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The Impact of Solar Panel Installation on Electricity Consumption and Production: A Firm's Perspective*

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Abstract

Since 2010, the Uruguayan government has fostered the installation of solar panels among firms to promote the production of small-scale renewable electricity. Under this policy, firms that have installed solar panels are allowed to feed any surplus electricity into the grid. Using a novel data set on firm-level electricity consumption and grid injection, we study the economic and environmental consequences of this policy. First, we find that installing a solar panel reduces the amount of electricity extracted from the grid. Second, we find that it increases the electricity injected into the grid. Third, we find that it reduces CO_2 emissions only marginally. Fourth, we provide evidence of a rebound effect, which ranges from 20% to 26%. Lastly, we propose an alternative policy that allows firms to store their excess electricity in batteries rather than immediately injecting it into the grid. This policy would further reduce CO_2 emissions by 2.7%, incentivizing the injection of electricity at night, when fossil-fuel-based facilities meet the demand at the margin.

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1 Introduction

Energy production contributes significantly to greenhouse gas (GHG) emissions, which are responsible for anthropogenic climate change. Consequently, many countries are transitioning to cleaner energy production (Álvarez et al., 2024). Governments are implementing different policies to incentivize and accelerate this transition, including the promotion of microgeneration from renewable sources (Change et al., 2014).

Since 2010, the Uruguayan government has incentivized the installation of solar, wind, and small hydro microgenerators by households and firms. More specifically, the government initiated a net-metering policy that allows agents with clean microgenerators to sell any surplus electricity into the grid at the retail price.

In this paper, we study the economic and environmental consequences of solar panel adoption by firms. First, we study how the installation of solar panels affects the amount of electricity extracted and injected into the grid. After installing a solar panel, the electricity extracted from the grid is expected to decrease while electricity injected into the grid is expected to increase. The magnitude of these effects, however, is an empirical question. We use a dynamic event study approach to quantify these effects, following Sun and Abraham (2021). Second, we calculate the effect of the policy on CO_2 emissions and the "rebound effect," which is the potential increase in electricity consumption after the installation of a solar panel. Finally, we explore a more efficient policy from a social planner's perspective. More precisely, we study the effect of incentivizing firms to store any surplus electricity in batteries and, instead of immediately feeding it into the grid, feed it when optimal. This policy would reduce CO_2 emissions and spot prices, benefiting other consumers and alleviating the equity concerns associated with the net-metering policy.

We collect a novel dataset that includes the electricity extracted and injected into the grid for every agent with a microgenerator in the country, covering the 14-year period in which the policy has been in place. We focus exclusively on firms, which are the main participants in this policy, and on solar panels, which are the main microgenerators in the country. We observe the electricity extracted and injected into the grid at the firm-month level, 12 months before and 12 months after the solar panel installation. We also gather data on CO_2 emissions from fossil-fuel-based facilities per month, total electricity production per hour and source, and load per hour.

Our results can be summarized as follows. First, using Sun and Abraham (2021)'s approach, we find that, after the solar panel installation, the amount of electricity extracted from the grid decreases and the amount of electricity injected into the grid increases. More specifically, firms reduce their monthly electricity extraction by 1,180 kWh, a 13% reduction from their average electricity extraction, and increase the electricity injected into the grid by 2,090 kWh. Both effects remain constant over time. In our context, the dynamic study-event approach has two caveats. Firstly, it fails to consider that the timing of the solar panel installation is endogenous (Beppler, Matisoff, & Oliver, 2023; Boccard & Gautier, 2021): when an agent installs a solar panel, they may simultaneously decide to increase their electricity consumption or, conversely, start electricity conservation initiatives. This concern, however, is unlikely to be relevant in our case. Agents must navigate through various bureaucratic processes to install their solar panels and, thus, have no control over the exact moment when the panel starts producing. Secondly, early adopters may differ from future adopters; therefore, future adoption of solar panels may not necessarily yield the same results. We mitigate this concern by estimating the model year-by-year. We find no statistical difference between the yearly estimates and hence conclude that this form of selection is not prevalent. Since we cannot completely rule out either of these concerns, we interpret our estimates as an upper bound on the effect of the policy.

Second, we use our estimates to determine the impact of the policy on CO_2 emissions, studying two scenarios. Firstly, we assume that micro-generated electricity exclusively substitutes fossil-fuel-based electricity production and find that monthly CO_2 emissions are reduced by 0.4% compared to the baseline.[1] Secondly, we assume that micro-generated

[1] The "baseline" refers to the average monthly CO_2 emissions of the whole electricity sector.

electricity substitutes for fossil-fuel-based electricity production in proportion to its share of total production.[2] In this scenario, we find that monthly CO_2 emissions are reduced by 0.03% with respect to the baseline.

Third, we do some back-of-the-envelope calculations to quantify the rebound effect, which is the increase in electricity consumption after the solar panel installation. We find that, after the solar panel installation, firms increase their electricity consumption between 20% and 26%.[3] In theory, this increase could be explained by agents feeling richer, changing their consumption behavior, or facing a lower average electricity prices (Beppler et al., 2023; Boccard & Gautier, 2021). The welfare implications of the rebound effect are ambiguous. On the one hand, the rebound effect reduces the effectiveness of solar panels by attenuating the reduction in CO_2 emissions, especially if the electricity source used in the margin is fossil-fuel based. By the same token, it could also increase the generation cost of electricity. On the other hand, the increase in electricity consumption could have a positive impact if it fosters electrification; for example, if agents replace wood fireplaces with electric ones. This could reduce pollutants at the firm level (Beppler et al., 2023). Both effects are likely to be present in the context of our study.

Lastly, we investigate a more efficient policy from a social planner's perspective. Specifically, we propose that firms can feed electricity into the grid when optimal. Agents who install solar panels are wealthier and electricity prices are assumed to incorporate the cost of the grid (Feger et al., 2022; Eid et al., 2014). Since electricity prices are progressive in electricity consumption and richer agents tend to consume more electricity, the net-metering policy implies that richer agents are now contributing less to the costs of the grid. Furthermore, the marginal cost of solar electricity production is virtually zero. The net-metering policy, however, forces electricity providers to buy it at the retail price. In the long run, these two factors can raise electricity prices and create cross-subsidies from non-adopters to

[2]In our time period, fossil fuel production averages 8% of total generation. Therefore, we assume that, on average, 8% of the electricity injected into the grid displaces fossil fuel-based electricity production.

[3]This range is determined by different assumptions regarding the total peak hours of solar irradiance.

adopters (Eid et al., 2014; Simshauser, 2016; Ansarin, Ghiassi-Farrokhfal, Ketter, & Collins, 2020). To mitigate these concerns and improve the efficiency of the policy relating to CO_2 emissions, we propose an alternative policy: incentivize firms to store any surplus electricity in batteries and, instead of immediately injecting it into the grid, inject it when optimal, when CO_2 emissions or spot prices are the highest. We find that this change would reduce monthly CO_2 emissions by 2.7% with respect to the baseline. This reduction in emissions generates a positive spillover for other consumers, helping to alleviate the aforementioned issues related to the net-metering policy.

We expand the literature in several ways. First, while most of the literature focuses on household solar panel use (Borenstein, 2017; Boccard & Gautier, 2021; Sexton et al., 2021; Feger et al., 2022; Pretnar & Abajian, 2023; Beppler et al., 2023), we analyze how firms respond to the installation of solar panels, a scarcely explored topic. To the best of our knowledge, the only other paper that focuses on the non-residential sector is Frey and Mojtahedi (2018). The focus of such a paper, however, differs significantly from ours: whereas they study the effect of a solar panel subsidy on the capacity of the solar panels, we analyze the effect of solar panel installations on the electricity demand and supply of firms.

Firms differ from households in various ways. On the one hand, firms have a more straightforward decision-making process, as they are more clearly profit-maximizers. Firms are also richer on average, which implies that they tend to install much larger solar panels.[4] On the other hand, firms might present behavioral biases as households (Ferraro et al., 2024). We explore this empirically, using firm-level data on electricity extraction and injection into the grid. We find that, for example, firms present a similar rebound effect to households, suggesting some behavioral biases are present in their decision process.

We also contribute to the literature with the granularity of our data: we observe electricity extracted and injected into the grid at a firm level rather than an aggregated level. In that sense, our paper is closely related to Feger et al. (2022). Nevertheless, our paper has some

[4] Our data suggests exactly this: on average, firms' solar panels are more than twice as large as households' solar panels.

significant advantages. Firstly, we directly observe the electricity extracted and injected into the grid, whereas Feger et al. (2022) have to estimate it. Secondly, we use more recent data, covering the period between 2011 and 2022 instead of 2008 to 2014. This is particularly relevant given the significant decline in solar panel prices and the rise in uptake in the last years. Lastly, our study focuses exclusively on the net-metering policy, whereas Feger et al. (2022) study five years of feed-in-tariff policy and one year of net-metering policy.

Third, we contribute to the literature on equity problems associated with net metering policies, the misallocation of the electricity injected from microgenerators, and the use of batteries in solar panels (Pretnar & Abajian, 2023; Astier & Hatem, 2023; Sexton et al., 2021; Boampong & Brown, 2020; Eid et al., 2014; Bollinger et al., 2024). We propose and analyze an alternative policy to alleviate these concerns, in which firms would be incentivized to install small batteries to store electricity instead of injecting it immediately into the grid.

Lastly, we contribute to the growing body of research on the rebound effect of clean electricity microgeneration (Kattenberg et al., 2023; Beppler et al., 2023; Frondel et al., 2023; Qiu et al., 2019; La Nauze, 2019; Deng & Newton, 2017). The vast majority of the literature finds an increase in electricity consumption after the solar panel installation; our results are in line with this literature.[5] For example, Beppler et al. (2023), La Nauze (2019), and Deng and Newton (2017) find a rebound effect of 28%, 23%, and 21%, respectively. Our estimates are aligned with the literature. Our back-of-the-envelope calculations suggest that the rebound effect is between 20% and 26%.

The remainder of this paper is organized as follows. Section 2 describes the Uruguayan electricity market and microgeneration policy. Section 3 presents the data. Section 4 explains our identification strategy. Section 5 presents our empirical results. Section 6 describes and quantifies our alternative policy proposal. Our conclusions are presented in Section 7.

[5] A novel exception of this trend is Kattenberg et al. (2023).

2 Electricity Market

Uruguay's electricity market is highly regulated. It has five primary electricity sources, wind, hydro, biomass, solar, and fossil fuels, and two main institutions: ADME, the market operator, and UTE, the only company that sells electricity to Uruguayan consumers.[6] The market is structured as follows. Electricity facilities sell their electricity to ADME, which in turn buys it on a merit-order basis: from the facility with the lowest marginal cost to the facility with the highest marginal cost of electricity production. Then, UTE sells the electricity to consumers. The electricity price is set by the Executive Power and adjusted periodically, at least once a year. Different price schemes are charged to consumers, depending on the relative size. Specifically, firms are divided by the amount of electricity they (are expected) to consume annually, and they are then automatically enrolled in a particular price scheme. The vast majority of firms in our sample pay just two schemes: the "simple tariff" and the "medium-size consumer" rate. Figure 1 illustrates the price evolution of the latter.[7]

During the past two decades, Uruguay has promoted investments in renewable energy sources, wind, solar, and biomass, on both large and small scales. On a large scale, it has done so through public auctions, whereby firms submit a bid, including a power capacity and electricity selling price, and the government grants licenses to the best offers. This policy has resulted in 94% of the country's electricity grid being powered by renewable sources (MIEM, 2022; CAF, 2022). On a small scale, Uruguay has implemented a net-metering policy. This policy allows households and firms to produce and sell solar, wind, and hydro-based electricity. The policy works as follows. First, the agent consumes the renewable electricity that they produce. If, at any moment, electricity production exceeds consumption, the surplus electricity is sold to the grid. The selling price is equal to the agent's retail price, and the electricity injected into the grid is discounted on their monthly bill. In May 2017,

[6] ADME comes from the Spanish acronym "Administración del Mercado Eléctrico del Uruguay," and UTE comes from the Spanish acronym "Administración Nacional de Usinas y Trasmisiones Eléctricas."

[7] Both price schemes are rather similar. For example, the average electricity price per unit is the same for both.

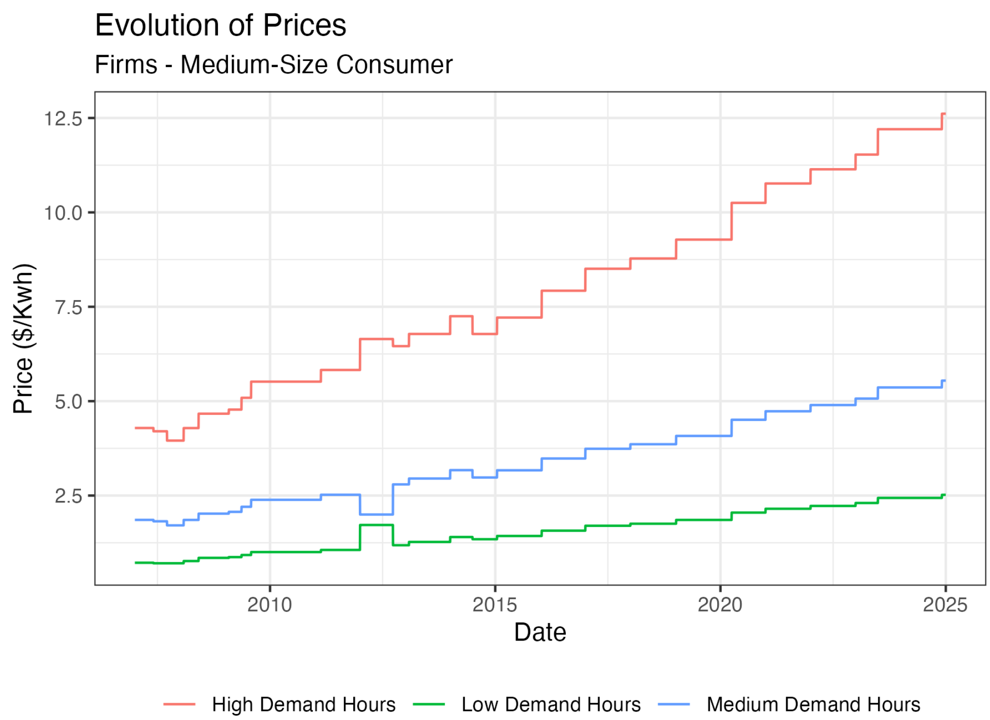


Figure 1: Electricity Price - Example.

Notes: This figure shows the evolution of the "Medium Consumer - C1" electricity rate. "High Demand Hours" are from 6 PM to 10 PM. "Low Demand Hours" are from 12 AM to 7 AM. "Medium Demand Hours" cover the remaining hours. The prices are in Uruguayan pesos per kWh.

the policy changed slightly, stipulating that the annual amount of electricity sold to the grid must not exceed the annual amount of electricity extracted from the grid (MIEM, 2017).

Figure 2 shows the evolution of solar panel installations in the country by month. The decline in 2017 can be attributed to the policy change. Later on, we analyze this change in more detail and find no significant difference in the amount of electricity extracted between firms that installed solar panels before and after the policy change.[8] [9]

[8]For further details, please see Section A.3 for further details.

[9]In practice, the policy did not change much. More precisely, there are only 87 agents whose annual electricity injected exceeds their annual electricity extracted at some point in our data. We repeat our main analyses eliminating these 87 agents and the results do not change. Table A.3 shows the results in the Appendix. We also compare the estimations before and after 2017 and do not find a significant effect.

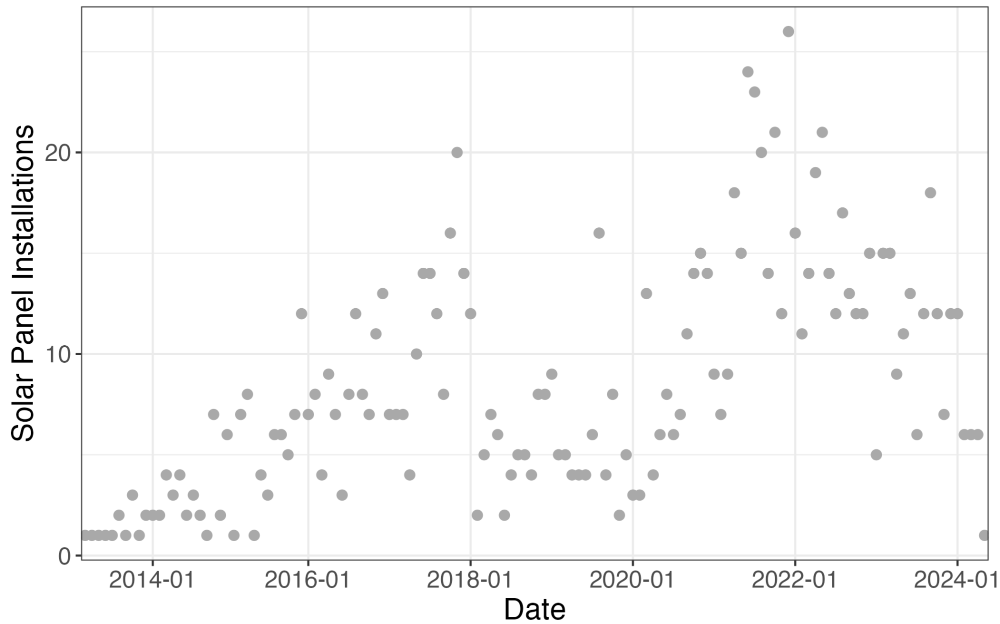


Figure 2: Evolution of Solar Panel Installations by Firms.
Notes: This figure shows the monthly solar panel installations by firms. It covers the period from April 2011 to May 2024.

3 Data and Descriptive Statistics

Our main data source was provided by UTE and consists of pseudo-anonymized administrative data on 1,126 firms from April 2011 to May 2024. It includes information on every firm that has installed a solar panel in the country.

We focus exclusively on the period from April 2011 to September 2022, when more precise data on electricity extraction is available, resulting in 912 firms for that period. For these companies, we observe the monthly electricity extraction from the grid for 12 months before the solar panel installation and the monthly electricity extraction and injection into the grid for the 12 months after the solar panel adoption. We also observe the solar panel capacity and the state in which they were installed.

Figure 3 shows the location of the solar panels for the entire country and the capital city, Montevideo. Although most microgenerators are concentrated in Montevideo, many are scattered throughout the country. The size of each dot reflects the solar panel's capacity in kW. Firms have an average installed capacity of 38 kW. In 2020, microgenerated solar capacity accounted for 12% of the solar installed capacity in the country, which in turn accounted for 6% of the total installed electricity capacity (MIEM, 2022).[10]

Firms are the primary adopters of solar panels in the country: they are around 70% of all solar panel adopters. Within the non-residential sector, firms are the very vast majority, representing 94% of the sample.[11] Moreover, solar panels are mostly adopted by (relatively) large corporations. For example, 70% of the firms in our sample are public limited companies.

The firms' sector varies substantially in our sample. The main sector is the agribusiness, representing 11% of our sample, followed by gas stations, which account for 8%. The rest of the sectors represent less than 8% each.[12]

Table 1 presents the descriptive statistics. The average amount of electricity extracted from the grid is 9,135 kWh before installing a solar panel and decreases to 7,145 kWh afterward. The average amount of electricity injected into the grid is 2,139 kWh.

Lastly, we construct the CO_2 emissions from fossil-fuel electricity generation by collecting monthly data on gas oil, fuel oil, and natural gas consumption from UTEb (2022) and combining it with the CO_2 emission factor derived from IPCC (2006).[13]

4 Methodology

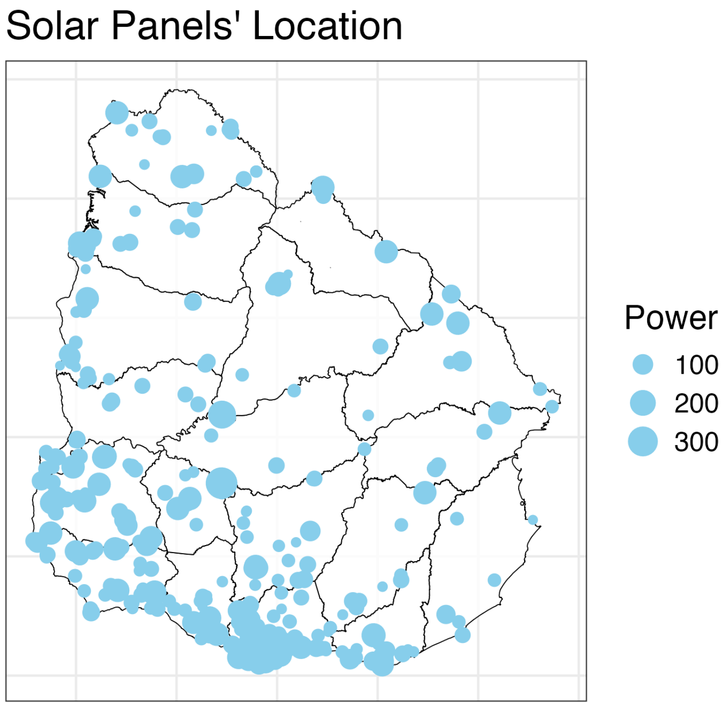
After installing a solar panel, a firm is expected to reduce the amount of electricity extracted from the grid and increase the amount of electricity injected into the grid. Figure 4 illustrates this point, showing the average electricity extracted and injected into the grid before and after the solar panel installation.

[10] This number includes 363 households as well, with an average capacity of 13.5 kWh.

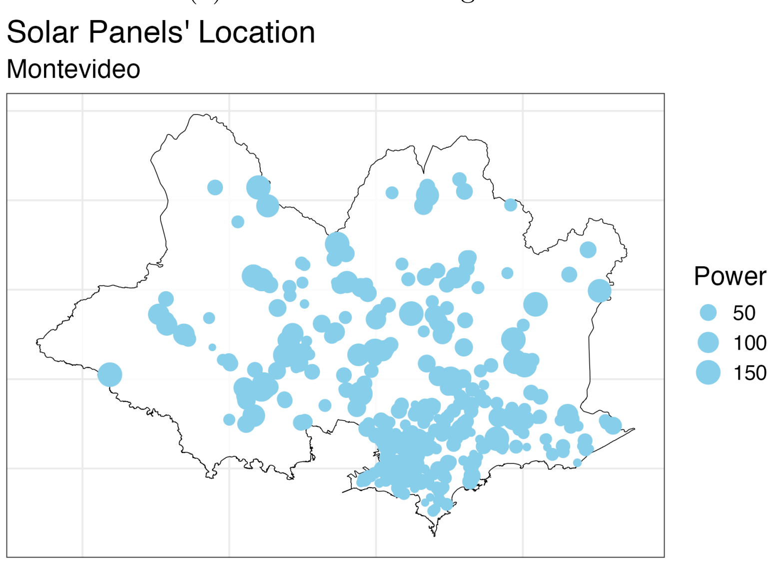
[11] The remaining 6% refers to non-profit and government entities.

[12] Unfortunately, this information cannot be linked to the pseudo-anonymized data that we use in our main analysis.

[13] The data is constructed from 1:00 AM to 1:00 AM of the following month.



(a) Location of Microgenerators



(b) Montevideo - Location of Microgenerators

Figure 3: Microgenerators' location.

Notes: Panel (a) shows the location of the solar microgenerators across the country. Panel (b) shows the location of the solar microgenerators in the capital city, Montevideo. "Power" refers to the installed capacity of the microgenerators in kW. Source: UTE (2022)

Table 1: Descriptive Statistics

	Mean	S.D	Min.	Max
Before				
Extraction (kWh)	9,135	16,355	0.08	256,032
After				
Extraction (kWh)	7,145	5,854	0.08	297,253
Injection (kWh)	2,139	3,877	0.00	136,844
N	17,409	17,409	17,409	17,409

Notes: All electricity variables are measured in kWh. "Before" and "After" refer to before and after the solar panel installation, respectively. "Extraction" refers to the electricity extracted from the grid. "Injection" refers to the electricity fed into the grid. Before the solar panel is installed, electricity extraction and consumption are equal. After installing the solar panel, the amount of electricity extracted may differ from the amount consumed, because firms may self-consume some of the solar electricity they produce. "N" is the total number of observations. 17,409 observations are obtained from 24 observations per firm. The difference in the number of observations is caused by missing values.

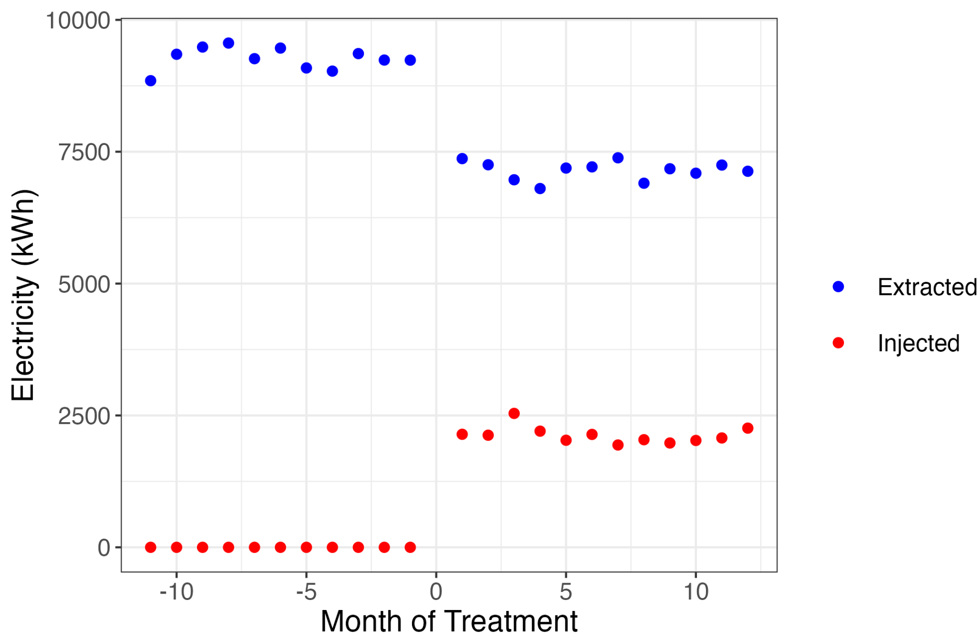


Figure 4: Electricity extracted and injected into the grid.
Notes: This figure shows the average amount of electricity extracted and injected into the grid in the 12 months before and after the solar panel installation.

4.1 Econometric Specification

To quantify the changes in the electricity extracted and injected into the grid after installing a solar panel, we follow Sun and Abraham (2021) and estimate Equation (1):

$$y_{ist} = \alpha_i + \delta_t + \sum_{e=04/2011}^{09/2022} \sum_{l=-12, l\neq -1}^{12} \beta_{e,l} \mathbb{1}[E_i = e] D_{it}^l + \epsilon_{ist} \tag{1}$$

where y_{ist} is the electricity extracted or injected into the grid by firm i in state s and month t; α_i is the firm fixed effect, which captures any time-invariant characteristics of the firm; δ_t is the month fixed effect, which captures weather and seasonal changes; l refers to 12 months before and after the solar panel installation; D_{it}^l is the treatment variable, equal to one if the firm i has already installed a solar panel by time t, firms adopt solar panels at different time, consequently we exploit this staggered adoption of solar panel; e is the cohort, which we define by the month-year of the solar panel installation; finally, ϵ_{ist} is the error term. Formally, the installation occurs at time $\tau = 0$; however, as we do not observe that month, all estimates are compared to $l = -1$. We cluster the errors at the state level.

As explained before, we estimate Equation (1) following Sun and Abraham (2021). Sun and Abraham (2021)'s estimation approach allows for dynamic and heterogeneous treatment effects across cohorts as well as staggered adoption of solar panels. This method is particularly useful in our scenario, because there are no "never treated" firms and the treatment is an absorbing state.[14] In addition, this technique allows each post-treatment month to vary non-parametrically.

One potential limitation of the event-study specification is that solar installation and adoption times are endogenous. If the agent installs a solar panel with the intention of increasing their electricity consumption, our results are upwardly biased (Beppler et al., 2023). Conversely, the estimates are downwardly biased if the agent simultaneously increases electricity conservation initiatives when installing a solar panel. Previous research has found

[14] Sun and Abraham (2021) defines an "absorbing" state as follows: once the treatment occurs, you are always treated.

more evidence for the former and, thus, we interpret these estimates as an upper bound on the effect of net metering. Regardless, we expect the magnitude of the bias to be small because firm has little control over the exact timing of the installation: before a solar panel is installed, the firm has to submit paperwork to the utility for approval and then, the utility has to send a technician to approve the installation.

Another concern could be that early adopters have larger systems and are able to produce more electricity than late adopters. We alleviate this concern by comparing the extraction and the net effect estimates year by year and find no statistically significant differences between the yearly estimates. The results are presented in Figure A.1 in the Appendix.

5 Results

In this section, we present our main findings. First, we discuss the effect of solar panel installation on the electricity extracted and injected into the grid. We also present the net effect of installing a solar panel, which we define as the difference between the electricity extracted from the grid and the electricity injected into the grid. Second, we compute the monetary value of the solar panel installation for firms. Third, we show a reduction in CO_2 emissions caused by the policy. Lastly, we do some back-of-the-envelope calculations to quantify the rebound effect.

5.1 Electricity extracted, injected, and the net effect

Table 2 presents the event-study results following Sun and Abraham (2021)'s estimation technique. Column (1) shows the results for the electricity extracted from the grid. After installing a solar panel, the firm's electricity extracted from the grid decreases, on average, by 1,182 kWh. This decline represents a 13% reduction with respect to the average electricity extracted from the grid before installing the solar panel.[15] Columns (2) and (3) show the

[15] We use Table 1 for this calculation.

effect of installing a solar panel on the electricity injected into the grid and the net effect. After installing a solar panel, the electricity injected into the grid increases by 2,094 kWh and the net effect is -3,484 kWh per firm and month.

Table 2: Main Estimation

Dependent Variables:	Extraction (kWh)	Injection (kWh)	Net Effect (kWh)
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	-1,182.3***	2,094.1***	-3,484.3***
	(237.8)	(100.9)	(352.4)
Fixed-effects			
ID	Yes	Yes	Yes
Month	Yes	Yes	Yes
Fit statistics			
Observations	17,404	13,031	13,031
R^2	0.89624	0.49697	0.88894
Within R^2	0.23589	0.28999	0.23256

*Notes: This table shows the effect of installing a solar panel on: the electricity extracted from the grid (Column 1), the electricity injected into the grid (Column 2), and the net effect (Column 3). We use ID + month fixed effects. Standard errors are clustered at the state level. Significance levels are: ***0.01 **0.05 *0.1.*

Figure 5 presents the coefficients of the dynamic event study model using ID and month fixed effects. The coefficients are calculated with respect to the month before the solar panel installation (month -1). As shown in the graph, the reduction in the electricity extracted from the grid remains constant over time. Furthermore, we do not find an anticipatory effect of the solar panel installation. This is consistent with firms not knowing the exact date on which the solar panel will start working, as discussed in the previous section.

Figure 6 plots the injection coefficients from the dynamic event study using ID and month fixed effects. The omitted month is the month before the solar panel installation (-1). As before, the increase in the amount of electricity injected into the grid caused by to the solar panel installation remains constant over time.

Lastly, Figure 7 illustrates the net-effect coefficients of the dynamic event study using ID

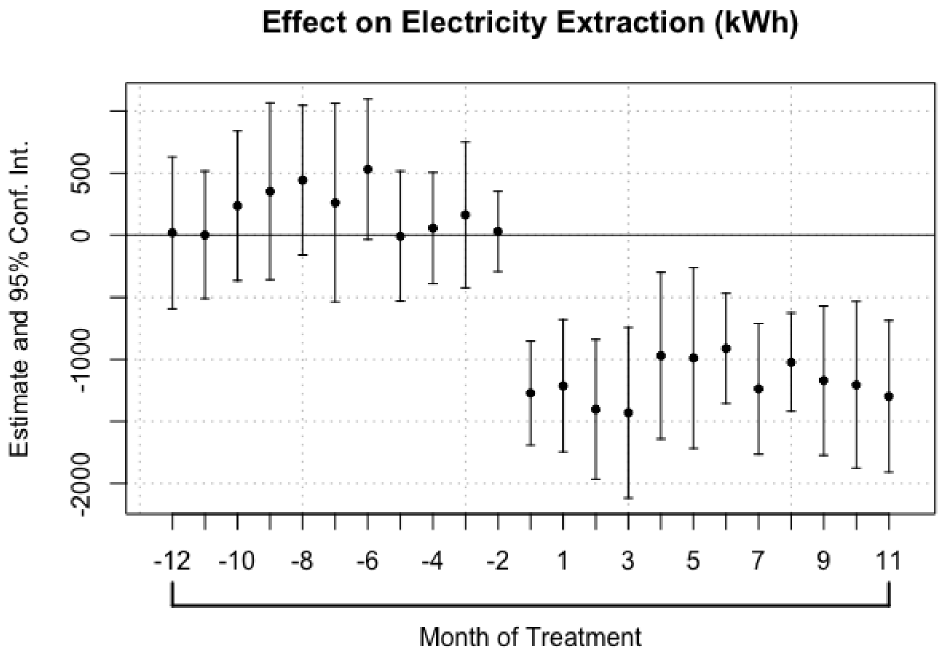


Figure 5: Event study plot - Extraction from the grid.

Notes: This figure shows the event-study coefficients using 12 lags/leads before and after the solar panel installation with ID + month fixed effects.

and month fixed effects. Similarly to the extraction and injection effects, the net effect is constant over time.

5.2 Value to Consumers

We use our estimates to quantify the effect of the policy on firms' savings. To do so, we need to make two assumptions. First, we make an assumption about the electricity pricing scheme under which the firms are charged. For simplicity, we assume that all firms pay the medium-size consumer rate, which is the most popular.[16] The medium-size consumer scheme divides the day into three tiers: peak hours, between 6 PM and 10 PM; off-peak hours, between 12 AM and 7 AM; and plain hours, the remaining hours. Second, since we only observe the monthly extraction and injection of electricity into the grid by firms; we

[16]Unfortunately, we cannot link the database with information on the price contracts with our main database. Nevertheless, around 80% of the firms pay either the medium-size consumer rate or the simple-tariff, which charge, on average, the same price per unit of electricity; hence, the assumption.

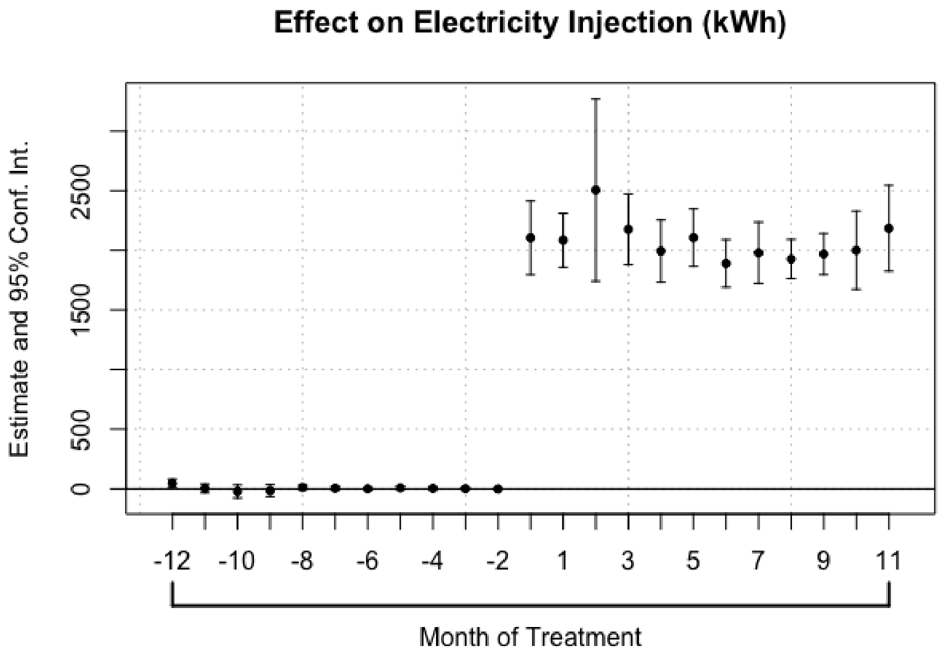


Figure 6: Event study plot - Injection into the grid.

Notes: This figure shows the event-study coefficients using 12 leads/lags before and after the solar panel installation with ID + month fixed effects.

need to make an assumption regarding the hourly distribution of these variables. We assume that they follow the hourly distribution of the large-scale solar electricity production in the country, as in Figure 8 - Panel (B).

If we only consider the effect on electricity injection into the grid, we find that a firm saves 293 USD at October 2022 prices per month on average. If we also consider the reduction in electricity extraction from the grid, this amount rises to 452 USD. Interpreting our results in terms of the necessary time to recover investment costs, a firm needs at least 6 years to recoup its investment for a 40 kW solar panel.[17]

5.3 Reduction in CO_2 Emissions

We use our estimates to calculate the effect of installing solar panels on CO_2 emissions. For this calculation, we make two assumptions. First, we construct an hourly CO_2 emission

[17]The cost of a 40 kW solar panel in the Uruguayan market is 36,500 USD, including installation.

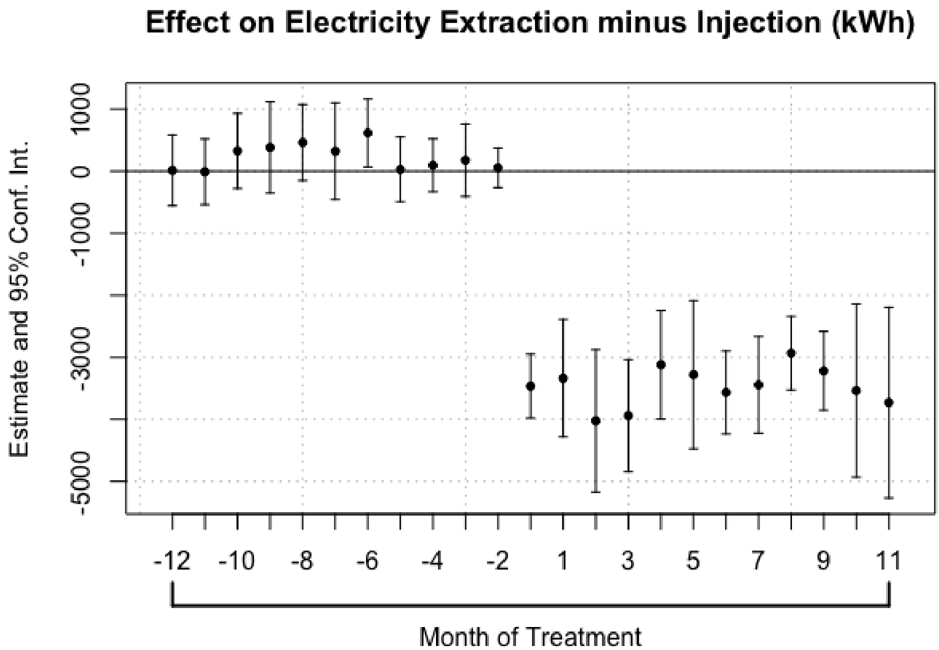


Figure 7: Event study plot - Net effect.

Notes: This figure shows the event-study coefficients of the net effect, which is defined as (electricity extraction − electricity injection) from the grid using 12 leads/lags before and after the solar panel installation with ID + month fixed effects.

factor for our study period. The hourly CO_2 emission factor reflects the amount of CO_2 that would be emitted for each unit of electricity if produced by a fossil-fuel-based facility at that hour. We explain this calculation further in the appendix (A.4). Second, we only observe the electricity extracted and injected into the grid at the monthly level. Therefore, we need to make an assumption about the hourly distribution of electricity extraction and injection within a month. As before, we assume that the electricity injected and extracted from the grid follows the hourly distribution of the large-scale solar electricity production, as presented in Figure 8 - Panel B.

Considering two different scenarios, we find that the policy reduces CO_2 emissions only marginally. Firstly, we study the scenario in which solar panels exclusively displace fossil fuel electricity production. If we consider only electricity injection, we find that, on average, the installation of a solar panel reduces the monthly CO_2 emissions by 0.24% with respect to the monthly CO_2 emissions of the electricity sector. If we include the reduction in electricity extraction, the number rises to 0.4%. Secondly, we study the scenario in which solar panels displace fossil fuel production in proportion to their share of total electricity production. In this case, we find that the installation of a solar panel reduces monthly CO_2 emissions between 0.02% and 0.03% with respect to the same baseline.

5.4 Rebound effect

The installation of solar panels can induce a "rebound effect," an increase in electricity consumption after the installation. In this section, we examine the extent of this effect.

Although we do not directly observe the consumption of electricity after the solar panel installation, we perform some back-of-the-envelope calculations to estimate the average change in electricity consumption and infer the rebound effect from there. In order to do so, we use data on (the average) installed solar panel capacity to estimate solar energy production and combine it with our data on electricity extraction and injection into the grid.

More specifically, at a firm level, we have:

$$Consumption_{\text{before solar panel}} = Extraction_{\text{before solar panel}} \tag{2}$$

$$Consumption_{\text{after solar panel}} = Production - Injection + Extraction_{\text{after solar panel}} \tag{3}$$

$$\begin{aligned} C_{\text{asp}} - C_{\text{bsp}} = {} & (Production - Injection) + \\ & (Extraction_{\text{asp}} - Extraction_{\text{bsp}}) \end{aligned} \tag{4}$$

where we first note that the electricity consumption is equal to the electricity extraction before installing the solar panel, hence Equation (2). After the solar panel installation, the electricity consumption equals the electricity production of the solar panel minus the electricity injected into the grid plus the electricity extracted from the grid, hence Equation 3. We then subtract Equations (3) and (2) to obtain Equation (4).

We can calculate the average rebound effect by averaging Equation (4) for all agents, as shown in Equation (5).[18]

$$
\begin{aligned}
\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} C_{it}-\sum_{-12}^{-1} C_{it}\right] =& \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} P_{it}-\sum_{-12}^{-1} P_{it}\right] \\
&-\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} I_{it}-\sum_{-12}^{-1} I_{it}\right] \\
&+\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} E_{it}-\sum_{-12}^{-1} E_{it}\right]
\end{aligned} \tag{5}
$$

As $\sum_{-12}^{-1} P_{it} = 0$ and $\sum_{-12}^{-1} I_{it} = 0$, we can simplify Equation (5) and obtain Equation (6)

$$
\begin{aligned}
\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} C_{it}-\sum_{-12}^{-1} C_{it}\right] =& \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} P_{it}\right] \\
&-\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} I_{it}\right] \\
&+\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} E_{it}-\sum_{-12}^{-1} E_{it}\right]
\end{aligned} \tag{6}
$$

where C_{it} is the electricity consumed by agent i at time t, P_{it} is the electricity produced by agent i at time t, E_{it} is the electricity extracted from the grid by agent i at time t, and I_{it} is the electricity injected into the grid by agent i at time t.

From our estimates, we recover $\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} E_{it}-\sum_{-12}^{-1} E_{it}\right]$ and $\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} I_{it}\right]$ (Table 2). We also observe $\frac{1}{N}\sum_{t=-12}^{-1} C_{it}$ in our data, which is 9,135 kWh (Table 1). Lastly, we use the capacity of the solar panels to estimate the electricity production.

Electricity production depends on the capacity of the solar panel and the peak sunlight

[18] We have to work with sample means because the installed capacity of the solar panel is in a different database (UTE, 2022) that cannot be linked to the extraction/injection dataset. Furthermore, this dataset has 187 more agents.

Table 3: Electricity production from solar panels

	Monthly Production
Cap. installed (kW)	37.91
Sunlight = 4.5 hours	5,118
Sunlight = 5 hours	5,687

Notes: This table shows the electricity production from solar panels given their installed capacity and the average peak hours of sunlight.

Table 4: Rebound effect

	Rebound Effect (kW)
Sunlight = 4.5 hours	1842 (20%)
Sunlight = 5 hours	2410 (26%)

Notes: This table shows the average rebound effect after installing a solar panel, which depends on the solar panel capacity installed and the average peak hours of sunlight.

hours.[19] In our sample, the average solar panel capacity is 38 kW. We obtain the "peak hours of sunlight" from the "Global Horizontal Irradiation," which is a theoretical indicator of available photovoltaic power that considers air temperature, wind, atmospheric pollution, and dust, among other factors. Uruguay has between 4.5 and 5 hours of sunlight per day;[20] therefore, the solar panel production ranges from 5,118 kWh to 5,687 kWh (Table 3).

Table 4 shows the average rebound effect. After installing a solar panel, electricity consumption increases between 20% and 26%, on average.[21] Our results are consistent with those found in the literature. For example, Beppler et al. (2023), La Nauze (2019), and Deng and Newton (2017) find a rebound effect of 28%, 23%, and 21%, respectively.

The rebound effect could be explained by several factors, such as agents feeling richer, a change in consumption behavior, or a perceived lower electricity price (Beppler et al., 2023; Boccard & Gautier, 2021). Each of these factors is likely present in our study. First, we find

[19]See, for example, these links from the industry: Solar and AE-Solar.
[20]This information can be retrieved from the Global Solar Atlas.
[21]For a numerical example, please see Section A.5 in the Appendix.

that, after the solar panel installation, firms save between 293 and 452 USD per month at 2018 prices (Section 5.2). Thus, agents could indeed feel wealthier and consequently consume more electricity. Second, firms may change their consumption behavior and utilize more electricity during solar hours by, for example, changing their charging patterns or increasing electrification. Lastly, firms buy and sell electricity at the retail price. Consequently, the opportunity cost of using electricity does not change after the solar panel installation and, hence, there should be no economic incentive to increase consumption. Nevertheless, Ito (2014) shows that agents react to the average price in the electricity market. Thus, the increase in electricity consumption could be explained by a decrease in the average price of electricity.

The impact of the rebound effect is ambiguous. On the one hand, the rebound effect reduces the effectiveness of solar panels, i.e., it diminishes the environmental benefits of reducing fossil-fuel-based electricity production. In addition, it could increase other electricity generation costs, implying a leakage effect from this policy. On the other hand, an increase in electricity consumption can be beneficial if the agents initiate the process of electrification. For example, the policy could enable agribusinesses to improve their equipment by buying electric pumps or air conditioning their establishments.

5.5 Robustness Checks

In this section, we present several robustness checks to further validate our main analysis. First, we estimate Equations 1 using a two-way fixed effects model directly. The results remain unchanged and can be found in Table A.1 in the Appendix. Second, we cluster our errors at the agent level instead of the state level. The significance of the estimates remains unchanged and can be found in Table A.2 in the Appendix. Third, we exclude firms that injected more electricity into the grid than they extracted in a given year, to check whether the legislative change in 2017 had any effect.[22] The results do not change significantly and

[22] For more information, please see Section A.3.

can be found in Table A.3 in the Appendix. Lastly, we trim our data by excluding the 5% of the firms with the highest and lowest electricity extraction. The results do not change substantially and are presented in Table A.4 in the appendix.

6 Batteries and Emissions

There is abundant evidence showing that households that install solar panels are wealthier and consume more electricity than the average household. This pattern is present in the United States in general (O'Shaughnessy, Barbose, Wiser, Forrester, & Darghouth, 2021) and California in particular (Borenstein, 2017; Lukanov & Krieger, 2019); the United Kingdom in general (Balta-Ozkan, Yildirim, & Connor, 2015) and England and Wales in particular (Grover & Daniels, 2017); Flanders, Belgium (De Groote, Pepermans, & Verboven, 2016); and Australia (Macintosh & Wilkinson, 2011).

The fact that wealthier households are the primary adopters of solar panels may result in negative spillovers for non-adopting consumers, such as cross-subsidies or a rise in electricity prices. That is the case, for example, in Madrid, Spain (Eid et al., 2014); Queensland, Australia Simshauser (2016); the United Kingdom (Strielkowski, Štreimikienė, & Bilan, 2017); and Austin, Texas, USA (Ansarin et al., 2020)[23].

Our dataset suggests a similar pattern: firms that install solar panels tend to be wealthy (see section 1 for more information). To mitigate the aforementioned problems, namely the increase in cross-subsidies and the distortion of electricity prices (Eid et al., 2014; Simshauser, 2016; Ansarin et al., 2020), and to improve the effect of the policy on CO_2-emissions, we propose a change in the policy. More specifically, the policy maker could incentivize (or force) firms to change the time at which they inject electricity into the grid. This could be achieved by installing a battery at the firm level.

In this section, we explore the potential benefits of such a policy.

[23]For a literature review of the subject, please check Ansarin, Ghiassi-Farrokhfal, Ketter, and Collins (2022).

6.1 Minimization Problem

To maximize the benefits of this alternative policy, we aim to minimize CO_2 emissions given firms' electricity production and total electricity demand. To do so, we complement our main dataset with additional data that contains hourly electricity production by source, hourly electricity demand, and CO_2 emissions from the electricity sector.

We then formulate the daily optimization problem as a linear programming problem, as shown in Equation 7. The goal of this minimization problem is to demonstrate that requiring firms to install batteries alongside solar panels improves the policy´s effectiveness to reduce CO_2-emissions. This reduction generates positive spillovers for other consumers, helping to mitigate the previously discussed issues associated with the net-metering policy.

$$
\begin{aligned}
\min_{q^i_{th}, F_{ht}} & \sum_{h=0}^{23} \alpha^{CO_2}_{th} \times F_{th} \\
s.t \ & \sum_{h=0}^{23} q^i_{th} \leq Q^i, \ \forall i \\
& \mathrm{RD}_{th} \leq F_{th} + \sum_i q^i_{th}, \ \forall h
\end{aligned}
\tag{7}
$$

where q^i_{th} is the electricity injected into the grid from firm i on day t at hour h; F_{th} is the fossil-fuel-based electricity production on day t and hour h; $\alpha^{CO_2}_{th}$ is the CO_2-emission-factor of producing a unit of electricity on day t at hour h from fossil-fuel-based facilities;[24] Q_i is the total electricity production of firm i within day t; and RD_{th} is the residual demand on day t at hour h, which is calculated as the hourly electricity demand minus the electricity production from wind, large solar, hydro, biomass, and exports plus imports. The first constraint requires that the total electricity injection into the grid by firm i equals its daily electricity injection. The second constraint ensures that fossil-fuel-based production plus the microgeneration production is at least equal to the (residual) demand. We provide further

[24] Please see Appendix A.4 for further details on how we construct the CO_2 emission factor.

details on the model in Section A.6.1 in the Appendix.

Ideally, we would like agents to inject their solar-generated electricity into the grid when CO_2 emissions are at their highest, which happens when fossil-fuel-based facilities are producing most of the electricity at the margin. This would be a clear improvement from the current policy, in which firms inject electricity only when production exceeds their own consumption. Hence, some of the injected electricity may be substituting for other clean energy sources, such as wind or large-scale solar production.

Figure 8 - Panel (a) shows the hourly distribution of electricity production by sources, and Panel (b) zooms in on the hourly distribution of large solar production. Figure 9 illustrates the electricity demand by hour.

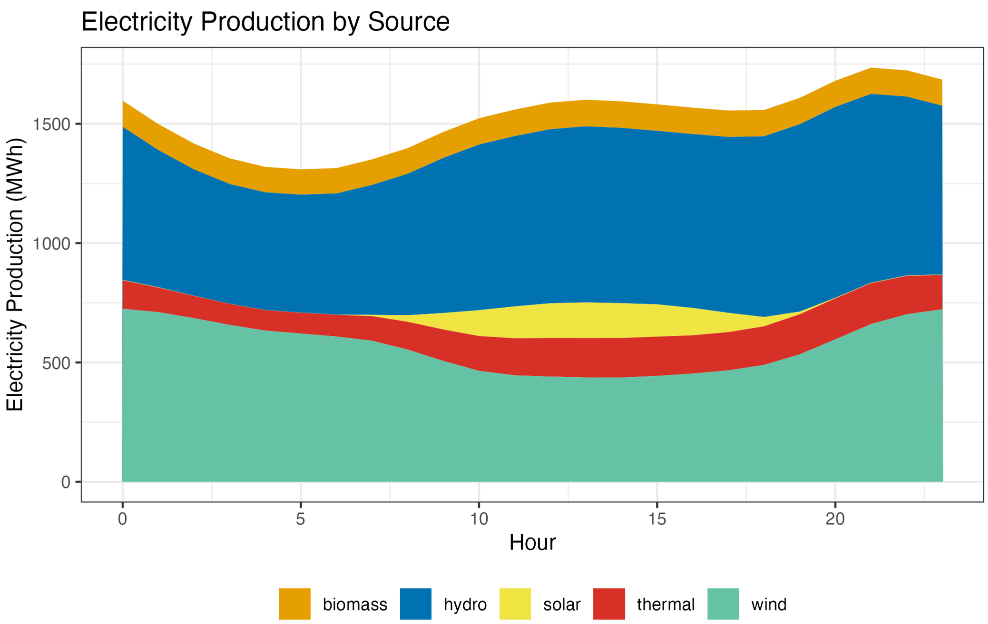
6.2 Solution

The solution to the linear programming problem indicates when firms should inject electricity into the grid to minimize CO_2 emissions. From that result, we can compute the CO_2 reduction associated with the optimal solution.

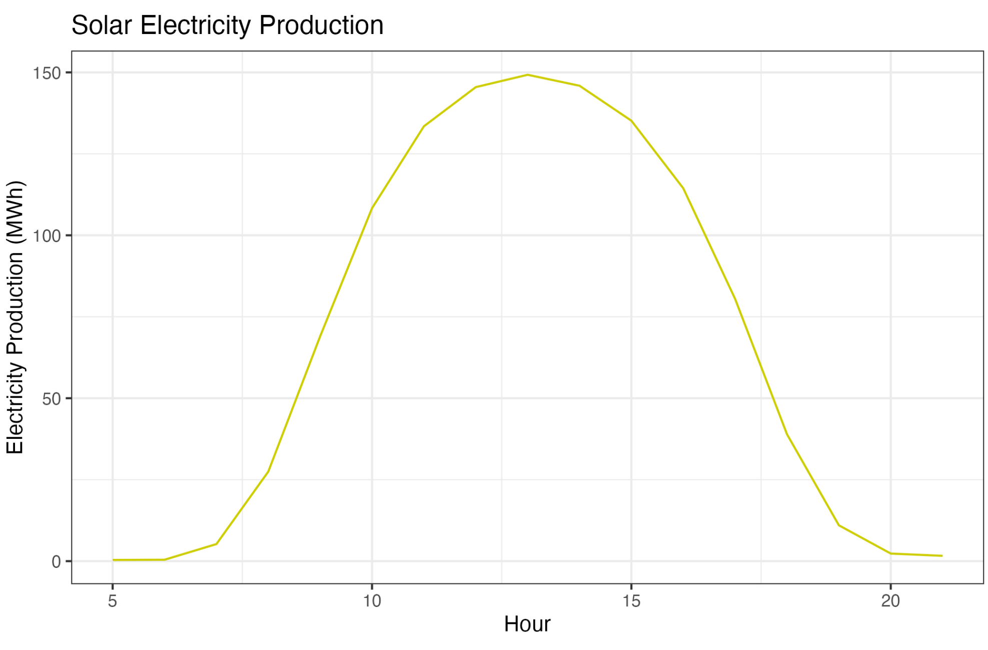
Figure 10 presents the result of the minimization problem. Each dot represents the frequency with which the model indicates the optimal hour for feeding the micro-generated electricity into the grid. We find that the optimal time to inject electricity into the grid is generally between 8 PM and 12 AM. The solution suggests that the electricity injection should be shifted toward peak demand hours, as shown in Figure 9. In terms of emissions, the optimal injection policy reduces CO_2 emissions by 2.7% with respect to the baseline, a substantial improvement from the current policy, which only reduces CO_2 by 0.4% (Section 5.3)

We also solve the model using hourly spot prices instead of the CO_2 emissions factors.[25] The results are fairly similar: the optimal time for firms to inject their electricity is after 6 PM. Figures A.3 and A.4 in the Appendix show the solution and the distribution of hourly

[25]The spot price reflects the marginal cost of increasing the demand for one unit of electricity.



(a) Electricity production by source



(b) Electricity production by large solar

Figure 8: Electricity source.

Notes: Panel (a) shows the hourly distribution of electricity production by source, from November 2018 to September 2022. Panel (b) zooms in on the hourly distribution of solar electricity production over the same time period. Source: ADME (2022)

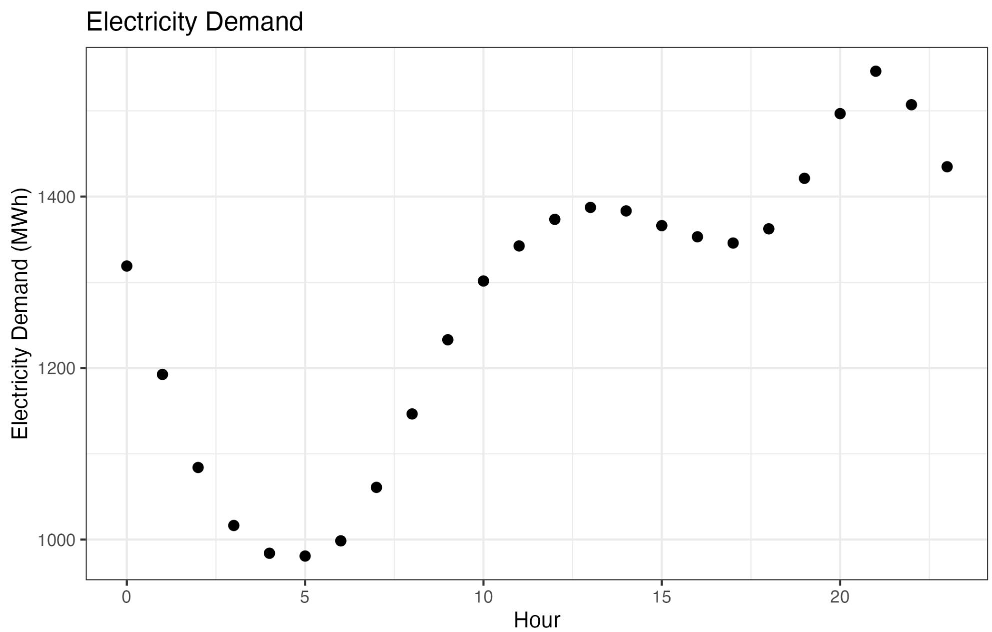


Figure 9: Hourly electricity demand

Notes: This graph shows the average electricity demand per hour for the period between November 2018 and September 2022.

spot prices.

7 Conclusion

We use granular data on electricity extraction and injection into the grid to study the net-metering policy for firms, a scarcely explored topic.

Our work can be summarized as follows. First, we analyze the effect of installing a solar panel on the electricity extracted and injected into the grid using a dynamic event-study approach. We exploit the staggered adoption of solar panels across firms following Sun and Abraham (2021). Second, we use the previous estimates to quantify the effect of the policy on CO_2 emissions and the rebound effect. Lastly, we solve a minimization problem that illustrates the benefits of incentivizing firms to install batteries, allowing them to store solar-generated electricity instead of immediately selling it to the grid.

On the one hand, the policy has clear positive effects. After installing solar panels,

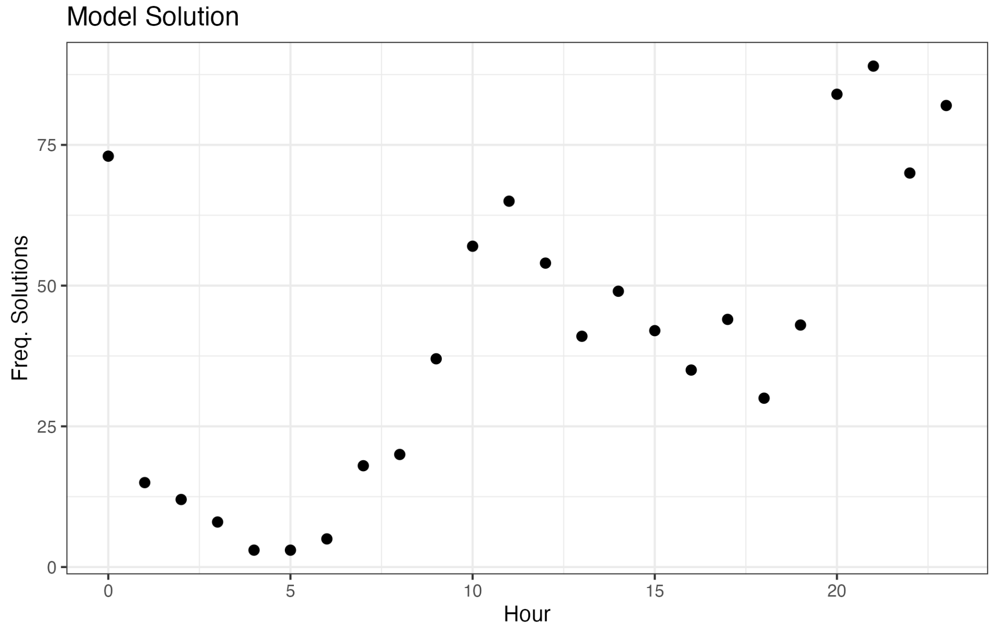


Figure 10: Model solution using CO_2

Notes: This graph shows the model solution that minimizes CO_2 emissions. The y-axis represents the number of times the model indicates it is optimal to inject electricity at that hour, between November 2018 and September 2022.

firms' electricity extraction decreases by 1,182 kWh on average, a 13% reduction in the average amount of electricity extracted from the grid. This effect remains constant over time. Second, firms now inject clean energy into the grid, which is then consumed by other agents. After the solar panel installation, the electricity injected into the grid increases by 2,094 kWh on average. This effect is also constant over time. Third, the policy has a positive yet small effect on CO_2 emissions. We find that the policy reduces CO_2 emissions by 0.4% with respect to the baseline. Lastly, our back-of-the-envelope calculation suggests that firms increase their electricity consumption after installing a solar panel between 20% and 26%, indicating a positive rebound effect.

On the other hand, the policy has important equity implications. Electricity prices reflect the cost of maintaining the grid (Feger et al. (2022)) and wealthier agents, who are more likely to install solar panels, tend to consume more electricity than the average. Since electricity prices are progressive in electricity consumption, these agents are now contributing less to the cost of the grid. In addition, the marginal cost of solar electricity is almost zero; yet, the net-metering policy dictates that the agents' micro-generated production is purchased by utility companies at the retail price. As a result, this policy may create cross-subsidies and increase electricity prices to the rest of the consumers (Eid et al., 2014; Simshauser, 2016; Ansarin et al., 2020). To alleviate these equity concerns and further improve the reduction of CO_2 emissions, we propose an alternative policy: instead of immediately selling the excess of electricity to the grid, firms could be incentivized to store it in batteries and sell when optimal, when CO_2 emissions and spot prices are the highest. To analyze this, we solve a linear minimization model and find that, by incentivizing firms to install batteries and injected the stored electricity between 8 to 12 PM, CO_2 emissions are reduced by 2.7%. This change in the policy would generate positive spillovers to the rest of the consumers by reducing CO_2 emissions and electricity spot prices, mitigating the regressive effects of the current policy for non-adopters.

In terms of monetary value, we find that a firm saves, on average, 262 USD monthly after installing a solar panel from solar electricity injections. In 2021, the cost for a 12V 200ha battery in the Uruguayan market was 1132 USD (Source: Mercado Libre). Therefore, these savings would allow a firm to recoup the battery cost within a few months. Firms could then either eliminate grid injection entirely or inject electricity when socially optimal, as shown in our linear programming model.

Future research could explore the mechanisms behind the rebound effect. Moreover, our analysis does not cover off-grid solar panels with battery systems, which could benefit households without the cost of extending the grid. This would be another interesting topic for future work.

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A Appendix

A.1 Robustness Checks

In this section, we present the robustness checks for our main analysis.[26]

A.1.1 Two-way Fixed Effect Model

We estimate the two-way fixed effect model. More precisely, we estimate Equation 8:

$$y_{ist} = \alpha_i + \delta_t + \beta D_{ist} + \epsilon_{ist} \tag{8}$$

where y_{ist} is the electricity extracted or injected into the grid by firm i in state s and month t; α_i is the firm fixed effect, which captures any time-invariant characteristics of the firm; δ_t is the time fixed effect, which captures weather and seasonal changes; D_{ist} is the treatment variable, equal to one if the firm i has already installed a solar panel by time t; and ϵ_{ist} is the error term. We cluster the errors at the state level.

Table A.1 shows ours results, which remain virtually unchanged.

[26]For simplicity, we present the ATT in every case. The dynamic estimates are available upon request.

Table A.1: Two-way Fixed Effect Model

Dependent Variables:	Extraction (kWh)	Injection (kWh)	Net Demand (kWh)
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	-1,491.2***	2,135.8***	-3,584.4***
	(97.51)	(109.2)	(305.2)
Fixed-effects			
ID	Yes	Yes	Yes
Month	Yes	Yes	Yes
Fit statistics			
Observations	17,409	13,033	13,033
R^2	0.86611	0.42555	0.86369
Within R^2	0.01395	0.18917	0.05805

*Notes: This table shows the effect of installing a solar panel on: the electricity extracted from the grid (Column 1); the electricity injected into the grid (Column 2); and the net effect (Column 3). We use ID + month fixed effects. Standard errors are clustered at the state level. Significance levels are: ***0.01 **0.05 *0.1.*

A.1.2 Alternative Cluster

In this section, we estimate the main regression, clustering the standard errors at the ID level. The significance does not vary and can be found in Table A.2.

Table A.2: Different Cluster

Dependent Variables:	Extraction (kWh)	Injection (kWh)	Net Effect (kWh)
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	-1,182.3***	2,094.1***	-3,484.3***
	(287.0)	(143.1)	(438.4)
Fixed-effects			
ID	Yes	Yes	Yes
Month	Yes	Yes	Yes
Fit statistics			
Observations	17,404	13,031	13,031
R^2	0.89624	0.49697	0.88894
Within R^2	0.23589	0.28999	0.23256

*This table shows the effect of installing a solar panel on the electricity extracted from the grid in Column (1); column (2) shows the effect of installing a solar panel on the electricity injected; and column (3) shows the net effect. ID + month fixed effects are used. Standard errors are clustered at the agent level. Significance levels: ***0.01 **0.05 *0.1.*

A.1.3 Exclude Agents with Injection Greater than Extraction

In 2017 the net-metering policy changed slightly, stipulating that agents cannot produce more electricity than they consume in a year.

In practice, only 87 firms produce more electricity than they consume in a year. In this section, we exclude them from the main regressions; the results are virtually unchanged. Table A.3 presents our results.

Table A.3: Excluding agents whose yearly injection is greater than extraction

Dependent Variables:	Extraction (kWh)	Injection (kWh)	Net Effect (kWh)
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	-1,137.0***	1,873.8***	-3,163.4***
	(256.0)	(115.5)	(430.8)
Fixed-effects			
ID	Yes	Yes	Yes
Month	Yes	Yes	Yes
Fit statistics			
Observations	15,822	11,514	11,514
R^2	0.89606	0.43175	0.89108

*This table shows the effect of installing a solar panel on the electricity extracted, injected, and the net effect in Column (1), column (2), and column (3), respectively. The net effect is defined as (extractions − injections) taken from the grid. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

A.1.4 Exclude Tails of Agents' Extraction from the Grid

Our results may also be driven by agents with very high or very low electricity extraction from the grid. Therefore, we exclude the 5% of firms with the highest and lowest total electricity extraction from the grid. The results do not change qualitatively. A summary of the results is shown in Table A.4.

Table A.4: Excluding 5% tails on electricity extracted from the grid

Dependent Variables:	Extraction (kWh)	Injection (kWh)	Net Effect (kWh)
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	-1,234.4***	2,045.5***	-3,186.2***
	(185.7)	(61.89)	(197.5)
Fixed-effects			
ID	Yes	Yes	Yes
Month	Yes	Yes	Yes
Fit statistics			
Observations	16,534	12,309	12,309
R^2	0.87739	0.58026	0.81671
Within R^2	0.21981	0.31042	0.28274

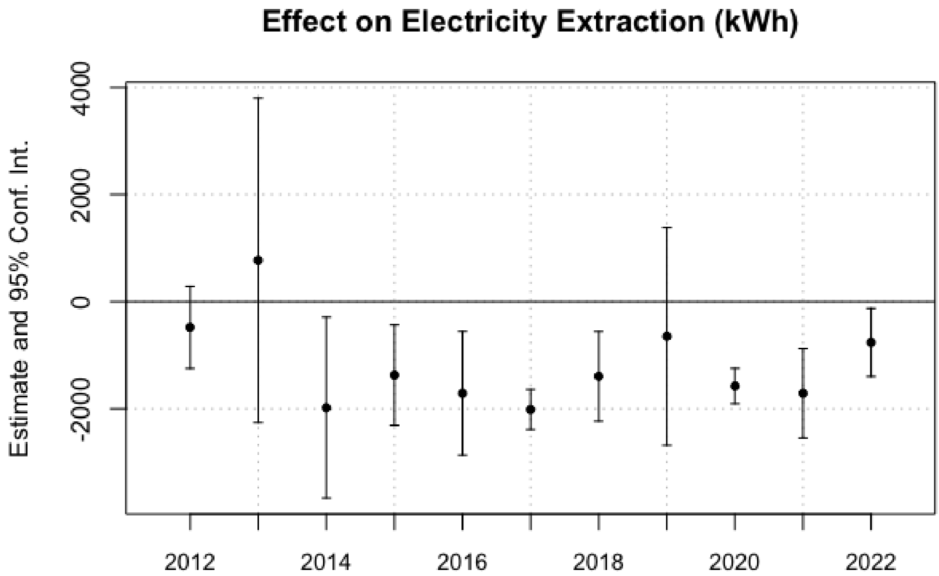
*This table shows the effect of installing a solar panel on the electricity extracted, injected, and the net effect in Column (1), column (2), and column (3), respectively. The net effect is defined as (extractions − injections) taken from the grid. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

A.2 Selection Bias

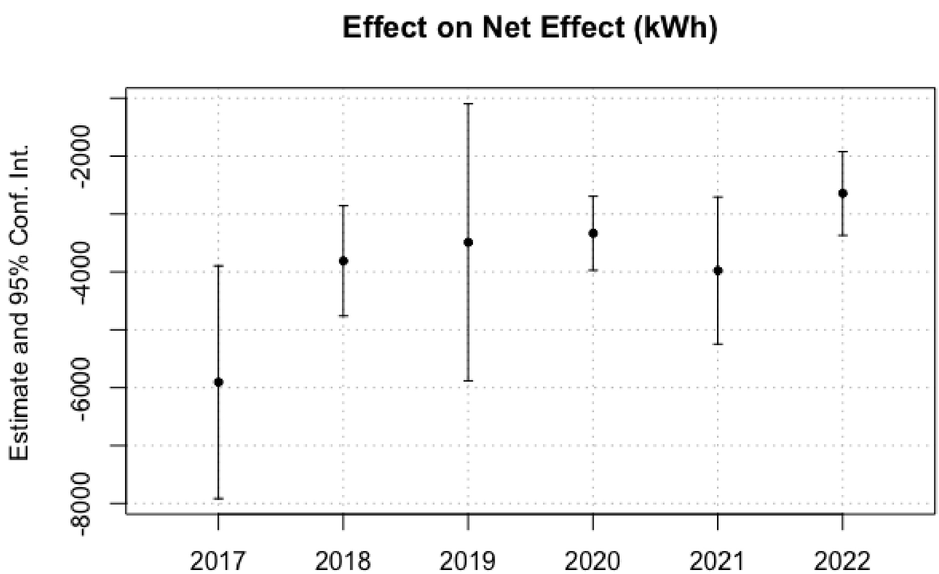
In this section, we examine whether early adopters are different from late adopters. More precisely, we compare the annual estimates of the electricity extracted and the net effect (electricity extraction − injection).

First, we interact the treatment variable with a yearly indicator variable, which equals one for a given year and zero otherwise. Then, we run Equation (8). We use the two-way fixed effect model as in Section A.1.1 with firm and month-fixed.

Figure A.1 shows our results. For the extraction estimates (Panel a), all coefficients are fairly similar. To explore this further, we compare the 2013 extraction estimates with those of 2014 and 2018. The p-values are 0.23 and 0.24, respectively. Therefore, we cannot reject the hypothesis that the extraction estimate for the year 2013 is not equal to the estimation for 2014 and 2018. We repeat this for the net effect and find similar results.



(a) Extraction estimations



(b) Net effect estimations

Figure A.1: Yearly estimations

Notes: Panel (a) shows the annual extraction estimates. Panel (b) shows the annual estimates using the net effect. Data prior to 2017 has many missing values. The regression uses ID and month fixed effects.

A.3 Change in the Policy - 2017

Since May 2017, the legislation mandates that the annual amount of electricity injected into the grid must be less than or equal to the amount of electricity consumed (MIEM, 2017). In this section, we examine the effect of this policy change in more detail. More precisely, we construct a variable equal to 1 if the installation date is after May 2017 and 0 otherwise. We then interact this variable with the treatment.

Table A.5 shows the results. We find no difference in the electricity extracted from the grid between firms that installed a solar panel before the change in legislation and those that did so after.

Table A.5: Effect of the change in the policy

Dependent Variable:	Extraction (kWh)
Model:	(1)
Variables	
Treatment	-1,546.0***
	(330.3)
Treatment × Post 2017	78.04
	(470.2)
Fixed-effects	
ID	Yes
Month	Yes
Fit statistics	
Observations	17,409
R^2	0.86611
Within R^2	0.01395

*This table shows the effect of installing a solar panel on the electricity extracted from the grid. ID + month fixed effects are used. Solar panel installation ∗ after May 2017 takes the value of one if the firm installs a solar panel after the regulatory change. Standard errors are clustered at the state level. Significance levels: ***0.01 **0.05 *0.1.*

A.4 CO_2 Emission Factor

As discussed in Section 5.3, the CO_2 emission reduction depends on which source is used in the margin. We reflect this in our study by creating hourly CO_2 emission factors as follows.

First, we construct the total CO_2 emissions from the electricity produced on a monthly level. To calculate this number, we collect monthly data on fuel oil, gas oil, and natural gas consumption for thermal electricity generation and then use the IPCC (2006)'s CO_2-emission factors to convert them to monthly CO_2 emissions. Second, we construct the average hourly CO_2 emission factor for the month by dividing the total CO_2 by the total monthly thermal production. Finally, we want to reflect that the higher the thermal production within a month, the more likely it is that facilities with higher CO_2 emissions are being used. We would also like to reflect that, if we multiply the CO_2-emission factor by the thermal production and sum up over the day, the associated CO_2 emissions will be equal to the CO_2 emitted that day. Thus, we construct a specific-weight within the hour-of-the-day, defined as w_d, in two steps. First, we construct a weight per hour equal to the total thermal production in that hour divided by the total thermal production in that day. Then, we re-weight such a weight by the square of the sum of the total thermal production of the day divided by the sum of the square of the total.

Mathematically, we can find this re-weighting as follows. Let the average hourly CO_2 emissions be α, the hourly thermal production be t_{dh}, and the re-weighting factor be w_d. The specific-weight is then defined as Equation 9.

$$\begin{aligned} \sum_h t_{dh} \times \alpha &= \sum_h \alpha \times t_{dh} \times \frac{t_{dh}}{\sum_h t_{dh}} \times w_d \\ \sum_h t_{dh} &= \frac{w_d}{\sum_h t_{dh}} \sum_h t_{dh}^2 \implies \quad w_d = \frac{(\sum_h t_{dh})^2}{\sum_h t_{dh}^2} \end{aligned} \tag{9}$$

A.5 Rebound Effect

In this section, we present an example of the rebound effect calculation.

$$\begin{aligned}\sum_{1}^{12} \frac{Consumption_i}{N} - 9135 =& 5118 - 2094.06 - 1182.34 \;\text{ if hours of sunlight } = 4.5 \\ \sum_{1}^{12} \frac{Consumption_i}{N} - 9135 =& 1842\end{aligned} \tag{10}$$

$$\begin{aligned}\sum_{1}^{12} \frac{Consumption_i}{N} - 9135 =& 5687 - 2094.06 - 1182.34 \;\text{ if hours of sunlight } = 5 \\ \sum_{1}^{12} \frac{Consumption_i}{N} - 9135 =& 2410\end{aligned} \tag{11}$$

Figure A.2 shows the lower and upper bounds of the monthly rebound effect.The estimates used in the calculation are presented in Table A.6.

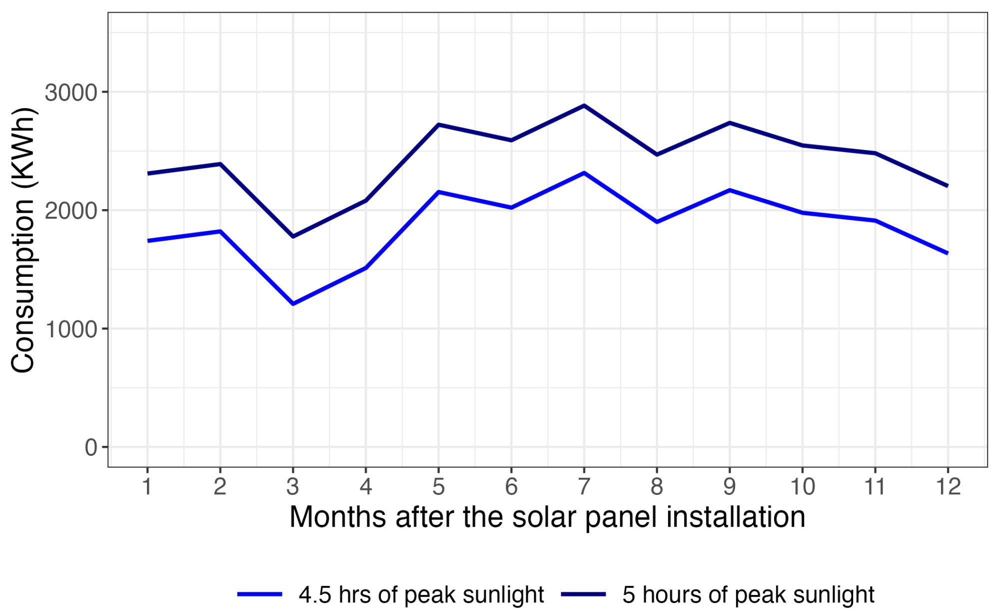


Figure A.2: Rebound effect.
Notes: This figure shows the monthly lower and upper bounds of the rebound effect after installing a solar panel.

Table A.6: Estimations used for the rebound calculation

	Extraction reduction	Injection
Month +1	-1272.40	2104.78
Month +2	-1213.25	2083.93
Month +3	-1404.65	2504.63
Month +4	-1429.93	2176.18
Month +5	-970.86	1993.73
Month +6	-989.72	2106.62
Month +7	-913.60	1889.72
Month +8	-1237.83	1979.48
Month +9	-1023.05	1926.127
Month +10	-1171.05	1969.02
Month +11	-1205.68	1999.95
Month +12	-1298.81	2184.56

This table shows the estimates used to calculate the rebound effect. These estimates are the same as those shown in Figure 5 and 6, where ID and month-fixed effects are used. Month +1 shows the estimates of extraction and injection after the first month following the solar panel installation.

A.6 Linear Model

A.6.1 Further Details

In this section, we explain our linear minimization problem in more detail. Recall:

$$\begin{aligned} \min_{q^i_{th}, F_{ht}} \sum_{h=0}^{23} \alpha_{th}^{CO_2} \times F_{th} \\ s.t \sum_{h=0}^{23} q^i_{th} \leq Q^i,\ \forall i \\ \mathrm{RD}_{th} \leq F_{th} + \sum_i q^i_{th},\ \forall h \end{aligned} \tag{12}$$

where q^i_{th} is the electricity injected into the grid from microgenerator i on day t at time h, and t_{th} is the thermal production during that day and hour.

We can rewrite the problem in matrix form. More precisely, the objective function is a matrix$_{48x1}$ times a matrix$_{1x48}$

$$\begin{bmatrix} \alpha_0 & \alpha_1 & \alpha_2 & \cdots & \alpha_{23} & 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \times \begin{bmatrix} t_0 \\ t_1 \\ t_2 \\ \vdots \\ t_{23} \\ \sum_i q_0^i \\ \sum_i q_1^i \\ \sum_i q_2^i \\ \vdots \\ \sum_i q_{23}^i \end{bmatrix}$$

The first constraint is two bind identity matrices of size 24

$$\begin{pmatrix}
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\end{pmatrix} \times \begin{pmatrix} t_0 \\ t_1 \\ t_2 \\ \vdots \\ t_{23} \\ \sum_i q_0^i \\ \sum_i q_1^i \\ \sum_i q_2^i \\ \vdots \\ \sum_i q_{23}^i \end{pmatrix} \geq \begin{pmatrix} \mathrm{rd}_0 \\ \mathrm{rd}_1 \\ \mathrm{rd}_2 \\ \mathrm{rd}_3 \\ \mathrm{rd}_4 \\ \mathrm{rd}_5 \\ \mathrm{rd}_6 \\ \mathrm{rd}_7 \\ \mathrm{rd}_8 \\ \mathrm{rd}_9 \\ \mathrm{rd}_{10} \\ \mathrm{rd}_{11} \\ \mathrm{rd}_{12} \\ \mathrm{rd}_{13} \\ \mathrm{rd}_{14} \\ \mathrm{rd}_{15} \\ \mathrm{rd}_{16} \\ \mathrm{rd}_{17} \\ \mathrm{rd}_{18} \\ \mathrm{rd}_{19} \\ \mathrm{rd}_{20} \\ \mathrm{rd}_{21} \\ \mathrm{rd}_{22} \\ \mathrm{rd}_{23} \end{pmatrix}$$

The second constraint:

$$\left(\begin{matrix} 0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1 \end{matrix}\right) \times \begin{pmatrix} t_0 \\ t_1 \\ t_2 \\ \vdots \\ t_23 \\ \sum_i q_0^i \\ \sum_i q_1^i \\ \sum_i q_2^i \\ \vdots \\ \sum_i q_2^i3 \end{pmatrix} = (Q^i)$$

where α_k is either the CO_2 emission coefficient or the spot price for hour $k = (0,\ 1,\ 2, \cdots,\ 23)$. rd_k is the residual demand for the hour k. The residual demand is found as: residual demand = demand - wind - hydro - solar - biomass.

A.6.2 Minimization Problem with Spot Prices

In this section, we show the results for the minimization problem using the spot price as a reference.

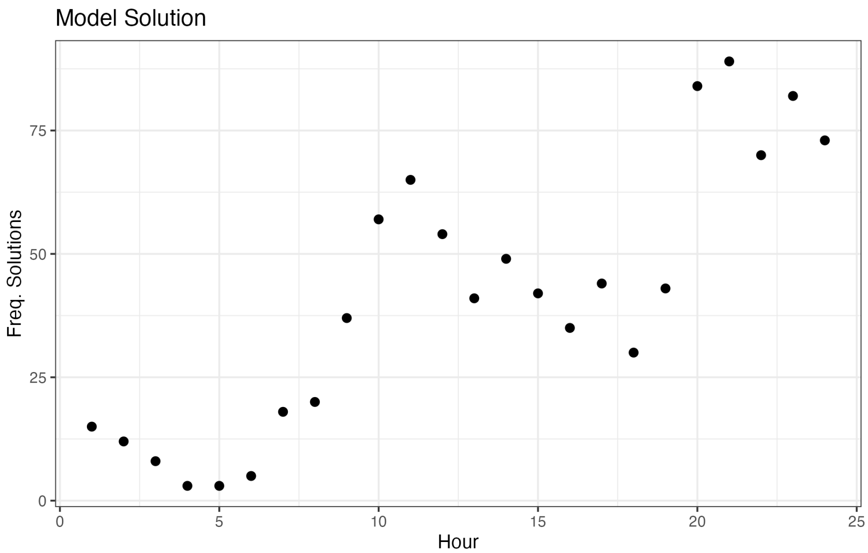

Figure A.3: Model solution using spot prices

Notes: This graph shows the minimization solution using spot prices. We focus on the period between November 2018 and September 2022.

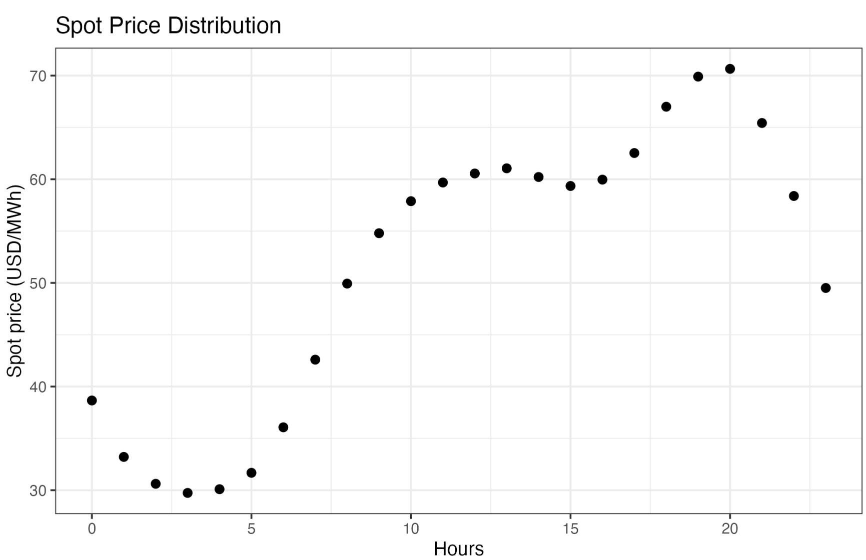

Figure A.4: Model solution using spot prices

Notes: This graph shows the average spot price distribution for the period from November 2018 to September 2022.