Do tax incentives increase solar energy adoption? Evidence from Brazil*

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Abstract

Renewable energies have become central for global sustainable development. Due to the great potential for exploring solar energy in Brazil, the states have adopted tax incentives to push for solar market development within the country. In this paper, we aim to estimate the effect of a state tax incentive on the solar photovoltaic (PV) system installation rate. We exploit a novel Brazilian administrative dataset of a small-scale distributed generation system to construct a monthly panel of municipalities from 2014 to 2019. We then use the policy staggered adoption from April 2015 to June 2018 and the recent developments of the staggered differences-in-differences literature to assess the causal effects of the policy. We find a positive impact of the state tax incentives on PV adoption. The policy has created 14% of the total installation after treatment, which translates into 8 GWh energy savings in five years. These results imply that regional tax design may help governments meet their climate goals.

Keywords: Renewable energy, tax incentive, staggered difference-in-differences

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1 Introduction

Renewable energies have become central for global sustainable development. The negative externalities from burning fossil fuels and the limited support for market-based policies, such as carbon pricing, increase the relevance of public policies to promote renewables (Borenstein, 2012). Particularly for solar photovoltaic (PV) systems, policymakers have been stimulating net metering mechanisms to increase its diffusion (da Silva et al., 2019). Governments have also adopted tax incentives to push for solar market development[1]. Although different incentives have been created in the past few years wordwide, the literature still lacks studies that establish the causal effect between tax incentives and solar energy adoption, and their cost-effectiveness as well.

In this paper, we aim to investigate the impact of a tax incentive on residential solar PV adoption in Brazil. The country is an interesting setting for this analysis due to its continental dimensions and the great potential for exploring solar energy[2]. In the least sunny place, it is possible to generate more solar electricity than in the sunniest place in Germany (Martins et al., 2017). The Brazilian solar energy capacity increased from 0.08 gigawatts (GW) in 2015 to 7.9 GW in 2020. Small-scale solar PV systems account for 80% of this capacity (EPE, 2021)[3]. Net metering regulation, which allows PV owners to return their excess electricity generated to the utility grid, was introduced in Brazil in 2012[4]. As a complementary policy, States began implementing tax incentives on electricity consumption for solar PV owners from 2015 to 2018, where they pay state taxes only on the net electricity usage rather than all electricity consumed from the distributor.

To investigate the impact of the policy, we exploit a novel Brazilian administrative dataset

[1] Some support policies available are: investment tax credit, renewable energy systems property tax exemption, and solar energy system equipment credit (da Silva et al., 2019).

[2] Brazil reached the thirteenth position in total solar PV capacity in 2021 (IRENA, 2021).

[3] Renewable energies represent the majority of the electric matrix in Brazil, but its main source (hydro-power) has been decreasing relevance in the past few years. Renewable energies account for 85% of the electricity generation in Brazil, mainly from hydro-power (EPE, 2021). The large share of hydroelectricity makes the Brazilian electricity system unique. However, this source is subject to climatic factors determining reservoir energy storage. In drought periods, the reservoirs may reach critical levels, which increases the need for backup power generation from plants that burn fossil fuels. In this context, alternative renewable resources, such as wind and solar energy, take a moment. Therefore, renewable sources such as solar energy are becoming more relevant. Brazil has great potential for exploring solar energy

[4] Since then, the PV owners' electricity bills include only the net electricity usage.

of the small-scale distributed generation system from ANEEL (Brazilian Electricity Regulatory Agency). The dataset has individual-level data of all systems put in place. We construct a panel of municipalities and combine them with covariates such as market, climate, and demographic information. Our identification strategy exploits the staggered rollout of the policy implementation from 2015-2018 across states, including many layers of fixed effects, to assess the impact on the residential installation rate. Due to the different timing of the policy, we rely on recent advances in the staggered differences-in-difference (DID) literature. We investigate this aspect while focusing on the following issues: i) how many installations the incentive generated, ii) the environmental benefits the program conferred, and iii) the cost.

We find a positive effect of the state tax incentive on solar PV adoption. Tax incentive increases the installation rate by 0.28 systems per 100,000 residents. Despite the modest effect, this result corresponds to more than ten thousand new systems by 2019, or 14% of the total PV adoption after treatment. This result does not change when we include *not-yet-treated* municipalities as a comparison group nor when we add covariates. The average impact by the length of treatment exposure suggests no specific trends in PV adoption twelve months before the treatment. Furthermore, it indicates a dynamic effect post-treatment, reaching the highest value ten months after the state adopts the incentive.

Some low-income municipalities have had no PV installations over the period. We thus find a larger effect when we include only the relevant markets. The result is 40% higher than the effect estimates considering the complete database. We also find that the tax incentive is more significant in small municipalities with lower population density due to the ease of the PV installation on top of roofs in these localities. Finally, we calculate that the tax incentive cost is near $500 per additional PV installation and saves $10 per ton of carbon dioxide over five years.

This work contributes to the literature investigating the impact of policy incentives on solar PV adoption. The empirical literature comprises studies that use structural models and studies that use reduced-form approaches. In the structural model approach, authors develop dynamic discrete choice models to explore subsidies schedules, wherein each period, households face the decision to adopt the new technology or to postpone their investment (Burr, 2016; De Groote and Verboven, 2019; Pavanini et al., 2021). This approach may not seem suited for our context since the incentive does not change after the consumers are exposed to the policy. Thus, the reduced-form is the closest to our empirical strategy.

Regarding the reduced-form approach, Hughes and Podolefsky (2015) explores rebate rates across electric utilities over time in California to identify the effect on residential PV systems adoption. Crago and Chernyakhovskiy (2017) examines the effectiveness of policy incentives to increase residential solar PV capacity using county-level data from US East Coast states. Gillingham and Tsvetanov (2019) propose a Poisson hurdle model to deal with excess zeros, unobserved heterogeneity, and endogeneity of prices to estimate demand for residential solar PV systems in Connecticut, US.

The evidence of tax incentives for renewable energy is largely based on policies applied in developed countries, mainly US (Hughes and Podolefsky, 2015; Crago and Chernyakhovskiy, 2017; Gillingham and Tsvetanov, 2019; Burr, 2016) and Europe (De Groote and Verboven, 2019; Pavanini et al., 2021). To the extent of our knowledge, this study is the first to assess the effect between taxes and the adoption of solar photovoltaic systems in a developing country context. Empirical studies applied to Brazil are particularly relevant. It is a large country with more than 210 million people, it has spatial and social heterogeneity, and the households face potential credit constraints for investment in new technologies, such as solar PV.

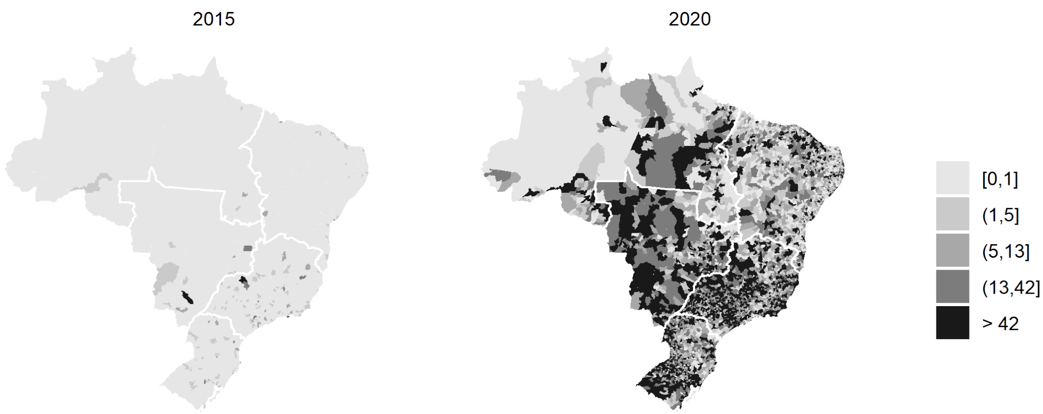
The remainder of this paper is organized as follows. Section 2 presents the institutional background. Section 3 presents the conceptual framework. Section 4 describe the dataset. Section 5 presents the empirical strategy. Section 6 presents the results. In Section 7, we calculate the cost and benefits the program conferred. Finally, Section 8 presents the concluding remarks and discussion.

2 Institutional background

Solar PV systems consist of solar panels that absorb sunlight and convert it into electricity. The residential solar PV system is a small-scale power plant located at or near the consumption place. According to Brazilian regulation, a small-scale system has a capacity of up to 5,000 kW. The typical Brazilian residential solar PV generation is local (roof-top), and its capacity is no larger than 20 kW (see Figure A1 in Appendix A).

The number of residential PV systems has increased in the past few years. There were 1.4 thousand systems in 2015. In 2020, the installation increased to around 290 thousand. Also, the spatial diffusion of technology has surged over time. In 2015, 380 municipalities had at least one solar PV in operation. This number rose to 4,673 in 2020, covering more than 80% of all localities, as indicated in Figure 1.

Figure 1: Distribution of residential PV systems by municipality



Source: Author's own prepared from the ANEEL data.
Notes: Residential PV systems up to 1,000 kW. Data sorted by quantile based on the 2020 distribution. Regions boundaries highlighted.

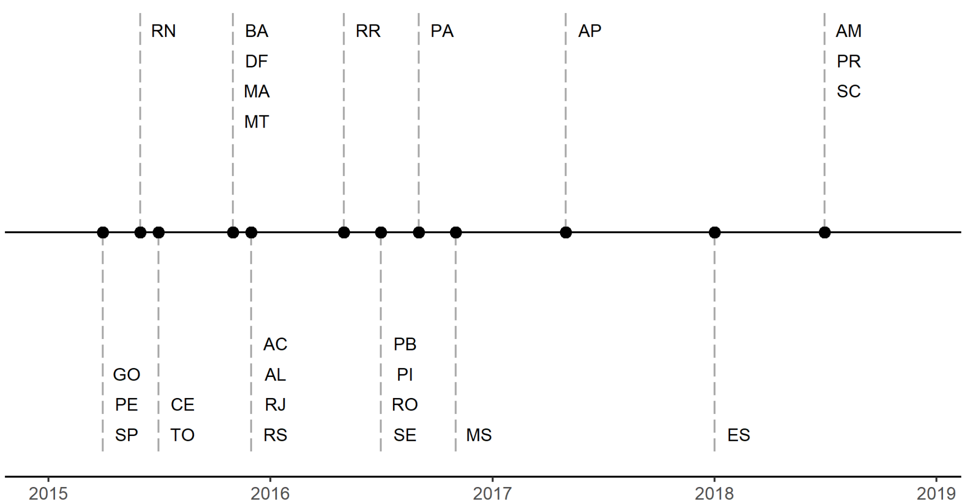
The up-front cost reduction may explain the technology diffusion worldwide (Borenstein, 2012). Besides this, the Brazilian government began encouraging small-scale solar PV adoption in the early 2010s. The main initiative was net metering, implemented in 2012 national-wide. Net metering is an electricity compensation system that allows PV owners to export the excess electricity generated to the distributor grid. This electricity offsets the electricity from the distributor used during times of nongeneration. This means that consumers can use the electricity from the grid when self-generation is not enough. The final bill thus includes only the net electricity usage[5].

A relevant complementary policy to net metering is the state tax incentives. In 2013, when the solar PV market was still in its infancy, Minas Gerais implemented an electricity tax exemption for PV owners. Under this policy, consumers pay state tax only on the net electricity usage

[5]Net metering rules allow solar PV owners to carry excess production credits for up to five years. Also, they are not charged for grid utility costs.

rather than all electricity supplied by the distributor[6] In 2015, when the solar PV market was increasing, the *National Financial Policy Council* (Confaz)[7] proposed an agreement that allowed the states to implement the same tax policy as Minas Gerais. As shown in Figure 2, states adopted the agreement between 2015 and 2018. The tax incentive beneficiaries are solar DG owners (including solar PV) with a capacity of up to 1,000 kW. The policy includes residential, commercial, industrial, and rural consumers. The electricity generation must be local or remote, i.e., the agent must produce electricity at or near the consumption place.

Figure 2: ICMS incentive adoption timeline under Confaz agreement



Note: The state tax exemption implementation (ICMS agreement n. 16/2015) refers to the publishing date in the *Diário Oficial da União* (DOU): Goiás (GO), São Paulo (SP) and Pernambuco (PE) on April 22, 2015; Rio Grande do Norte (RN) on June 23, 2015; Tocantins (TO) and Ceará on July 21 2015; Bahia (BA), Maranhão (MA), Mato Grosso (MT) and Distrito Federal (DF) on November 26, 2015; Acre (AC), Alagoas (AL), Minas Gerais (MG), Rio de Janeiro (RJ) , Rio Grande do Sul (RS) on December 30, 2015; Roraima (RR) on May 24, 2016; Paraíba (PB), Piauí (PI), Rondônia (RO) on July 15, 2016; Sergipe (SE) on July 21, 2016; Pará (PA) on September 13, 2016; Mato Grosso do Sul on November 10, 2016; Amapá (AP) on May 3, 2017; Espírito Santo on January 5, 2018; Amazonas (AM), Paraná (PR) and Santa Catarina on July 1, 2018.

[6]Brazilian households pay ICMS (*Imposto sobre Circulação de Mercadorias e Serviços*, a state value-added tax levied on the consumption of goods and services. The electricity tax rate, established by state law, ranges from 12% to 32%, depending on the state.

[7]Confaz is an institution that brings together representatives of the federal government and the 27 Brazilian states, and it aims to mitigate possible tax conflicts among states. In this context, the council must approve all state tax incentives policies proposed by states.

3 Conceptual framework

In this paper, we aim to investigate the impact of a tax incentive on residential solar PV adoption. We introduce a simple conceptual framework to describe its effect on the household decision to install a PV system. The goal here is to help us identify the effect of this policy with the empirical strategy.

Consider a PV owner who consumes C amount of electricity, and its system generates E. It consumes α from solar self-production and exports $(1-\alpha)$ to the distributor grid, such that $\alpha \in [0,1]$. Under the net metering mechanism the household electricity bill B is:

$$\begin{aligned} B &= [C - \alpha E - (1-\alpha)E]\, P + (C - \alpha E)T \\ &= (C - E)P + (C - \alpha E)T \end{aligned}$$

where P is the pre-tax electricity price, and T is the electricity tax. The household is billed on consumption minus production $(C - E)$, and it pays tax on the net electricity consumption $(C - \alpha E)$.

The household solves a constraint utility maximization problem to choose its optimal electricity consumption. We can then distinguish between the two indirect utilities that a household derives depending on whether it chooses to adopt or not a PV system. What differentiates the two utility functions is the presence of the solar electricity generation E, the system cost S, and the solar PV revenue in the budget constraint. The household adopts the technology if net present value $R \geq 0$, where:

$$R = EP + \alpha ET - S$$

State tax incentive - Consider now that the state government implemented a tax incentive on solar PV owner electricity consumption based on the net metering mechanism. The household receives a tax reduction T^* on the amount of electricity exported to the grid $(1-\alpha)E$. Under this incentive, the household electricity bill B' is:

$$
\begin{aligned}
B' &= B - (1-\alpha)T^* \\
&= (C-E)P + (C-\alpha E)T - (1-\alpha)T^*
\end{aligned}
$$

where $T \geq T^* = \theta T$ and $\theta \in [0,1]$ is the discount rate. In this case, the net present value is:

$$R' = EP + \alpha ET + (1-\alpha)\theta T - S$$

With this simple framework, it is possible to characterize the household decision based on electricity tax. Given T, the technology adoption depends on θ and the policy effect is given by the mass of households that face a discount rate $\theta \in (0,1]$. In our study case, the state governments exempt the payment of energy tax corresponding to the amount of electricity exported to the grid. Thus our empirical challenge is to identify the effect of $\theta = 1$ on solar PV adoption.

4 Data

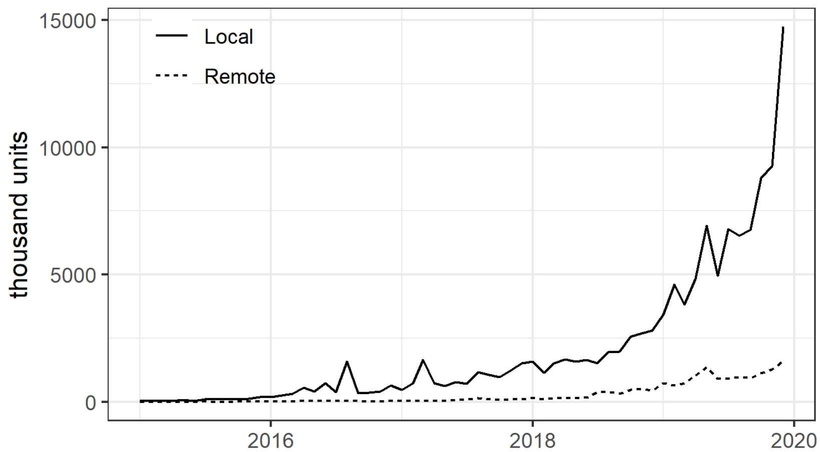
Our study explores the Brazilian Electricity Regulatory Agency (ANEEL) administrative dataset of small-scale distributed generation (DG) systems to test whether the state tax incentive impacts residential solar PV adoption. This dataset provides individual-level information on all systems up to 5,000 kW capacity, such as grid connection date, location, generation type (local, remote, shared, and condominium), capacity size, sector (residential, commercial, industrial, rural), and energy source (solar irradiation, biomass, wind, and others). Distributors must provide the information of PV systems connected to their grid to ANEEL through the *Distributed Generation Registration System*. Under the ANEEL regulation, the information are available within six months after the consumer requests access to the grid, following the steps defined by the regulator:

i Consumer request access to the local utility grid,

ii Utility responds up to 30 days,

iii Consumer request the utility inspection within 120 days, and

Figure 3: Number of residential solar PV installations per month



Notes: Residential solar PV installation, connected to a low-voltage grid, less than 1,000 kW capacity, and local or remote electricity generation.

iv Utility includes consumer information in the database until the tenth day of the following month that the solar PV system was placed in service.

Based on the policy eligibility criteria, we select the residential solar PV installation, connected to the low-voltage grid, less than 1,000 kW capacity, and local or remote electricity generation. We select installations from 2015 to 2019 to ensure the balance of the event study approach, described below. We thus keep 129.171 solar PV systems information from ANEEL. Figure 3 summarizes this data.

Our treatment is defined at the state level. The treatment begins when the state adopts the Confaz agreement. We use the Confaz administrative records to define these dates. The Confaz records incate the dates of board meetings at which each state adopted the incentive.

We aggregated the data by municipality, type of generation, and month. We excluded four states from the database: Rio Grande do Sul, Acre, Roraima, and Amapá. We exclude Rio Grande do Sul and Acre because they changed the electricity tax rate between 2015 and 2019. We exclude Roraima and Amapá because they are states with few municipalities and are not part of a treatment group with more states. In addition, we exclude the municipalities of Fernando de Noronha and Ilha Bela, as they are not located in the continental Brazil territory. Our final database is a panel with 5,018 units and 60 periods.

We combine the solar PV data with several additional datasets. First, we include the average electricity price by municipalities. We calculate the average electricity price from *Consumption and Distribution Revenue Reports* from ANEEL. It provides detailed monthly data from 115 electricity utilities. We select the low voltage residential sector average information for each utility. We thus matched municipality-distributor data and applied the Extended National Consumer Price Index (IPCA) from IBGE to deflate the prices. Despite households experiencing nonlinear pricing, they might respond to average price rather than marginal or expected marginal price (Ito, 2014). Second, we use economic and demographic information from IBGE, such as population and average income. We interpolate by quarter the annual population data using a cubic spline. Finally, the National Institute for Space Research (INPE) provides climate information.

Table 1 provides the summary statistics for our variables, where the unit of observation is a municipality by month. Installation rate is the ratio between the number of installation and the population on a given month, multiplied by 100,000. The solar irradiation is the the annual average of direct normal irradiation in the municipality. GDP per capita is in BRL.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Installation rate for local systems	0.81	11.40	0.00	3,042.07
Solar irradiation	4,602	714	2,219	6,307
Pre-tax electricity price (BRL/kWh)	0.50	0.08	0.21	0.76
Electricity tax rate	0.27	0.02	0.12	0.32
GDP per capita (BRL)	17,339	17,952	2,736	472,562
Population	38,646	227,915	777	12,286,082

5 Empirical strategy

In our empirical strategy, we explore the staggered adoption of the state tax incentive to assess the causal effect on the residential solar PV installation rate. We define the treatment at the state level. A municipality i is treated ($D_i = 1$) after its state adopts the tax incentive in period g. In time t before this period the municipality is not treated ($D_i = 0$ for all $t < g$) and after g the municipality i remains treated ($D_i = 1$ for all $t \geq$).

Table 2 provides the treatment times, group size, and treatment share of tax incentive adoption. We have ten treatment groups. The first treated group contains three states and 21% of municipalities and remains treated 70% of the time. The last group with three states and 15% of the municipalities is treated 40 months after the first group and remains treated 20% of the period. The table also reports that 17% of municipalities were treated two years before the Confaz-agreement, when the market was still in its infant phase, as discussed in Section 2. We assume that this group is our main comparison group.

Table 2: Treatment times, group sizes, and length of treatment exposure

Tax incentive adoption	Number of states	Number of of municipalities	Share of municipalities	Length of exposure
Pre-Confaz Agreement	1	853	0.17	-
2015-04	3	1,076	0.21	0.70
2015-06	1	167	0.03	0.68
2015-07	2	323	0.06	0.66
2015-11	4	776	0.15	0.62
2015-12	2	194	0.04	0.60
2016-07	4	574	0.11	0.52
2016-09	1	144	0.03	0.49
2016-11	1	79	0.02	0.47
2018-01	1	78	0.02	0.30
2018-07	3	756	0.15	0.23

Notes: The table lists the dates of state tax incentive adoption, the number of states, the number and the share of municipalities that adopt by month, and the share of periods each treatment timing group spends treated in the estimation sample from April 2015 to December 2019.

5.1 Average Treatment Effect

Our goal is to estimate the Average Treatment Effect (ATT). In a potential outcome framework, we can represent the ATT as:

$$ATT = E[Y_t(1) - Y_t(0)|D_t = 1]$$

where $Y_t(1)$ is the treated potential outcome and $Y_t(0)$ is the untreated potential outcome of the treated group ($D = 1$). We observe only one potential outcome for each municipality in period t. Relying on parallel trends assumption and using a group of the municipalities that do not adopt the agreement as a comparison group, we could use the canonical DID framework to estimate the

ATT if the policy adoption did not vary over time. But, states adopted the policy in different periods between 2015 and 2018.

The discrete events time adoption could suggest the estimation of DID with multiple periods in a Two Way Fixed Effects (TWFE) model approach:

$$Y_{ijt} = \beta D_{jt} + \theta X_{it} + \varphi_{jt} + \alpha_i + \delta_t + \varepsilon_{ijt} \tag{1}$$

where y_{ijt} is the residential installation rate in municipality i, state j and time t; D is an indicator that identifies the state j after the policy adoption; X is a vector with covariates; α_i is the municipality fixed effects; δ_t is the time fixed effects; and φ_{jt} is a state- by year fixed effects. State by year effect absorb unobserved factors that may vary over time and state, such as PV marketing programs, third-party installers, familiarity with PV technology, and peer effects.

OLS estimates of TWFE model may introduce bias if the effect is heterogeneous across groups and over exposure time to treatment (Goodman-Bacon, 2021; Sun and Abraham, 2021). In our study case, the tax incentive effect may not be homogeneous. This follows from the agent's time spent assimilating the policy, due to marketing campaigns and adaptation to regulation. Another source of potential heterogeneity is the different electricity tax rates among states.

Considering the TWFE limitation, Callaway and Sant'Anna (2020) propose an staggered DID approach to estimate $ATT(g, t)$, which gives the average treatment effect at time t for the group first treated in time g. The method is robust under arbitrary heterogeneity of treatment effects and makes transparent which units are being used as a comparison group. Relying on *parallel trends* and *no anticipation* assumptions, we can identify $ATT(g, t)$ by comparing the expected change in outcome for group g between $g-1$ and t to that for a control group not-yet treated at period t:

$$ATT(g,t) = E[Y_t - Y_{g-1}|G = g] - E[Y_t - Y_{g-1}|G = g'], \text{ for any } g' > t$$

If the tax incentive is an important variable, we do not expect individuals to anticipate their decision. If the individuals anticipate and the state does not adopt the policy, the investment net present value will be lower than expected. Yet, municipal governments have no control over their treatment status, given that states government are those to choose to implement or not the policy. Therefore, the *no anticipation* assumption may be valid.

The policy implementation depends on the state climatic characteristics, which makes the treatment possibly random. The first states to implement tax incentives are those with the highest solar irradiation, i.e., the states with the highest solar PV potential (Figure A2, Appendix A). If policy adoption depends on X_{it} and φ_{jt}, we should rely on *parallel trends conditional on covariates* assumption. In this case, we combine the outcome regression with inverse probability weighting (IPW) to form *doubly-robust* method proposed by Sant'Anna and Zhao (2020).

When using the *not-yet-treated* as the unique comparison group, we must restrict our data to ensure that we have at least one comparison group for each treated municipalities. Addressing this assumption is challenging since the number of treated municipalities decrease over time. To address this issue, we include the municipalities located in Minas Gerais as a comparison group. Minas Gerais implemented the tax incentive in 2013, two years before the Confaz agreement when the solar PV market was still in its infant phase. These municipalities are good candidates for the comparison group since they did not face idiosyncratic shocks after the policy implementation. Minas Gerais also presents substantial socio-economic and climatic heterogeneity. For instance, the greatest solar irradiation in Brazil occurs in the semi-arid climate area, which includes the northern region of the state. In addition, the lowest values of solar irradiation occur in the state's southern area.

Regarding inference, tax reduction adoption is state-specific but installation is observed at the municipality level. Following recommendations in Bertrand et al. (2004), the standard errors are clustered by state.

6 Results

In this section, we show that state tax incentives on the electricity consumption of PV owners have a positive effect on the residential solar PV installation rate.

Table 3 shows the results of the TWFE model. Column 1 presents the result using no covariates nor additional fixed effects. The point estimate indicates that the installation rate increases by 0.25 units per 100,000 inhabitants, but it is not significant. Column 2 includes the state-year fixed effects. The estimate decreases to 0.21 units and becomes significant at 10%. This result suggests that unobserved state characteristics may be correlated with the state tax incentive adoption. Column 3 includes the covariate population, and column 4 adds the pre-tax electricity price. The result does not change with the addition of covariates due to their correlation with the state-fixed effect. State tax rate, solar irradiation, and PV system price may also determine the adoption of the technology. The municipalities' fixed effects include the state tax rate and solar irradiation, time-invariant variables. The time-fixed effects include the PV system price that does not vary among localities in the same time.

Table 3: Tax incentive on solar PV installation rate: TWFE model

	(1)	(2)	(3)	(4)
State tax incentive	0.254	0.210*	0.210*	0.210*
	(0.538)	(0.113)	(0.113)	(0.112)
Average installation rate	0,514	0,514	0,514	0,514
State-year fixed effects		✓	✓	✓
Population			✓	✓
Pre-tax electricity price				✓
Observations	301,080	301,080	301,080	300,886

Notes: This table presents the results of the OLS estimator of *Two-Way Fixed Effects* model. The dependent variable is the number of installations of the local systems per 100,000 residents. Standard errors clustered at the state level. Significance *** 1 percent, ** 5 percent, and * 10 percent levels.

Table 4 reports the ATT estimates proposed by Callaway and Sant'Anna (2020). Based on the *parallel trends* assumption, column 1 shows the result using Minas Gerais municipalities as the comparison group. The result indicates that the tax incentive increases the installation rate by 0.25 units. Column 2 adds *not-yet-treated* to get a more stable comparison group and estimate the effect more consistently. Installation rate increases to 0.28 units. In column 3, we rely on the *parallel trends conditional on covariates* assumption and add the solar irradiation covariate. The result does not change significantly with the covariates. We do not add the pre-tax price and the state tax rate. These variables are state-specific, and their inclusion reduces the variability and the number of valid observations due to overlap assumption. Besides, the pre-tax price is a regulated tariff whose value changes every four years based on the beginning of the distributor's concession contract. Thus, its variation is random and not correlated with the treatment periods (see Table A2, Appendix A).

Table 4: Effects of state tax incentive on solar PV adoption

	(1)	(2)	(3)
State tax incentive	0.268	0.286*	0.278*
	(0.169)	(0.155)	(0.157)
Average installation rate	0,514	0,514	0,514
Pre-Confaz control group	✓	✓	✓
Not-yet-treated control group		✓	✓
Solar irradiation			✓
Number of municipalities	5,018	5,018	5,018
Number of groups	10	10	10
Number of months	60	60	60

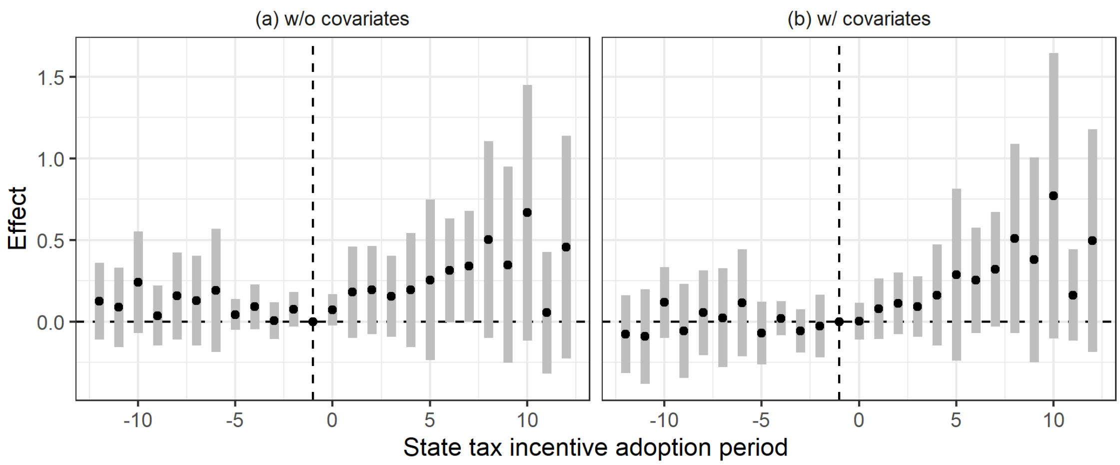
Notes: This table reports the *average treatment effects on treated* (ATT) using the estimator proposed by Callaway and Sant'Anna (2020). Dependent variables are the number of installations per 100,000 residents. Standard errors clustered at the state level. Significance *** 1 percent, ** 5 percent, and * 10 percent levels.

Although TWFE is a naive approach, as discussed in Section 5, their estimates are close to robust estimates in Table 4. The TWFE point estimates range between 0.21 and 0.25, and the robust estimates range between 0.26 and 0.28. These results suggest that the TWFE bias due to heterogeneity between groups and over time may be small in our case study.

Figure 4 presents the tax incentive effect by the length of treatment exposure. The figures report the results without covariates (Figure 4 *a*) and with covariates (Figure 4 *b*), based on Table 4 (columns 2 and 3) specifications. The figures suggest that there are no specific trends in the installation rates when comparing treatment and control groups twelve months before the treatment. Although the points estimate pre-treatment for the specifications without covariates is very close to zero, we improve the parallel trends by adding population and solar irradiation covariates.

The figure shows a wide confidence interval. This may be because we estimate the ATT

Figure 4: Effect of state tax incentive on solar PV adoption by length of exposure



Notes: This table reports the Average Treatment Effects on Treated (ATT) using the estimator proposed by Callaway and Sant'Anna (2020). Dependent variables are the number of installations per 100,000 residents. It uses always treated and not-yet-treated as comparison groups and covariates (solar irradiation and population). Each point presents a different ATT and the 90% confidence interval.

for each period, and the number of comparison groups decreases over time. Furthermore, our database contains many values equal to zero which reduces the outcome variability and increases the estimation uncertainty. However, the point estimations are above zero for all months after the treatment. The estimations suggest that the state tax incentive has a dynamic effect on solar PV adoption. As shown in Figure 4, the average ATT increases over the year after treatment. In our preferred specification (Figure 4 b), the average ATT is 0.16 for the first half year and 0.44 for the last six months.

6.1 Aggregated effects on relevant market

Our main result indicates a positive effect of the state tax incentives on the solar PV installation rate. We estimate these effects using the complete database. A concern in the empirical literature on small-scale solar PV is to deal with a large number of observations equal to zero, i.e., markets with no solar PV (Gillingham and Tsvetanov, 2019; De Groote and Verboven, 2019). Here, we estimate the policy effect on a subset of municipalities with at least one solar PV over the period, the relevant markets. These municipalities present the same solar irradiation but higher population and GDP per capita (see Table A1). Thus, we assume that the tax incentives alone may not be enough to create a solar PV market in these locations.

Table 5 reports the *ATT* estimates for the relevant markets. The columns present the same specifications as Table 4. The results are positive and significant at 5%. The estimates range from 0.40 to 0.42. Our preferred specification, column 3, indicates that the installation rate increases by 0.40 units. This result is 40% higher than the *ATT* estimates reported in Table 4.

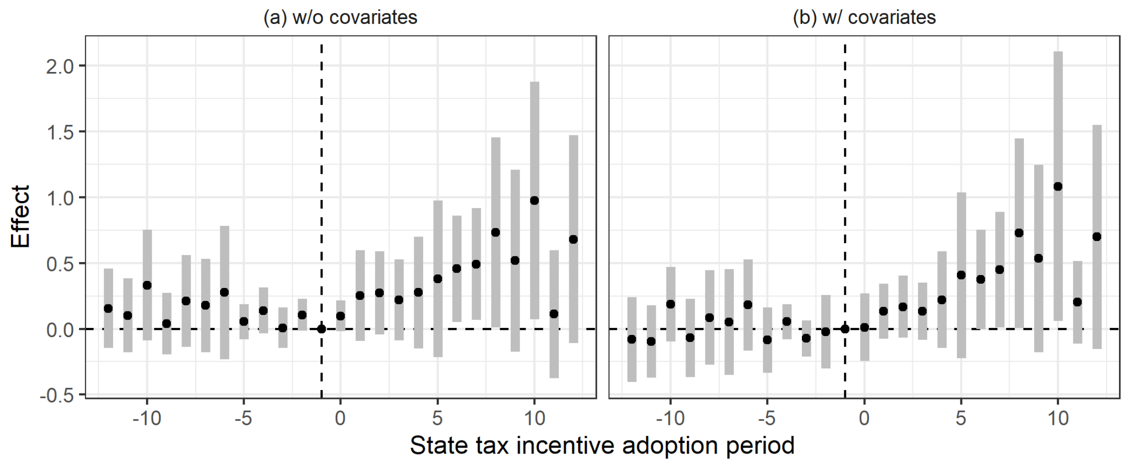
Table 5: Effects of state tax incentive on solar PV adoption: relevant market

	(1)	(2)	(3)
State tax incentive	0.403**	0.419**	0.395**
	(0.194)	(0.181)	(0.180)
Average installation rate	0,666	0,666	0,666
Pre-Confaz control group	✓	✓	✓
Not-yet-treated control group		✓	✓
Solar irradiation			✓
Number of municipalities	3,639	3,639	3,639
Number of groups	10	10	10
Number of months	60	60	60

Notes: This table reports the *average treatment effects on treated* (ATT) using the estimator proposed by Callaway and Sant'Anna (2020). Dependent variables are the number of installations per 100,000 residents. Standard errors clustered at the state level. Significance *** 1 percent, ** 5 percent, and * 10 percent levels.

Figure 5 presents the effect of the state tax incentive by the length of treatment exposure for the relevant markets, based on Table 5 (columns 2 and 3) specifications. The figure suggests no specific trends in the installation rate before the treatment. The figure still presents a wide confidence interval but is significant in the same periods. The point estimates are above zero for all months after the treatment, suggesting a dynamic effect on solar PV adoption. The *ATT* is significant between the eighth and tenth months. If we focus on point estimation, the average *ATT* is 0.24 units for the first half year and 0.60 units for the last six months.

Figure 5: Effect of state tax incentive on solar PV adoption by length of exposure: relevant market



Notes: This table reports the Average Treatment Effects on Treated (ATT) using the estimator proposed by Callaway and Sant'Anna (2020). Dependent variables are the number of installations per 100,000 residents. It uses always treated and not-yet-treated as comparison groups and covariates (solar irradiation and population). Each point presents a different ATT and the 95% confidence interval.

6.2 Heterogeinity

Our database allows for heterogeneity analyses to provide suggestive evidence of the forces driving the overall point estimates. Table 6 reports the results using the complete database, Minas Gerais and not-yet treated units as the comparison group, and the population and solar irradiation covariates. Panel A shows the results for municipality size, measured by the number of residents. Panel B indicates the results for GDP per capita. Each column corresponds to a quartile of the variable distribution at baseline (January 2015), where Column 1 reports the first quartile and Column 4 the fourth quartile.

The smaller (first quartile) and the larger (fourth quartile) municipalities present the highest pre-treatment average installation rates. However, the smallest localities (first and second quartile) have the highest and significant tax incentive effect on PV installation rate. These results are consistent with Graziano and Gillingham (2015) finding that solar PV installations occur predominantly in lower population areas, given the difficulty of installing the systems in densely populated regions.

Regarding GDP per capita, high-GDP municipalities (third and fourth quartile) present the highest pre-treatment average installation rates. The municipalities in the first and second quartiles report ATT close to zero, i.e., the tax incentive has no effect in these locations. This result suggests that just the tax incentives may not generate solar markets in low-income municipalities. Installation rates increase by 0.44 units in the third quartile municipalities, but we do not find any effect in the fourth quartile municipalities, the high-income localities.

Table 6: Effects of ICMS incentive on installations by quartile

	(1)	(2)	(3)	(4)
Panel A. Municipality size				
State tax incentive	0.474*	0.481**	0.111	0.093
	(0.252)	(0.215)	(0.120)	(0.116)
Average installation rate	1,372	0,889	0,733	1,070
Number of municipalities	1,255	1,254	1,254	1,255
Number of groups	11	11	11	11
Number of months	72	72	72	72
Panel B. Average income				
State tax incentive	-0.004	-0.001	0.444**	0.106
	(0.039)	(0.043)	(0.219)	(0.185)
Average installation rate	0.124	0.357	1.716	2.473
Number of municipalities	1,380	1,330	1,210	1,094
Number of groups	9	10	10	10
Number of months	72	72	72	72

Notes: This table reports the Average Treatment Effects on Treated (ATT) using the estimator proposed by Callaway and Sant'Anna (2020). Dependent variables are the number of installations per 100,000 residents. It uses always treated and not-yet-treated as comparison groups and covariates (solar irradiation and population). Each point presents a different ATT and the 95% confidence interval.

7 Overall impact

Given the tax incentive effects estimates on PV adoption in Section 6, we aim to understand the overall policy effects along several dimensions. We are interested in how many installations the incentive generates, the environmental benefits, and the policy cost. We focus here on the local generation of residential PV. Table 7 summarise the results.

We use the ATT estimates of our preferred specification, where we include Minas Gerais municipalities and *not-yet treated* as the comparison group and add the covariates (Table 4, column 3). We then predict the number of installations due to state tax incentives and compare it with the number of PV systems pos-treatment. The number of installations after the incentives is 76,598 units by December 2019. We find a weighted average ATT of 0.28 systems per 100,000 people. Taking into account the residents in each municipality after the treatment, the tax incentives increase installations by 11,011 units. This suggests a modest effect, but it translates into approximately 14% of total PV adoption.

One of the justifications for implementing the tax incentive is to reduce CO_2 emissions associated with electricity generation. We use the predicted results above to calculate these reductions. We assume for simplicity that the PV system has a 25-year system life and zero discounting rate. We also assume a PV capacity factor of 0.15 (de Martino Jannuzzi and de Melo, 2013). We use the CO_2 emission rate of the National Interconnected System (SIN) calculated by the Ministry of Science, Technology, and Innovation (MCTI). Total solar capacity increases by 496 MW after treatment, and the tax incentives increase the capacity by 72 MW by December 2019. At the average emissions rate, total emissions savings are 3,32 $MMTCO_2$.

A measure of cost-effectiveness is the cost of the policy. We calculate the cost of the policy as the total tax subsidy divided by new electricity generations or carbon abatement. Policy cost is a useful metric for comparing the direct cost of the tax incentive with other policies. Ranking policies by cost may allow policymakers to achieve their goals at a possible lower cost. Table 7 shows that the average policy cost is 57 BRL per ton of carbon dioxide. We estimate the tax incentive per megawatt hour by 59 BRL. Finally, the policy cost per additional PV installation is 2,470 BRL.

8 Conclusions

The goal of this paper is to understand the effect of a tax incentive on residential solar PV system adoption in Brazil. The country is an interesting setting for this analysis due to

Table 7: Cost effectiveness under state tax incentive

Total installations	76,598
Installations due to incentive	11,011
Total capacity (MW)	496
Capacity due to incentive (MW)	72
Electricity generation due to incentive (MWh)	7,730
CO_2 abatement (Million ton CO_2)	3.32
Cost-effectiveness:	
Installations (BRL per unit)	2,470
Generation (BRL per MWh)	58.63
CO_2 values (BRL per ton)	56.92

Notes: Carbon abatement calculations under MCTI emission rate between 2015 and 2019. Cost-effectiveness measures calculated as program cost per additional PV installation, MWh, or ton CO_2.

its continental dimensions and the great potential for exploring solar energy. We explore this question in the context of the state tax incentives for solar PV owners' electricity consumption. We then use the policy staggered adoption from 2015 to 2018 to assess the causal effect on the number of residential installations. We focus on residential local PV generation.

We find a positive effect of the state tax incentive on solar PV adoption. State tax incentive increases the installation rate by 0.28 systems per 100,000 residents. Despite the modest effect, this result corresponds to more than ten thousand new systems by 2019, or 14% of the total PV adoption after treatment. The result does not change when we include *not-yet-treated* municipalities as a comparison group nor when we add covariates. The average impact by the length of treatment exposure suggests no specific trends in PV adoption twelve months before the treatment. The results also indicate a dynamic effect post-treatment, reaching the highest value ten months after the state adopts the incentive.

We calculate the cost of the policy as the total tax subsidy divided by new electricity generations or carbon abatement. The average policy cost is 57 BRL per ton of carbon dioxide. We estimate the tax incentive per megawatt hour by 59 BRL. Finally, the policy cost per additional PV installation is 2,470 BRL. Policy cost is a useful metric for comparing the direct cost of the tax incentive with other policies. Ranking policies by cost may allow policymakers to achieve their goals at a possible lower cost.

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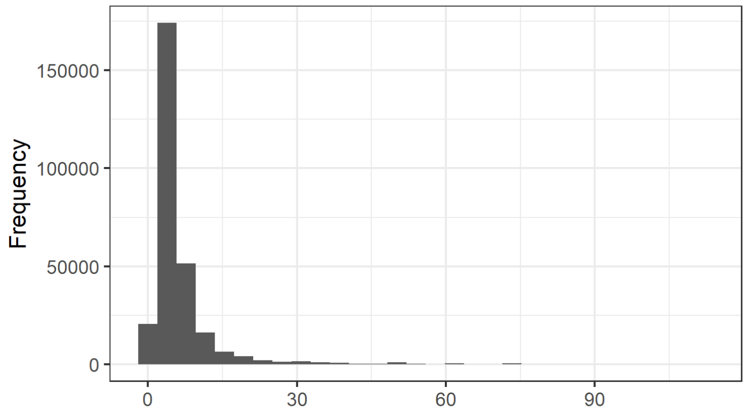
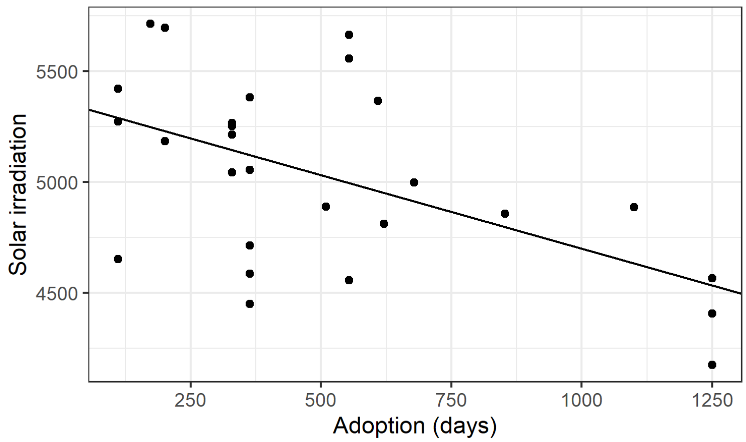
A Appendix

Figure A1: Capacity size of residential solar PV systems



Source: Author's own prepared from the ANEEL data.
Note: Histogram setting with 30 bins.

Figure A2: Solar irradiation and adoption timing of tax incentive by state



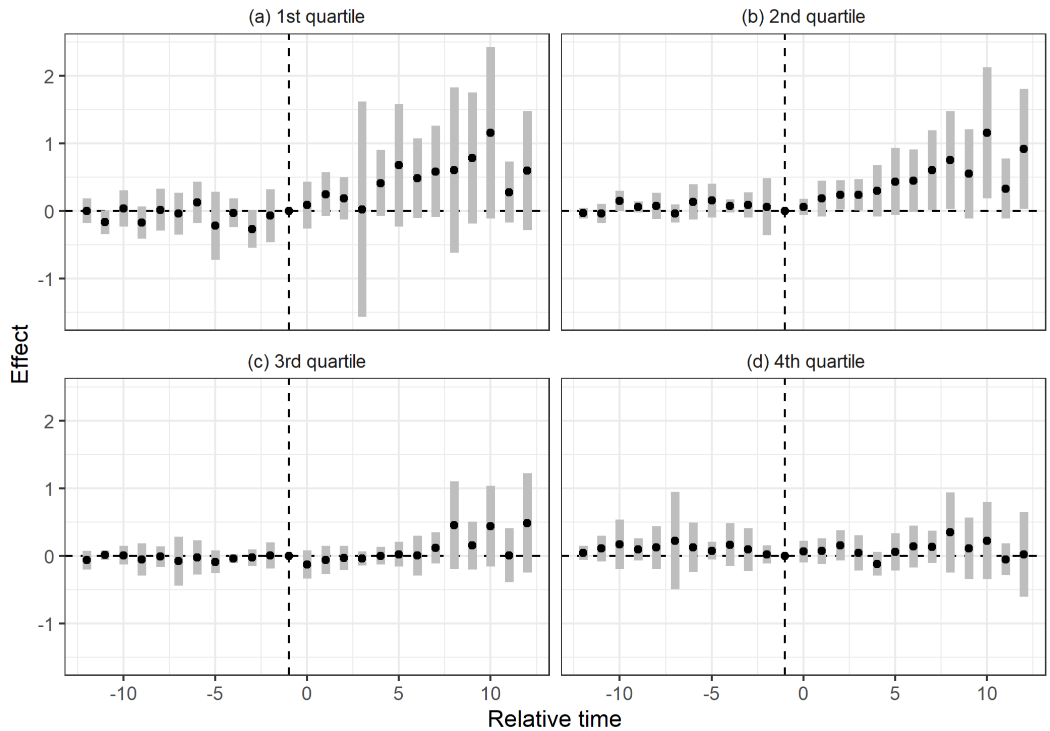
Note: Normal direct solar irradiation and relative time to Confaz agreement adoption 1st January 2015.

Table A1: Mean difference at baseline

Variable	Solar PV	No Solar PV	Difference	t-statistic
Solar irradiation	4,601.47	4,602.50	-1.03	-0.04
Pre-tax electricity price	0.313	0.316	-0.003	-3.13
Electricity tax rate	0.272	0.265	0.007	9.62
GDP per capita	20,442	11,250	9,192	19.17
Population	48,282	10,183	38,099	8.77
Observations	3,648	1,401	2,247	

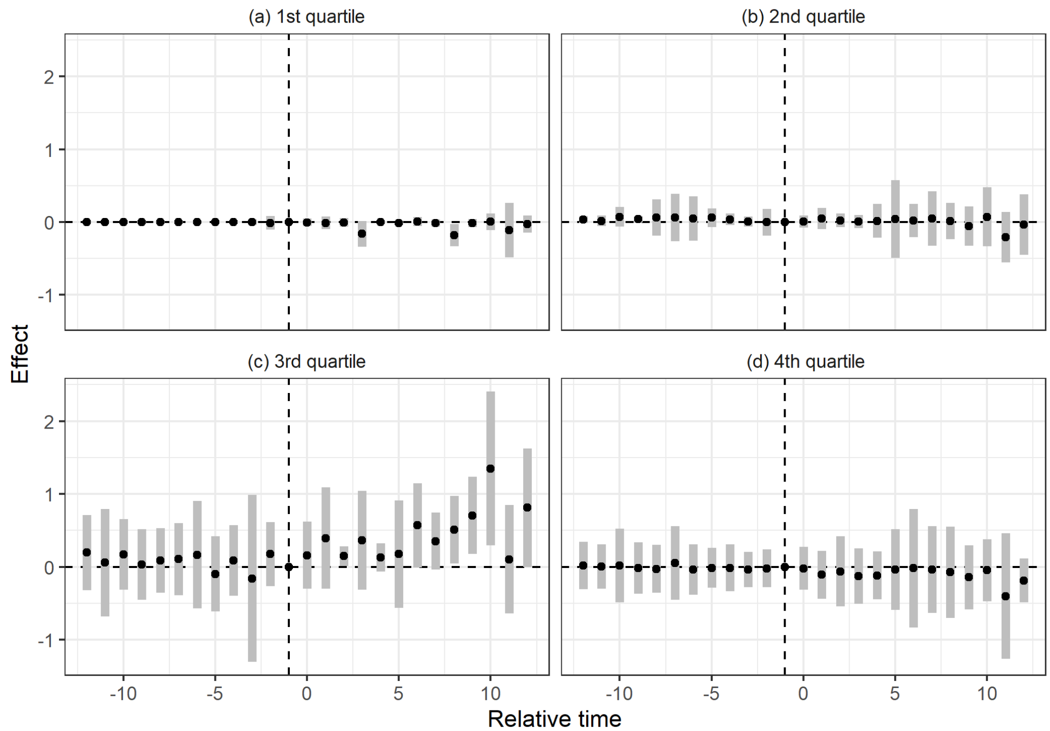
Notes: This table presents the results of mean difference t-test. Variables value correspond to January 2014

Figure A3: Effect of the state tax incentive by length of exposure (municipality size quartile)



Notes: This table reports the Average Treatment Effects on Treated (ATT) using the estimator proposed by Callaway and Sant'Anna (2020). Dependent variables are the number of installations per 100,000 residents. It uses always treated and not-yet-treated as comparison groups and covariates (solar irradiation and population). Each point presents a different ATT and the 90% confidence interval.

Figure A4: Effect of the state tax incentive by length of exposure (income quartile)



Notes: This table reports the Average Treatment Effects on Treated (ATT) using the estimator proposed by Callaway and Sant'Anna (2020). Dependent variables are the number of installations per 100,000 residents. It uses always treated and not-yet-treated as comparison groups and covariates (solar irradiation and population). Each point presents a different ATT and the 90% confidence interval.

Table A2: Effects of state tax incentive on electricity price

	(1)	(2)
State tax incentive	0.001	0.003
	[-0.0019, 0.0035]	[-0.0002, 0.0054]
Covariates		✓
Number of municipalities	5,042	5,042
Number of groups	12	12
Number of months	72	72

Notes: This table reports the Average Treatment Effects on Treated (ATT) using the estimator proposed by Callaway and Sant'Anna (2020). Dependent variable is the pre-tax electricity price in logarithm form. Standard errors clustered at the state level. Square brackets present the 90% confidence interval. Significance * at 10 percent level.