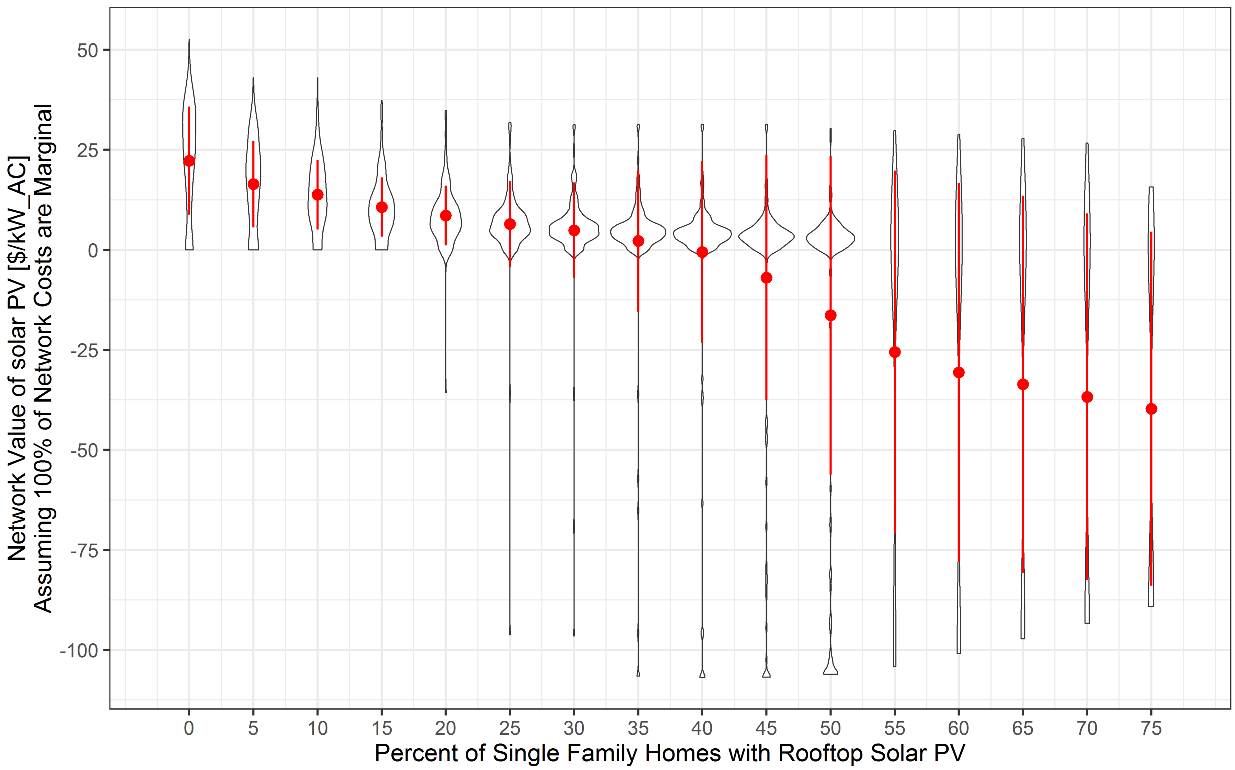
κ: Peak Demand PV Case. **Azimuth: 135.** Adoption Probabilities: 2016 Distribution Case.

Figure 30: Estimation of cost impact distribution loss avoidance value of distributed solar PV
Azimuth Sensitivity



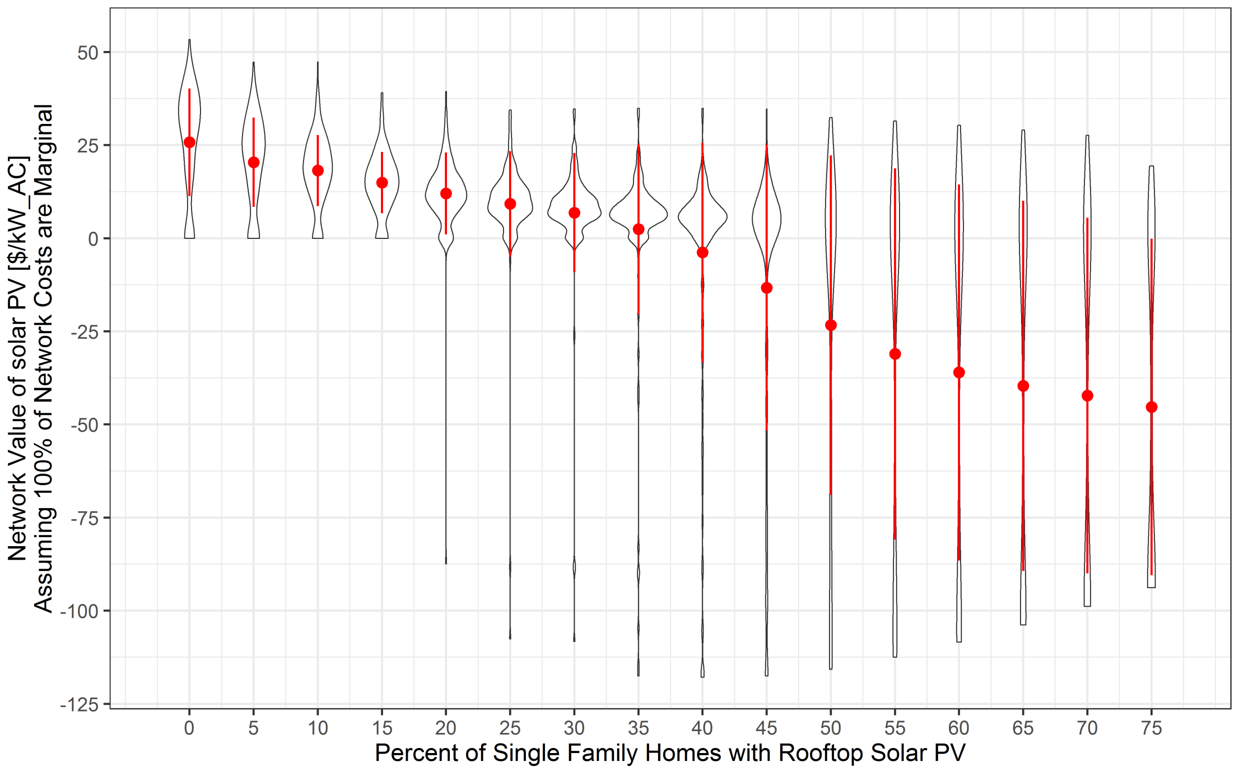
κ: Peak Demand PV Case. **Azimuth: 225.** Adoption Probabilities: 2016 Distribution Case.

Figure 31: Estimation of network capacity value of distributed solar PV
Coincident Peak Sensitivity



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case. **100 Coincident Peak Half-Hourly Periods.**

Figure 32: Estimation of network capacity value of distributed solar PV
Coincident Peak Sensitivity



κ: Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case. **400 Coincident Peak Half-Hourly Periods.**

MIT CEEPR

MIT Center for Energy and Environmental Policy Research

Since 1977, the Center for Energy and Environmental Policy Research (CEEPR) has been a focal point for research on energy and environmental policy at MIT. CEEPR promotes rigorous, objective research for improved decision making in government and the private sector, and secures the relevance of its work through close cooperation with industry partners from around the globe. Drawing on the unparalleled resources available at MIT, affiliated faculty and research staff as well as international research associates contribute to the empirical study of a wide range of policy issues related to energy supply, energy demand, and the environment.

An important dissemination channel for these research efforts is the MIT CEEPR Working Paper series. CEEPR releases Working Papers written by researchers from MIT and other academic institutions in order to enable timely consideration and reaction to energy and environmental policy research, but does not conduct a selection process or peer review prior to posting. CEEPR's posting of a Working Paper, therefore, does not constitute an endorsement of the accuracy or merit of the Working Paper. If you have questions about a particular Working Paper, please contact the authors or their home institutions.

MIT Center for Energy and Environmental Policy Research
77 Massachusetts Avenue, E19-411
Cambridge, MA 02139
USA

Website: ceepr.mit.edu

MIT CEEPR Working Paper Series is published by the MIT Center for Energy and Environmental Policy Research from submissions by affiliated researchers.

Copyright © 2020
Massachusetts Institute of Technology

For inquiries and/or for permission to reproduce material in this working paper, please contact:

Email ceepr@mit.edu
Phone (617) 253-3551
Fax (617) 253-9845