

MIT Center for Energy and Environmental Policy Research

## **Working Paper Series**

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

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### SEPTEMBER 2020

## CEEPR WP 2020-017



MASSACHUSETTS INSTITUTE OF TECHNOLOGY

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

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#### 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.

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#### 1 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 8 a century, rates today remain inefficient for the vast majority residential and commercial 9 consumers. Many factors contribute to this gap between theory and practice. One key 10 factor is that electricity is essential to modern life and is regulated as such. The result is that 11 economic efficiency is often not the primary—and almost never the sole—goal for regulators 12 when setting prices. Rather, regulators often prioritize goals of fairness and distributional 13 equity<sup>1</sup> when setting prices. For example, of the California Public Utility Commission's 14 (CPUC) rate design principles, the first relates to access and affordability to electricity for 15 vulnerable populations (California Public Utilities Commission, 2018).<sup>2</sup> The CPUC is not 16 alone—regulators across the U.S. are broadly concerned with the distributional impacts of 17 tariffs (Levinson and Silva, 2019). 18

The emergence of distributed energy resources (DER) adds a new dimension to the challenge 19 of assessing the distributional impacts of rate design. A full accounting of the distributional 20 impacts of rate design must now consider not only how any given rate will impact different 21 customer types, but also how the rate will influence DER adoption, how rates change as 22 customers install DERs, and how these changes impact customers of different socioeconomic 23 groups. While some literature analyzes the distributional impacts of transitioning to time 24 varying energy charges (see, e.g., Horowitz and Lave (2014)) or to alternative network charges 25 (see, e.g., Borenstein (2011), Borenstein and Davis (2012), and Azarova et al. (2018)), there 26 is a dearth of research analyzing how efficient or inefficient rates perform as DER adoption 27

28 increases.

<sup>&</sup>lt;sup>1</sup>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).

<sup>&</sup>lt;sup>2</sup>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.<sup>3</sup> Second, the costs of DER adoption and support programs are often recovered through the retail tariff.<sup>4</sup>

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 39 that captures a utility's costs, the structure of the tariffs used to recover these costs, and the 40 changes in the utility's costs and rates as the penetration of rooftop solar PV among residen-41 tial customers increases. We parameterize these models with half-hourly energy consumption 42 data for 100,170 customers in the Chicago, Illinois region, and with U.S. census (American 43 Community Survey) data on the socioeconomic characteristics of these customers. Finally, 44 we leverage data from the Lawrence Berkeley National Laboratory on the income trends of 45 rooftop solar PV adopters to simulate the demographics of PV adoption (see Barbose et al. 46 (2018)).47

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<sup>5</sup> 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-

<sup>&</sup>lt;sup>3</sup>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).

<sup>&</sup>lt;sup>4</sup>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.

<sup>&</sup>lt;sup>5</sup>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 67 PV for the network loss and capacity cost reductions that it may create, even under very 68 aggressive assumptions about the magnitudes of these cost reductions. More specifically, 69 the marginal revenue per-kilowatt (kW) of solar PV under tariffs that accurately value the 70 impact of solar PV adoption on future network costs is less than the marginal revenue per-71 kW of solar PV under the default (flat) tariff. This reinforces the idea that time invariant 72 rates with volumetric residual cost recovery mechanisms are crude and imperfect subsidies 73 for distributed solar PV. 74

This paper proceeds as follows. Section 1.1 introduces the literature covering issues related 75 to rate design and the distributional impacts of rooftop PV adoption. Section 2 reviews the 76 methods used to assess the potential distributional impacts of DER adoption in this paper. 77 The data used in this study are extensive, and are thus detailed separately in Appendix 6.1. 78 Section 3 assesses the distributional impacts of efficient and inefficient rates as distributed 79 PV penetration among residential customers increases. Given the lack of data regarding the 80 topology and investment needs in the distribution system in the ComEd service territory, 81 Section 3 assumes that the distribution network is sufficiently sized such that no new distri-82 bution investments are needed, meaning that solar PV penetration does not reduce network 83 costs. Section 4, on the other hand, assumes that all distribution network costs are marginal 84 with respect to consumption and production, and designs a tariff that accounts for these 85 marginal distribution network costs. Section 4 then analyzes the distributional impacts of 86

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 92 design beginning in the early 20th century (Coase, 1946; Houthakker, 1951; Vickrey, 1971; 93 Borenstein, 2005). More recently, the theoretical benefits of efficient rate design have been 94 demonstrated in empirical research (Jessoe and Rapson, 2014; Wolak, 2011; Allcott, 2011; 95 Savolainen and Svento, 2012). The overarching message of this theoretical and empirical 96 research is that the societal benefits of electricity consumption are maximized when the 97 marginal price that customers pay for consuming (and are paid for producing) energy is 98 equal to the social marginal cost of producing that energy. This implies that any electricity-99 related costs that do not vary with short run production and consumption decisions and that 100 are not recovered by short run social marginal costs<sup>6</sup> are most efficiently recovered through 101 non-marginal charges. 102

Economic efficiency is not the only consideration in rate design. For example, many consid-103 erations exist alongside economic efficiency in the widely used rate design principles outlined 104 in Bonbright (1961) and Chapter 8 of Pérez-Arriaga (2014). Among these considerations, 105 equity—and, in particular, the distributional effects of rate design—loom large. Indeed, reg-106 ulation has long been used as a means of distributing benefits (Posner, 1971). As evidence 107 of this fact, Levinson and Silva (2019) found that utilities in regions with higher levels of 108 income inequality had more income redistributive electricity rates. Most commonly this 109 entails recovering residual costs<sup>7</sup> through volumetric, rather than fixed, charges. Transition-110 ing from volumetric to fixed charges that are uniform for all customers would be regressive 111 with respect of income (Borenstein, 2012b; Burger et al., 2020). However, non-uniform fixed 112 charges can be designed to recover residual costs in an income neutral or even progressive 113 way (Burger et al., 2020). 114

<sup>&</sup>lt;sup>6</sup>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).

<sup>&</sup>lt;sup>7</sup>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 115 between DER adoption and retail rates, with a focus on the distributional impacts of DER 116 adoption. Given the scale of the distributed solar industry relative to other distributed 117 resources, the bulk of the literature on the net social benefits of DERs and the distributional 118 impacts of DER support schemes has focused on solar PV. Vaishnav et al. (2017) analyzes the 119 costs of support programs for rooftop solar PV and the benefits of the associated climate and 120 air pollution reductions, and finds that, between 2011 and 2015, private benefits exceeded 121 public benefits by roughly \$13.5 billion in the U.S.<sup>8</sup> Vaishnav et al. (2017) also find that 122 these benefits have accrued predominately to more affluent households. Similarly, Borenstein 123 (2017) analyzes the private benefits of solar PV adoption in California, and finds that these 124 benefits have disproportionately accrued to affluent households. Borenstein and Davis (2016) 125 analyze support programs beyond solar PV, including tax credits for home weatherization, 126 hybrid and electric vehicles, and other types of "clean energy;" the authors again find that 127 the top income quintiles receive the lion's share of the benefits of these programs. 128

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

<sup>&</sup>lt;sup>8</sup>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).

<sup>147</sup> consumption and production decisions on network costs. While the magnitude and design
<sup>148</sup> of the optimal marginal network tariff is uncertain, one thing is clear: the magnitude of the
<sup>149</sup> optimal marginal network tariff will vary widely depending on location and time (Burger
<sup>150</sup> 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 157 flown predominately to the affluent, has led to a review of the role of tariffs in the dis-158 tributional impacts of DER adoption. Nelson et al. (2011) argues that the mechanism for 159 supporting rooftop solar PV in Australia is regressive, benefiting high-income customers at 160 the expense of lower income customers. Simshauser (2016) concurs, finding that, as rooftop 161 solar PV penetration increases, flat, volumetric rates cause a net cost shift from low-income 162 to higher-income customers in Australia, and argues for coincident-peak demand-based tariffs 163 as a potential remedy. Simshauser (2016) extrapolates from a small set of customers intended 164 to represent typical Queensland Australia customers. Using a model of nine customers in-165 tended to be representative of customers in New Jersey in the United States, Johnson et al. 166 (2017) similarly finds that DER adopters tend to benefit at the expense of non-adopters. 167 Leveraging a data set of 199 customers in the United Kingdom, Strielkowski et al. (2017) 168 duplicates Simshauser (2016)'s model and, logically, find similar results. Using a robust 169 data set of annual consumption<sup>9</sup> from roughly 135,000 customers in Switzerland, Feger et al. 170 (2017) calculates tariffs that equalize bill increases across income classes while meeting a 171 specified distributed solar adoption target. 172

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.

<sup>&</sup>lt;sup>9</sup>The authors partner with a Swiss startup to simulate hourly consumption profiles based on household characteristics.

#### $_{179}$ 2 Methods

<sup>180</sup> We first detail the method used to simulate solar PV adoption. We then detail how this <sup>181</sup> adoption information is used to estimate the distributional impacts of different tariffs.

#### <sup>182</sup> 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:

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

 $\phi$  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	Customer Adoption Probability				
PV Penetration Level	$1^{st}$ Quintile	$2^{nd}$ Quintile	$3^{rd}$ Quintile	$4^{th}$ Quintile	$5^{th}$ Quintile
$\phi$	$\alpha_1$	$\alpha_2$	$lpha_3$	$\alpha_4$	$\alpha_5$
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  $\lambda_{i,\phi} = 1$ ). <sup>193</sup> 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 194  $\kappa_i$  is the size of the solar PV array adopted by customer *i*. We explore two different models 195 for  $\kappa_i$ . First, we size each adopting customer's solar PV system according to that customer's 196 annual peak demand ( $\kappa_i = \hat{x}_{i,t}$ ). We refer to this as the "Peak Demand PV Case." Second, 197 we size each customer's solar PV system such that it meets 80% of the customer's energy 198 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 199 Case." In the Annual Consumption PV Case, the average PV unit size in our sample is 3.6 200 kW. In the Peak Demand PV Case, the average PV unit size is 5 kW. The average rooftop 201 PV unit size in the U.S. is 5 kW according to the Solar Energy Industries Association, the 202 trade association representing the U.S. PV industry (Solar Energy Industries Association, 203 N.D.). We discuss the impact of sizing assumptions in Section 3. 204

Figure 1 displays the peak demand and net demand for three solar PV penetration cases 205 under the Annual Consumption PV Case and with a PV azimuth of 180. The blue line on 206 each plot is the peak demand at that penetration level. Two observations are particularly 207 relevant. First, the aggregate peak demand of all of the customers in our sample decreases 208 by only 0.8% as the penetration of rooftop PV increases. This is particularly relevant for 209 assumptions about the recovery of residual costs, discussed in Section 3. Second, large 210 injections of power become fairly common in the winter and shoulder seasons. We discuss 211 these trends in more detail in Section 4. 212

One of the primary impacts of solar adoption is to shift the period of peak net demand on 213 the system. However, this effect is not uniform. Due to low or no solar production during 214 winter and shoulder month peak demand periods, solar PV production does not impact the 215 period of coincident peak demand during winter and shoulder months. However, solar PV 216 does produce during periods of coincident peak during the summer months, shifting peak 217 net demand later in the day. This phenomenon is depicted in Figure 2. Figure 2 shows 218 the marginal impact on net demand of a one percent increase in penetration of solar PV 219 during a week in January (left panel) and a week in July (right panel) for three levels of 220 solar penetration: 0% on top, 30% in the middle, and 60% on the bottom. The vertical blue 221 lines represent the hour of peak net demand on each day. We see clearly that solar PV has 222 little impact on winter peak demand, but shifts summer peak demand by several hours as 223 penetration increases. 224



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

 $\kappa$ : Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

#### 225 2.2 Modeling the Distributional Impacts of Rate Designs

The primary goal of this paper is to understand the potential distributional impacts of 226 PV adoption under different tariff designs. The optimal tariff contains price signals for 227 marginal energy, generation capacity, and network capacity costs, and recovers all remaining 228 residual costs through a fixed charge. While fixed charges are the most efficient mechanisms 229 for recovering residual costs, most U.S. and European utilities also recover some portion 230 of residual costs through volumetric charges. Further, the vast majority of tariffs charge 231 a constant, time invariant price for energy and do not contain marginal price signals for 232 network and generation capacity. 233

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 ( $\phi$ ). 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

 $\kappa$ : 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*,  $p_{i,t,\phi}$ .<sup>10</sup> Depending on the tariff structure,  $p_{i,t,\phi}$  may include the following components:

- 242 1.  $p_{i,t}^e$ : The volumetric charge for energy
- 243 2.  $p_{i,t}^{ccc}$ : The volumetric charge for marginal generation capacity ("CCC" stands for coin-244 cident capacity charge)
- 245 3.  $p_{t,z,\phi}^{cp}$ : The volumetric charge for marginal network capacity ("CP" stands for coincident 246 peak)
- 247 4.  $p_{i,t,\phi}^r$ : The volumetric charge for residual cost recovery

<sup>&</sup>lt;sup>10</sup>The consumption data used in this study are reported as kWh used over a half-hourly period. Demandbased 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— $p_{i,t}^e$ —reflects the short-run marginal price of energy at the ComEd trading hub of the electricity market operated by the Regional Transmission Operator, PJM.<sup>11</sup> As a result, for the RTP tariffs studies here,  $p_{i,t}^e$  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.

<sup>262</sup> Consumer expenditures are calculated as follows:

$$E_{i,\phi} = F_{i,\phi} + \sum_{t} \left( p_{i,t,\phi} (x_{i,t} - g_{i,t,\phi}) \right).$$
(3)

The charge for marginal network capacity should only be non-zero when and where marginal 263 consumption or production decisions will drive investments in new network capacity (Pérez-264 Arriaga et al., 2016; Abdelmotteleb et al., 2018). Ideally this charge would vary on a feeder-265 by-feeder basis, and the magnitude of the charge would be determined using measured load, 266 network topology, and accurate forecast data. In the case of a congested feeder with necessary 267 upgrades, the charge should equal the marginal change in the time value of money between 268 the point at which a network investment would have been required in the absence of a DER 269 and the point at which the network investment is required given the DER. This is depicted 270 in Figure 3. Likewise, if a feeder were congested due to DER-driven injections of power, 271 the charge should convey the marginal time discounted cost of the investments necessary to 272 accommodate increased peak injections. 273

<sup>274</sup> Given the lack of distribution network topology and technical data and the lack of load

<sup>&</sup>lt;sup>11</sup>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 275 extreme cases. First, a case in which we assume that no distribution feeders are congested, 276 and thus that there are no marginal distribution network costs. This case will tend to show 277 large distributional impacts of PV adoption, as a greater share of network costs are assumed 278 to be residual, enabling larger cost shifts as PV adoption increases. Second, we model a case 279 in which we assume that all distribution feeders are congested, and thus that all distribution 280 network costs are marginal. This case will tend to show smaller distributional impacts of 281 PV adoption, as a smaller share of network costs are assumed to be residual, decreasing cost 282 shifts as PV adoption increases. We detail the methods for estimating the price signal for 283 marginal network costs in Section 2.3. Together, these two cases provide a range of possible 284 distributional impacts of efficient and inefficient rates as PV adoption increases. 285

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, 289 2) develop an intuition for the potential distribution of the cost shift, and 3) understand the 290 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  $R^r = \sum_{i,t} \left( F_{i,\phi=0} + x_{i,t} p_{i,t,\phi=0}^r \right)$ , 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:

$$R^{r} = F_{i,\phi} + \sum_{i,t} \left( (x_{i,t} - g_{i,t,\phi}) p_{i,t,\phi}^{r} \right) \forall \phi = 0, ..., 75$$
(4)

As solar penetration ( $\phi$ ) increases, total solar generation increases and net demand (demand minus solar generation) decreases. For an efficient tariff,  $p_{i,t,\phi}^r = 0 \forall \phi$ . However, in practice,  $p_{i,t,\phi}^r$  is typically greater than zero (as it is under ComEd's default rate). Since  $p_{i,t,\phi}^r$  is greater than zero at  $\phi = 0$ ,  $p_{i,t,\phi}^r$  or  $F_{i,\phi}$  must increase as  $\phi$  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  $\phi$ ; 304 that is, solar adopters do not modify their consumption behavior after adopting solar. Note 305 that under a net-metering scheme as modeled here, the temporal profile of the customer does 306 not affect the change in  $p_{i,t,\phi}^r$ —only the sum of the net demand. Second,  $R^r$  remains constant 307 as  $\phi$  increases. This assumption likely overstates the potential distributional impacts at low 308 penetrations, and understates the distributional impacts at high penetration. Modeling 309 results indicate that distributed PV adoption can reduce distribution system costs at low 310 penetration, and increases these costs at higher penetrations (Schmalensee et al., 2015; Cohen 311 et al., 2016). While empirical work on this issue is limited, there is initial evidence that 312 distributed PV may increase network costs (and thus residual costs) even at low penetrations 313 (Wolak, 2018). The third core assumption in Equation 4 is that all residual costs must 314 be recovered. There is legal precedent for writing off assets that are not longer valuable. 315 However, this is not common in practice. Further, as we show in Figure 1, peak demand 316 remains fairly consistent as PV penetration grows, indicating that the assets in this case 317 study are likely still useful. 318

#### <sup>319</sup> 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. 327 Note that peak network loading may occur during times of PV injection and thus negative 328 net demand. We sum the net demand across all customers i in each time period t and identify 329 the top  $200^{12}$  half-hourly network loading periods in each z. Note that the demand in this 330 case is the demand across all 100,170 customers in the sample, not the subset of single-331 family homes. This follows from the fact that networks are built to meet the demand of all 332 customers. We refer to the times of these coincident peak periods as  $\hat{t}_{z,\phi}$ . We then calculate a 333 per-kWh coincident-peak charge, referred to as  $p_{t,z,\phi}^{cp}$ , that recovers all distribution facilities 334 costs from expected net demand in these coincident peak hours. We do this by dividing 335 all distribution facilities  $costs^{13}$  by the sum of the absolute value of net demand in these 336 200 half hours. This charge is symmetric—that is, a marginal increase in demand during a 337 coincident peak demand period will increase customer expenditures, and a marginal increase 338 in injection during a coincident peak injection period will also increase expenditures. 330

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

 $<sup>^{12}</sup>$ We discuss the sensitivity to this peak period assumption in the appendices to this paper.

<sup>&</sup>lt;sup>13</sup>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,<sup>14</sup> ohmic losses are related to the square of the current flowing through the network. That is,  $l_{t,z,\phi} \propto I_{t,z,\phi}^2 R_z$ . Where  $l_{t,z,\phi}$  is ohmic losses at time t in location z and solar penetration  $\phi$ ;  $I_{t,z,\phi}^2$  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:  $\frac{\partial l_{t,z,\phi}}{\partial I_{t,z,\phi}} \propto 2I_{t,z,\phi}R_z$ . 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  $s_{z,\phi,\bar{l}}^l$ . We calculate marginal losses and loss avoidance values for two values of  $\bar{l}$ : 4% and 7%. This process is depicted in Equation 6:

$$R_{z,\bar{l}} = \bar{l} \frac{\sum_{t} (x_{t,z,\phi=0})}{\sum_{t} (x_{t,z,\phi=0}^2)},$$
  

$$\frac{\partial l_{t,z,\phi,\bar{l}}}{\partial I_{t,z,\phi}} = 2(x_{t,z,\phi} - g_{t,z,\phi})R_{z,\bar{l}},$$
  

$$p_{i,t}^{e'} = p_{i,t}^{e} \left(1 + \frac{\partial l_{t,z,\phi,\bar{l}}}{\partial I_{t,z,\phi}}\right).$$
(6)

<sup>367</sup> Considering all volumetric energy, marginal network and generation, and marginal losses <sup>368</sup> 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 <sup>369</sup> given tariff.  $p_{i,t,\phi}$  is the total variable (dollar per kilowatt-hour) charge and contains several <sup>370</sup> components (e.g.,  $p_{i,t,\phi}^r$  and  $p_{i,t,\phi}^e$ ).

<sup>&</sup>lt;sup>14</sup>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.

# <sup>371</sup> 3 The Distributional Impacts of Rate Design with So <sup>372</sup> lar PV Adoption:

#### <sup>373</sup> Zero Marginal Network Costs

In this section, we explore the potential distributional impacts of DER adoption under 374 ComEd's default flat tariff and under the RTP-CCC and RTP-CCC-APD (defined below) 375 tariffs under the assumption that zero percent of network costs are marginal. That is, in 376 this section,  $p_{t,z,\phi}^{cp} = 0$ . In Section 4 we explore the possibility of non-zero values for  $p_{t,z,\phi}^{cp}$ . 377 The RTP-CCC and RTP-CCC-APD tariffs recover all residual costs through fixed charges. 378 As a result,  $p_{i,t,\phi}^r = 0$  for all *i*, *t*, and  $\phi$ . This provides a useful contrast to the default tariff, 379 in which  $p_{i,t,\phi}^r \approx 0.05$  \$/kWh for  $\phi = 0$ . Customer expenditures under the default tariff 380 and the RTP-CCC tariffs are calculated as in Equation 7. Note that the RTP-CCC and 381 RTP-CCC-APD tariffs are identical except for the fixed charge design. 382

<sup>383</sup> Under the RTP-CCC tariff, fixed charges recover all residual costs—that is,  $p_{i,t,\phi}^r = 0 \forall i, t$ — <sup>384</sup> and are equal for all customers—that is,  $F_{i,\phi} = F_{j,\phi} \forall i, j$ . However, under the RTP-CCC-APD <sup>385</sup> 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 <sup>386</sup>  $\hat{x}_i$  is customer *i*'s peak demand throughout the year, given by:

$$E_{i,\phi}^{default} = F_{i,\phi} + \sum_{t} \left( (p_{i,t}^e + p_{i,t,\phi}^r) (x_{i,t} - g_{i,t,\phi}) \right),$$
$$E_{i,\phi}^{RTP-CCC} \& E_{i,\phi}^{RTP-CCC-APD} = F_{i,\phi} + \sum_{t} \left( (p_{i,t}^e + p_{i,t}^{ccc}) (x_{i,t} - g_{i,t,\phi}) \right).$$
(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  $p_{i,t,\phi}^r$  as  $\phi$  increases, holding  $F_{i,\phi}$  constant. The results in Figure 4 are driven in part by an increase in  $p_{i,t,\phi}^r$  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

 $\kappa:$  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  $\kappa$  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.<sup>15</sup>

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

<sup>&</sup>lt;sup>15</sup>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

 $\kappa$ : 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  $p_{i,t,\phi}^r$ . Solar adopters save money by decreasing their energy costs and non-adopters are not impacted.

<sup>416</sup> Transitioning rate design is not without its impact. The RTP-CCC tariff recovers all residual <sup>417</sup> costs through uniform fixed charges (i.e. every customer faces the same fixed charge). The <sup>418</sup> RTP-CCC-APD tariff recovers all residual costs through fixed charges that scale according <sup>419</sup> to a customer's annual peak demand. The result is that low-income customers would face a <sup>420</sup> 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 ( $\phi$ ) 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



 $\kappa$ : Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

<sup>424</sup> line represents expenditures under the RTP-CCC and RTP-CCC-APD tariffs respectively.

<sup>425</sup> At low solar penetrations, expenditures for low-income customers are higher under the RTP-

426 CCC tariff than under the default tariff. However, as penetration increases, we see that

<sup>427</sup> low-income expenditures are lower under the RTP-CCC tariff than under the default tariff.

<sup>428</sup> Under the RTP-CCC-APD tariff, low-income customer expenditures are lower in all cases.

RTP-CCC and RTP-CCC-APD Tariffs

Figure 7: Average Change in Annual Expenditures By Income Quintile



 $\kappa:$  Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.



Q5

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**Q**4

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Income Quintile:  $- \alpha_1 - \alpha_2 - \alpha_3$ 

Tariff: - Default (Flat) -- RTP-CCC

 $\kappa$ : Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

Figure 8: Total Expenditures vs.  $\phi :$  Flat and RTP-CCC Tariffs



Figure 9: Total Expenditures vs.  $\phi$ : Flat and RTP-CCC-APD Tariffs

 $\kappa$ : 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 429 (flat) tariff studied here is that such tariffs are believed to protect low-income and other 430 vulnerable customers. For example, the National Consumer Law Center, a non-profit ded-431 icated to "advancing fairness in the marketplace for all," states plainly that "high utility 432 fixed charges harm low-income, elders and households of color" (National Consumer Law 433 Center, 2016). It is possible to design progressive fixed charges that do not harm vulnerable 434 customers. Further, what this section demonstrates is that, as rooftop solar PV penetration 435 increases, rates with volumetric residual cost recovery do not necessarily protect low-income 436 customers. In fact, low-income customer expenditures may be higher under tariffs with 437 volumetric charges for residual cost recovery than under tariffs that recover residual costs 438 through fixed charges as PV penetration increases. 439

# 440 4 The Distributional Impacts of Rate Design with So 441 lar PV Adpotion: 442 Marginal Network Cost Cases

The previous section demonstrated the potential distributional impacts of distributed solar 443 PV adoption under the assumption that zero percent of network costs are marginal. However, 444 in practice, some portion of distribution network costs may be marginal in the long run, as 445 highlighted in Section 2.2. In fact, some analysts have argued that distributed solar PV does 446 not in fact create any cost shifts, as distributed solar is reducing system costs.<sup>16</sup> In this 447 section, we explore the potential distributional impacts of a tariff that includes a charge for 448 marginal network capacity and model the potential for distributed solar to impact the costs 449 of distribution network capacity and losses. 450

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

#### 456 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  $s_{\phi,z}^{cp}$ , 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:

$$s_{\phi,z}^{cp} = \sum_{t} (s_{t,\phi,z}^{cp}), \text{ where } s_{t,\phi,z}^{cp} = \begin{cases} \tilde{g}_t p_{t,z,\phi}^{cp} & \text{if } \sum_i (x_{i,t,z} - g_{i,t,z,\phi}) \ge 0\\ -\tilde{g}_t p_{t,z,\phi}^{cp} & \text{if } \sum_i (x_{i,t,z} - g_{i,t,z,\phi}) < 0. \end{cases}$$
(8)

Figure 10 shows the distribution of network capacity values per kW of rooftop solar  $(s_{\phi,z}^{cp})$ 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

<sup>&</sup>lt;sup>16</sup>See, for example, Whited et al. (2017) pages 156-164.

<sup>466</sup> the standard deviation of the values. Several trends are immediately clear.

- 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).

471 3. As solar penetration increases, peak network loading periods in some regions begin
472 being driven by solar PV injections, rather than demand withdrawals. This implies
473 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, 474 while in others it exhibits no or very low value. This is consistent with other estimates of 475 network capacity cost impacts of rooftop solar PV (Cohen et al., 2016). The reason for the 476 non-linearity exhibited in Figure 10 is that, in some areas, once the number of households 477 in that area with solar PV passes a certain threshold, nearly all of the peak loading periods 478 begin being driven by peak injections. Thus, solar may go from driving marginal network 479 cost reductions to driving large marginal network cost increases with small changes in solar 480 penetration. 481

Figure 11, along with Figure 2, provides intuition as to why we see a large distribution of 482 potential network values of rooftop solar. Figure 11 plots the capacity factor<sup>17</sup> of the solar 483 PV in three areas during the areas coincident peak periods. We see first that the capacity 484 factor is not the same across all areas—that solar PV in some areas is producing a larger 485 portion of its rated capacity during the peak demand periods at low penetrations in some 486 areas than in others. Further, we see that as penetration increases to moderate penetrations, 487 the capacity factor falls across the board. This is due to the fact that solar PV shifts the 488 peak net demand period away from peak solar production periods (i.e. earlier in the morning 489 or later in the day). Finally, in some areas, in this case zip 60053, capacity factor increases 490 dramatically at high penetrations. This is due to the fact that solar PV is now driving peak 491 network loading, and is producing at 50% of its rated capacity during these injection periods. 492

<sup>&</sup>lt;sup>17</sup>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

 $\kappa$ : Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

#### 493 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  $s_{\phi,z}^l$ . 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:

$$s_{z,\phi,\bar{l}}^{l} = \sum_{t} \left( \tilde{g}_{t} p_{i,t}^{e} \frac{\partial l_{t,z,\phi,\bar{l}}}{\partial I_{t,z,\phi}} \right).$$

$$\tag{9}$$

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

 $\kappa$ : Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case.

504 and costs.

#### <sup>505</sup> 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:

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

<sup>511</sup> 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

 $\kappa$ : 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 516 non-adopters of PV. We see again that efficient tariffs, at low penetrations, do not shift 517 costs between adopters and non-adopters as PV penetration increases. We also see that the 518 average cost savings for adopters falls as PV penetration increases, highlighting the declining 519 marginal value of solar PV. As PV adopters begin increasing peak network loading, costs 520 fall for non-adopters. This is due to the fact that marginal increases in consumption during 521 periods of peak network injections decreases costs. Note that PV adopters still reduce their 522 energy bills on average at high PV penetrations due to the energy and generation capacity 523 value of the PV installations. This implies that efficient tariffs do not fully eliminate the 524 economic case for PV adoption, even at high penetrations (that is, solar adopters still save 525

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



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

<sup>526</sup> 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.

#### 532 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



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

538 
$$s^{em} = \sum_t (\tilde{g}_t p_t^{em}).$$

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 ( $\phi = 0, p_{t,z,\phi}^{cp} = 0$ ), as discussed in Section 3.<sup>18</sup> We see that the value of avoided emissions is greater than the value of the cost shift in every case.<sup>19</sup>

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

<sup>&</sup>lt;sup>18</sup>The cost shift does not depend on the damages model used.

<sup>&</sup>lt;sup>19</sup>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.  $\phi$ : Flat and RTP-CCC-CP Tariffs

 $\kappa$ : 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 551 Chicago under net metering may drive cost shifts, but may not necessarily be *economically* 552 *inefficient* on average. That is, the average private marginal cost of energy may not exceed 553 the average social marginal cost of energy. However, net metering schemes may still drive 554 cost shifts between adopters and non-adopters as the utility changes rates to recover its 555 residual costs. Second, improving the efficiency of residual cost recovery mechanisms could 556 reduce welfare if the cost of energy does not fully internalize the cost of externalities. This 557 implies that in a second best world without carbon pricing, regulators may face tradeoffs 558 between economic efficiency and distributional equity. 559



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

## 4.5 Interpreting the cost impacts of rooftop solar PV in the con text of residual cost shifts

Given the prevalence of net metering programs in the U.S., it is worthwhile to ask how well 562 PV remuneration under net metering programs matches PV remuneration under an optimal 563 tariff. Figure 17 compares the sum of  $s^{cp}_{z,\phi}$  and  $s^{l}_{z,\phi,\bar{l}}$ —the network capacity and losses cost 564 reductions per kW of solar—with the total residual cost shifts under the assumption that 565  $p_{t,z,\phi}^{cp} = 0$ . In Figure 17, the black lines show the distribution of network capacity and losses 566 cost impacts across "feeders" (zip codes), while the blue vertical lines show the residual 567 cost shifts at 0%, 30%, and 60% solar penetration. We see that, as PV's network cost 568 impacts shrink, the potential cost shift rises. We also see that even at low penetrations, 569 a net metering program in Chicago likely over-remunerates rooftop solar PV for network 570 cost reductions. This latter point implies that, even under aggressive assumptions about the 571 potential network cost reductions of solar PV—that is, even under the assumption that 100% 572 of distribution network costs are marginal—solar PV adoption under net metering schemes 573 will lead to cost shifts. 574

 $<sup>\</sup>kappa$ : Peak Demand PV Case.  $\phi = 0$ .



Figure 17: Residual cost shift vs. distribution network value

 $\kappa$ : 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.

#### 579 5 Conclusions

This paper analyzes the potential distributional impacts of solar PV adoption in the presence 580 of inefficient and efficient rate designs. We leverage a data set of electricity consumption 581 for 100,170 consumers, roughly 60,000 of which live in single-family homes, and data on the 582 income trends of distributed solar PV adoption. We simulate PV adoption among single-583 family homes, accounting for the propensities of customers in different income quintiles to 584 adopt solar. We build a simple model of utility costs to analyze the changes in customer 585 expenditures by income quintile as rooftop solar PV adoption increases. We first model the 586 distributional impacts of PV adoption assuming that distributed PV cannot reduce network 587

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 590 in the presence of tariffs that inefficiently recover residual costs through volumetric (i.e. per-591 kWh) charges. Rooftop solar PV adoption reduces net demand (demand minus generation). 592 When residual network and policy costs are recovered through volumetric charges, this re-593 duction in net demand creates an under recovery of costs; charges for residual cost recovery 594 must increase to ensure cost recovery. This implies that, in the standard electricity tariff, 595 the bills of non-adopters must increase. Given that solar PV adopters tend to be affluent 596 (see Figure 18), average expenditures across all customers in the top three income quintiles 597 decrease, while average expenditures across all customers in the bottom two income quintiles 598 increase under rates with volumetric residual cost recovery. Average annual expenditures 599 across the entire income quintile<sup>20</sup> for the lowest 20% of incomes increase by 6%, 18%, and 600 46% at 25%, 50%, and 75% rooftop solar penetrations, respectively. Average annual expen-601 ditures for non-adopters in the lowest 20% of incomes increase by 13%, 35%, and 80% at 602 25%, 50%, and 75% rooftop solar penetrations, respectively. Meanwhile, customers in the 603 top income quintile that adopt solar nearly entirely eliminate their contributions to residual 604 cost recovery. This very substantial impact may be occurring in some locations today, as 605 rooftop solar penetration has already reached 25+% in some markets, including Hawaii and 606 parts of Australia. 607

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.

<sup>&</sup>lt;sup>20</sup>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 621 charge for marginal network capacity and an energy charge adder for marginal distribution 622 network losses—further highlights the potential benefits of efficient rate design. We first 623 design marginal network capacity and distribution loss charges. We then calculate: 1) the 624 potential network capacity and losses impacts of solar PV under such charges, and 2) the 625 distributional impacts of a tariff incorporating these charges as PV penetration increases. We 626 find that distributed PV can substantially reduce the costs of network capacity and losses in 627 some areas at low to modest penetrations. However, we find large variance in the distribution 628 of these cost reductions, and find that rooftop solar PV at high penetrations may increase 629 rather than reduce costs. We then show that an efficient rate design that incorporates these 630 marginal charges results in significantly lower expenditures for low-income customers at high 631 PV penetrations than does ComEd's default tariff. Additionally, at low PV penetrations, 632 there is almost no change in the average expenditures of the bottom income quintile under 633 these charges. 634

These findings have important implications for rate design. First, that the potential for PV 635 adoption threatens to reverse the redistributional effects of volumetric rates for residual cost 636 recovery. New solutions are needed. Second, that rates that better reflect the time- and 637 location-varying value of energy may be more distributionally equitable than alternatives as 638 the power system incorporates higher penetrations of DERs. Finally, rates that better reflect 639 system costs create opportunities for adopters of DERs like rooftop PV to save money by 640 lowering system costs. These efficient rates avoid the potentially undesirable distributional 641 impacts of net metering under today's time invariant, predominately volumetric rates. 642

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#### 6 Appendices

#### <sup>794</sup> 6.1 Data

#### <sup>795</sup> 6.1.1 Half-Hourly Household Electricity Metering Data

The residential electricity consumption data used in this work come from Commonwealth Edison (hereafter: ComEd).<sup>21</sup> 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<sup>22</sup> 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 806 and residential, should have limited overall impact on our findings. In addition to ComEd's 807 data cleaning for anonymity, we perform our own data cleaning to ensure the integrity of our 808 sample. The data obtained from ComEd contained data on 344,717 customers. However, 809 consumption observations for many of these customers was missing or potentially flawed. 810 Only 278,821 customer have a complete time series of observations. We removed all customers 811 without complete time series. The sum of the half-hourly consumption observations did not 812 match the reported sum of daily consumption for some customers. We removed all customers 813 with at least one case of a deviation of 5% or more between the reported daily energy 814 consumed and the sum of the half-hourly consumption observations. The demographics of 815 the final sample roughly matched that of the original sample, implying that the data cleaning 816 effort did not meaningfully skew the data. 817

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

 $<sup>^{21}</sup>$ Note that this is the same dataset that underpins Burger et al. (2020).

<sup>&</sup>lt;sup>22</sup>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).

Hosting Type	Single-Family		Multi-Family	
Incating Type	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%

Table 2: Breakdown of customer types

We combine the consumption data with socioeconomic data from the 2016 American Com-823 munity Survey (U.S. Census Bureau, 2018). The most detailed geography for which the 824 American Community Survey publishes public data are the Census Block Group (CBG). In 825 total, our sample contains customers in 2,315 CBGs. The geographic boundaries of CBGs 826 are not the same as those of 9-digit zip-code areas. Thus, to match census data to our 827 household-level consumption data, we have to match CBGs to zip codes. We use a data 828 set from Melissa Data for the matching.<sup>23</sup> 1,975 customers are removed from the sample 829 while merging the two geographic data sets because the zip codes do not have corresponding 830 CBGs. 831

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 lowincome 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.

<sup>&</sup>lt;sup>23</sup>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.<sup>24</sup> 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.<sup>25</sup>

Within the consumption data, we focus primarily on single-family homes. The vast majority 850 (more than 99%) of rooftop solar PV adopters live in single-family dwelling, most often 851 owner occupied dwellings (Barbose et al., 2018). We assign customers to income quintiles 852 according to the median income of the census block group within which they live. Table 4 853 contains the breakdown of the number of single-family homes in our sample by income 854 quintile. In Table 4, the  $1^{st}$  Quintile represents the bottom 20% of incomes, and the  $5^{th}$ 855 Quintile represents the top 20% of incomes. The income quintiles are established based on 856 the entire 100,170 customer sample, not on the subset of single-family homes; this explains 857 why the number of customers in each income quintile  $(N_Q)$  are not equal. 858

#### <sup>859</sup> 6.1.2 PV Adoption Income Trend Data

The Lawrence Berkeley National Laboratory collected household-level income data for more 860 than 781,000 solar PV adopters across 13 U.S. states between the years 2000 and 2016 861 (Barbose et al., 2018). These data are summarized in Figure 18. In Figure 18, the 0 to 20th 862 Percentile represents the bottom 20% of incomes, and the 80 to 100th Percentile represents 863 the top 20% of incomes. The income distribution data are relatively consistent across time 864 and states. Through 2016, the largest share of PV adoption in the bottom income quintile 865 was 8% (in Nevada), while the lowest share was 5% (in Washington D.C.). The average 866 share of adoption in the bottom two income quintiles across all states through 2016 was 867

<sup>&</sup>lt;sup>24</sup>For example, high earners may spend time in graduate school.

<sup>&</sup>lt;sup>25</sup>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 868 across states was 21%. Phrased differently, a customer in the top three income quintiles was 869 roughly four times more likely to adopt solar than a customer in the bottom two income 870 quintiles. While there is greater variation across states in the share of adoption in the top 871 three income quintiles, capturing this variation is less critical for assessing the distributional 872 impacts between higher and lower income quintiles. The distribution of PV adoption between 873 the top three income quintiles has remained nearly constant since 2000, while the distribution 874 between quintiles has changed slightly. Due to the relatively consistent income distributions 875 across time and location, we feel the national average income trends are appropriate for the 876 analysis in this paper. 877



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 884 the adoption rates in the bottom two income quintiles to 2040, and assume that the top 885 three income quintiles are all equally likely to install solar.<sup>26</sup> In the "2000 to 2016 Trend" 886 sensitivity, we linearly extrapolate the 2000 to 2016 changes in the adoption rates across all 887 income quintiles to 2040. These data are represented in Table 5. The interpretation of these 888 data are as follows: in the 2016 Distribution case, for every 100 solar adopters in 2016, we 889 would expect roughly 25 to be in the top income quintile, 8 to be in the bottom income 890 quintile, and so on. We describe the use of these data in more detail in Section 2. 891

#### <sup>892</sup> 6.1.3 Solar PV Simulation and Production Data

The second primary source of data used in this analysis are solar insolation and weather 893 data and a solar PV production model. The design and specifications of the model used 894 to translate solar insolation and weather data into solar PV production is outside of the 895 scope of this thesis. The model used, pylib python, is a Python-based tool developed and 896 extensively vetted by Sandia National Laboratories (Holmgren et al., 2018).<sup>27</sup> The model 897 uses solar insolation data and weather (e.g., temperature, wind speed, etc.) data and PV 898 system parameters (e.g., module efficiency, azimuth, inverter sizing, etc.) and estimates the 899 output of the specified solar PV system. We modeled three systems with different azimuths 900 (degree to which the panels are facing south). The output of the model with an azimuth of 901 180 degrees is shown in Figure 19. 902

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.<sup>28</sup>

 $<sup>^{26}</sup>$ 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.

<sup>&</sup>lt;sup>27</sup>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).

<sup>&</sup>lt;sup>28</sup>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.

#### 906 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<sup>29</sup> for SO<sub>2</sub>, NO<sub>x</sub>, PM<sub>2.5</sub>, and CO<sub>2</sub>. 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<sub>2</sub>. The damages models used are the AP2 model<sup>30</sup> and the EASIUR model<sup>31</sup>. The two models

<sup>&</sup>lt;sup>29</sup>The breakdown for seasonal factors is: Winter (November through March), Summer (May through September), and Transition (April and October).

 $<sup>^{30}</sup>$ See Muller (2014)

<sup>&</sup>lt;sup>31</sup>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<sub>2</sub>, NO<sub>x</sub>, PM<sub>2.5</sub>, and CO<sub>2</sub>) at any given time as  $p_t^{em}$ .



Figure 20: Marginal Damages for the RFC Region in 2016

Data source: Azevedo et al. (2017)

#### 924 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.

<sup>932</sup> This Appendix includes sensitivities on the following assumptions:

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

- <sup>934</sup> 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.

#### 940 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.<sup>32</sup> 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-

 $<sup>^{32}</sup>$ 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

 $\kappa$ : 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 lowincome 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





 $\kappa:$  Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2008 to 2016 Trend Case.

<sup>977</sup> solar PV for lower-income groups may not be able to fully counteract the cost shifting im-<sup>978</sup> pacts of rooftop PV adoption under inefficient rates. This is depicted in Figures 23 and <sup>979</sup> 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.

#### 982 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<sup>33</sup> 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

<sup>&</sup>lt;sup>33</sup>Sized according to the peak alternating current (AC) output.



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

 $\kappa:$  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 ( $\phi$ ) 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.

#### 995 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.  $\phi:$  Flat and RTP-CCC Tariffs Income Trend Sensitivity

 $\kappa$ : 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 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  $(s_{\phi,z}^{cp})$  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



 $\kappa:$  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. 1012 The average cost reduction under azimuths of 135° is substantially lower (nearly 66% lower) 1013 than the average cost reduction under azimuths of 225°. This is due largely to the fact that 1014 residential demand tends to peak well after 12:00PM in Chicago, and thus the maximum 1015 coincident demand peaks are more concentrated in these later afternoon hours. This indicates 1016 that if planners or developers were interested in maximizing the network cost reduction value 1017 of rooftop PV, they would favor west-facing roofs or sites. This is consistent with the existing 1018 literature on the value of PV (see, for example, Hummon et al. (2013)). 1019

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.  $\phi$ : 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.

#### 1029 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 1030 distribution network costs. In Section 2.3, We calculate the network cost impact of a marginal 1031 kWh of consumption or production, assuming that the top 200 half-hourly periods of 1032 demand drive distribution system capacity costs. Today, distribution systems are typically 1033 sized to meet demand in the single highest demand hour, plus some margin. Should network 1034 costs be considered marginal according to the single peak demand hour? Networks must also 1035 be able to operate in all hours—should network costs be considered to be marginal across 1036 all hours of demand? The answer to these questions is outside the scope of this dissertation. 1037



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

 $\kappa$ : Peak Demand PV Case. Azimuth: 135. Adoption Probabilities: 2016 Distribution Case.

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

Figures 31 and 32 show the distribution of network capacity cost reduction values of rooftop 1040 PV assuming that distribution network costs are marginal across the top 100 half-hourly 1041 periods (50 hours) and 400 half-hourly periods (200 hours) respectively. For context, the 1042 New York Department of Public Service compensates distributed solar PV units for potential 1043 distribution network cost reductions based on their production during roughly the top 240 1044 hours of peak demand throughout the year (See New York Department of Public Service 1045 (2019)). Comparing with Figure 10 provides interesting insight into the impact of increasing 1046 the number of coincident peak hours. We see that, in this case study, increasing the number 1047 of peak demand hours in which network costs are considered to be marginal slightly increases 1048 the average network capacity cost reduction impact of rooftop solar PV. Likewise, decreasing 1049 the number of peak demand hours slightly decreases the cost reduction impact. While the 1050 impacts are relatively limited, they are noteworthy. 1051



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

 $\kappa:$  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
	Less than \$15,000	10.49%	13.72%
	\$15,000 - \$24,999	8.43%	10.33%
	\$25,000 - \$34,999	9.25%	9.35%
ue	\$35,000 - \$49,999	14.36%	12.37%
con	\$50,000 - \$74,999	20.06%	16.73%
In	\$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%
	0-17	25.37%	22.82%
e	18-24	9.41%	9.79%
β Υ	25-64	53.52%	54.97%
	65+	11.7%	12.42%
	White alone	65.05%	55.91%
	Black or African Amer. alone	16.91%	23.19%
ce	Amer. Indian & Alaska native alone	0.33%	0.30%
Ra	Asian alone	5.43%	6.82%
	Native Hawaiian & other Pac. Isl. alone	0.06%	0.04%
	Other racial designations	12.22%	13.74%
lt	Less than 9th Grade	6.89%	8.32%
neı	Some High School, no diploma	7.62%	7.45%
ini	High School Graduate (or GED)	25.44%	23.94%
tte	Some College, no degree	20.20%	19.07%
al 8	Associate Degree	6.69%	6.36%
oná	Bachelor's Degree	20.43%	21.22%
ati	Master's Degree	9.22%	9.88%
duc	Professional School Degree	2.39%	2.47%
Ĕ	Doctorate Degree	1.12%	1.29%
	Civilian employed	61.73%	60.00%
loy	Civilian unemployed	6.41%	6.39%
mp	Armed forces	0.16%	0.02%
[[ 또]	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

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

 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	







 $\kappa:$  Peak Demand PV Case. Azimuth: 135. Adoption Probabilities: 2016 Distribution Case.





Azimuth Sensitivity

 $\kappa$ : 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

 $\kappa:$  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

 $\kappa:$  Peak Demand PV Case. Azimuth: 180. Adoption Probabilities: 2016 Distribution Case. 400 Coincident Peak Half-Hourly Periods.



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