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Grid impact of non-residential distributed solar energy and reduced air emissions: Empirical evidence from individual-consumer-level smart meter data

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HIGHLIGHTS

- Empirical estimation of the impact of non-residential distributed solar panels.
- Reduction in electricity purchased from the grid much smaller than solar electricity.
- These consumers do not reduce their monthly maximum demand in July and August.
- Solar rebound effects are important for evaluating the environmental benefits.

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ABSTRACT

Most existing assessments of the energy saving and environmental benefits from distributed solar panels assume that the entire amount of electricity generated by distributed solar panels goes to replace the same amount of electricity needed from the electric grid. However, such an assumption can overestimate the actual environmental benefits because it incorrectly ignores the existence of rebound effects – increases in energy service usage. We provide the first empirical evidence of the grid impact of non-residential distributed solar energy and the associated reduced air emissions. Using consumer-level high frequency electricity consumption and solar panel installation data from Arizona, United States, we estimate the actual hourly reduction in electricity needed from the grid of commercial and industrial consumers through an econometric analysis. We show that this reduction is much smaller than the actual solar electricity generation. We also show that business distributed solar consumers create a further challenge to the utilities by not reducing their monthly maximum demand in July and August. Lastly, we calculate the benefit of reduced air emissions by multiplying the measured hourly reduction in electricity purchased from the grid by the marginal emission factors of CO_2, SO_2, NO_x, and particulate matter. We estimate that the annual benefit of reduced air emissions from an average-size business distributed panel system is $1147.

1. Introduction

Recent scientific evidence [1,2] of global warming highlights the urgent need for deep de-carbonization. The UN Intergovernmental Panel on Climate Change report [1] indicates that "In 1.5 °C pathways […] renewables are projected to supply 70–85% (interquartile range) of electricity in 2050 (high confidence)." Such projection necessitates a much wider adoption of solar electricity generation [3–6]. Indeed, there are various types of state and sub-national policies which provide incentives for consumers to adopt distributed solar panels, such as feed-in tariffs, net metering, tax credits, and direct rebates [7–10]. To justify these government programs, policymakers, climate scientists, and environmental researchers need to accurately quantify the climate and environmental benefits associated with distributed solar energy as well as the impact on the electric grid.

Existing studies and policy reports generally use the amount of

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electricity generated by distributed solar panels to replace the same amount of electricity needed from fossil fuel electricity generation. [11–17] The climate and environmental benefits of distributed solar energy in existing studies are calculated by multiplying the marginal emissions damages by the amount of solar electricity generated. Most integrated assessment models (IAMs) currently use such an approach [18,19]. The obvious logical flaw of this approach is that the usage of solar electricity might not reduce the usage of fossil-fuel electricity in a one-to-one fashion. It is completely conceivable that consumers increase their overall electricity consumption when solar energy becomes available if they perceive a zero marginal cost of electricity generated by solar panels- so-called solar rebound effects [20]. Electricity consumers typically purchase electricity from utility companies. After net-metered consumers adopt solar panels, they first consume the solar electricity generated by their own solar panels, and any unused solar electricity is sold back to the grid. This lowers their electricity bill payment and their average effective electricity price [20]. When the average electricity price falls, consumers increase their electricity consumption [21].

There is already empirical evidence of such solar rebound effects due to average electricity prices falling in the residential sector [20]. While rebound effects have been discussed in the energy efficiency literature [22–26], solar rebound effects are rarely studied except for a few empirical studies. Deng and Newton [21] focus on residential feed-in-tariff solar customers in Australia and use quarterly electricity data; they find that residential adoption of solar panels is associated with an electricity consumption increase of 19%. Havas et al. [27] use monthly electricity consumption data and find a 15% rebound effect for solar households in Australia. Qiu et al. [20] use high-frequency daily and hourly data and find that net-metered residential solar consumers in Phoenix, Arizona (United States) have a rebound effect of 18%. Spiller et al. [28] use high-frequency electricity data and find that residential solar consumers in Austin, Texas (United States) have a rebound effect of 9%. Finally, Toroghi and Oliver [29] use numerical simulation to estimate that residential solar rebound effects are between 2.9 and 5.8% in Fulton County, Georgia (United States). Also, using high-frequency data of households in Australia, La Nauze [30] provides empirical evidence that solar consumers do indeed increase their electricity expenditures. Because of the solar rebound effects, empirical estimation of the change in electricity consumption of distributed solar consumers is important which is the net change after factors such as rebound effects. However, such empirical assessment is lacking for the non-residential sector. We hypothesize that such solar rebound effects also exist for business consumers. The electricity consumption of a business not only depends on providing a service or a product but also on the thermal comfort of its building occupants [31] as well as building energy management practices [24]. Business consumers might change the ways they operate the business or the way they use heating, cooling, lighting, or electronics in the building [32], which can lead to solar rebound effects. The temporal time scales of price changes in the solar rebound effects estimated in the existing literature of the residential sector include quarterly [21], daily [20], and hourly [30]. In our study, we use the hourly time scale.

The problem being solved by this paper is what are the grid impact of non-residential distributed solar energy and the change in air emissions due to the change of electricity purchased from the grid. A key limitation of current studies on the solar panel impact assessment of business consumers is that most existing studies on solar panels in commercial buildings are based on simulations from engineering models instead of observable usage data. These studies use engineering simulation models such as eQUEST to study the impact of solar energy technologies on the energy performance of commercial buildings [33,34], collect actual performance data of just one or a few buildings to conduct a case study [35,36], or discuss potential applications of solar energy technologies in commercial settings [37,38].

Our study makes four important contributions to the existing literature. First, to the best of our knowledge, we provide the first empirical evidence of the impact of distributed solar panels on business consumers' hourly electricity consumption. We define business electricity consumers as firms, rather than individuals or households, that directly pay electric bills to utilities. Business electricity consumers include both commercial and industrial electricity consumers, and are responsible for 62% of electricity consumption in the U.S. as of 2017 [39] and 63% of the worldwide consumption as of 2016. [40] Business distributed solar consumers constitute a significant portion of the total distributed solar panels and are therefore important for mitigating climate and environmental damages from fossil fuel consumption. In 2019, the new non-residential distributed solar PV deployment (including distributed solar panels installed by commercial and industrial, non-profit, and government entities) was about 1516 MW in the U. S., which was about 71% of all distributed solar panel new installations of that year in the U.S. market. [41] Despite the importance of the business sector, there has been a lack of empirical studies using data on actual solar panel installation and electricity consumption for the commercial and industrial sectors [42].

Second, we use a rich dataset of consumer-level hourly smart meter electricity-usage data for more than 17,000 business customers, as well as the solar panel installation information for more than 300 business solar customers between 2013 and 2018 from Arizona, United States. Data availability enables us to apply more robust methods to provide a better estimation of the actual change in electricity consumption due to solar panel installation. High-frequency data is also essential for estimating the benefit of reduced air emissions when controlling for the potentially different magnitudes of the rebound effects by hour of day.

Third, we estimate the change in maximum monthly electricity demand from solar panel adoption. This is important because the increasing penetration of distributed solar energy has created an ongoing tension between electric utilities and distributed solar development. [43–45] Electricity consumers with distributed solar energy reduced their payments to the utilities, leading to the utilities enjoying less revenue than before. In the case when there is no demand charge for electricity consumers, such tension will be exacerbated, because electric utilities need to make a large amount of upfront investments such as in transmission and distribution infrastructure (i.e., fixed costs) to meet the maximum demand, not the average demand, of all consumers [46]. Demand charge is a type of electricity price charged based on the monthly maximum electricity demand of a consumer (i.e., the highest hourly electricity usage of a month). If there is no demand charge, then utilities will mainly rely on electricity sales to recover their upfront investment [44,47]. Furthermore, if the distributed solar consumers are not reducing their maximum monthly electricity usage, then their reduced payments to the utilities imply that they are not paying for their proper share of using the grid infrastructure. As a result, some utilities may increase their energy price for all of their consumers, including non-solar consumers, leading to the ongoing debate about the distributional or equity impact of distributed solar energy.

Fourth, we provide a more precise assessment of the reduced air emissions due to distributed solar panels adopted by business consumers, using the actual hourly change in electricity usage instead of the solar electricity generation. It is estimated that governmental financial incentives can reduce the costs of distributed solar panels paid by adopters by 30–50% [48]. These government programs cost the taxpayers a significant amount of money. A natural question to the policymaker is whether the cost of these programs can justify the gain. Climate and environmental benefits constitute an important aspect of the gain.

2. Data, empirical strategy, and models

2.1. Data

We compile a rich dataset from an electric utility company called Salt River Project (SRP) in Arizona, United States. Arizona is a particularly suitable study area for solar energy research because of its abundant

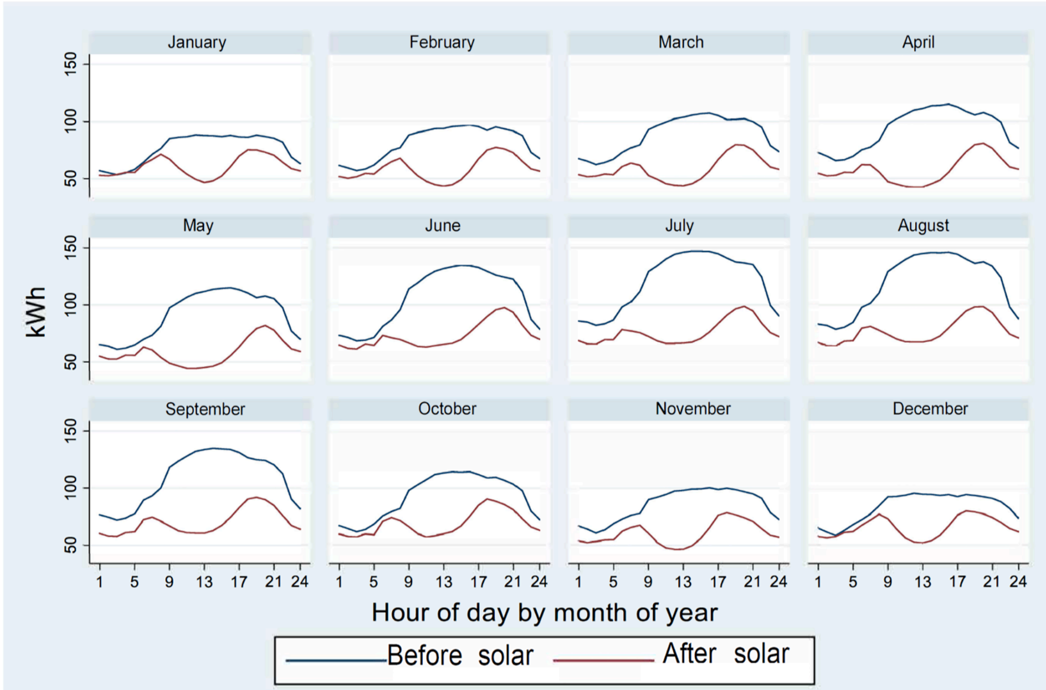

Fig. 1. Average load profiles by month of the 330 business consumers before and after installing solar panels. Notes: The y-axis is the average hourly electricity delivered from the grid to the consumers (in kWh). The x-axis is the hour of day indicators. "Before solar" indicates the data before installing solar panels; "After solar" indicates the data after installing solar panels.

solar resources. As of the third quarter of 2018, the cumulative capacity of installed solar energy capacity in Arizona ranked 3rd in the United States [49]. Our dataset contains 330 business distributed solar customers and more than 17,000 business electricity customers in total. The dataset includes hourly electricity consumption for individual consumers from 2013 to 2018 as well as solar panel installation dates for individual consumers. Fig. 1 shows the average load profiles (hourly electricity purchased from the electric grid) by month of the 330 business consumers before and after installing solar panels. Fig. 1 is a descriptive figure which is generated by averaging the hourly electricity purchased from the grid by each month. The figure shows that after installing solar panels, business consumers drop their electricity purchased from the grid significantly from about 10am-5 pm, during which the solar panels generate the most electricity. Another observation from Fig. 1 is that the electricity purchased from the grid after installing solar panels is non-zero for all hours, implying that the electricity generated from solar panels is not enough to offset all the electricity consumption of these business consumers. Recall that these solar consumers in our dataset are net-metered consumers: they first consume the solar electricity generated by their own solar panels, and any unused solar electricity is sold back to the grid.

Table S5 in the Supplementary Information shows the industry distribution of solar business customers and the top three sectors are health care/social assistance, real estate/rental/leasing, and retail trade. Fig. S1 in the Supplementary Information shows the distribution of the solar panel systems in our sample and the average size of panels is 66 kW (in AC). Fig. S1 also shows the distribution of solar panel adoption per year. The panels were installed between 2006 and 2017. Fig. S2 in the Supplementary Information shows that there is a wide range of daily electricity generated per kW by the solar panel system, due to the variations in panel performance and solar irradiance.

Our data is at the account-level instead of at the building level. One building can have multiple accounts with the utility company. Even within a business, there can be multiple accounts. If a certain business is spread within several buildings, each building/business combination will have a separate account. If each of the businesses has its own electricity account and they were to be combined into the same building, then they would still maintain their original individual accounts. If an account changes its address, the account number does not change, and the utility still records the electricity information for the same account. In such a case, our data will not show a higher consumption just because of business consolidation into one building.

2.2. Summary of empirical strategy

We use fixed panel regressions to estimate the impact of distributed solar panel installations on electricity consumption behaviors. Intuitively, the panel regression method compares the electricity purchased from the grid of a consumer before and after solar panel adoption and measures the difference of the electricity amount, while controlling for various other factors that can influence electricity consumption [50]. Also, the non-solar consumers that enter into the panel regression model provide baseline change in electricity amount, which will be compared against the change of solar consumers. This panel regression method has the advantage of controlling for time-invariant consumer-level unobserved confounding factors as well as time-dimensional factors that can bias the estimation of the causal impact [51]. This panel regression method is widely used in the energy economics literature which estimates the impact of various types of technologies on electricity consumption behaviors, such as energy efficiency technologies [52–53] and recently residential solar panels [20,30]. In addition, we use two matching methods, propensity score matching (PSM) and coarsened

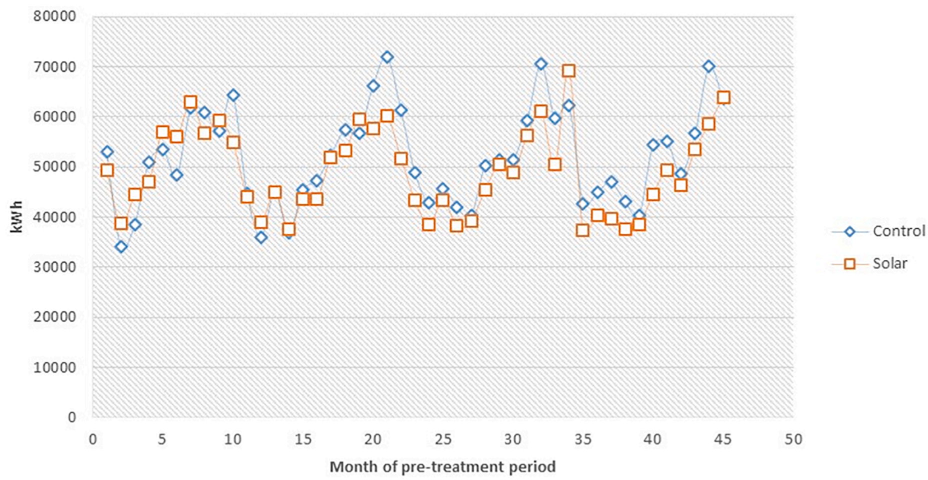

Fig. 2. Monthly electricity consumption of the control and solar customers in the pre-treatment period. Notes: The y-axis is the monthly average electricity consumption (in kWh). Orange color represents the average consumption of the solar customers and blue color represents that of the control customers. The x-axis is the month number in the pre-treatment period, with the first month normalized to be month #1. In total there are about 4 years of pre-treatment billing data. This figure is generated using the sample from propensity score matching. Coarsened exact matching shows similar parallel trends.

exact matching (CEM) to further help eliminate any systematic differences between the control and treatment consumers. The matching methods are also commonly used in the literature to evaluate the impact of energy technology adoption [54–56]. Details of the panel regression and matching methods are described below.

There could be several confounding factors when estimating the impact of solar panel adoption on electricity consumption behavior. First, adopting solar panels is voluntary. For example, more environmentally conscious business consumers might be more likely to adopt solar panels, but they are also more likely to pay more attention to energy-saving practices in general. Second, business consumers might adopt contemporaneous energy efficiency projects or other business expansion projects, concurrently with solar panels. Third, conditional on adoption, if business consumers make certain changes (e.g., they remove barriers such as trees to increase the sunlight exposure of the panels), then these unobservable practices can impact their electricity consumption[1].

To address these potential challenges, we use a panel regression with consumer-year fixed effects to control for consumer-level time-variant confounding factors such as consumer environmental awareness, occupancy change, tree-shade change, and business expansion or energy efficiency projects. Essentially, these fixed effects give each individual consumer a different baseline electricity consumption profile due to individual-specific characteristics as measured in different years. For example, a consumer that is very environmentally friendly might have a relatively small fixed effect which would indicate a low level of baseline electricity consumption. The consumer-year fixed effects can also control for yearly business expansion activities. For more detailed explanations of the panel regression model, please refer to "Supplementary Information – Explanations of Fixed Effects Panel Regression".

As robustness checks, we use two main matching methods: propensity score matching (PSM) and coarsened exact matching (CEM). Matching helps construct a non-equivalent control group similar to the treatment group for a quasi-experimental design [57,58]. In other words, for each solar consumer, the matching method selects similar non-solar consumers for comparison. The selected non-solar consumers will be similar to the solar consumer in terms of the key attributes such as the industry sector and the average size of electricity consumption (in the absence of solar installation). These matched non-solar consumers will serve as the control group for the solar consumers. A key assumption when using matching for causal inference is conditional independence – only observable factors can impact the treatment and outcome variables, which is normally difficult to justify. As a result, we apply a fixed-effects panel regression on the matched control and treatment groups in order to control for any potentially confounding unobservable factors, similar to the method used by Qiu and Kahn. [54] In our PSM, a logit model is used in the first stage to calculate the predicted probability of a consumer adopting solar panels. Then in the second stage, non-solar consumers are matched with solar consumers based on similarity in the predicted probability of adoption. We use the nearest neighbor matching algorithm and the heteroskedasticity-consistent analytical standard errors as in Abadie and Imbens [59] in the second stage of PSM. CEM first coarsens the matching variables into strata and then matches consumers based on which strata they belong to. We use the programming-generated strata for CEM instead of pre-specified strata. Compared to PSM, CEM can control for the difference between the treatment and control groups ex-ante [60]. We match consumers based on their pre-adoption monthly electricity consumption to ensure that the control and treatment groups have a similar pre-solar electricity consumption profile. For the non-solar consumers, we randomly assign them the solar installation dates. In addition, we match the businesses on their two-digit industry code and city. In Tables S3–S4 in the Supplementary Information, we present the results of the balancing tests conducted to ensure that the treatment and control groups are comparable to each other after the matching process. Table S2 shows the number of solar and non-solar consumers before and after matching. Tables S3–S4 list the types of tests and statistics used for the balancing checks as well as the sample distribution of the matched control and treatment groups. The matching methods will generate different samples with different numbers of solar and non-solar consumers [61] because in the matching process, if a solar consumer cannot be matched well the matching process will drop that solar consumer. We will run the panel regression models using the samples generated by the two different matching methods as well as using the original sample without matching, to show the robustness of our statistical results.

A potential important selection bias is the likelihood that businesses installing solar panels are also those that are doing well financially and growing or are about to be growing. In order to reduce this bias and to check that the matched treatment and control groups share a common trend in electricity consumption prior to the installation of solar panels by the treatment businesses, we plot the monthly average electricity consumption of the treatment and control groups in the pre-treatment

[1] Here electricity consumption means the total amount of electricity consumed by the business including the electricity consumed via both the electricity purchased from the grid and the electricity generated from the solar panels. When electricity consumption changes, that will also change the amount of electricity purchased from the grid. In terms of why such changes can impact electricity consumption, if they remove the barriers and increase sunlight exposure, it can change the space cooling or heating needs, and thus electricity consumption will change because sunlight can go through the window to warm up the rooms.

periods. Fig. 2 confirms that the treatment and control groups have parallel trends and thus it is unlikely that solar consumers are only those businesses that were experiencing growth.

We use the software Stata to process the data and to conduct the econometric analyses. The steps to process the data are as follows. (1) We merge the hourly electricity consumption data of individual consumers obtained from SRP with hourly temperature data obtained from National Oceanic and Atmospheric Administration (NOAA) [62] by the location, the hour, and the date. We use the weather station that is the closest to the zip code where each consumer is located for the merging process. (2) Based on the electricity price plan faced by each consumer on each day, we assign the hourly electricity price to each consumer based on SRP's rate book [63]. (3) Next, we merge the dataset with the solar panel installation dataset by the consumer identification numbers. For each solar consumer, the installation dataset contains the commissioning date of each distributed solar panel, based on which we can know the pre-installation and post-installation periods. (4) We next use statistical matching methods including PSM and CEM to find comparable control (non-solar) consumers for the distributed solar consumers. (5) We then run the fixed effects panel regression models on the matched control and solar consumers which will be explained in detail in Eqs. (1) and (2).

2.3. Research hypotheses

For net-metering consumers, when solar panels generate electricity, the solar electricity will be consumed by the consumers first, and then any excess electricity will be sold back to the grid. This means that part of the electricity originally needed from the electric grid can be supplied by solar electricity. As a result, we have the following hypothesis, to be tested in Eq. (1) described in the next section:

Hypothesis 1. Installation of distributed solar panels will reduce the electricity purchased from the electric grid during the hours when solar panels generate electricity.

Due to the solar rebound effects, consumers might increase their electricity consumption, especially during the months when the space cooling needs are high, such as in July and August. During these two months, the lower electricity bills from solar electricity can make the building occupants use more electricity to cool the space and increase their thermal comfort levels. Such an increase in electricity consumption might completely offset the reduction in electricity needed from the grid during the hottest hours (when maximum electricity demand happens) of these two months. Thus we make the following hypothesis about the change in maximum monthly demand, to be tested in Eq. (2) described in the next section:

Hypothesis 2. The installation of distributed solar panels does not reduce the monthly maximum demand in July and August.

2.4. Models

2.4.1. Hourly load profile

In order to more precisely evaluate the benefit from reduced air pollution associated with burning fossil fuel, including CO_2, SO_2, NOx, and particulate matter, the solar panels' impact on the hourly electricity consumption is needed. This is because the marginal fuel being used to supply electricity, such as from coal, natural gas, or renewables, could be different depending on the hour of day, and because each of these fuel options has different air emissions. Thus, the marginal damage factor from one additional kWh of electricity supplied from the electric grid differs by hour of day. Our paper improves existing evaluations of the benefits of distributed solar panels by estimating the actual change in hourly electricity usage from the grid for the distributed solar consumers in the commercial and industrial sector, after incorporating the behavior change due to the rebound effects.

Specifically, we regress hourly electricity delivered from the grid to the consumer on the solar panel adoption status, controlling for various confounding factors. We run the following regression model:

$$\mathrm{Grid\_kWh}_{ih} = \alpha_{iy} + \sum_{H=1}^{24} \beta_H Solar_{ih} {}^* I_H + \boldsymbol{p}_{ih}\boldsymbol{\gamma} + f(HDD_{ih})\boldsymbol{\theta} + f(CDD_{ih})\boldsymbol{\eta} + \delta Holiday_d$$
$$+ Hour\ of\ day + Day\ of\ month + Day\ of\ week + month\ of\ year + \varepsilon_{ih} \quad (1)$$

where $\mathrm{Grid\_kWh}_{ih}$ is the electricity delivered from the grid to business consumer i in hour h of sample. α_{iy} is a consumer-year fixed effect which can control for time-variant unobservable factors at business consumer level as these could impact solar adoption and solar generation; examples of such factors are consumer environmental awareness, occupancy change, tree-shade change, and contemporaneous projects for each customer at the yearly level. $Solar_{ih}$ is a dummy variable that is equal to 1 if consumer i has a solar panel at that time, while I_H is an indicator variable indicating the hour of the day. β_H measures the change in hourly electricity delivered from the grid after adopting solar panels for hour H of the day and there are 24 such coefficients.[2] $\boldsymbol{p}_{ih}$ is a price vector containing both the marginal electricity price[3] and the demand charge. $\boldsymbol{\gamma}$ are the coefficients measuring the impact of electricity prices on electricity purchased from the grid. HDD represents heating degree days as calculated by 65 – temperature; CDD represents the cooling degree days as calculated by temperature − 65; f is a spline function for HDD and CDD.[4] $\boldsymbol{\theta}$ are the coefficients in each of the HDD piecewise linear functions. $\boldsymbol{\eta}$ are the coefficients in each of the CDD piecewise linear functions. *Holiday* is an indicator variable for federal holidays. We also include a set of time fixed effects including hour of day, day of the month, day of the week, and month of the year, all of which control for factors that change over time for all customers such as changes in energy efficiency policies and incentives, or the changing prices of solar panels.[5] Note that *year of sample* is not included since we include consumer-year fixed effects. Standard errors are clustered at the business customer level to avoid autocorrelation of the error term ε_{ih}.

Our Hypothesis 1 states that β_H will be negative during the hours when solar panels generate electricity and consumers use solar electricity. We will test the hypothesis empirically from the regression. The dependent variable in the hourly analysis is the electricity that was delivered from the grid. Hourly data is needed here because the marginal emissions produced by the electricity supply vary throughout the day based on the different marginal fuels (e.g., natural gas, coal, or

[2] h is the h^{th} hour of the sample while H is the H^{th} hour within 24 h of a day. For example, for hour 1am-2am on the 31st day of the sample, h will be 24 * 30 + 2 = 722, while H will be 2.

[3] The marginal electricity price information comes from the utility company. It is a price paid by the consumers. The business consumers are on several price plans and each price plan has a different marginal price in different hours. Table S6 in the Supplementary Information summarizes the price information.

[4] For the temperature spline function, the number of knots is 4 such that the data is divided into 5 equal-width groups of CDD or HDD, respectively, for piecewise linear function. In other words, the linear relationship between temperature and electricity consumption has different coefficients in each of the temperature intervals [64].

[5] The coefficients of each term have their own units so that the unit of the left side of the equation (kWh/hour) will be equal to that of the units of the right side of the equation. For example, for the fixed effect term "Day of month", it includes both the coefficient and the day of month indicator, meaning "coefficient (unit is kWh/hour) * Day of month indicator (unit is normalized and is 1 since it is an indicator variable)". The units for each term in the equation are: $\mathrm{Grid\_kWh}_{ih}$ (kWh/hour), α_{iy} (kWh/hour), I_H (unit is normalized and is 1), $Solar_{ih}$ (unit is normalized and is 1), β_H (kWh/hour), $\boldsymbol{p}_{ih}$(dollar), $\boldsymbol{\gamma}$ (kWh/dollar/hour), HDD_{ih} (degree/hour),$\boldsymbol{\theta}$ (kWh/degree), CDD_{ih} (degree/hour), $\boldsymbol{\eta}$ (kWh/degree), $Holiday_d$ (unit is normalized and is 1), δ (kWh/hour), *Hour of day* (kWh/hour), *Dayofmonth*(kWh/hour), *Day of week*(kWh/hour), *month of year*(kWh/hour), ε_{ih} (kWh/hour).

renewables) used to supply electricity at different times of day.

2.4.2. Maximum monthly demand

To measure the impact of solar panel adoption on the maximum monthly electricity demand, we run the following regression model:

$$\text{max\_kW}_{im} = \alpha_{iy} + \sum_{M=1}^{12} \beta_{SM} Solar_{im} {}^* I_M + \boldsymbol{p}_{im}\boldsymbol{\gamma} + f(HDD_{im})\boldsymbol{\theta} + f(CDD_{im})\boldsymbol{\eta} + month\ of\ year + \varepsilon_{im} \tag{2}$$

where max_kW_{im} is the maximum monthly electricity demand by business consumer i in month m; $Solar_{im}$ is a dummy variable which is equal to 1 if in month m consumer i has had a solar panel; β_{SM} measures the change in maximum electricity demand by month-of-year M after adopting solar panels. Our Hypothesis (2) states that β_{SM} will be zero in the hottest months of a year – July and August. We will test the hypothesis empirically from the regression.

2.4.3. Air emissions calculation

We use the hourly marginal pollution damage factors from Holland et al. [64] to calculate the benefit of reduced air emissions due to solar panels.[6] We analyze the four major air emissions including CO_2, SO_2, NO_x, and particulate matter. Our formula to calculate the daily benefit from a pollutant is $\sum_H MD_H \beta_H$, where MD_H is the marginal damage factor in hour H of a day and β_H is the coefficient estimated from regression Eq. (1), which measures the change in electricity delivered from the grid in hour H of a day. After calculating the daily benefit, we then calculate the annual benefit using the number of days in a year.

3. Results

3.1. Hourly load profile

Fig. 3 shows the results of the changes in hourly electricity purchased from the grid estimated from Eq. (1). The solid blue dots indicate the coefficients for each hour, measuring the impact of an average-size business distributed solar panel system on the electricity delivered from the grid. Most reduction (statistically significant at 5% level) happens during the day when the solar radiation is the strongest. The coefficients around 8 pm are positive, implying rebound effects. After consumers install solar panels they pay lower electricity bills and thus consider electricity cheaper than before. As a result, they increase their electricity consumption. During the day when there is solar electricity to supply part of the electricity consumption, such an increase in electricity consumption can on average be offset by the solar electricity and thus we still see a reduction in electricity needed from the grid. In the early evenings when there is no solar electricity, such rebound effects will cause an increase in electricity purchased from the grid.

We then demonstrate how the actual reduction in hourly electricity delivered from the grid can deviate from the amount of electricity generated by the solar panels. Fig. 4 shows that the average hourly solar electricity generation in our sample is much higher than the actual average hourly reduction in electricity delivered from the grid. This implies that using the amount of solar electricity generated to replace the same amount of electricity needed from the grid can significantly overstate the environmental and climate benefits of distributed solar panels[7].

3.2. Maximum monthly electricity demand

Quantifying the change in the maximum monthly demand is critical to assessing the challenge created for the utilities. This has not been done before using a large solar consumer sample as well as actual electricity demand and solar electricity generation data. Fig. 5 shows the change in the maximum monthly electricity demand estimated from Eq. (2). Results show that due to rebound effects business distributed solar consumers do not reduce their maximum electricity demand during July and August, as illustrated by the positive and statistically non-significant coefficients.[8] Even though there is a reduction in the maximum demand for other months, only the maximum demand in July and August is of interest. July and August are the two months when the system peak load tends to be reached. Electric utilities make their investment based on the system peak load of the whole year. As a result of the rebound effects, business distributed solar consumers create further challenges to the utilities by not reducing their maximum load in the peak summer months. From a social equity perspective, this implies that demand charges for business solar consumers are important in order to mitigate this potential challenge faced by the utilities.

In order to examine the impact on the actual system peak load of the utility, we first plot the monthly system peak load for the past 10 years; panel (a) of Fig. 6 shows that the system peak has not declined. We then plot the residuals from a regression of system peak loads controlling for various confounding factors in Fig. 6 panel (b), which shows that there is still no decline in the system peak load. This descriptive evidence is

[6] We not only examine the emissions of these pollutants but also the damage associated with the emissions. The marginal damage factors in Holland et al. [64] measure the damages in dollar values associated with the additional emissions of the pollutions. The damages from local air pollution in these factors include impacts on human health, buildings and material, visibility and recreation, and crop and timber yields. Holland et al. calculate these marginal damage factors for each North American Electric Reliability Corporation (NERC) interconnection region. They first use an econometric model to estimate the amount of pollutants emitted from an additional kWh of electricity generation. They regress an individual power plant's hourly emissions of each of the pollutants on the corresponding hourly electricity load of the regions the power plant is connected to, in order to obtain the change in emissions at an individual power plant from an increase in electricity usage in a given region by hour of the day. Then they use an integrated assessment air pollution model called AP2 to determine the damages from local air pollution. AP2 maps the reported emissions of pollutants to the ambient air pollution concentrations in the United States. Then AP2 links the ambient concentrations to physical effects, exposures, and monetary damages, based on data on population, crop and timber yields, infrastructure and recreation, as well as concentration–response functions and damage functions reported in relevant existing literature [65,66]. Next, AP2 calculates the damages from a baseline air pollution level. Then it adds one ton of an air pollutant and calculates the total damages again. The incremental damages from a unit of air pollution emission are then the difference between the baseline case and the add-one-unit case. Then combining the damages per unit of additional pollutant estimated from AP2 and the change in emissions from an increase in electricity usage, the marginal damage factors of an additional kWh of electricity generation of each region can be obtained. The NERC interconnection region where Arizona is located is the Western Electricity Coordinating Council (WECC). Thus we use the marginal damage factors estimated for the WECC in our calculation.

[7] Eq. (1) is essentially comparing the change in electricity demand of consumers before and after they install solar panels. The comparison was conducted via the econometric model instead of simply subtracting pre-installation demand from post-installation demand, because the econometric model can also control for other confounding factors. It is an empirical estimation rather than a simulation model.

[8] Although the coefficients in July/August are positive, the 95% confidence intervals indicate that the coefficients are not statistically significantly different from zero. This means that we cannot infer that the maximum power demand increased in July/August. Instead, the results indicate that their maximum demand did not change in these two months. This can be a result of the rebound effect. After consumers install the solar panels, their electricity bills decline and thus they tend to increase their electricity consumption especially during the hours when they usually have maximum monthly demand (the hottest hours and thus with the largest cooling needs), so that the solar electricity does not reduce their monthly maximum demand.

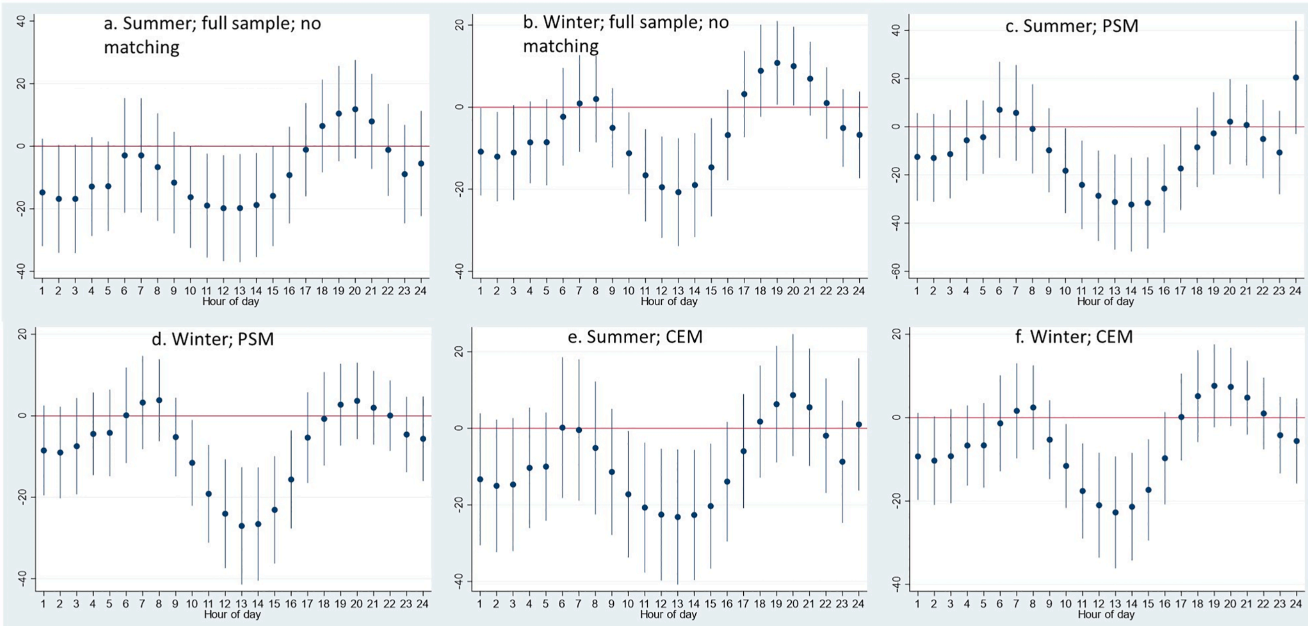

Fig. 3. Change in hourly electricity delivered from the grid (kWh/hr) due to solar panel adoption, by hour of day. Notes: The solid dots indicate the magnitude of the coefficients for solar panel adoption, while the vertical lines show the 95% confidence intervals. The values of the coefficients measure the change in hourly electricity delivered from the grid due to solar panel adoption. PSM stands for propensity score matching. CEM stands for coarsened exact matching. The matching variable for PSM and CEM in this figure is the pre-adoption average monthly electricity consumption in summer and winter.

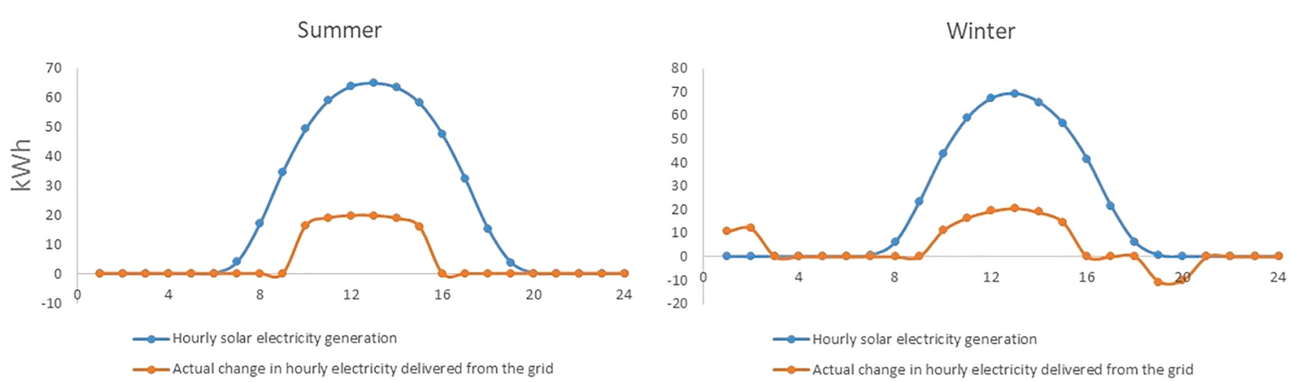

Fig. 4. Comparison of hourly solar electricity generation and actual reduction in electricity delivered from the grid. Notes: The actual reduction in hourly electricity delivered from the grid is obtained using the coefficients from panels (a & b) in Fig. 3. It has the opposite sign as the coefficients for illustration purposes. When the coefficient is not statistically significant at the 5% level, we treat it as zero.

consistent with our finding that the distributed solar energy generation by businesses has not reduced system peak loads in the past few years. Fig. 6 panel (b) even shows an increasing trend of monthly peak load after controlling for population, GDP, and energy efficiency policies. This could be due to rebound effects where consumers increase their electricity consumption due to lower perceived cost of using energy services. We also check the temperature trends (Fig. S3 in Supplementary Information) but do not find increasing needs for cooling or heating during our study time periods and thus the temperature trends cannot explain the increasing trend of peak load.

3.3. Assessment of reduced air emissions

We find that the annual benefit of reduced air emissions due to an average-size business distributed panel system (66 kW AC) is $1147 (in 2018 U.S. dollars). Table S1 in the Supplementary Information shows the details of the calculation. Assuming a 30-year lifetime and a 3% discount rate, the lifetime benefit of reduced air emissions is $22,474 per system.

4. Discussion and conclusion

This study takes advantage of a unique and previously unavailable dataset on consumer-level high-frequency electricity demand and the installation information at the level of solar panel systems; we provide the first empirical evidence of the change in hourly electricity purchased from the grid due to distributed solar panel adoption for business consumers. In this study, we conduct three critical analyses. First, we estimate the actual hourly reduction in electricity needed from the grid of commercial and industrial consumers through an econometric analysis. We show that this reduction is much smaller than the actual solar electricity generation. Second, we show that business consumers of

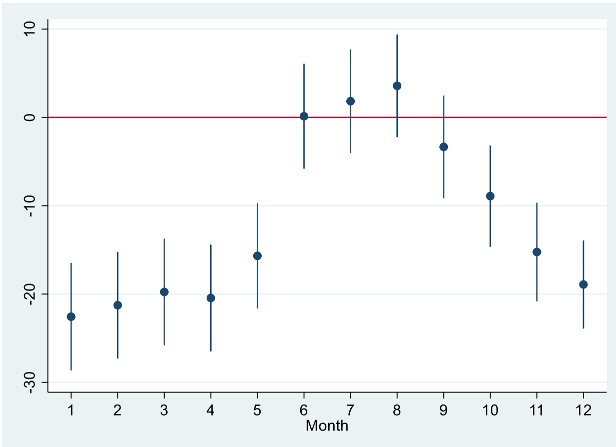

Fig. 5. Change of maximum monthly electricity demand (kW) from solar panel adoption, by month. Notes: The solid dots indicate the magnitude of the coefficients for solar panel adoption, while the vertical lines show the 95% confidence intervals. The values of the coefficients measure the change in the maximum monthly electricity demand due to solar panel adoption. This figure is generated using the full sample without matching.

distributed solar create additional challenges to utilities by not reducing their maximum monthly demand in July and August, which contradicts previous studies that found a reduction in maximum-capacity investment [13]. Third, we conduct a more precise assessment of the reduced air emissions due to businesses' distributed solar panels using the actual hourly reduction in electricity needed from the grid. The assessment includes reduction in CO_2, NO_x, SO_2, and PM (particulate matter). We show that not relying on empirical evidence can overestimate the benefit of reduced air emissions from distributed solar panels being used by businesses.

Our estimated coefficients from running regression Eq. (1) test for Hypothesis 1 and the coefficients and their 95% confidence intervals indeed confirm that the electricity purchased from the electric grid during the hours when solar panels generate electricity reduced after adopting solar panels. Our estimated coefficients from running regression Eq. (2) test for Hypothesis 2 and the results confirm that the monthly maximum electricity demand does not change for July and August. We use two matching techniques (PSM and CEM) as well as no matching (using the original sample) to check for the robustness of our conclusions. Our results are consistent across using different samples generated by the two different matching methods. In addition, we test for the parallel trends of the control and treatment consumers in Fig. 2 to further check for the validity of using panel regression models. Our results show the validity of our methods.

Our finding has important implications. Most existing studies assume that the entire amount of electricity generated by solar panels leads to a reduction in electricity needed from the grid [67,68]. We show that such an approach can drastically overestimate the benefits of reduced air emissions from solar energy by ignoring factors such as solar rebound effects. Solar rebound effects also demonstrate the importance of cleaning the grid by adding the portion of utility-scale renewable energy. If the grid is dirty with a significant share of energy generation with fossil fuel, then solar rebound effects mean that it will be harder for distributed solar panels to reduce air emissions that arise from electricity consumption.

We show that distributed solar panels can create challenges to utilities by not reducing the maximum monthly demand of business consumers for the months of July and August, which are when the system load peak tends to happen. This implies that, when more businesses adopt distributed solar panels, the investment in grid infrastructure remains unchanged, while electricity sales are reduced. Such imbalance between the infrastructure needs and the reduction in electricity sales highlights the importance of a demand charge for business solar consumers, so that utilities can better recover their upfront investment to serve the broader community [43,44].

To conclude, our results imply that any impact evaluation of distributed solar panels should rely on empirical assessment due to factors such as rebound effects as it can offset the theoretical savings of electricity needed from the grid. More comprehensive studies are needed to evaluate the costs and benefits of distributed solar energy after incorporating our empirical results of the grid impacts from distributed solar panels.

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.

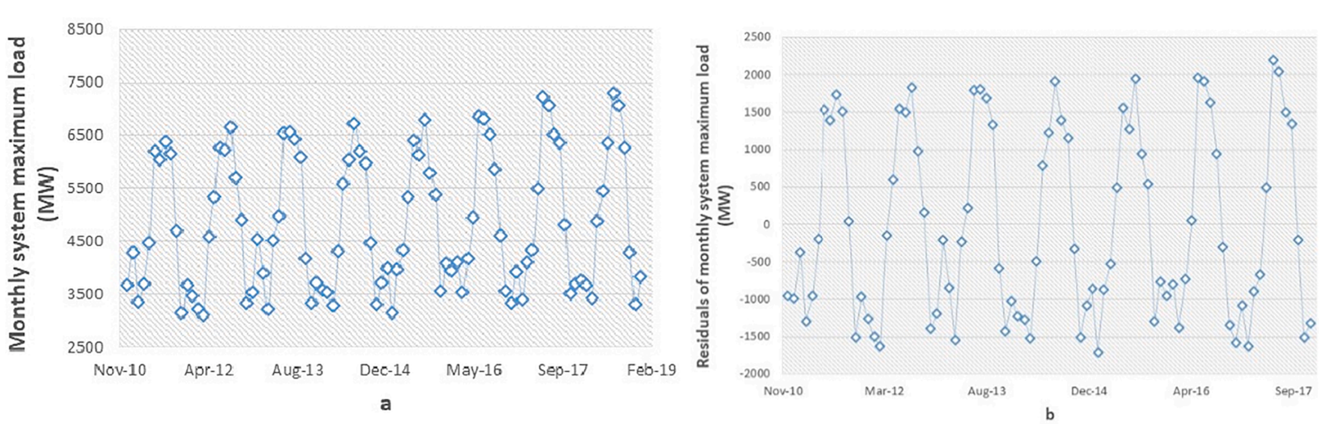

Fig. 6. The utility's monthly system peak loads. Notes: Panel (a) plots the actual monthly system peak loads. Panel (b) plots the residuals of a regression which regresses the monthly system peak loads on annual population and GDP in Phoenix metropolitan area as well as state-level energy efficiency scores. The annual state-level energy efficiency scores are developed by American Council for an Energy-Efficient Economy which reflect states' energy efficiency policy stringency and actual energy efficiency investments (https://aceee.org/state-policy/scorecard).

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.116804.

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