Cross-subsidies among residential electricity prosumers from tariff design and metering infrastructure

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ABSTRACT

Distributed renewable energy sources (D-RES) are growing, transforming electricity consumers into producer–consumers ("prosumers"). Retail electricity tariffs require new mechanisms to fairly purchase D-RES generation from and transfer costs to prosumers. Otherwise, cross-subsidy (wealth transfers from some prosumers to others) can worsen tariff outcomes. Tariffs depend on metering infrastructure, where two choices can significantly impact cross-subsidies: (a) metering generation and consumption separately, and (b) using advanced metering infrastructure (AMI) that allows for more granular accounting of energy trade. We use high-resolution energy data from 2016 from Austin, TX, USA, to study these impacts in a high-D-RES distribution grid. We consider multiple tariffs and metering scenarios, thus separating their effects. We find that traditional tariffs using legacy metering create median annual cross-subsidy values from 38% to 100% of real costs. However, AMI can reduce these values by 2 to 3 orders of magnitude when a tariff that utilizes AMI's options is used. In contrast, metering generation separately from consumption appears to have little impact on cross-subsidies. Our results have implications for metering infrastructure choices and tariff design for grids undergoing rapid growth of D-RES generation.

1. Introduction

The electricity supply chain is undergoing significant upheaval. As renewable energy sources (RES, renewables) are favored over fossil fuels for electricity generation, they are rapidly displacing conventional plants in many regions. Some of this displacement is happening within distribution grids, where distributed RES (D-RES, e.g. solar photovoltaic panels) are installed. Electricity production thus becomes cleaner and less centralized.

Owners of D-RES typically purchase electricity from a distribution grid retailer. Such retailers purchase electricity wholesale, transfer it via a distribution grid to end-users, and recover costs via tariff subscriptions. These tariffs are designed to meet specific objectives based on specific assumptions (Reneses and Ortega, 2014). However, the increase in D-RES is swiftly upending many of these assumptions, particularly for smaller residential users. For example, these users were often assumed to be passive consumers. Installing D-RES changes these consumers into active producer–consumers, or "prosumers". Consequently, the tariffs they are subscribed to fail to meet multiple of their intended objectives (Picciariello et al., 2015a). In particular, D-RES can impact tariff fairness considerations, i.e. ensuring equal customers pay equal prices for the same good. Past research has shown D-RES can worsen "cross-subsidies", where one consumer subsidizes the product for another (Simshauser, 2016). Thus, tariff design must be revisited to properly account for the impact of D-RES growth.

Tariff design is by nature dependent on how electricity is measured. As D-RES increases, jurisdictions have approached the issue of metering generation from two directions: metering generation and consumption separately (FiT[1] metering) or together (net metering). While the former allows for more versatility in tariff design, the latter is simpler (and thus cheaper) to bill and account and requires a smaller up-front investment in infrastructure. However, the cross-subsidies of most FiT metering tariffs have not been directly compared with net metering tariffs. In particular, there is little prior research on these tariffs regarding a distribution grid with high levels of D-RES (Picciariello et al., 2015a).

Tariff design also depends on the measurement capabilities of grid infrastructure. Advanced metering infrastructure, also known as "smart

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meters", have many benefits and are rapidly being adopted across many regions (Alahakoon and Yu, 2016). Smart meters measure and communicate (and sometimes control) electricity flow with far more time granularity than legacy metering infrastructure. This finer time granularity is particularly important for measuring D-RES generation, which can vary over short time spans. High-resolution measurements are important for electricity pricing, particularly for grid infrastructure costs (Hu et al., 2015). Thus, AMI's influence in tariff design has become a common focus of study, for example in dynamic pricing (Feuerriegel et al., 2016).

Despite these developments, existing literature lacks a comprehensive assessment of how these matters affect fairness within a high D-RES grid. We take a data-driven approach with high-resolution electricity consumption, generation, and pricing data from Austin, TX, USA, for 2016, to understand the influence of tariff and metering choices on this matter. We implement commonly-used and -debated tariff designs that differ in their dependence on (a) FiT versus net metering, and (b) legacy versus smart meters. These tariffs include flat-rate volumetric prices, two-tier Time-of-Use rates, real-time pricing, and demand charges. Our metric of fairness is cross-subsidization, or cost transfers between households subscribed to a common tariff.

Our methods and data differ from most past work in two important ways: first, we use high-resolution per-minute consumption and generation data, which can significantly impact cost calculations (Hu et al., 2015). Less granular rates may prevent some cross-subsidies from being calculated, e.g. in Picciariello et al. (2015b). Second, most past work calculates cross-subsidy by comparing revenues from two tariffs. Our work separates the real costs of electricity delivery from tariff revenue, thus creating a common reference for comparing cross-subsidies between all tariffs.

Our results show significant variation in cross-subsidy. Key insights from our work include (details in Section 6):

1. Using AMI instead of legacy infrastructure appears to significantly impact cross-subsidies. Non-AMI based tariffs exhibit cross-subsidies two or three orders of magnitude higher on the median (dependent on tariff) than AMI-based tariffs.
2. Metering consumption and generation separately (under FiT metering) or together (under net metering) has a far smaller effect on cross-subsidies.
3. Aside from metering choices, tariff design can significantly impact cross-subsidy. When compared against a real-time pricing tariff, a simpler two-tier time-of-use tariff creates an order-of-magnitude increase in cross-subsidies, mainly due to divergences in real-time energy cost from energy value. However, a tariff based on peak demand charges creates cross-subsidies two order-of-magnitude higher by mispricing capacity costs.
4. Price elasticity of consumption does not significantly alter our results.

Thus, metering and tariff choices have varying effects on cross-subsidies within a distribution grid. We discuss the overlaps and divergences in the effects of these choices and form recommendations for high-renewables distribution grids. In particular, the common discussion focus of net versus FiT metering appears less consequential in terms of fairness than AMI versus no AMI. Elasticity may marginally impact cross-subsidy and should be considered; however, its effects on cross-subsidy are far weaker than installing AMI.

In the following section 2, we review previous research related to cross-subsidies in electricity tariffs. Section 3 provides details on calculating costs, cross-subsidies, and demand elasticity. We describe the datasets used in this analysis in Section 4 and their numerical results in Section 5. Section 6 discusses policy implications, and includes some limitations of work and further study options.

2. Background and literature review

Historically, retail electricity tariffs have been influenced by both politics and economics (Yakubovich et al., 2005). An interested reader can refer to Simshauser (2016, Section 3) for a concise historical review. Based on Bonbright's original principles (Bonbright, 1961), Reneses and Ortega (2014) list the following principles for electricity tariff design:

P1. Sustainability or Sufficiency of revenue: Recovering sufficient revenue for grid operation from tariffed consumers.

P2. Equity or non-discriminatory access: Ensuring equal charges for equal power consumption, irrespective of user characteristics.

P3. Economic efficiency: Allocating resources to those who value them most.

P4. Transparency: Clarity in tariff design process and outcome.

P5. Simplicity: Tariff designs being easy to understand and react to for subscribers.

P6. Stability: Controlling the variation of tariff design (tariff formulation) and tariff charges (the values within the formulation) over long time periods.

P7. Consistency with larger regulatory framework: Ensuring that regulation of the electricity sector is not at odds with regulation in (other) public goods.

P8. Additivity of costs elements: Ensuring that the final charge is equal to the added sum of each tariff component.

Realistically, it is impossible to simultaneously adhere to all principles. Hence, tariff design has been a (often political) process of compromise, prioritizing some principles over others (Reneses and Ortega, 2014).

Practical difficulties in measuring product consumption have directly impacted tariff design possibilities. The most common metering approach for residential users, based on volume of energy consumed over a long time horizon (volumetric metering), has limited the diversity of possible tariffs (Borenstein, 2016). Recent increases in D-RES ownership by prosumers can make these tariffs no longer suitable for recovering the costs of electricity generation and transport (Borenstein, 2016; Picciariello et al., 2015a). For these smaller users, retailers and regulators struggle with simultaneously meeting P1 (sufficiency of revenue), P2 (equity), and P6 (stability) (Sakhrani and Parsons, 2010 detail some examples from tariffs used in Spain and Portugal).

These challenges can be partially addressed by advances in metering infrastructure. Advanced metering infrastructure (AMI) can provide instantaneous power measurement and bi-directional information and (in some cases) control signals. These capabilities create many more options for tariff design (Alahakoon and Yu, 2016). Designing tariffs based on hourly pricing has drawn much attention recently (Eid et al., 2014; Fridgen et al., 2018; Sakhrani and Parsons, 2010). AMI can also significantly increase demand elasticity for end-users, making elasticity potentially more important for tariff design.

We focus here on P2, the equity (or fairness) principle, constrained by the principles of revenue neutrality (P1) and tariff stability (P6). One measure of equity in tariffs is cross-subsidy, which occurs when one population of tariff subscribers pays more than they should for a product, while another population pays less (Heald, 1997). High cross-subsidies exist within many distribution grids, mainly because of other tariff design principles taking precedence over equity. Many studies use consumption-based data to calculate cross-subsidies and discuss their implications for various stakeholders (Faruqui, 2010; Borenstein, 2007; Simshauser and Downer, 2016; Passey et al., 2017; Blank and Gegax, 2014; Azarova et al., 2018; Burger et al., 2019b). Although informative, results from these consumption-based studies may not be applicable to high D-RES grids. Increasing D-RES has myriad effects on the distribution grid and on retailers, which cannot be captured by studies based on consumption patterns alone (Picciariello et al., 2015b).

Some past studies of high D-RES scenarios detail these effects for cross-subsidy and equity in general. Johnson et al. (2017) show some
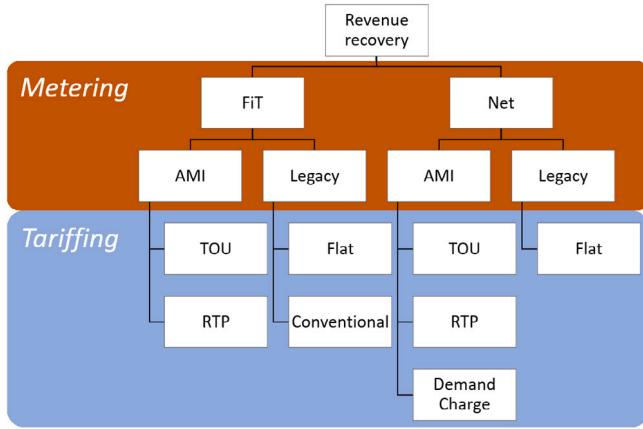
Fig. 1. Tariffs used in this study and their dependence on metering infrastructure.

between-sector cross-subsidies caused by renewables. We focus here on residential within-sector cross-subsidies, i.e. transfers from households to households. Using Australian data, Simshauser (2016) investigated the effect of capacity costs on wealth transfer in a solar-heavy distribution grid. With a similar model, Strielkowski et al. (2017) study wealth transfers between customer groups in the UK. Borenstein (2017) compares wealth transfers resulting from various economic instruments (direct payments, tax incentives, and tariff-based transfers) on the cost distribution of solar PV panels in the US state of California. Picciariello et al. (2015b) simulated various US-based distribution grids and calculated the effects of solar PV panels on tariff-based cross-subsidies. Clastres et al. (2019) similarly simulate French distribution grids and focus on cross-subsidies formed by self-consumption of D-RES generation. Fontana (2016) also study a case of cross-subsidies in a simulation of a Portuguese grid. These past studies do not consider all cost components of electricity trade and/or do not use a representative range of tariffs. The former may mask the actual cross-subsidies of a tariff (Burger et al., 2019a), while the latter would allow us to separate the effects of metering infrastructure and tariff design. Thus, our goal is to conduct such a comprehensive analysis and separate the effects of metering and tariffs on cross-subsidy in a high D-RES grid.

3. Methods

3.1. Choice of tariffs

Tariff design is constrained by its dependence on metering infrastructure (Fig. 1). In a distribution grid with high penetration of D-RES generation, electricity metering requires two important choices. The first choice is whether to meter generation and consumption separately or together. Some jurisdictions (e.g. Austin, TX, USA) choose separate (FiT) metering, while others (e.g. US state of California) opt for metering the two together as net demand (indicated by "Net" in Fig. 1). This choice usually follows D-RES growth policies and how each jurisdiction chooses to compensate D-RES generation.

There is a second choice with regard to devices used for metering. Traditional (or legacy) meters allow for tariff designs dependent on monthly accounting and billing, such as flat-rate and volumetric tariffs. An upgrade to AMI is required for metering and billing with high time resolution or to measure separated capacity costs. Given these metering choices, we choose and formulate tariffs based on common use by utilities, discussion between utilities and regulators, and prior academic studies (Fig. 1). These tariffs are summarized in Table 1.

The tariffs are designed to recover the retailer's costs for electricity supply (and provide its credits for purchase). These costs typically consist of three elements. The first, *energy costs*, relates to the provision

of electricity from the transmission grid or from the utility's local generation units. These costs are usually a function of how much energy is demanded by the grid at each time. The second element, *capacity costs*, consists of the sunk and fixed costs of maintaining network infrastructure. These costs typically reflect returns on investment or maintenance costs, which depend on how much power (i.e. energy flow) the grid can support with specific reliability constraints (Simshauser, 2016). Finally, other costs, such as billing, accounting, and other overhead costs, depend mainly on how many subscribers the retailer has. Similar to most past studies, we assume this final group of costs do not contribute to cross-subsidies and ignore them here.

Crediting D-RES generation of subscribers can also be considered an "energy cost" source. These credits are akin to negative energy costs and are often treated in the same way. In some rate designs, bonuses for D-RES are included in the scheme as a subsidy for (or an "internalization" of) the positive externalities of clean renewable generation. Based on Rábago et al. (2012), we assume the positive externalities of this generation can be best represented and compensated for by a per-kWh bonus.

3.2. Tariff design and cross-subsidy calculations

We first explain our study's assumptions and formulation and then detail calibration methods for each tariff. All prices are from the perspective of households, i.e. negative prices are a funds transfer from utility to household. Nomenclature is listed in Table 2.

For this study, our main assumptions are:

1. Household metering infrastructure is homogeneous: all households either have or lack AMI, and all households measure generation and consumption either together or separately.
2. All households in the study population are subscribed to the same tariff.
3. The retailer, who trades electricity on behalf of the households with the external grid, operates on a revenue-neutral basis. In other words, its revenues match costs.

To model tariff prices and cross-subsidies, we first need to define the billing period T. This is the period within which we take tariff design and subscriptions to be constant. Like most past studies (e.g. Burger et al., 2019a) and most utility tariff update cycles, we assume accounting is done yearly, i.e. T = 1 year. Let M and N represent the household set and the tariff set, with index i and j referring to household $i \in M$ and tariff $j \in N$, respectively. x_i, g_i, and d_i are energy consumption, generation, and net demand of household $i \in M$ at every time interval $t \in T$, where $d_i = x_i - g_i$.[2] Take $p_{max,i}(\tau)$ as peak net power (capacity) use of household i within given time horizon τ; the price per energy unit of consumption (E_j), generation (G_j), and net demand (D_j) are specified based on tariff $j \in N$; and $\alpha_{j,i}$ is any extra credit reimbursed for D-RES generation, for household i and tariff j, aside from regular tariff reimbursements (e.g. reimbursements from the sale of Renewable Energy Certificates). Finally, C_j represents the per power unit capacity price of tariff j, i.e. revenue for all costs related to long term capacity-related investments and maintenance. These prices and values can be a function of time, energy volume over a time horizon, and/or power flow.

With this notation, for each household $i \in M$ and tariff $j \in N$, total tariffed costs of electricity supply, $\theta_{j,i}$, is

$$\theta_{j,i} = \sum_{t \in T} E_j x_i(t) + \sum_{t \in T} G_j g_i(t) + \sum_{t \in T} D_j d_i(t) + \sum_{\tau \in T} C_j p_{max,i}(\tau) + \alpha_{j,i}. \quad (1)$$

Total costs for the entire population M for tariff j is $\theta_j = \sum_{i \in M} \theta_{j,i}$.

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[2] Net demand is separately defined here as it is separately measured in net metering scenarios. This simplifies later comparisons between net and FiT metering.

Table 1
Tariffs used in this study.

Tariff	AMI Required	FiT/Net	Notes	Past Studies / Relevance
Conventional	No	FiT	Status quo	Current tariff in use
Flat-rate	No	FiT/Net	Most common tariff design	Borenstein (2007, 2017, 2016), Picciariello et al. (2015b)
Two-tier time-of-use	Yes	FiT/Net	Intended as middle-ground between simpler Flat-rate and accurate RTP pricing	similar to pilot tariffs in Texas and Netherlands
Real-time pricing	Yes	FiT/Net	Sacrifices simplicity and predictability for accurate pricing	Azarova et al. (2018), Horowitz and Lave (2014)
Demand charge	Yes	Net	Encourages households to flatten demand	Passey et al. (2017), Simshauser (2016), Borenstein (2016)

Table 2
Nomenclature.

Label	Unit	Description
x	kWh	Consumption
g	kWh	Generation (always > 0)
d	kWh	Net Demand
$p_{max}(\tau)$	kW	Maximum Net Power over period τ
E	$/kWh	Consumption price
G	$/kWh	Generation price
D	$/kWh	Net Demand price
C	$/kW	Capacity price
P_g	$/kWh	Green Certificate reimbursement price
α	$	Green Certificate reimbursement cost
δ_p	$	Capacity surcharge per unit of power
δ	$	Capacity surcharge
θ	$	Total costs
L	$	Lump sum payment (extra fixed cost)
i	–	House index
j	–	Tariff index
r	–	Real costs index
t	min	Time unit (1 min)
T	–	Billing period
τ	–	Time horizon
λ	–	Cross-subsidy Ratio
ν	$	(Cross-subsidy) Net difference

Our study assumes revenue neutrality, i.e. all tariffs return the same revenue to the electricity provider, and this revenue is equal to the real costs of electricity delivery (denoted by index r):

$$\forall j \in N : \theta_j = \theta_r. \tag{2}$$

Some tariff calibrations require an additional degree of freedom to ensure this constraint is met. For these, we add a lump sum L_j to each household's bill. This extra charge is distributed equally across households so as not to mask the cross-subsidies inherent in each tariff.

We first detail the makeup of the real costs of electricity trade, then explain each tariff's calibration.

3.2.1. Real costs

As discussed in 3.1, the real costs of electricity trade depend on energy costs and credits and capacity costs, plus any additional D-RES reimbursements. For consumed energy E_r, the real price at each instant is assumed to be equal to real-time locational-marginal prices (RTLMP). These prices are real-time wholesale market clearing prices at each instance in a region, biased by network conditions (e.g. congestion, losses) at each location (or node). The generation credit G_r is set to E_r, plus the bonus $\alpha_{r,i}$, which is based on a per-kWh credit P_g. To simplify, we integrate both as $G_r = E_r + P_g$.

Capacity costs of the utility's distribution grid mainly depend on the maximum net power demand over a time horizon (Simshauser, 2016). Thus, C_r is taken to be a constant per-kW price, which is then multiplied by the net power demand of the utility that remunerates these costs. Since the real costs of consumption and generation are calculated separately, $D_r = 0$.

We next discuss how different tariffs are calibrated with respect to real costs.

3.2.2. FiT metering tariffs

The FiT Metering tariffs consist of tariffs under conventional metering, i.e. the Conventional tariff and the flat-rate tariff; and tariffs under AMI, namely the Time-of-Use and the Real-Time Pricing tariffs (see Fig. 1). Since generation and consumption are metered separately, net demand is not used to price electricity and $D_j = 0$.

(1) Conventional tariff[3]: This is the tariff currently used in the area under study. Our dataset is from households in a neighborhood of Austin, TX, USA, currently subscribed to Austin Energy's residential tariff. This tariff consists of tiered volumetric consumption prices and a flat-rate generation credit. The consumption price $E_{1,i}$ for household i depends on the total monthly consumption of the household and the month of the year ($T_m, m \in \{1..12\}$). Hence, each household sees a different price per month, $E_{1,i}(\sum_{t \in T_m} x_i(t), T_m)$. The generation price G_1 is set to Austin Energy's Value of Solar rate for 2016 (11.3 c/kWh, details in Rábago et al., 2012). Since all values are known, $\theta_{1,i}$ is known. Note that this is the only tariff where consumption prices $E_{1,i}$ differ among households.

As all tariff elements are calibrated by Austin Energy, a lump sum L_1 is added to households as a fixed charge to ensure revenue neutrality (Eq. (2)) is met. This additional cost is levied equally across all households so that it does not contribute to cross-subsidies:

$$\theta_r = \theta_1 = \sum_{i \in M} (\theta_{1,i} + L_1). \tag{3}$$

(2) Flat-rate FiT tariff:

The volumetric tariff described above was designed to promote energy efficiency, at the expense of equal prices. To compare this tariff with one designed for equal prices, we include a flat-rate tariff, i.e. E_2 and G_2 are constant values:

$$\theta_2 = \sum_{i \in M} \theta_{2,i} = \sum_{i \in M} \sum_{t \in T} [E_2 x_i(t) + G_2 g_i(t)] \tag{4}$$

G_2 is set based on a fixed rate calculated as the value of D-RES (e.g. in Rábago et al., 2012), including additional subsidies (i.e. $\alpha_{2,i} = 0$). In addition, capacity is not separately priced ($C_2 = 0$), and the related costs are included in the flat rate for consumption E_2. The only unknown is E_2, which can be calculated by the revenue neutrality constraint, i.e. setting $\theta_2 = \theta_r$.

(3) TOU FiT tariff:

The Time-of-Use tariff depends on AMI, and hence can have differing prices for consumption (E_3) according to the hour of day. We

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[3] To refer to the formulations, we index tariffs $j \in \{1..8\}$. Within the results, however, the tariffs are only referenced by name.

investigate a two-tier TOU which prices electricity during daytime (T_d) and nighttime hours (T_n) separately:

$$E_3 = \begin{cases} E_{3,d} & \text{when } t \in T_d \\ E_{3,n} & \text{when } t \in T_n. \end{cases} \tag{5}$$

We set G_3 to the real-time value of solar generation detailed in the Real-time Pricing tariff below. Since p_{max} is known at each instance, capacity costs can be recovered separately. Hence, the price for these costs is set similar to C_r. In total, we have:

$$\theta_3 = \sum_{i \in M} \sum_{t \in T_d} \left[E_{3,d} x_i(t) - G_3 g_i(t) \right] + \sum_{i \in M} \sum_{t \in T_n} \left[E_{3,n} x_i(t) - G_3 g_i(t) \right] + C_2 p_{max} \tag{6}$$

By setting this equal to real costs θ_r, we have one equation with two unknowns ($E_{3,n}$ and $E_{3,d}$), i.e. one degree of freedom. To solve this equation, we require another constraint. We assume that $E_{3,d}$ and $E_{3,n}$ are proportionally scaled (with scaling factor r_3) based on average RTLMP prices during daytime (P_d) and nighttime (P_n):

$$\begin{cases} E_{3,d} = r_3 P_d \\ E_{3,n} = r_3 P_n \end{cases} \tag{7}$$

With this additional constraint, Eq. (6) can be solved for r_3.

(4) RTP FiT tariff:

For the Real-time Pricing tariff (RTP), consumption prices are taken to be equal to average RTLMP prices per hour. Thus, each hour has its own price, $E_4(t)$. The generation remuneration price G_4 is taken to be E_4 with a known bonus element for reimbursements, $G_4 = E_4 + P_g$. Capacity prices C_4 are set equal to C_r. Hence, θ_4 is defined, but may not meet the revenue neutrality constraint (Eq. (2)). To this end, an equally shared lump sum (L_4) is added:

$$\theta_4 = \sum_{i \in M} (\theta_{4,i} + L_4) = \theta_r, \tag{8}$$

and Eq. (8) is solved for L_4.

3.2.3. Net metering tariffs

Net demand tariffs, as the name suggests, assume a net metering scenario. Hence, $E_i = G_i = 0$, while $D_i \neq 0$. To allow for a comparison of costs with FiT metering tariffs, we assume prices for net metering tariffs, $D_i(t)$, are independent of net demand, $d_{i,j}(t)$.

In all net metering tariffs, D-RES bonuses are accounted for as $\alpha_{j,i}$, separate from the metering of net demand. We assume here that the kWh generated by each solar panel can be accurately calculated based on panel characteristics and weather data. Thus, a lump bonus of $\alpha_{j,i}$ can be calculated based on a fixed per-kWh credit, P_g. This ensures that any cross-subsidies due to choosing net versus FiT metering relate to tariff design itself, rather than how D-RES subsidies are distributed among producers. The following tariffs fall into the Net Metering category (Fig. 1).

(5) Flat-rate net tariff:

This tariff is defined based on a fixed price for net demand at any instance, i.e. D_5 is a constant. Similar to the flat-rate FiT tariff, capacity costs are included in the flat rate, $C_5 = 0$. For θ_5 we have:

$$\theta_5 = \sum_{i \in M} \theta_{5,i} = \sum_{i \in M} \left[\sum_{t \in T} D_5 d_i(t) + \alpha_{5,i} \right] = D_5 \sum_{i \in M} \sum_{t \in T} d_i(t) + \alpha_5 \tag{9}$$

By setting $\theta_5 = \theta_r$, Eq. (9) can be solved for D_5.

(6) TOU net tariff:

The TOU net tariff is defined as a TOU tariff similar to the TOU FiT tariff, where the consumption price formulation is used instead for the net demand price D_6. $D_{6,d}$ and $D_{6,n}$ are defined according to

RTLMP daytime and nighttime prices with a ratio r_6. Capacity costs are calculated similar to the TOU FiT tariff.

(7) RTP net tariff:

Likewise, the RTP Net Demand Tariff is defined to be similar to the RTP FiT metering tariff. D_7 is defined according to average hourly RTLMP prices and a lump sum is added to ensure revenue neutrality. Capacity costs are similarly calculated.

(8) Demand Charge tariff:

The Demand Charge tariff combines real-time pricing of energy costs with a monthly demand charge for capacity costs. The price for net demand at each instance is set similar to the RTP net tariff, or $D_8 = D_7$. To recover capacity costs, for each household i there is a price (C_8) per kilowatt of maximum power demand during each month T_m, $p_{max,i}(T_m)$. The cost for household i over T equals $C_8 \sum_{T_m \in T} p_{max,i}(T_m)$.

The per-kilowatt capacity price C_8 is set to ensure capacity costs are equal to real capacity costs:

$$C_r p_{max}(T) = C_8 \sum_{T_m \in T} p_{max,i}(T_m). \tag{10}$$

The equation can be solved for C_8.

Similar again to the RTP net tariff, the overall energy costs θ_8 are defined as equal to real energy costs θ_r, with a lump sum L_8 required (based on Eq. (2)) to ensure the equality:

$$\theta_r = \theta_8 = \sum_{i \in M} \left[\sum_{t \in T} D_8 d_i(t) + \sum_{T_m \in T} C_8 p_{max,i}(T_m) + \alpha_{8,i} + L_8 \right] \tag{11}$$

3.2.4. Cross subsidies

Cross-subsidy is the ratio of the difference in real versus tariffed costs, divided by the absolute value of the real cost of electricity supply, or

$$\forall i \in M; j \in N : \lambda_{j,i} = \frac{\theta_{j,i} - \theta_{r,i}}{|\theta_{r,i}|}. \tag{12}$$

This ratio is used in most prior literature to calculate and compare cross-subsidies.[4] However, these studies mostly do not consider generation, and/or use a denominator that depends on a tariff's revenue. Thus, their per-household cross-subsidy ratios all include denominators that are well above zero. In our study, some households' real costs are offset by generation credits and the total costs of electricity transfer become close to zero. This leads to the denominator of Eq. (12) being very small, leading to exaggerated cross-subsidy ratios. We include these ratios to allow for a comparison of our results to past studies. However, we rely on the numerator of Eq. (12) instead to compare our tariffs, which represents the "Net Difference" between real costs and tariffed costs:

$$\forall i \in M; j \in N : \nu_{j,i} = \theta_{j,i} - \theta_{r,i}. \tag{13}$$

3.3. Demand elasticity

Electricity for residential households generally has very low demand elasticity. Similar to past research (Borenstein, 2012; Horowitz and Lave, 2014; Burger et al., 2019b), we assume that each household i is demand-elastic in each timeslot t according to a constant elasticity rate ϵ, i.e. $x = A E^\epsilon$ (black curve in Fig. 2). The constant A depends on initial consumption and initial price values, i.e. $A_{i,t} = x_{i,conv,t}/(E^\epsilon_{i,conv,t})$.

We make the following assumptions to ensure a change in prices at each instance induces an appropriate change in consumption:

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[4] Examples of such studies include Azarova et al. (2018), Borenstein (2017, 2007), Simshauser and Downer (2016), Strielkowski et al. (2017), Passey et al. (2017), Johnson et al. (2017).
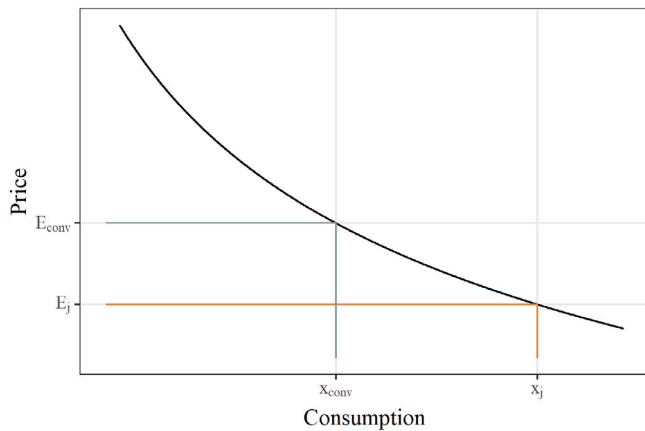
Fig. 2. The Demand Curve (black) shows the relationship between prices and (consumption) quantities.

1. We choose elasticity values at the low ($\epsilon = -0.1$) and high ($\epsilon = -0.3$) ends of past empirical results, similar to past research (Burger et al., 2019b; Borenstein, 2012, 2007). These are close to estimates of short- and long-term elasticity (respectively) for residential households (Labandeira et al., 2017).

2. The initial observed price $E_{i,conv,t}$ is chosen as the conventional tariff's average prices. For our dataset, this consists of increasing-block prices, where the marginal price increases with monthly consumption. However, following Ito (2014), we take the household's average price in each month to be its initial observed price.

3. Demand elasticity functions are applicable to positive prices. However, some timeslots may have negative or zero prices. In these cases, we choose the consumer's observed price to be 0.1 c/kWh, which, when compared to a new price of 10 c/kWh (and $\epsilon = -0.1$), creates a consumption increase of 58%. This happens most for the RTP tariff, for 1.5% of instances overall.

4. For tariffs that separate capacity costs, we assume these costs are discounted from price estimates of the average conventional price, i.e. $E_{i,conv,t}$ is reduced to reflect that it also contained capacity costs. This follows from past evidence that consumers discount (i.e. do not respond to) fixed charges (Burger et al., 2019b).

The Demand Charge tariff is designed to also induce demand elasticity based on the demand charge for capacity costs. Using a similar model, we assume "acceptable" peak demand over a month is dependent on the change in price of capacity costs per kW of peak demand. Thus, all timeslots are checked versus new acceptable peak demand. If lower, all timeslots with higher consumption are lowered to the new peak; if higher, consumption is increased to its original value or to the new acceptable peak demand (whichever is lower). This accounts for the demand charge signal of flattening demand, while allowing for deviations due to exceptionally low (or high) energy prices.

We use these elasticity approaches to calculate a new consumption profile per household per tariff. Much of tariff price calibration depends on real costs, which depend on consumption profiles, which depend on tariff prices. This requires iteration until an equilibrium is reached. Our algorithm iterated on costs until the sum of absolute changes in household bills was less that 0.1% of all bills combined. The final household bills were used to calculate net differences and cross-subsidy ratios.

4. Data

One could quantitatively compare cross-subsidies for various tariffs and metering setups with suitable high-resolution real-world data from a distribution grid and its consumer population. We were able to obtain such data containing all necessary elements for a grid in Austin, TX, USA. These datasets consist of two parts:

1. **Energy consumption and generation data**. This data was obtained with an academic license from the Pecan Street Dataport.[5] The dataset was narrowed down based on multiple criteria:

    (a) Per-minute data available for entire year of 2016. Tariff design and utility costs calculations are done annually, so a duration of one year was chosen as a representative period. 2016 was chosen due to higher data availability.
    (b) Household contains solar photo-voltaic panels.
    (c) Consumption and generation data contained less than 5% missing or erroneous data points.

    144 households' energy data met all criteria and was included.

2. **Electricity pricing data for calibrating tariffs.** This data was collected from two sources local to the energy data. We gathered real-time locational-marginal clearing prices (RTLMP) at the Austin load zone from the transmission grid (and wholesale market) operator, Electric Reliability Council of Texas (ERCOT).[6] These nodal prices are cleared in quarter-hourly intervals. The dataset obtained from ERCOT contained no missing values. Tariff rates from Austin Energy, a local public utility, were also obtained to calibrate tariff values.[7] These two data sources were used for tariff calibration in the following ways:

    (a) ERCOT's RTLMP values were used as real energy costs (E_r) at each time.[8]
    (b) Real capacity price (C_r) was set equal to the capacity price of a similarly-sized commercial or industrial entity on the Austin Energy grid.[9]
    (c) Austin Energy's 2016 Value of Solar rate (11.3 c/kWh) was used for the flat FiT tariff's generation price, G_2, based on calculations from Rábago et al. (2012).
    (d) Texas includes a market for solar Renewable Portfolio Standards (also known as Renewable Energy Certificates), which returns about 2.5 c/kWh for each unit of solar generation (Rábago et al., 2012). We took this value as P_g, i.e. the bonus for D-RES generation.
    (e) The Time-of-Use tariff's high- and low-price hours were chosen similar to pilot tariff schemes from Austin Energy and other local utilities as 6:00–22:00 for daytime and 22:00–6:00 for nighttime.

The final tariff set is summarized in Table 3.

Figs. 3 and 4 show summary statistics of the two datasets. A histogram of annual household consumption (Fig. 3(b)) matches the log-normal distribution expected of a distribution grid with residential

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[5] More information at https://www.pecanstreet.org/dataport/.
[6] ERCOT RTLMP details and values can be found at http://ercot.com.
[7] Dataset and more information at https://austinenergy.com/ae/.
[8] Our data has assumed energy costs equal to the ERCOT RTLMP prices at each instance. While this is commonly used a proxy for the value of energy at each instance (Burger et al., 2019b; Fridgen et al., 2018; Rábago et al., 2012), energy is often procured through multiple other sources, which differ in price compared to real-time market prices, in this case ERCOT RTLMP prices. These deviations are assumed to be relatively small and have been shown to have a negligible effect on cross-subsidies (Borenstein, 2007).
[9] Prices can be found at https://austinenergy.com/ae/commercial/rates/commercial-electric-rates-and-line-items.

Table 3
Tariff values (all values in c/kWh, except C_j in $/kW).

#	Tariff name	Consumption (E_j)	Generation (G_j)	Net demand (D_j)	Capacity (C_j)	REC Credit (P_g)
1	Conventional	E_1	−11.3	0	0	0
2	Flat-rate FiT	E_2	−11.3	0	0	0
3	TOU FiT	$E_{3,d}, E_{3,n}$	$-(E_4 + 2.5)$	0	8.3	0
4	RTP FiT	RTP hourly (E_4)	$-(E_4 + 2.5)$	0	8.3	0
5	Flat-rate net	0	0	D_5	0	−2.5
6	TOU net	0	0	D_6	8.3	−2.5
7	RTP net	0	0	D_7	8.3	−2.5
8	Demand charge [net]	0	0	D_8	C_8	−2.5
–	*Real costs*	*ERCOT RTLMP (E_r)*	$-(E_r + 2.5)$	*0*	8.3	*0*
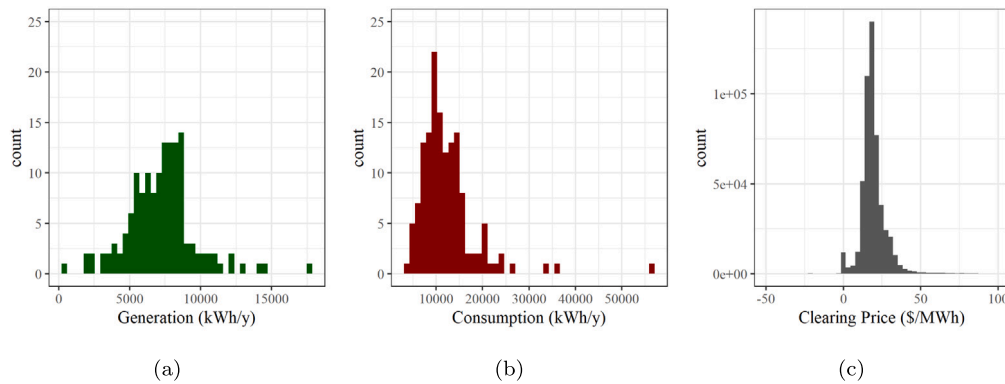
Fig. 3. Total annual per-household generation (a) and consumption (b) distributions and ERCOT RTLMP clearing price distribution for 2016 (c). 0.86% of clearing prices are not displayed in the ercot histogram, as they represented extreme values in the range of {100,1511} $/MWh.

end users in the Austin, TX, area. These households generally experience peak consumption in the early evening hours, mainly due to use of HVAC units (Fig. 4(b)). Annual household generation (Fig. 3(a)) is also distributed as expected, with values close to the 7289 kWh/y average value. A histogram of hourly ERCOT RTLMP values for the Austin load zone for the year of 2016 are plotted in Fig. 3(c). On rare occasions, prices rise above 1000$/MWh. On average, however, these prices fluctuate strongly during the day, with very high prices at high demand moments during the early evening hours (Fig. 4(c)).

5. Results and discussion

For each household, we first calculate the real costs of electricity trade and each tariff's revenues. We then compare these values based on net difference and cross-subsidy ratio. To illustrate this, Fig. 5 shows tariffed revenue and real costs for one sample household from the population. The differing tariff revenues are compared with real costs (Fig. 5, beige) to find the net difference, which is compared within and across tariffs. All net difference values reported here are on a per annum basis.

5.1. Comparison of tariffs based on legacy metering

The residential tariff currently employed by Austin Energy, albeit flat-rate, consists of a volumetric increasing price for consumption. That is, each month a high energy user would pay more per kWh than a low energy user. This policy choice, while sacrificing some welfare transfer, intends to motivate energy efficiency by residential users (Borenstein, 2017). Thus, comparing such a tariff with other tariffs would not only consider cross-subsidies from flattening the temporal dynamics of energy prices, but also from this intentional policy choice. To balance this out, another conventional tariff, a flat-rate fee, was designed and

calibrated to match this volumetric tariff without the added volumetrically increasing prices, and thus without cross-subsidy from the policy instrument (ibid). This Flat-rate tariff is designed in two ways, with one based on Net metering and the other based on FiT metering (Table 3).
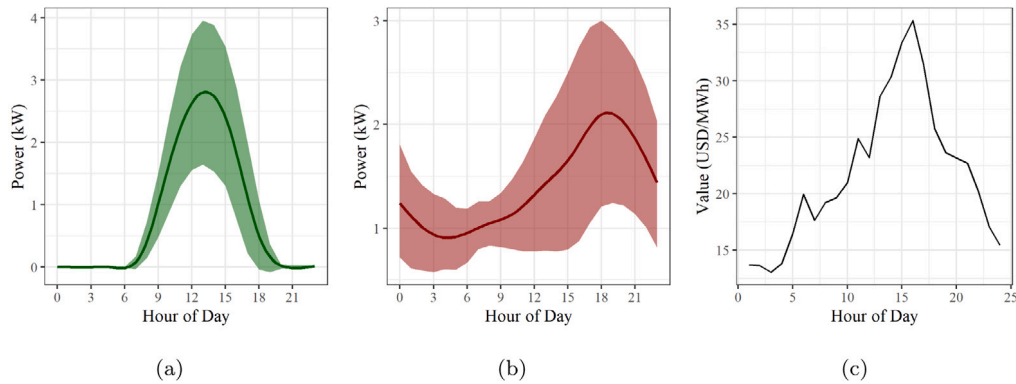
Fig. 6 shows the cross-subsidy spread from the three non-AMI tariffs, per household, sorted based on value. While some households observe fairer costs under a flat-rate tariff (i.e. closer to the horizontal axis), others are put into a less fair position (further to the extremes). However, at the medians, results are marginally different. The median values of positive and negative cross-subsidies (i.e. the median of all positive and all negative cross-subsidy ratios) from the flat-rate tariffs are worse than the conventional tariff (Table 4). In terms of net differences, the flat-rate tariffs see median positive "transfers" of $229.50 (FiT) and $259.07 (Net) and median negative transfers of −$212.53 (FiT) and −$232.64 (Net), while the conventional tariff's median transfers are $157.12 and −$164.59, respectively. Thus, the flat-rate tariffs are marginally worse overall at ensuring cost-causality. The flat fee added for calibration to the conventional tariff reduces some cross-subsidies that are due to capacity costs. These cross-subsidies are larger than the cross-subsidies inherent in the volumetric design of the energy portion of the Conventional tariff. As a result, this tariff maintains lower overall cross-subsidies than the flat-rate tariffs.

### 5.2. Comparison of tariffs based on AMI

Our AMI tariffs consisted of two sets of tariffs (TOU and RTP) dependent on two different metering setups (FiT and net metering). These 4 tariffs are compared with each other and the corresponding flat-rate tariffs in Figs. 7 and 8. Both TOU and RTP tariffs produce far less cross-subsidy than the flat-rate tariffs. In FiT metering (Fig. 7) for example, median net differences for the flat-rate tariff are $229.50 (positive transfers) and −$212.53 (negative transfers). Compare this

**Table 4**
Numerical comparison of tariff cross-subsidies.

Tariff	Prosumers w/ negative Cross-subsidy, NegRatio (% of population)	Median negative cross-subsidy, MedNegCross	Median positive cross-subsidy, MedPosCross	Median household negative costs transfer, MedNegTransfer (USD)	Median household positive costs transfer, MedPosTransfer (USD)
Conventional	64	−0.7234	0.3807	−164.59	157.12
Flat-rate FiT	62	−0.8886	0.4815	−212.53	229.50
TOU FiT	72	−0.05072	0.04877	−7.26	7.75
RTP FiT	45	−0.002041	0.001803	−0.53	0.55
Flat-rate net	63	−1.008	0.5391	−232.64	259.07
TOU Net	48	−0.01953	0.02399	−6.60	6.90
RTP Net	47	−0.002270	0.001954	−0.61	0.55
DC Net	63	−0.302	0.209	−65.8	91.8

Fig. 4. Generation (a) and consumption (b) of households and average ERCOT RTLMP (c) per hour-of-day. Shaded areas indicate one standard deviation (Except for (c), whose standard deviations were too large to display with averages).
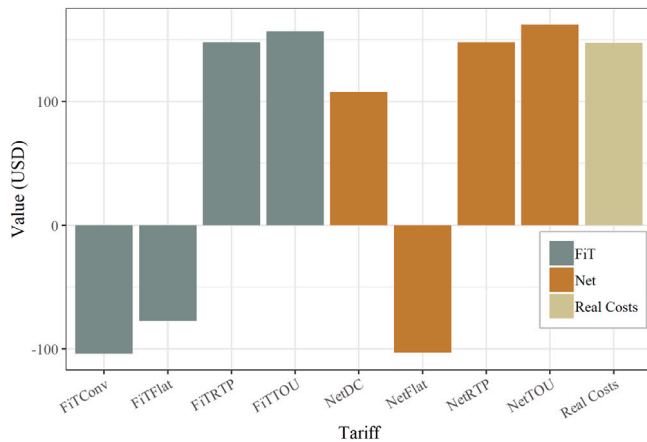
Fig. 5. Sample household costs per tariff and real costs.
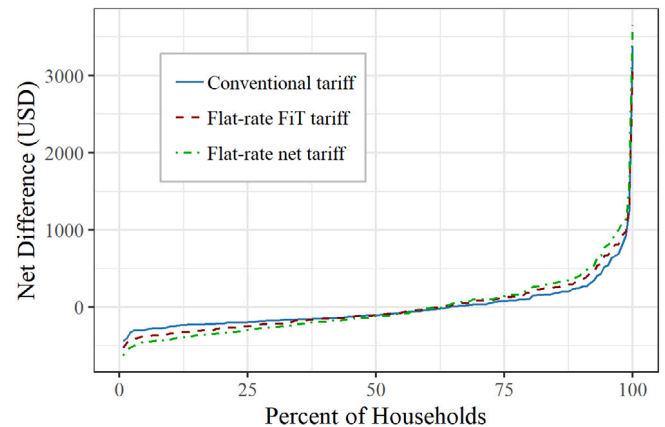
Fig. 6. Net difference (sorted) for the conventional Austin Energy tariff and the flat-rate tariffs under FiT and Net metering per household.

with median positive and negative transfers of $7.75 and −$7.26 for TOU and $0.55 and −$0.53 for the RTP tariff. This 2-order-of-magnitude difference is due to two factors. First, tariffs based on AMI (TOU and RTP) capture the capacity costs of the distribution grid and can recover those separately from the per kWh energy charge. Second, they are able to reflect the temporal dynamics of wholesale energy prices. These both contribute to a significantly reduced cross-subsidy spread, which is reflected in the median values of positive and negative net differences.

The TOU tariff performs similarly to the RTP tariff in most cases (Fig. 9, Table 4). While the cross-subsidies spread between the TOU tariffs and the RTP tariffs are quite different, they are very small compared to the flat-rate tariffs. For example, the TOU net tariff's median positive and negative cross-subsidy ratios amount to 2.4% and

−1.9%, respectively, while those of the RTP tariff are one order of magnitude less (namely 0.2% and −0.2%, respectively).

The TOU tariff is designed to reflect some of the temporal dynamics of energy price fluctuations, while remaining relatively simple in design. That is, it provides a suitable economic signal while reducing some of the cross-subsidies from energy prices. In previous research, simulations have shown that new peaks can form due to consumers reacting to the new price signal (Valogianni and Ketter, 2016). Energy prices are from wholesale market locational-marginal rates for electricity supply at the transmission level, a market in which the utility is assumed to be a price-taker (i.e. its demand changes do not significantly impact market prices). Hence, the formation of these new peaks in a distribution grid is not expected to increase energy prices, and thus energy costs, at peak demand moments. Yet they may cause higher peak demand, thus increasing capacity costs (ibid). A time-of-use tariff's
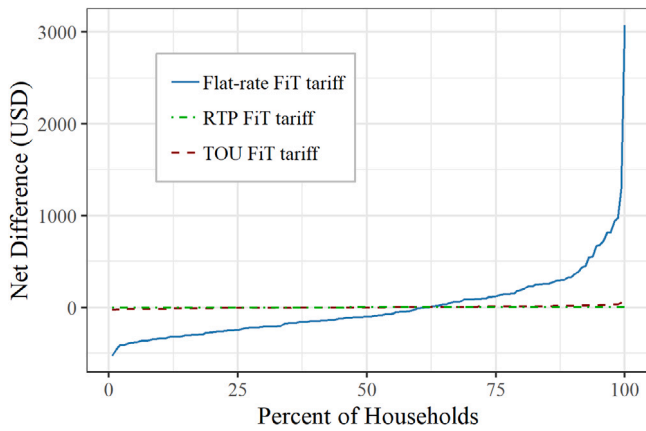
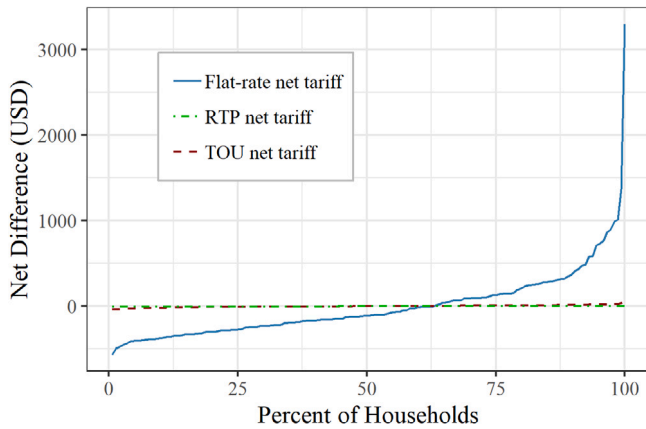Fig. 7. Net difference for FiT metering tariffs per household.

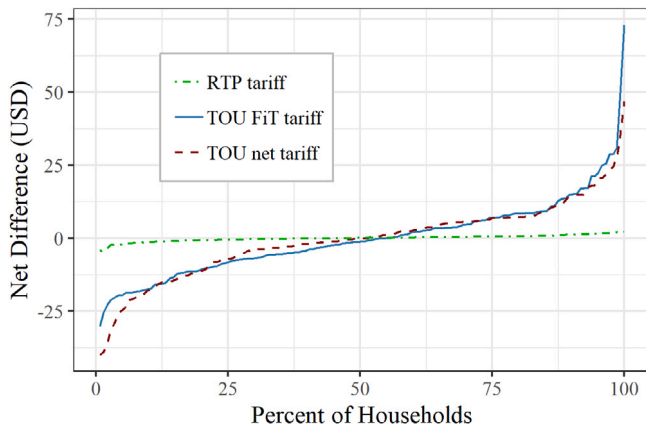Fig. 8. Net difference for net metering tariffs per household.

Fig. 9. Net difference for tariffs based on advanced metering infrastructure (AMI) per household. RTP tariff results under net metering and FiT metering are very similar, so only one line is plotted.
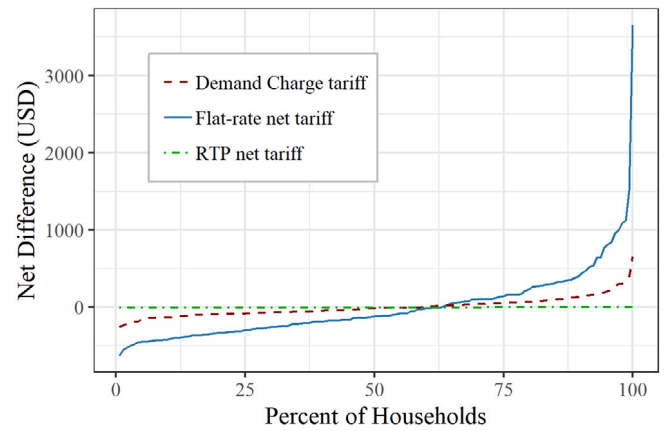

Fig. 10. Net difference for Flat-rate, Demand Charge, and RTP tariffs, all under net metering, per household.

algorithm, such a tariff often requires that a household installs automatic control and monitoring of switchable devices (i.e automated demand response) in order to act on the economic signal. In other words, the economic signal is both "difficult to decode" and "difficult to react to". Moreover, these devices need to be able to elicit and/or represent consumer preferences in a way that is simultaneously effective in demand response and accurate in its elicitations/representations (Bichler et al., 2010). Hence, we see that the tariff indeed performs best in cost causality, at least by an order of magnitude compared to the TOU tariff. However, it lags behind the TOU tariff and others in simplicity and providing suitable economic signals.

5.3. Evaluating the demand charge tariff

The Demand Charge tariff is designed to recover energy costs based on the RTP tariff while offering a net demand flattening signal to households. Despite sacrificing some cross-subsidy, this pricing ensures that suitable economic signals are given to households for stabilizing net demand. The cross-subsidies for this tariff, with median costs transfers of −$65.8 and $91.8, are less than that of the Flat-rate Net tariff (medians −$232.64 and $259.07) and more than that of the RTP Net tariff (medians −$0.61 and $0.55, Fig. 10).

Implementing this tariff can significantly increase demand elasticity for the capacity portion of electricity costs. These costs typically account for about 60% of a distribution grid's costs, (Simshauser, 2016) with percentage being generally lower for higher-density grids. In this study's case, these costs were about 55% of total costs (excluding generation credits). Most residential households experience demand peaks at similar times. However, there are differences between individual demand peaks and the distribution grid's demand peak. Consequently, there is cross-subsidy when households are charged based on individual peaks (as in the Demand Charge tariff) whereas costs depend on the utility's peak demand (as is priced in the RTP tariff). Given that the charge depends on maximum kilowatts used per month, there is a direct incentive for households to flatten (or reduce) their demand, rather than shift it to a period where electricity use is "cheaper", as in the TOU and RTP tariffs. As this demand flattens, updates of capacity costs would reduce the DC tariff's demand charge, leading to an equilibrium of all elastic demand flattened, without direct increases in other (energy) costs. Hence, this tariff can be expected to consistently motivate a reduction in overall peak demand, and thus capacity costs, in the long run.

prices are not reactive to such peak demand changes and thus do not provide a suitable economic signal for peak demand reductions in the long term. A possible solution for passing on such an incentive would be the Demand Charge tariff, which is discussed in the next subsection.

The RTP tariff is designed to be the least cross subsidy-inducing tariff as cross-subsidies from both energy and capacity costs are mostly removed. However, this tariff's pricing mechanism is difficult for households to act on. Even with the presence of a suitably accurate prediction

5.4. Comparing fit metering and net metering

The FiT and Net metering tariffs perform relatively similarly in cross-subsidy (Figs. 6 and 9). The primary costs of electricity trade depend on energy and capacity for the utility. Both these costs components depend on the net demand of the entire grid as a function of time. Hence, the choice of metering generation and consumption separately or together cannot be expected to significantly influence costs of electricity supply.

The same cannot be said for the credits given for generation resources. These credits often are energy prices over time, plus any subsidies given by local, national, or international governments or institutions. Energy prices, similar to electricity supply, depend on net demand per time. Subsidies, however, often depends on the D-RES unit itself; sometimes the nature of the resource (e.g. whether it is a wind-based or solar-based unit), often also the total electricity produced by the unit. In the case of our dataset, in Austin, TX, USA, these additional credits take the form of the Renewable Energy Certificate reimbursement, calculated as 2.5 c/kWh (Rábago et al., 2012). Without separate measurement of generation via a feed-in tariff, this reimbursement cannot be accurately credited. Thus, the policy goal of promoting renewable energy uptake depends on this metering choice. On the other hand, there are multiple ways this promotion can happen without incentives that depend on precise generation metering. Examples of these can be found in Germany (Yildiz et al., 2015) and the US state of California (Borenstein, 2017). In this article, we separately account for these costs, and thus they do not contribute to cross-subsidy. The study of which form of subsidy best promotes uptake of renewables is a topic for future analysis.

As real costs between FiT and net metering cannot be expected to differ, we turn our attention to tariff revenue. We find that our (generalized) tariff setups do not create significant differences between net metering and FiT metering. For the flat-rate tariffs, the differences between FiT and net metering can be reduced to choosing two different flat rates, or just one flat rate. Aligning with intuition, we find that using two flat rates creates a fairer scenario with cross-subsidies curves closer to the horizontal axis in Fig. 6. However, this difference is far smaller than the difference between non-AMI and AMI-based tariffs. For TOU and RTP tariffs, we find similar results, mainly due to similar differences between using two rates versus one. Consequently, we find that measuring generation and consumption separately (under FiT metering) or together (under Net metering) does not affect cross-subsidies as strongly as implementing AMI.

5.5. Demand elasticity effects

Finally, we examine the effect of demand elasticity on the comparison between net and FiT metering, and between AMI and non-AMI tariffs.

Elasticity affects the cross-subsidy rates of each tariff in differing ways, shown in Figs. 11 and 12. For the flat-rate tariffs in both net and FiT metering, elasticity has a minimally increasing effect on cross-subsidies (Figs. 11(a) and 11(b)). This is mainly because the flat-rate tariffs have prices close to the initial price at consumption, which also includes capacity costs. Hence, a user has little incentive at each instance to reduce or increase consumption. Tariffs based on legacy metering show the same cross-subsidy rates, with little dependence on elasticity.

The case for AMI-based tariffs is more nuanced. For the TOU tariff in both metering setups, we also find that elasticity increases cross-subsidies (Figs. 11(c) and 11(d)). However, the effect is stronger than for the legacy tariffs. Compared to the flat-rate tariffs, the price signals for TOU tariffs are more divergent from initial prices. Thus, consumers react with stronger changes in demand, causing further cross-subsidy. For the RTP tariff, the results are reversed (Figs. 11(e) and 11(f)). As elasticity increases, both net and FiT metering-based RTP tariffs show

significant decreases in cross-subsidy, with net difference curves closer to the horizontal axis. The RTP tariff is designed to signal the most cost-reflective price to end-users. Consequently, any change in consumption would lead to tariff revenue being closer to real costs, i.e. reduced cross-subsidies.

We witness increasing cross-subsidies for the DC tariff as well (Fig. 12(a)). The demand charge misprices capacity costs, which encourages households to change their monthly peak. Indeed, the sum total of all household monthly demand peaks decreases if there is elasticity (with larger decreases with more elasticity, Fig. 12(b)). However, demand charges signal for reductions in a household's peak, not on the grid peak. Thus, users often change demand at times different from the grid peak hour, with little benefit for grid costs. Surprisingly, we find that the grid peak instead is higher for high elasticity scenarios (Fig. 12(b)). This indicates that the demand charge indeed gives poor signals for reducing grid costs, with worse results in high elasticity scenarios. This mirrors predictions by Borenstein (2016), which appear extensible to a high-D-RES grid.

We can compare the effects of elasticity to those of AMI and net-versus-FiT metering. From this relative perspective, elasticity's effects are weak. The ratio of median net difference for flat-rate FiT and TOU FiT tariffs (absent elasticity) is 29.21 on the positive (losing) side and 29.09 on the negative (winning) side. We can compare this with a similar ratio for high- and zero-elasticity results for the tariffs most influenced by elasticity (the RTP FiT or Net tariffs). This ratio is 1.98 (positive side) and 1.57 (negative side), far lower than differences between AMI and non-AMI based tariffs. Hence, elasticity's effects are far weaker than AMI, but similar to or stronger than net-versus-FiT metering choices.

6. Conclusion and policy implications

Electricity has historically been thought of as a public good and its supply (and consequent pricing) has been as much subject to politics as to economics (Yakubovich et al., 2005; Reneses and Ortega, 2014). As a result, tariff design has sometimes followed economically suboptimal but politically viable paths. With an increasing share of D-RES, a distribution grid subject to democratic decision-making can be politically bound to pursue tariffs that do not cause widespread resentment. Some (socially progressive) tariffs have been designed to transfer costs from the vulnerable to the privileged; despite their higher cross-subsidies, they have been considered acceptable (Heald, 1997). For a distribution utility organized as a highly regulated and non-profit entity, we can expect two metrics to influence decision-making; (1) the ratio of subscribers negatively impacted, and (2) how strongly they are affected. For our study, the ratio of prosumers paying less than their real costs (NegRatio) is above 50% for tariffs based on legacy metering (Table 4). This is often the equilibrium for current tariffs (Borenstein, 2007; Simshauser and Downer, 2016). However, a NegRatio above 50% implies that in a high D-RES grid using conventional tariffs, a tariff change would *negatively impact most subscribers* and would be unpopular. The value of the cost transfer (median negative transfer, MedNegTransfer, and median positive transfer, MedPosTransfer) define the pressure to support new tariff designs. In simpler terms, while NegRatio shows how much of a subscriber group would support tariff design change, MedPosTransfer and MedNegTransfer indicate how strong that support would be.

While there is a big benefit overall in switching from a traditional tariff to a less cross-subsidizing tariff, the initial unpopularity makes such a change difficult. This has been documented for industrial and commercial users with only consumption; Borenstein (2007) has recommended a payback mechanism for reducing the significance of the initial overall cost increase for the majority of negatively affected users. However, for such a payback mechanism to lead to a long-term (closer to) optimal solution, end-user demand must become (more) elastic (ibid). Historically, industrial and commercial consumers have
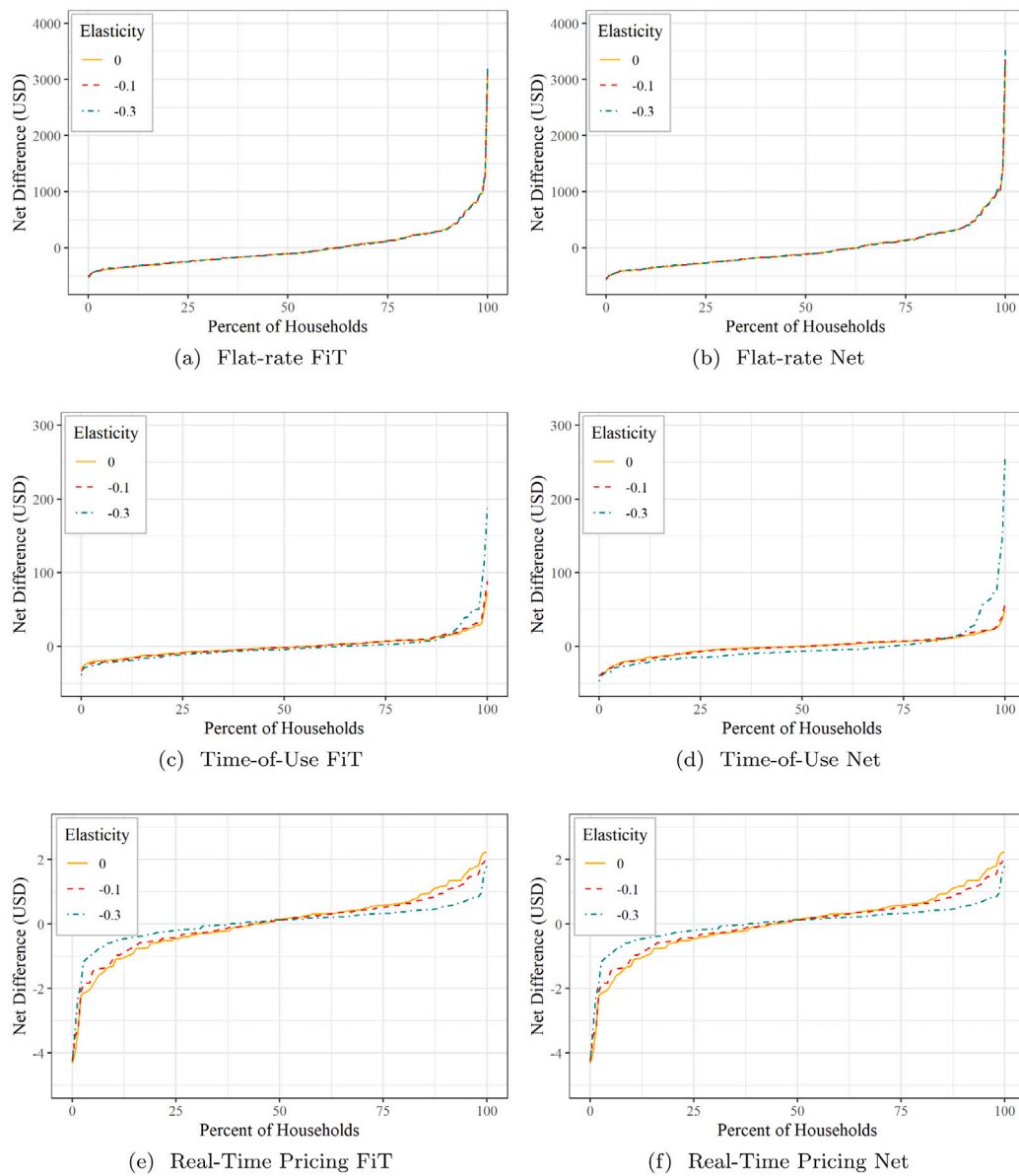
Fig. 11. Net difference sorted per household per elasticity rate (colors). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
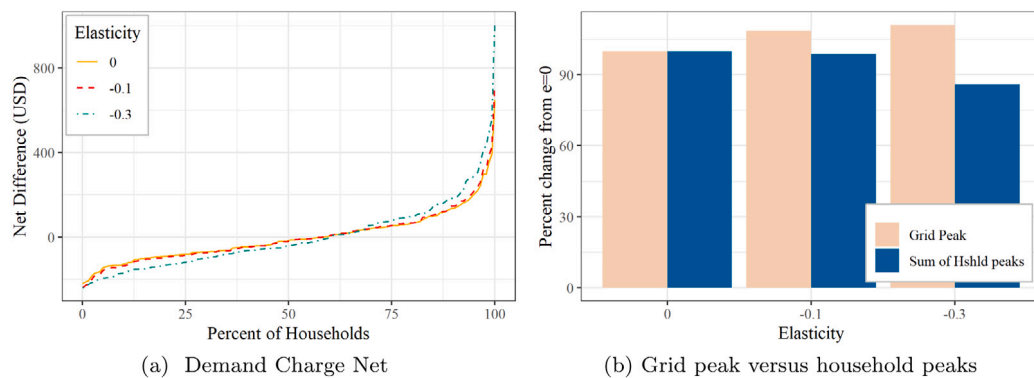

Fig. 12. Net difference sorted per household for Demand Charge Net tariff 12(a) and overall population peak versus sum of individual household peaks, per elasticity ratio, as percentage of zero-elasticity case 12(b).

had higher demand elasticity than residential users. This may still hold, but the advent of AMI may significantly boost residential demand elasticity (Alahakoon and Yu, 2016). Hence, such a payback mechanism may work for residential users in the future.

Table 5
Qualitative comparison of tariffs.

Tariff	AMI required	Short-term economic signaling	Long-term economic signaling	Energy costs cross-subsidies	Capacity costs cross-subsidies	Precise transfer of D-RES subsidies
Conventional	No	Poor	Average	High	High	Yes
Flat-rate FiT	No	Poor	Poor	High	High	Yes
TOU FiT	Yes	Good	Poor	Low	Low	Yes
RTP FiT	Yes	Average	Average	Low	Low	Yes
Flat-Rate Net	No	Poor	Poor	High	High	No
TOU Net	Yes	Good	Poor	Low	Low	No
RTP Net	Yes	Average	Average	Low	Low	No
DC Net	Yes	Poor	Poor	Low	Medium	No

There is a separate question of how the costs of AMI compare to the benefits. The costs of AMI have been well documented, both in utility reports and in academic articles (for example see Feuerriegel et al. (2016)'s cost–benefit analysis of AMI for demand response). Some studies have investigated the benefits of tariffs dependent on AMI (citations towards end of Section 2). We are not aware of any prior analysis focused on AMI's impact on cross-subsidies in a high-D-RES grid. However, a cost–benefit analysis of AMI requires weighting the benefits of cross-subsidy against other benefits and costs. It is not clear what these weights would be: e.g. how the difference between median cost transfers for the Flat-rate FiT and the TOU FiT tariffs (a difference of $157.33) translate into a value stream for AMI. Determining these weights enters the territory of what can be considered "due" and "undue" discrimination. Heald (1997) and Yakubovich et al. (2005) describe these considerations and clarify that they do not respond well to attempts to be quantified. They, and tariff design in general, are often matters of public debate. Hence, we focused our study on quantifying cross-subsidies and leave such value judgments to policymakers.

In this study, we used two datasets: one of energy (consumption and generation values over time) and one of prices (market prices, tariff calibrations, etc.). Both datasets are strongly region-dependent. Energy consumption is a slave to weather and household habits, and generation depends on weather and location. Additionally, prices depend on many factors, including regulations, weather, demand, and regional geography. This implies that the quantitative results can be expected to change per region and this analysis mainly holds for Austin, TX. However, our methods can be applied for any region, should the aforementioned data be available. The main influencers in our analysis are weather and electricity wholesale market prices, so similar results can be expected for regions similar to Austin, TX, in these two matters. However, a qualitative interpretation of these results should hold across regions as well. For example, while the difference in cross-subsidy between the Flat-rate tariff and RTP tariff might be smaller in a region with fewer sunlight hours per year, the RTP tariff would still perform far better. From this point onward, a more qualitative discussion follows, intended to be generally applicable to other regions.

Our study shows that the differences between FiT and net metering are dwarfed by differences between non-AMI and AMI. Net metering is well-known to create distortion by pricing generation and consumption together, leading to many problems including cross-subsidies (Borenstein, 2017). However, in the hypothetical scenario of a grid with rapidly expanding D-RES generation, policy-makers concerned with cross-subsidies should prioritize AMI implementation over installing extra meters for generation sources.

Choosing a specific tariff (e.g. TOU, RTP, or DC) under an implemented AMI system can also impact cross-subsidies. The cross-subsidies in the TOU tariff entirely result from divergences in real-time electricity value from the price of each tier at each minute. These divergences mostly disappear for the RTP tariff, which more closely follows real-time value and finds median cross-subsidies of one order-of-magnitude lower. The DC tariff creates additional cross-subsidies on top of the RTP tariff; these cross-subsidies are due to capacity value being different from capacity charges. As discussed in Section 5.3, household monthly peaks are often misaligned and thus misrepresent the true capacity costs for which a household is responsible. These differences cause cost transfers between households, higher by one order of magnitude than those of the TOU tariff. Hence, the DC tariff and TOU tariff create cross-subsidies, but from distinct sources and in differing amounts.

Our conclusions appear to be relatively agnostic to household demand elasticity. Even with high elasticity, AMI-based tariffs strongly outperform non-AMI-based tariffs whereas differences between FiT and net metering are minor. The effect of elasticity itself is also comparatively small. Elasticity appears to be a weaker concern when considering the effects of metering setup on cross-subsidies.

Reducing cross-subsidies is often considered good. However, its importance is sometimes diminished by more pressing concerns, such as sending proper economic signals to end-users. We summarize these conclusions in Table 5. The economic signaling aspects of various tariffs have been discussed extensively in and follow from past literature, e.g. Azarova et al. (2018). The cross-subsidy values for energy and capacity costs are higher for flat rate tariffs than for the TOU, RTP, and DC tariffs. On the other hand, precise transfer of D-RES subsidies depends on their being measured separately (see e.g. Verbruggen and Lauber (2012)). In this respect, FiT tariffs are better than Net tariffs. Overall, we can formulate a suitable tariff design in a high-prosumer grid. A Time-of-Use tariff for energy prices may offer the best middle ground between simplicity and cost causality. A peak-coincident capacity charge for capacity costs may provide poor signals for reducing the grid peak, but minimizes cross-subsidies. For generation credits, a separate feed-in tariff designed with a premium over energy rates may be the optimal design.

Our analysis of cross-subsidy in a high-DRES distribution grid has two main conclusions: There is little difference between FiT and net metering, and there is a large difference between using and avoiding AMI. In addition, these conclusions appear unaltered by demand elasticity. Our results are based on a numerical analysis of household, market, and retailer data from 2016 from Austin, TX, USA. Insofar as electricity consumption and generation and trade costs are similar to Austin, TX, the quantitative results may be valid for other locales as well.

6.1. Future work

With regards to tariff design, this analysis was not intended to explore the full design space. Instead, we picked common tariffs within that space and used them to describe the various dimensions along which tariffs can differ, leading to various economic and political consequences. These consequences are often not only a function of quantitative metrics, but also regional and local infrastructure and politics. One tariff may work very well in Austin, TX, but perform poorly in other regions. In addition, all tariff design changes require transition management, e.g. paybacks to losing households that will compensate for the higher (but fairer) costs they face.

Elements of this transition management are suitable for future research in this area. One such topic can be the payback mechanisms that most suitably compensate losers from tariff changes. In addition, Picciariello et al. (2015b)'s simulations notwithstanding, there is little written previously about how increases in D-RES affect cross-subsidies. We intend to continue this research with such an investigation.

CRediT authorship contribution statement

Mohammad Ansarin: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation. **Yashar Ghiassi-Farrokhfal:** Conceptualization, Methodology, Validation, Formal analysis. **Wolfgang Ketter:** Conceptualization, Methodology, Validation, Formal analysis, Supervision. **John Collins:** Conceptualization, Methodology, Validation, Formal analysis, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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