The Impact of Solar Panel Installation on Electricity Consumption and Production*

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Abstract

Since 2010, the Uruguayan government has fostered the installation of solar panels among households and firms to promote small-scale renewable electricity production. Under this policy, agents with solar panels are allowed to feed any electricity surplus into the grid. We study the economic and environmental consequences of this policy. We collect a novel dataset on electricity extraction and injection into the grid at a household/firm level for the whole country. First, we find that installing a solar panel reduces the 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 by 0.15% with respect to the baseline. Fourth, we find evidence of a rebound effect: electricity consumption after the solar panel installation increases between 20% and 26%. Lastly, we propose an alternative policy that allows agents to store their electricity surplus in batteries instead of immediately injecting it into the grid. This policy would reduce CO_2 emissions by 2.7%, allowing electricity injection into the grid at night when fossil-fuel facilities satisfy most of the electricity demand. We leverage household and firm-level data to study the effect of a net-metering policy on electricity extraction and injection, showing what countries can expect from implementing such a policy.

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1 Introduction

Energy production contributes substantially to greenhouse gas (GHG) emissions, which are responsible for anthropogenic climate change. Consequently, numerous countries are transitioning toward cleaner energy production. Governments employ different policies to incentivize and accelerate this transition, including the promotion of microgeneration from renewable resources.

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

In this paper, we study the economic and environmental consequences of this policy. We collect a novel data set in which we observe the electricity extracted and injected into the grid at a household/firm level for all the agents with a microgenerator. We focus exclusively on solar panels, which are the main microgenerator. We observe the monthly electricity extracted and injected into the grid at the agent level 12 months before and 12 months after the solar panel installation. Additionally, we gather data on monthly CO_2 emissions from fossil-fuel-based facilities, hourly total electricity production by source, and hourly load.

We analyze several aspects of the net-metering policy. First, we study how the installation of solar panels affects the electricity extracted and injected into the grid. After the installation of a solar panel, the electricity extracted from the grid is expected to decrease, and the electricity injected into the grid is expected to increase. The magnitude of such effects, however, is an empirical question. We use an event-study approach to quantify these effects. 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 solar panel installation. Finally, we propose an alternative policy to be implemented: households and firms would be allowed to store any surplus of electricity in batteries and, instead of injecting it immediately into the grid, sell it when optimal. This optimal allocation would reduce CO_2

emissions and spot prices, benefiting other consumers and lessening the equity concerns of the net-metering policy.

Our findings can be summarized as follows. First, we find that after the solar panel installation, the electricity extracted from the grid decreases, and the electricity injected into the grid increases. More specifically, agents decrease their monthly electricity extraction by 1,100 kWh, a 16% reduction from their average extraction, and increase the electricity injected into the grid by 1,570 kWh. Both effects are constant over time. Additionally, we consider heterogeneity by agent and analyze households and firms separately. We find that both groups decrease (increase) the amount of electricity extracted from (injected into) the grid. We find that firms and households decrease their electricity extracted by 16% and 11% with respect to the total electricity extracted before installing the solar panels, respectively. This difference could be explained by firms having a larger capacity and household consumption patterns, as households tend to consume more electricity during the evening when solar production is low (La Nauze, 2019).

In our context, the study-event approach has two caveats. Firstly, it fails to consider that the timing of solar panel installation is endogenous (Beppler, Matisoff, & Oliver, 2023; Boccard & Gautier, 2021): when the agent installs a solar panel, she might simultaneously decide to increase her electricity consumption, or, on the contrary, she might start electricity-conservation initiatives. This concern is unlikely to be present in our context. Agents must navigate through various bureaucratic processes to get their solar panels installed and thus lack control over the exact moment at which the solar panel starts working. Secondly, early adopters may differ from future adopters, and hence future adoption of solar panels might not necessarily yield the same results. We alleviate this concern by estimating the model year by year. We find no statistical difference between the yearly estimators, and hence conclude this form of selection is not prevalent. Since we cannot entirely rule out either of these concerns, we read our estimates as an upper bound of the effect of the policy.

Second, we use our estimates to determine the policy impact on CO_2 emissions and the rebound effect. To study the reduction in CO_2 emissions, we focus exclusively on electricity injection; our exercise is thus a lower bound on the total CO_2 emission reduction.[1] We analyze two scenarios. Firstly, we assume that the electricity injected into the grid substitutes fossil-fuel production exclusively. In this scenario, we find that CO_2 emissions are reduced by 0.15% with respect to the baseline. Secondly, we assume that micro-generated electricity substitutes fossil fuels proportionally to their share in total electricity production.[2] In this scenario, we find that CO_2 emissions are reduced by 0.03% with respect to the baseline.

The rebound effect is the increase in electricity consumption after the solar panel installation. We find that after installing the solar panel, firms increase their electricity consumption between 22% and 30%, and households increase their electricity consumption between 19% and 22%.[3] In theory, this increase in electricity consumption could be explained by agents feeling richer, changing their consumption behavior, or facing a lower average electricity price (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 decreasing the reduction of CO_2 emissions, especially if the source that is used in the margin is fossil-fuel-based. By a similar token, it could also increase the costs of generation. On the other hand, the increase in electricity consumption could have a positive impact if agents begin an electrification process, such as replacing wood fireplaces with electric ones. This can lead to reduced pollutants at the household and firm level (Beppler et al., 2023). Both implications are likely to be present in our context.

Finally, we propose an alternative policy in which households and firms can inject electricity into the grid when optimal. Agents who install solar panels are richer than average. It is usually assumed that electricity prices incorporate the cost of the grid (e.g., Feger et al. (2022); Eid et al. (2014)). Since electricity prices are progressive in electricity consumption

[1] Unfortunately, we do not have a good measure of the distribution of the electricity-extraction reduction within months and hours of the day, thus the exclusion.

[2] On average, fossil fuel production accounts for 8% of the total electricity production. Therefore, we assume that the electricity injected into the grid substitutes, on average, 8% of the fossil fuel production.

[3] The range is given by various assumptions on the total peak hours of solar irradiance.

and richer agents tend to consume more electricity, this implies that richer agents are now contributing less to the grid's costs. Furthermore, the marginal cost of solar electricity is virtually zero. The net-metering policy, however, forces electricity providers to buy solar-produced electricity at the retail price. In the long run, both of these factors may raise electricity prices for all consumers. To lessen these concerns and improve the effectiveness of the net-metering policy on CO_2 emissions, we propose an alternative approach: households and firms could be allowed to store any surplus of electricity in batteries and, instead of injecting it immediately into the grid, inject it when optimal. We find that this policy would reduce CO_2 emissions by 2.70% with respect to the baseline. Optimally, agents would sell their solar production late in the evening, when CO_2 emissions from fossil-fuel-based electricity production and spot prices are high.

We contribute to the literature in several ways. First, we expand the literature on agents' use of solar panels (Borenstein, 2017; Boccard & Gautier, 2021; Sexton et al., 2021; Feger et al., 2022; Pretnar & Abajian, 2023; Beppler et al., 2023). Importantly, and unlike other studies, we observe electricity extracted and injected into the grid directly - we do not infer it. Furthermore, we use individual-level rather than aggregate data. On that front, our paper is close to Feger et al. (2022). We expand it in numerous ways. First, we directly observe the electricity extracted and injected into the grid, while Feger et al. (2022) have to estimate it. Second, we use more recent data, covering the years 2010-2022 instead of 2008-2014. Given the significant reduction in solar panel prices, this factor is particularly relevant. Lastly, our study focuses exclusively on net metering in contrast to Feger et al. (2022), which studies five years of feed-in tariff policy and one year of net-metering policy.

Second, we contribute to the literature on equity problems associated with the net metering policy, the miss-allocation of the electricity injected from microgenerators, and the use of batteries in solar panels (Pretnar & Abajian, 2023; Sexton et al., 2021; Boampong & Brown, 2020; Eid et al., 2014; Bollinger et al., 2024). More specifically, we explore an alternative policy that could improve net metering, lessening some of the equity implications.

We propose that households and firms install small batteries and store the electricity instead of selling it immediately into the grid.

Third, we contribute to the extensive body of research on calculating the rebound effect (Kattenberg et al., 2023; Beppler et al., 2023; Frondel et al., 2023; Qiu et al., 2019; La Nauze, 2019; Deng & Newton, 2017). Our results are in line with those found in the literature. For example, Beppler et al. (2023) find a rebound effect of 28.5%, La Nauze (2019) finds an increase in consumption of 23%, and Deng and Newton (2017) finds a rebound effect of 21%. Lastly, we find a negative rebound effect, that is, an increase in electricity consumption, contrary to Kattenberg et al. (2023), who find a decrease in electricity consumption after the solar panel installation.

Finally, the discussion on microgenerators has been focused exclusively on the developed world (Feger et al., 2022; De Groote & Verboven, 2019; Islam & Meade, 2013; Jeong, 2013). We use data from another context not yet explored.

The remainder of this paper is organized as follows. Section 2 describes the Uruguayan electricity market and the microgeneration policy. Section 3 describes the data. Section 4 presents our identification strategy. Section 5 shows our empirical results. Section 6 describes the minimization problem to optimize the timing of electricity injected into the grid and its results. Section 7 concludes.

2 Electricity Market

The Uruguayan electricity market is highly regulated. It has five primary electricity sources, wind, hydro, biomass, solar, and fossil fuels, and two main institutions, ADME and UTE.[4] The structure of the market is as follows. Electricity facilities sell their electricity to ADME, the market operator, on a merit-order basis: from the facility with the lowest to the highest marginal cost. Then UTE, the only electricity company, sells electricity to the consumers.

[4] 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."

Lastly, the electricity price is set by the Executive Power and has periodic adjustments, at least once a year. Different pricing plans are offered to consumers. Figure 1 illustrates the evolution of the prices of one of these plans, "Residential Simple."

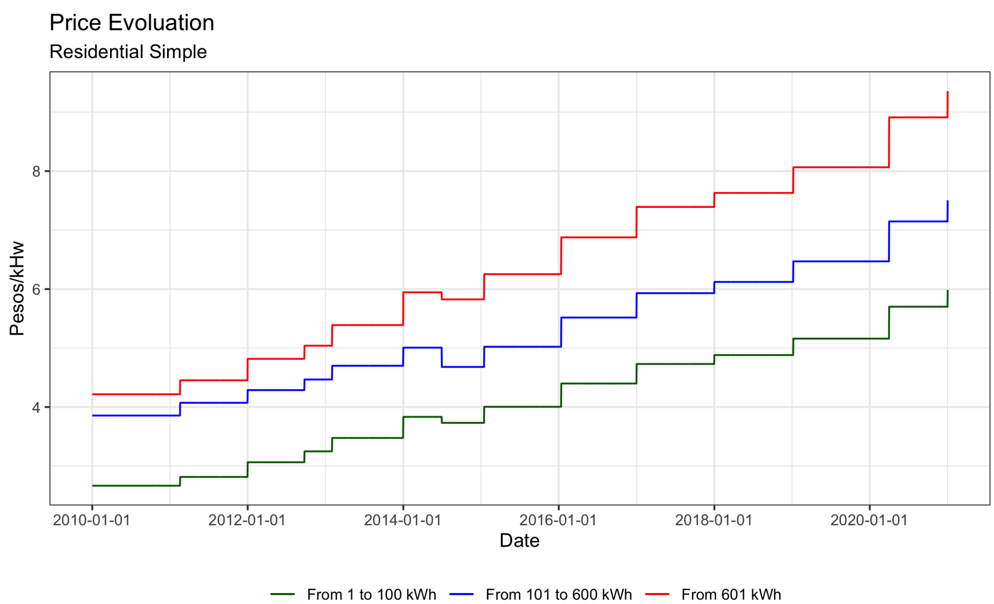


Figure 1: Price Example.
Notes: This figure shows the evolution of the "Residential Simple" electricity rate. Source: UTEi (2022)

In the last two decades, Uruguay has fostered investments in renewable sources, wind, solar, and biomass, on both large and small scale. On a large scale, it has done so through public auctions, where firms submit a bid containing a power capacity and an electricity price. Afterward, the government grants permission to install and produce renewable energy 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. The agent first consumes the renewable electricity that he produces. If, at any given moment, her electricity production exceeds her electricity consumption, the surplus is injected into the grid. The selling price is the retail price that the agent faces, and the electricity injected into the grid is discounted in her current month's bill. In May 2017, the policy changed slightly, stipulating that the yearly amount of electricity sold must not exceed the amount of electricity consumed (MIEM, 12/17).[5] Figure 2 shows the evolution of solar panel installation by month.

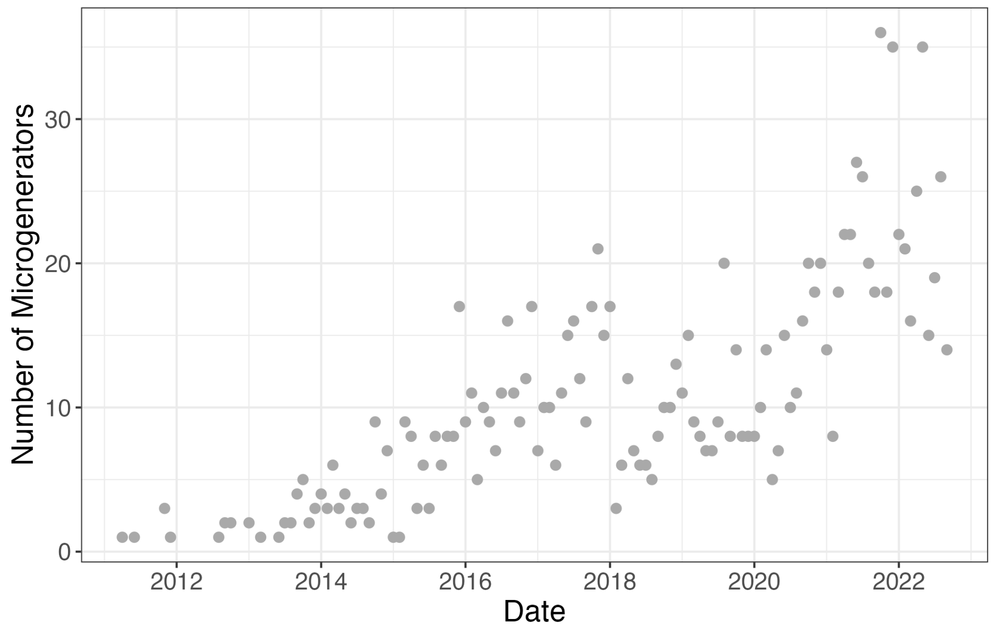


Figure 2: Solar Panels.

Notes: This figure shows the new solar microgenerators installed by month in gray. Source: UTEi (2022)

3 Data and Descriptive Statistics

We use administrative data at the household/firm level to analyze how the electricity extracted and injected into the grid changes after installing a solar panel under the net-metering policy. The data was provided by UTE. It includes, for every household and firm that has installed a solar panel in the county, their monthly electricity consumption from the grid the 12 months before the solar panel installation and electricity extracted and injected into the

[5]In practice, there are 139 agents whose annual electricity injected surpassed the annual electricity extracted at any given year. Of those, 87 are firms and 52 are households. We repeat our main analyses, eliminating these 139 agents and the results do not change. Table A.9 shows the results in the Appendix.

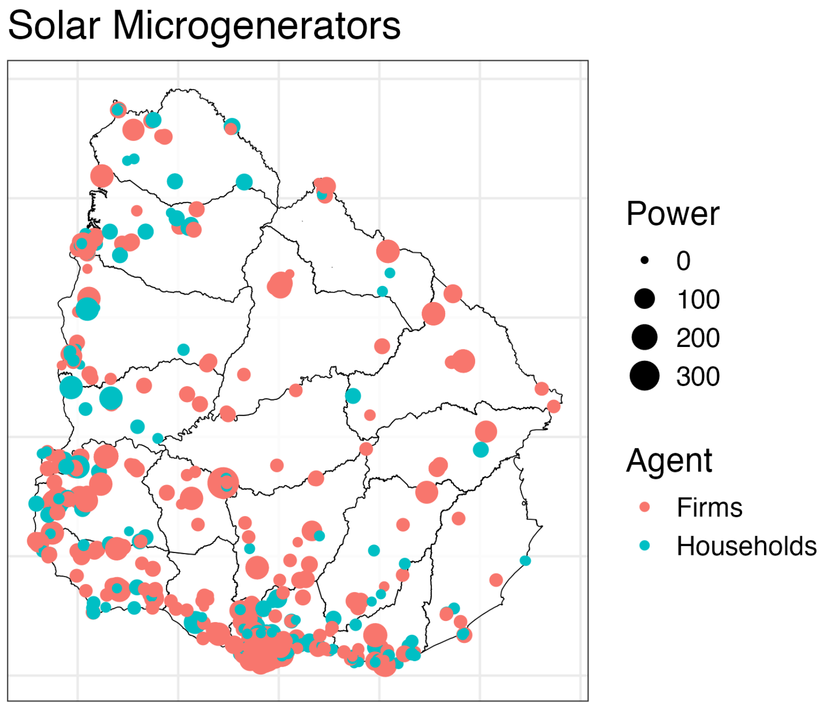
grid 12 months after the solar panel installation.

In total, the dataset contains 1,275 agents: 904 firms and 371 households. Figure 3 shows the location of solar panels color-coded by type of agent. The size of each dot reflects the capacity installed of the solar panel in kW, for both the whole country and the capital city, Montevideo. Although most microgenerators are concentrated in Montevideo, many are scattered throughout the country. Furthermore, the number of firms adopting solar microgenerators is higher than the number of households, with firms exhibiting higher installed capacity on average. Firms have a capacity installed of 37.64 kWh and households have a capacity installed of 13.5 kWh. In 2020, solar capacity accounted for 6% of the total installed electricity capacity, with microgeneration being 12% of such a capacity (MIEM, 2022).

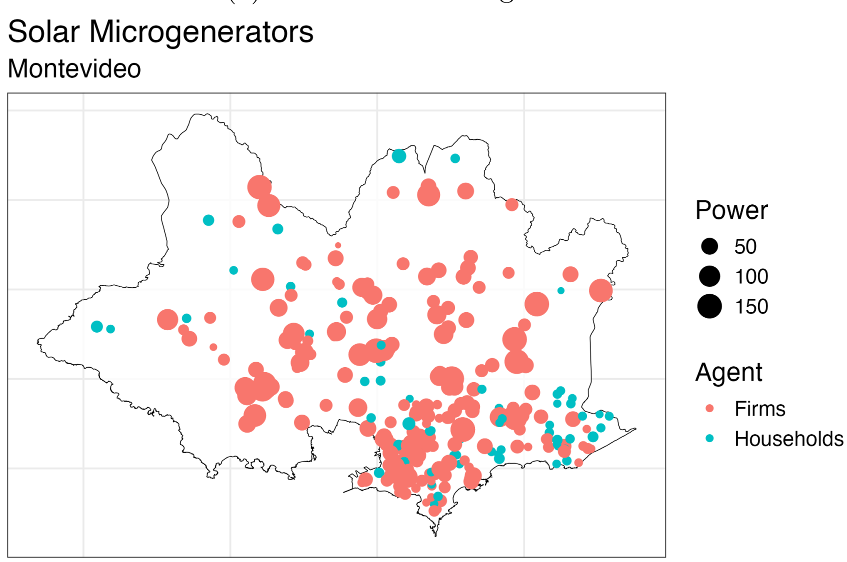
We also construct CO_2 emission from fossil-fuel-based electricity generation, collecting monthly data on gas oil, fuel oil, and natural gas consumption from UTEi (2022) and combining it with the CO_2 emission factor derived from the IPCC (2006).[6]

The descriptive statistics are presented in Table 1. As shown, the average amount of electricity extracted from the grid is 6,740 kWh before installing the solar panels and decreases to 5,388 kWh afterward; the amount of electricity injected into the grid is, on average, 1,546 kWh; and firms exhibit higher extraction and injection levels compared to households.

[6]The data is constructed from 1:00 AM to 1:00 AM of the following month. For example, from midnight October 1 until midnight November 1.



(a) Location of Microgenerators



(b) Capital city - Location of Microgenerators

Figure 3: Microgeneratos location.

Notes: Panel (a) shows where the different solar microgenerators are distributed across the country. Panel (b) shows where the different solar microgenerators are distributed in the capital city, Montevideo. Color-coded by residential or commercial customers. The capacity installed, "Power," is in kW. Source: UTEi (2022)

Table 1: Descriptive Statistics

	Mean	S.D	Min.	Max
Before				
Extractions (kWh)	6,740.13	14,274.64	0.08	25,6032.2
Firms	9,134.80	16,354.92	0.08	25,6032.2
HH	995.48	2,042.16	0.43	33,108.8
After				
Extractions (kWh)	5,388.75	13,795.12	0.08	297,253.2
Firms	7,144.57	15,854.25	0.08	297,253.2
HH	810.63	1,463.37	2	27,704.48
Injections (kWh)	1,545.98	3,272.36	0	136,844.1
Firms	2,139.35	3,877.2	0	136,844.1
HH	448.41	925.15	0	24,405.6
Household	0.29		0	1
Firms	0.71		0	1
N	24,386	24,386	24,386	24,386

Notes: Data provided by UTE. Extraction before installing the solar panel is the same as total consumption. After installing the solar panel, while extractions show the amount of electricity taken from the grid, injections show the average of electricity sold into the grid. HH is short for households.

4 Methodology

After installing a solar panel, agents are expecting to decrease the electricity extracted from the grid and increase the electricity injected into the grid. Figure 4 illustrates the average changes in electricity extracted and injected into the grid before and after installing a solar panel.

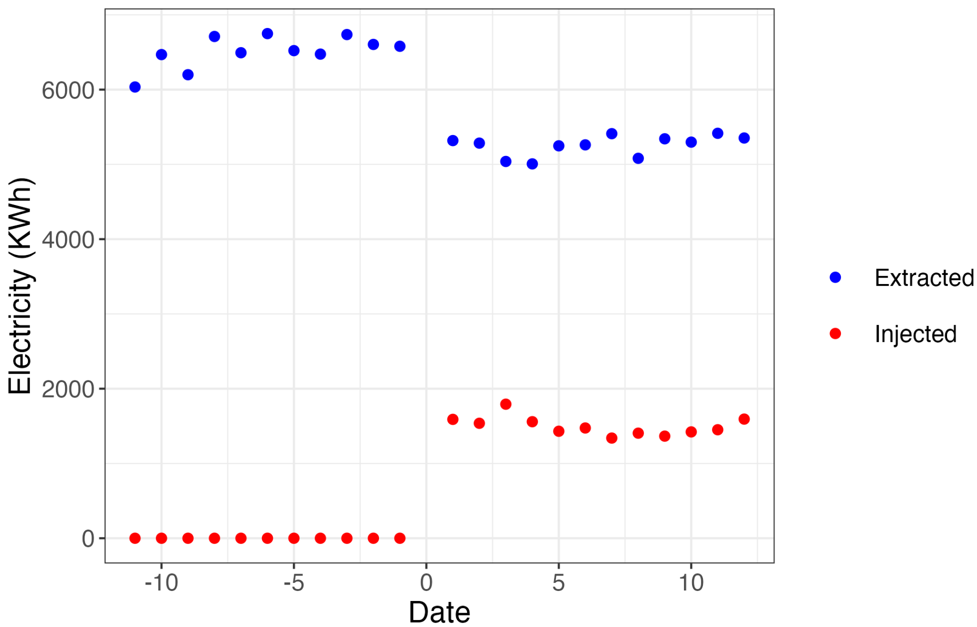


Figure 4: Electricity extracted and injected into the grid.
Notes: This figure shows the average amount of electricity extracted and injected into the grid 12 months before and after the solar panel installation. Source: UTEi (2022)

4.1 Econometric Specification

To quantify the changes in the electricity extracted and injected into the grid after installing a solar panel, we run regression (1):

$$y_{ist} = \alpha_i + \beta D_{ist} + \delta_t + \epsilon_{ist} \tag{1}$$

where y_{ist} is the electricity extracted or injected into the grid for agent i in state s at month t; D_{ist} is the treatment, a variable equal one if the agent i installed the solar panel at time

t; α_i is the agent fixed effect, where any time-invariant household/firm characteristics are captured; δ_t is the time fixed effect, e.g. month, month + year or month $*$ year, capturing weather and seasonal changes; and ϵ_{ist} is the error term, which is clustered at state level.

We also study the dynamic effect of solar panel installation estimating equation (2):

$$y_{ist} = \alpha_i + \sum_{\tau=-12}^{-2} \rho_\tau D_{is\tau} + \sum_{\tau=1}^{12} \lambda_\tau D_{is\tau} + \delta_t + \epsilon_{ist} \tag{2}$$

where the first summation shows the anticipatory effects of installing a solar panel; the second summation quantifies the post-treatment effects of the solar panel installation; and the remainder is as specified in regression (1). Formally, the installation occurs at time $\tau = 0$. Since we do not observe that month, all the estimations are compared to $\tau = -1$.

A potential limitation in our specification is that solar installation and adoption time 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, if the agent simultaneously increases electricity conservation initiatives when installing a solar panel, then the estimator is downwardly biased. Previous research has found more evidence supporting the former, and thus, we interpret these estimations as an upper bound of the effect. Regardless, we expect that the extent of the bias is low. In our case, the agent has little control over the installation timing. In order to install a solar panel, she has to upload paperwork to the electricity company to be approved, then the electricity company has to send a technician to approve the installation, and finally, the solar panel is installed.

Another concern could be that early adopters have larger systems and are able to produce more electricity than late adopters. We explore this concern by comparing the extraction and the net effect estimations year by year. We find that there is no statistically significant difference between yearly estimators. We present these results in Figure A.1 and Table A.2 in the appendix.

5 Results

In this section, we show our main results. First, we discuss the effect of solar panel installation on the electricity extracted and injected into the grid for all the agents, firms, and households separately. The net effect result, which is defined as the difference between the electricity extracted minus the electricity injected, is presented in Section A.4 in the appendix. Second, we show the monetary value for consumers of this policy. Third, we show the CO_2 emissions reduction due to the policy. Lastly, we calculate the rebound effect.

5.1 Electricity Extracted from the Grid

Table 2 presents the event study results using electricity extracted from the grid as the dependent variable. After installing a solar panel, the agent's electricity extracted from the grid decreases by 1,100 kWh, on average. This decline represents a 16% reduction in the average electricity taken from the grid before installing the solar panel for the entire period.[7] This result is robust to different fixed-effect specifications.

Table 2: Electricity taken from the grid

	Electricity taken from the grid (kWh)		
	(1)	(2)	(3)
Solar panel installation	-1099.2***	-1085.68***	-1091.55***
	(71.41)	(146.19)	(142.94)
ID F.E	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y
N	24,386	24,386	24,386

*This table shows the effect of installing a solar panel on the electricity extracted from the grid, using different time-fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month $*$ year. Standard errors are clustered at the state level. Significance levels: ***0.01 **0.05 *0.1.*

Figure 5 presents the event study coefficients using ID + month fixed effects (column

[7] See Table 1.

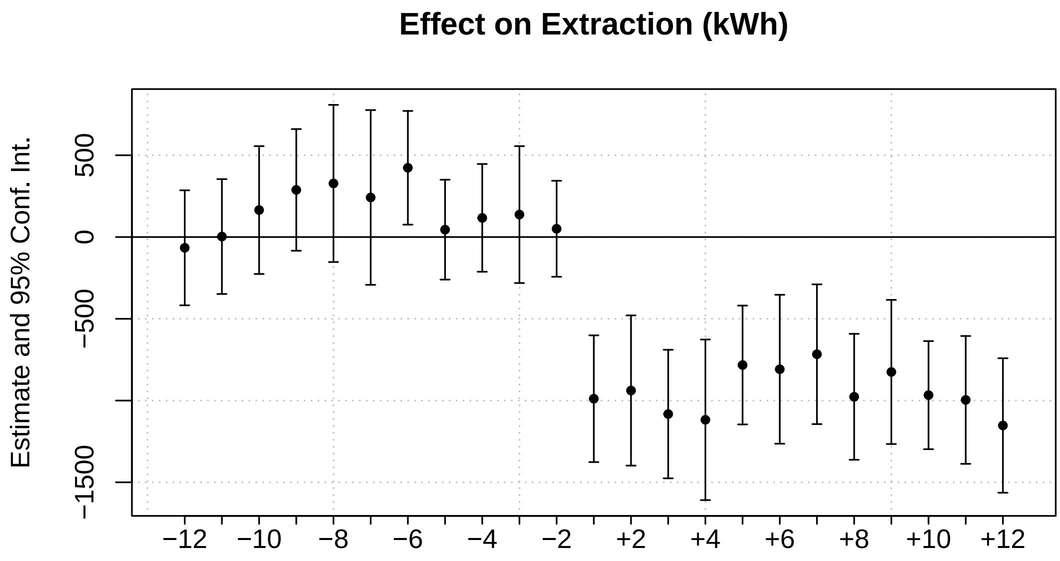


Figure 5: Event study plot - Extraction from the grid.
Notes: This figure shows the event study plot using 12 lags/leads before/after the solar panel installation, controlling for ID + month fixed effects.

(1)). All the results are compared with the month before installing the solar panel (-1). Figure 5 shows that the reduction in the electricity extracted remains constant over time.

5.1.1 Heterogeneity by Agent

In this section, we analyze how the electricity extracted from the grid changes depending on the type of agent, firm or household. The results are presented in Table 3. For firms, the installation of solar panels decreases the electricity extracted from the grid between 1,427 and 1,491 kWh. This represents a 16% reduction on average extraction for the firms. In addition, results are robust to different specifications. For households, however, the effect is smaller and varies with the specification. Using specification (1), the reduction of electricity extracted represents 12% of the average electricity extracted for the households.

Table 3: Electricity taken from the grid by type of agent: household or firm

	Panel (a): Electricity taken from the grid - Firms		
	(1)	(2)	(3)
Solar panel installation	-1491.19***	-1427.34***	-1439.81***
	(97.51)	(204.10)	(200.91)
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y
N	17,409	17,409	17,409

	Panel (b): Electricity taken from the grid - Households		
	(1)	(2)	(3)
Solar panel installation	-108.87***	-191.25**	-193.71**
	(25.87)	(89.55)	(89.523)
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y
N	6,977	6,977	6,977

*This table shows the effect of installing a solar panel on the electricity taken from the grid, using different sets of time fixed effects and different types of agents. Panel(a) uses only firms, whereas Panel (b) uses only households. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month$*$year. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

5.2 Electricity Injected into the Grid

Table 4 presents the event study results using electricity injected into the grid as the dependent variable. After installing the solar panel, the agent's electricity injected into the grid increases by 1,570 kWh on average (column (1)). The result changes slightly depending on the time-fixed effects used.

Table 4: Electricity injected into the grid

	Electricity injected into the grid		
	(1)	(2)	(3)
Solar panel installation	1569.75***	1708.83***	1697.76***
	(110.65)	(128.93)	(122.93)
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y
N	18,964	18,964	18,964

*This table shows the effect of installing a solar panel on the electricity injected into the grid, using different time-fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month + year fixed effects; finally, column (3) uses ID + month$*$year. Standard errors are clustered at the state level. Significance levels: ***0.01 **0.05 *0.1.* [4] *The difference in N comes from having more missing values in the injections observations than in the extractions observations.*

Figure 6 plots the event study coefficients using ID + month fixed effects. All the results are compared with the month before installing the solar panel (-1). Figure 6 shows the increase in electricity injected in the grid remains constant over time.

5.2.1 Heterogeneity by Agent

In this section, we explore how the electricity injected into the grid changes depending on the type of agent, firm or household. The results are presented in Table 5. For firms, the installation of solar panels increases the electricity injected into the grid between 2,136 and 2,2286 kWh. For households, the electricity injected grid increases between 455 and 496 kWh.

Table 5: Electricity injected into the grid by type of agent: household or firm

	Panel (a): Electricity injected into the grid - Firms		
	(1)	(2)	(3)
Solar panel installation	2135.82***	2286.01***	2257.25***
	(109.20)	(137.41)	(136.88)
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month ∗ year	N	N	Y
N	13,033	13,033	13,033

	Panel (b): Electricity injected into the grid - Households		
	(1)	(2)	(3)
Solar panel installation	455.28***	495.76***	491.71***
	(33.39)	(42.62)	(43.02)
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month ∗ year	N	N	Y
N	5,931	5,931	5,931

*This table shows the effect of installing a solar panel on the electricity injected into the grid, using different sets of time fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month∗year. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

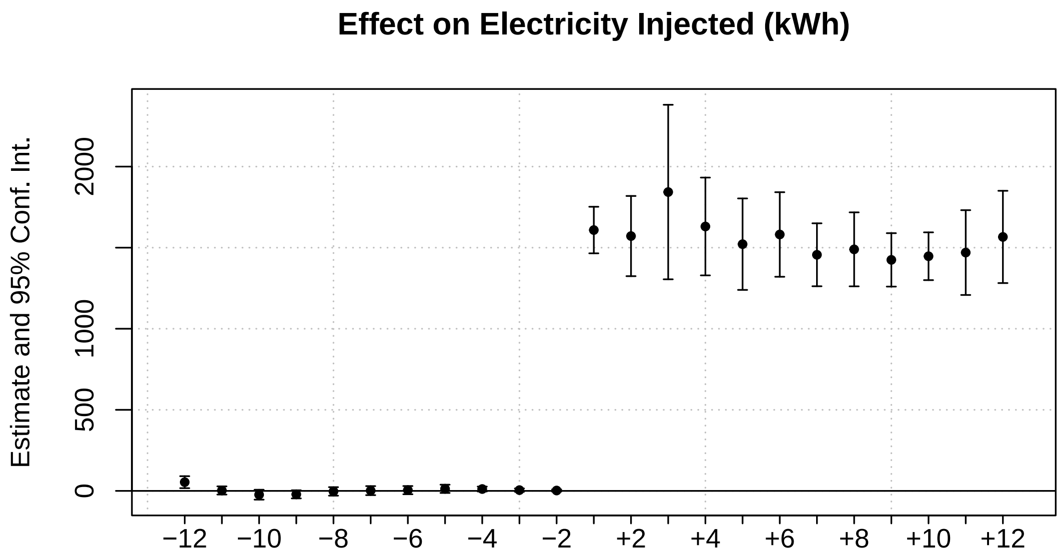


Figure 6: Event study plot - Injection into the grid.

Notes: This figure shows the event study plot using 12 leads/lags before/after the solar panel installation, controlling for ID + month fixed effects.

In the previous sections, we show that firms and households increase the amount of electricity injected into the grid. Furthermore, the decrease in electricity extracted from the grid is more pronounced for firms than households with respect to their baseline. This difference could be explained by differences in electricity usage patterns. For example, households consume more electricity at night, leading to relatively stable extraction patterns, while firms consume more electricity during daylight hours, resulting in a higher reduction in the extraction level (La Nauze, 2019).

5.3 Policy Change - 2017

Since May 2017, the legislation mandates that the yearly amount of electricity injected into the grid must be less or equal to the amount of electricity consumed (MIEM, 12/17). We explore the effect of this policy change in more detail in this section. 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.

The results are presented in Table A.5 in the appendix. We find there is no difference in the electricity extracted from the grid between agents that installed a solar panel before and after the change in legislation. Unfortunately, we cannot perform the same estimation for the electricity injected into the grid due to a lack of data.

5.4 Robustness Checks

In this section, we present a series of robustness checks to further validate our main analysis. First, we study the effect of clustering our errors at the agent level rather than at the state level. The results are unchanged and can be found in Table A.8 in the Appendix. Second, we exclude the agents who, in any given year, injected more electricity than they extracted, due to the discussion in Section 5.3. The results barely change and are presented in Table A.9 in the Appendix. Third, we trim our data, excluding the 5% with the highest and lowest electricity extraction. The results do not change substantially and can be found in Table A.10 in the Appendix. Lastly, we estimate our model using the Sun and Abraham (2021) approach. The results do not change and are presented in Table A.11 in the Appendix.

5.5 Value to Consumers

In this section, we quantify the effect of the policy on cost savings. In order to do so, we need an assumption on the electricity pricing plan that firms and households are enrolled in, which we do not observe. For firms, we use the "middle consumers" rate, which divides the day into three tiers: peak, off-peak, and plain rate. For households, we use the "intelligent rate," which also consists of three tiers: peak, off-peak, and plain. Furthermore, we take the weighted average of these rates. For more information about the calculation, please refer to Appendix Section A.8.

We find that at 2017 prices (Xavier, 2022), each firm saves between 268 and 450 USD per month, considering the injection and the extraction-reduction-plus-injection effect estimation, respectively. In addition, each household saves between 54 and 68 USD per month, considering the injection and the extraction-reduction-plus-injection estimation, respectively. In terms of the time to recoup the initial investment, we find that, for a solar panel with a capacity of 40 kW for firms and 15 kW for households, firms need at least 6 years to break even and households need at least 15 years.[8]

5.6 Reduction in CO_2 Emissions

We use our estimates to compute the effect of installing solar panels on CO_2 emissions. We need a few assumptions for this computation. First, total CO_2 emissions due to electricity production depend on the sources used to produce such electricity. One way to reflect that is by constructing hourly CO_2 factors, which would establish how much CO_2 would be emitted per extra unit of electricity at that hour. We construct such factors for the days and months of our study using total CO_2 emissions by fossil-fuel-based facilities in our study period; please check Appendix A.7 for further details on how the emission factor was constructed. Second, we only observe electricity extracted and injected into the grid monthly. Thus, we need an assumption on the hourly distribution within a month. We assume the electricity injected into the grid follows the hourly distribution of the large solar electricity production, which we observe. Unfortunately, we cannot make such an exercise for electricity extracted from the grid, and thus we focus exclusively on electricity injected in our analysis.

We study two different scenarios. First, we assume that the electricity injected into the grid exclusively substitutes fossil fuel electricity production. We find that the solar panel installation reduces CO_2 by 0.15% with respect to the baseline. Second, we assume that solar panels substitute fossil fuel production proportionally to their share of total electricity production. We find that the solar panel installation reduces CO_2 by 0.03% with respect to the baseline.

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

5.7 Rebound effect

Solar panel installation can induce a "rebound effect," an increase in the electricity consumption after the installation. This increase could be explained by agents feeling richer, electricity being cheaper on average, or changes in their consumption behavior (Beppler et al., 2023; Boccard & Gautier, 2021). Conversely, a solar panel installation can lead to an increase in energy conservation and, thus, a decrease in electricity consumption after the installation. For example, Rai and McAndrews (2012) find that solar panel installations were associated with increased environmental and electricity use awareness in Central and Northern Texas.

Unfortunately, we do not observe electricity consumption post-solar panel installation directly. We can, however, study the average change in consumption by using the solar panel capacity to estimate production. More specifically, we write:

$$Consumption_{\text{before solar panel}} = Extraction_{\text{before solar panel}} \tag{3}$$

$$Consumption_{\text{after solar panel}} = Production - Injection + Extraction_{\text{asp}} \tag{4}$$

$$\begin{aligned} C_{\text{asp}} - C_{\text{bsp}} = {} & (Production - Injection) + \\ & (Extraction_{\text{asp}} - Extraction_{\text{bsp}}) \end{aligned} \tag{5}$$

Consumption before installing the solar panel is the same as extraction before installing the solar panel (hereafter bsp), hence Equation (3). After installing the solar panel (hereafter asp), the consumption of electricity equals the production of the solar panel minus the electricity injected plus the electricity extracted, hence Equation 4. We then subtract (4) and (3) to reach (5).

We can find the average rebound effect by averaging Equation 5 over all agents, as in Equation 6:[9]

[9] We use the sample means because the capacity installed of the solar panel is in a different database, which has an additional 13 agents.

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

Given that $\sum_{-12}^{-1} P_{it} = 0$ and $\sum_{-12}^{-1} I_{it} = 0$, we write Equation (7):

$$
\begin{aligned}
\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12}C_{it}-\sum_{-12}^{-1}C_{it}\right] =& \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12}P_{it}\right] \\
&-\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12}I_{it}\right] \\
&+\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12}E_{it}-\sum_{-12}^{-1}E_{it}\right]
\end{aligned} \tag{7}
$$

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

From our estimation, we recover $\dfrac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} E_{it} - \sum_{-12}^{-1} E_{it}\right]$ and $\dfrac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{12} I_{it} - \sum_{-12}^{-1} I_{it}\right]$ (Table 2 and Table 4, respectively). We also observed $\sum_{t=-12}^{-1} C_{it}$ in our data, which is 6740.13 kWh.[10] Finally, we use the capacity of the solar panels to infer electricity production.

electricity production depends on the solar panel capacity and peak sunlight hours (Solar, AE solar). The average solar panel capacity is 29.56 kW, with 37.64 kW for firms and 13.45 kW for households. Uruguay has between 4.52 and 5.0 hours of sunlight per day (Global Solar Atlas); therefore, the production of the solar panel ranges between 5,100 and 5,646

[10] Before the solar panel installation, extraction from the grid and consumption is the same.

Table 6: Electricity production from solar panels

	Monthly Production		
	Total	Firms	Households
Cap. installed (kW)	29.56	37.64	13.45
Sunlight = 4.52 hours	4008	5104	1824
Sunlight = 5 hours	4434	5646	2018

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

Table 7: Rebound effect

	Rebound Effect (kW)		
	Total	Firms	Households
Sunlight = 4.52 hours	1338 (20%)	1477 (22%)	1260 (19%)
Sunlight = 5.0 hours	1764 (26%)	2019 (30%)	1454 (22%)

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

kWh for firms, and between 1,824 and 2,018 kWh for households (Table 6).

We present the average rebound effect in Table 7. After installing solar panels, electricity consumption increases on average between 20% and 26%. The calculation differs by agent, while firms increase their rebound effect between 22% and 30%, households increase their electricity consumption between 19% and 22%. For an example of how we calculate this number, please see Section A.1 in the Appendix. Figure 7 shows the lower and upper bounds of the rebound effect by month for all agents. The estimations used for the calculation are presented in Table A.1 in the Appendix. The result is in line with the literature. For example, after installing a solar panel Beppler et al. (2023), La Nauze (2019), and Deng and Newton (2017) find a rebound effect of 28.5%, 23%, and 21% respectively.

The "rebound effect" could be explained by several factors, such as agents feeling richer, electricity being cheaper on average, and changes in their consumption behavior (Beppler et al., 2023; Boccard & Gautier, 2021). Each one of these factors is present in our case.

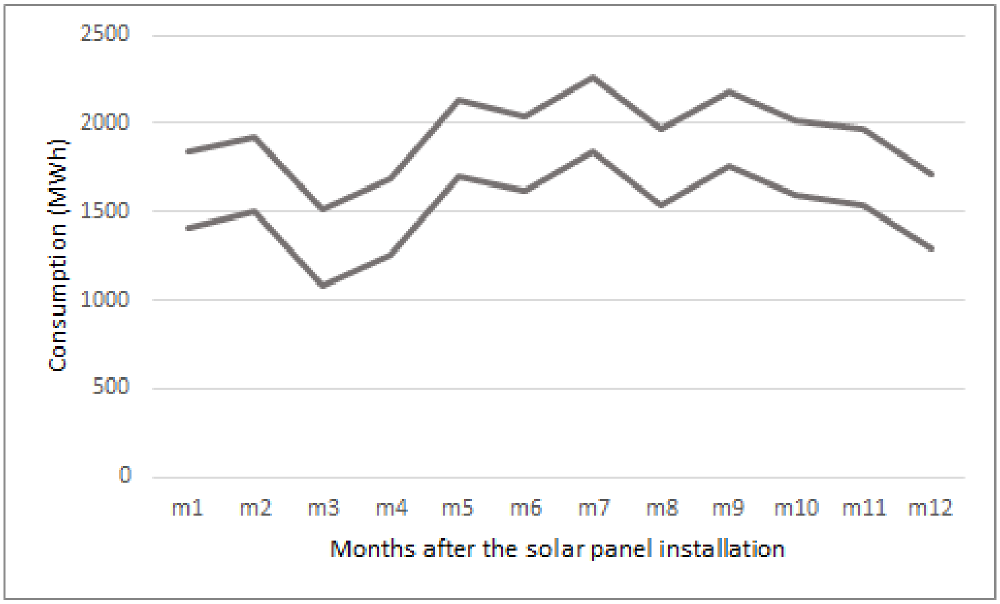


Figure 7: Rebound effect.

Notes: This figure shows the lower and upper bound of the rebound effect, for each month after installing a solar panel.

First, we find that after installing the solar panel, firms and households save between 268-450 USD and 54-68 USD per month at 2017 prices, respectively. Thus, agents could feel richer and consume more electricity. Second, agents buy and sell the electricity at the retail price; hence, the opportunity cost of electricity consumption does not change -there is no economic incentive to increase consumption. Nevertheless, Ito (2014) shows that in electricity markets, agents react to the average price. The increase in electricity consumption could thus be explained by the reduction in the average electricity price. Lastly, agents may change their consumption behavior and use more electricity during solar hours or change their charging patterns and increase electrification (e.g., changing from a gas heater to an electric heater).

This increase in electricity consumption has an ambiguous effect. On the one hand, the rebound effect reduces the effectiveness of solar panels, i.e., it reduces the environmental benefits of reducing fossil-fuel-based electricity production. In addition, it could also increase other costs of electricity generation and imply a leakage effect from this policy. On the other hand, an increase in electricity consumption can be beneficial if the agent initiates a process of electrification, e.g., by changing the wood fireplace to an electric one. This shift would reduce the location and potentially harmful effects of other pollutants (Beppler et al., 2023).

6 Batteries and Emissions

The reduction of CO_2 emissions could be further improved if households and firms were allowed (and incentivized) to improve the timing of electricity injection into the grid. This could be achieved by allowing agents to have batteries. In this section, we explore the potential benefits of such a policy.

We want to find an optimal way to minimize CO_2 emissions given agents' electricity production. To do so, we complement our main dataset with another one containing hourly electricity production by source and electricity demand. We focus on the period from November 2018 to August 2022.[11]

The daily solution to this optimization can be expressed as a linear programming problem, namely Equation (8):

$$\begin{aligned} \min_{q^i_{th}, F_{ht}} & \sum_{h=0}^{23} \alpha^{CO_2}_{th} \times F_{th} \\ s.t & \sum_{h=0}^{23} q^i_{th} \leq Q^i, \ \forall i \\ & \mathrm{RD}_{th} \leq F_{th} + \sum_i q^i_{th}, \ \forall h \end{aligned} \tag{8}$$

where q^i_{th} is the electricity injected into the grid from solar panels for agent i on day t at hour h; F_{th} is the fossil-fuel-based electricity production at day t and hour h; $\alpha^{CO_2}_{th}$ is the CO_2-emissions-factor of producing a unit of electricity on the day t at hour h from fossil-fuel-based facilities;[12] Q_i is the total electricity production of agent i within a day; and RD_{th}

[11] In this period, we observe electricity injection for all agents that installed a solar panel within the 12-month window.

[12] Please see Appendix A.7 for further details on how we construct such factors.

is the residual demand at time t and hour h.[13] The first restriction imposes that the total injection into the grid by agent i is equal to its total daily injection. The second restriction ensures that fossil-fueled-based production plus the microgeneration production is at least as much as the (residual) demand. We detail the calculations of the model in Section A.2 in the Appendix.

Intuitively, we would like agents to inject their solar-produced electricity when CO_2 emissions are at their highest, which occurs when fossil-fuel-based facilities are producing. Since currently, firms and households only inject solar electricity when they generate it, the only possible way to substitute fossil fuel production with solar production is through the use of batteries. Figure 8 Panel (a) shows how different sources behave hourly, and Panel (b) shows large solar and microgenerator production by the hour.

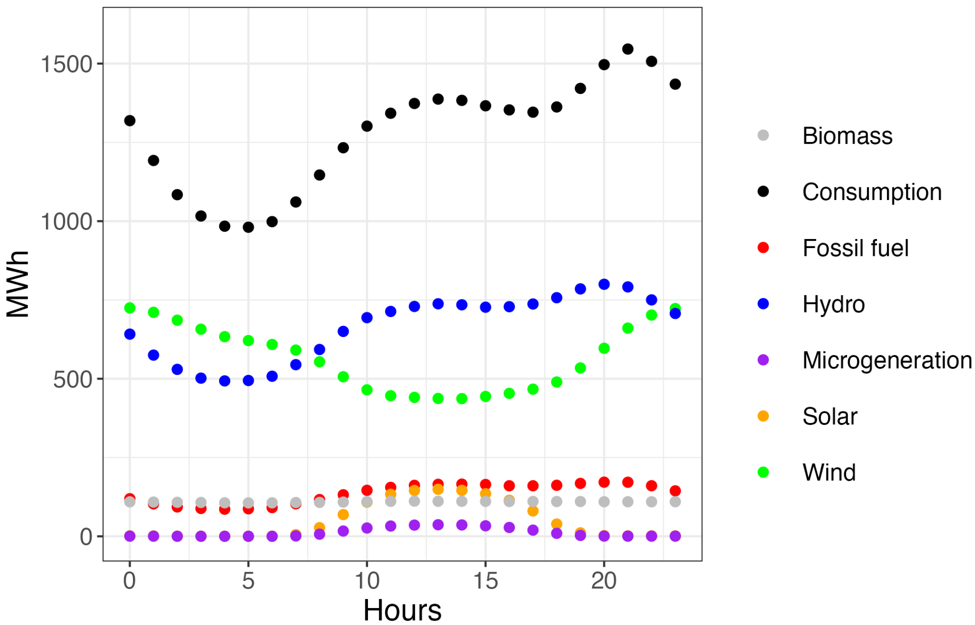
6.1 Results

The linear programming problem finds the optimal allocation of electricity injections into the grid. This allows us to recover the potential (social) benefits of offering batteries to households and firms.

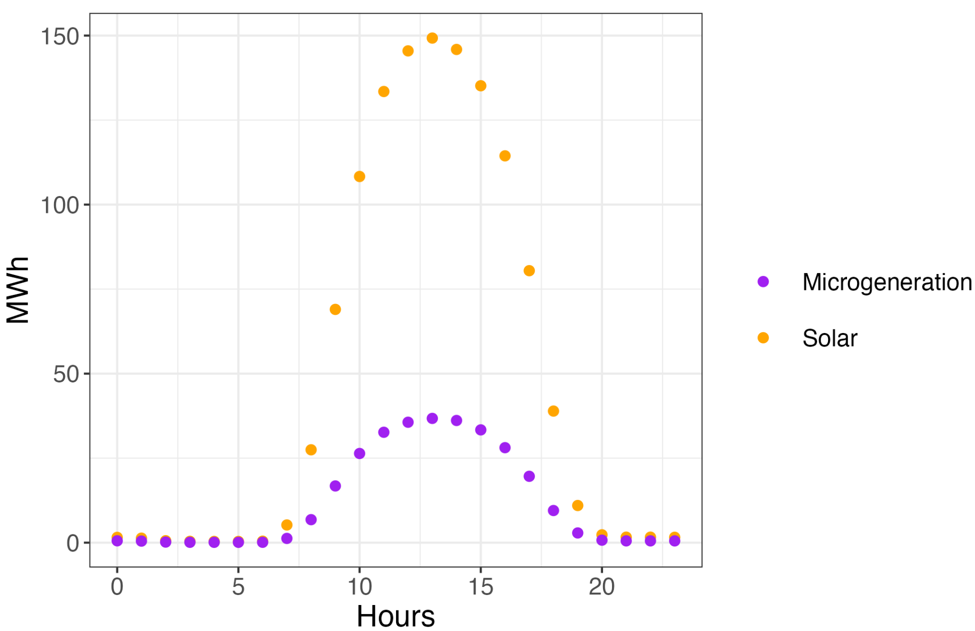
We solve the model using both the CO_2 emission factors and the spot price.[14] Figure 9 presents the results. Each dot represents the number of times the model chooses that hour as the optimal time to inject the microgenerator-electricity into the grid for the whole period. Using the CO_2 emission factors, we find that the optimal time for injecting electricity into the grid is between 8 PM (21 hrs) and 12 PM (24 hrs). This would imply a 2.70% reduction in CO_2 with respect to the baseline. Using the spot prices, we find that the optimal time to inject microgenerator production is after 6 PM (18 hrs).

[13] The residual demand is calculated as the hourly demand minus the production of wind, large solar, hydro, biomass, and exports plus imports.

[14] Please check Appendix A.7 for further details on how we construct such factors. The spot price was provided by UTE and consists of the marginal cost of increasing the demand for one unit of electricity.



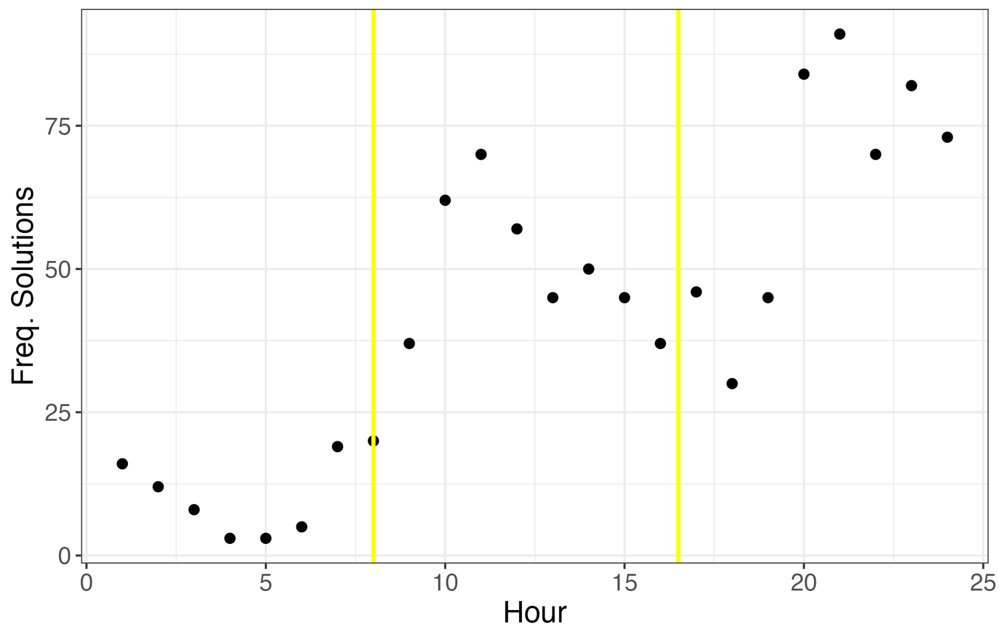
(a) Electricity production by source



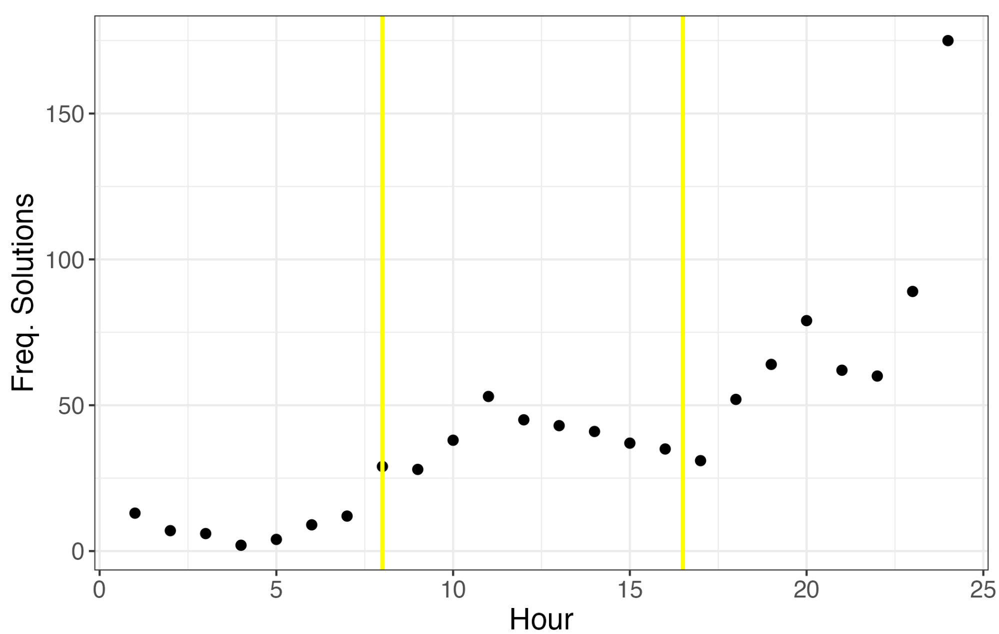
(b) Electricity production by large solar and microgenerators

Figure 8: Electricity source.

Notes: Panel (a) shows how the different electricity sources behave hourly, from November 2018 until August 2022. The black line is the consumption (load), the blue line is the hydro dispatch, the green line is the wind dispatch, the red line is the fossil fuels dispatch, the grey line is the biomass dispatch, the orange line is the solar dispatch, finally the purple line is the solar injection from microgenerators. Panel (b) shows how the large solar and the microgenerator production behaves. Source: (UTEi, 2022)



(a) Model solution using CO_2



(b) Model solution using spot prices

Figure 9: Minimization solution.

Notes: Panel (a) shows the model solution minimizing the CO_2 emissions. Panel (b) shows how the minimization solution using spot prices. We change the 12 PM to 24 hrs for display.

7 Conclusion

We use granular data on electricity injected and extracted into the grid to study Uruguay's net-metering policy. First, we run an event study to analyze the effect of installing a solar panel on the electricity extracted and injected into the grid. Second, we use our estimates to determine the policy's effect on CO_2 emissions and the rebound effect. Finally, we perform a minimization problem that illustrates the benefits of installing batteries to store solar-produced electricity instead of selling it immediately into the grid.

On the one hand, the policy has clear positive effects. First, agents extract less electricity from the grid. After installing the solar panel, the electricity extracted from the grid decreases by 1,100 kWh on average, a 16% reduction in the average electricity extracted from the grid. This effect is constant over time. Second, the agent is now injecting clean energy into the grid, which is then consumed by other agents. After installing the solar panel, the electricity injected into the grid increases by 1,570 kWh on average. This effect is constant over time. Second, the policy has a positive impact on CO_2 emissions. We find that the policy reduces CO_2 emissions by 0.15% with respect to the baseline. Third, we use the solar panel's capacity to study the rebound effect. We find that, after installing a solar panel, agents increase their electricity consumption between 20% and 26%, on average.

On the other hand, the policy has important equity implications. Electricity prices embed the cost of the grid (Feger et al. (2022)). Since agents who install solar panels are richer than average, prices are progressive in electricity consumption, and richer agents tend to consume more electricity, this implies that richer agents are now contributing less to the grid costs. Moreover, the marginal cost of solar electricity is almost zero, but the net-metering policy implies that it is purchased by the electric company at the retail price. In the long run, these may increase electricity prices. To alleviate these concerns and to further improve the reduction of CO_2 emissions, we propose an alternative policy: rather than immediately selling surplus electricity into the grid, households and firms could store it in batteries and sell it at another time. Installing a battery has some positive spillovers to the rest of the consumers by decreasing CO_2 emissions and spot prices. To analyze this, we solve a minimization linear problem, which reduces CO_2 emissions in a 2.7%, a 2.55% improvement with respect to 0.15%.

To translate our results to dollars, we find that, after installing a solar panel, firms save between 268 and 450 USD, and households save between 54 and 68 USD in 2017 prices. In 2017, the maximum cost of a solar panel with a battery in the Uruguayan local market was 717 USD for 12V and 100ha and 1132 USD for 12V 200ha (Mercado Libre). Thus, the agent could completely eliminate the injection of electricity into the grid by buying a battery, and the cost of the battery would pay for itself in a few months, or the agent could sell the electricity to the grid when optimal, as studied in our linear model solution.

Future studies could explore the mechanism explaining our rebound effect. Moreover, our work does not include solar panels with batteries off-grid (i.e., not connected to the grid), which could benefit households without the cost of expanding the grid—another interesting topic for future work.

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A Appendix

A.1 Rebound Effect - Further Details

In this section, we display an example of how we calculate the rebound effect.

$$\begin{gathered}\sum_{1}^{12}\frac{Consumption_i}{N}-6740.13=4008-1,110-1,570 \text{ if hours of sunlight } =4.52\\ \sum_{1}^{12}\frac{Consumption_i}{N}-6740.13=1338\end{gathered}\tag{9}$$

$$\begin{gathered}\sum_{1}^{12}\frac{Consumption_i}{N}-6740.13=4434-1,110-1,570 \text{ if hours of sunlight } =5\\ \sum_{1}^{12}\frac{Consumption_i}{N}-6740.13=1764\end{gathered}\tag{10}$$

Table A.1: Estimations used for the rebound calculation

	Extraction reduction	Injection
Month +1	-988.72	1608.69
Month +2	-938.55	1571.57
Month +3	-1082.51	1843.01
Month +4	-1117.69	1630.63
Month +5	-782.62	1521.61
Month +6	-808.50	1581.30
Month +7	-716.73	1456.12
Month +8	-977.08	1489.62
Month +9	-825.01	1424.70
Month +10	-966.85	1447.13
Month +11	-996.14	1469.76
Month +12	-1152.42	1566.19

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

A.2 Linear Model - Further Details

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

$$\begin{aligned}
&\min_{q^i_{th}, t_{th}} \sum_i \sum_{t=1}^{T} \sum_{h=0}^{23} CO_2^{th}(q^i_{th}) + \sum_{t=1}^{T} \sum_{h=0}^{23} CO_2^{th}(t_{th}) \\
&s.t \;\; \sum_{t=1}^{T} \sum_{h=0}^{23} q^i_{th} \geq Q^i, \forall i \\
&\qquad T_{ht} + q_{th} \geq \text{Residual Demand}
\end{aligned} \tag{11}$$

where q^i_{th} is the electricity injected into the grid from the microgenerator i, and t_{th} is the thermal production in a certain hour and day.

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

$$\begin{bmatrix} D_0 & D_1 & D_2 & \cdots & D_{23} & 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \times \begin{bmatrix} t_0 \\ t_1 \\ t_2 \\ \vdots \\ t_23 \\ \sum_i q^i_0 \\ \sum_i q^i_1 \\ \sum_i q^i_2 \\ \vdots \\ \sum_i q^i_23 \end{bmatrix}$$

The first constraint takes the value equal one on their diagonal,

(i.e. $a_{(1,1)}, a_{(1,24)}, b_{(2,2)}, b_{(2,25)}, c_{(3,3)}, c_{(2,26)}, ..., x_{(24,24)}$, and $x_{(24,48)}$)

$$
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
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\end{pmatrix}
\times
\begin{pmatrix}
t_0 \\ t_1 \\ t_2 \\ \vdots \\ t_23 \\ \sum_i q_0^i \\ \sum_i q_1^i \\ \sum_i q_2^i \\ \vdots \\ \sum_i q_2^i3
\end{pmatrix}
\geq
\begin{pmatrix}
\mathrm{rd}_0 \\ \mathrm{rd}_1 \\ \mathrm{rd}_2 \\ \mathrm{rd}_3 \\ \mathrm{rd}_4 \\ \mathrm{rd}_5 \\ \mathrm{rd}_6 \\ \mathrm{rd}_7 \\ \mathrm{rd}_8 \\ \mathrm{rd}_9 \\ \mathrm{rd}_10 \\ \mathrm{rd}_11 \\ \mathrm{rd}_12 \\ \mathrm{rd}_13 \\ \mathrm{rd}_14 \\ \mathrm{rd}_15 \\ \mathrm{rd}_16 \\ \mathrm{rd}_17 \\ \mathrm{rd}_18 \\ \mathrm{rd}_19 \\ \mathrm{rd}_20 \\ \mathrm{rd}_21 \\ \mathrm{rd}_22 \\ \mathrm{rd}_23
\end{pmatrix}
$$

The second constraint:

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

Where D_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 hour k. The residual demand is found as: residual demand = demand - wind - hydro - solar - biomass.

A.3 Selection Bias

This section tries to lessen the selection bias concern that the early adopters are different from the late adopters. We compare the yearly estimations of the electricity extracted and the net effect (electricity $extracted - injected$).

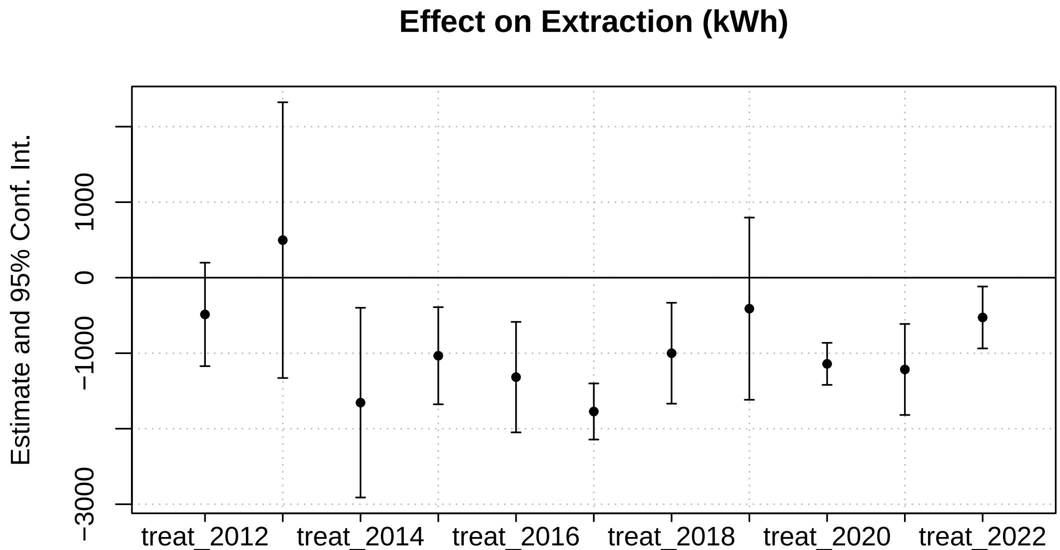
First, we multiply the treatment variable for a year dummy, a variable equal to one for a specific year, and zero otherwise; then we run Regression (1). Results are shown in Figure A.1. For the extraction estimations (panel a), all the estimations are similar. For the net effect, the only different year is 2017.

To explore this further, we compare the extraction estimation of 2013 versus 2014 and 2018. Results are in Table A.2. We are not able to reject the hypothesis that the extraction estimation of the year 2013 is not equal to the estimation of the years 2014 and 2018.

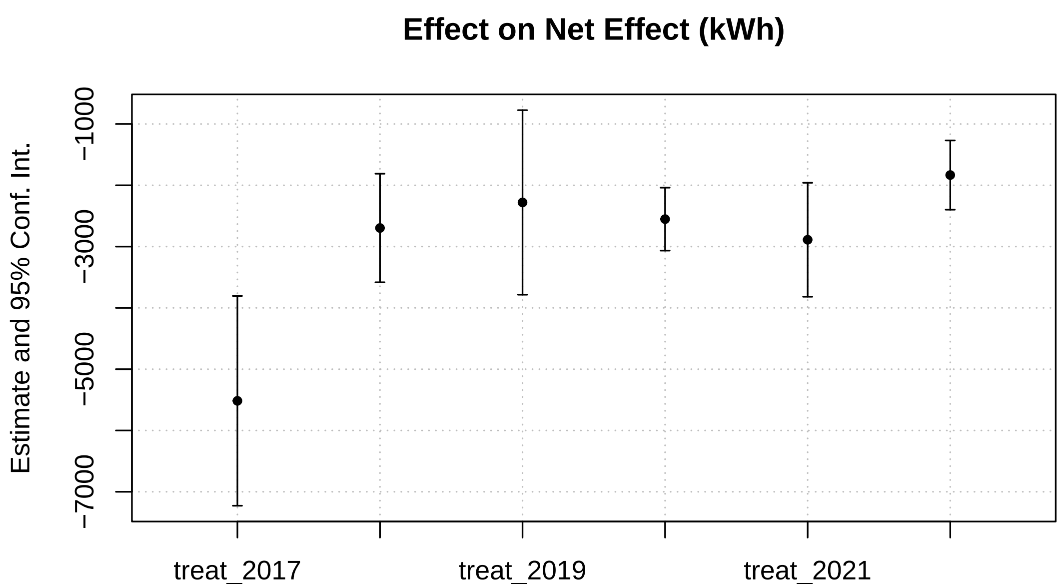
Table A.2: Time Variation

	P-values		
	Model 1	Model 2	Model 3
$\beta_{2013} - \beta_{2014} = 0$	0.145	0.197	0.201
$\beta_{2013} - \beta_{2018} = 0$	0.218	0.296	0.526
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y
N	24,386	24,386	24,386

*This table shows the difference between the extraction estimation of the year 2013 versus 2014 and 2018, using different especifications. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month $*$ year. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*



(a) Extraction estimations



(b) Net effect estimations

Figure A.1: Yearly estimations.

Notes: Panel (a) shows the yearly estimations of extractions. Panel (b) shows the yearly estimations using the net effect. Data before 2017 have many missing values. The regression uses ID and month fixed effects.

A.4 Net Effect

Table A.3 shows the net effect of installing a solar panel (i.e., extractions − injections). After installing a solar panel, the net effect decreases by 2,565 kWh.

Table A.3: Net effect

	Net effect (extractions − injections (kWh))		
	(1)	(2)	(3)
Solar panel installation	-2564.97***	-2839.05***	-2830.68***
	(249.20)	(363.62)	(354.73)
ID F.E	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month ∗ year	N	N	Y
N	18,964	18,964	18,964

*This table shows the effect of installing a solar panel on the net electricity (extractions − injections) taken from the grid, using different sets of time fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month∗ year. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

Figure A.2 plots the event study coefficients using ID + month fixed effects. All the results are compared with the month before installing the solar panel (lead1). As Figure A.2 shows, the net effect reduction is constant over time.

In section A.5, we introduce agent heterogeneity to explore potential differences between firms and households.

A.5 Heterogeneity by Agent

The results are presented in Table A.4. Firms that install solar panels decrease the net effect by 3,584 kWh, and households reduce the net effect by 566 kWh.

Table A.4: Electricity injected into the grid by type of agent: household or firm

	Panel (a): Net effect (kWh) - Firms		
	(1)	(2)	(3)
Solar panel installation	-3584.38***	-3822.37***	-3768.55***
	(305.23)	(482.84)	(497.86)
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y
N	13,033	13,033	13,033

	Panel (b): Net effect (kWh) - Households		
	(1)	(2)	(3)
Solar panel installation	-566.31***	-734.09***	-752.83***
	(56.72)	(155.00)	(172.92)
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y
N	5,931	5,931	5,931

*This table shows the effect of installing a solar panel on the net effect, i.e., the difference between electricity extracted minus injected, using different sets of time-fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month $*$ year. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

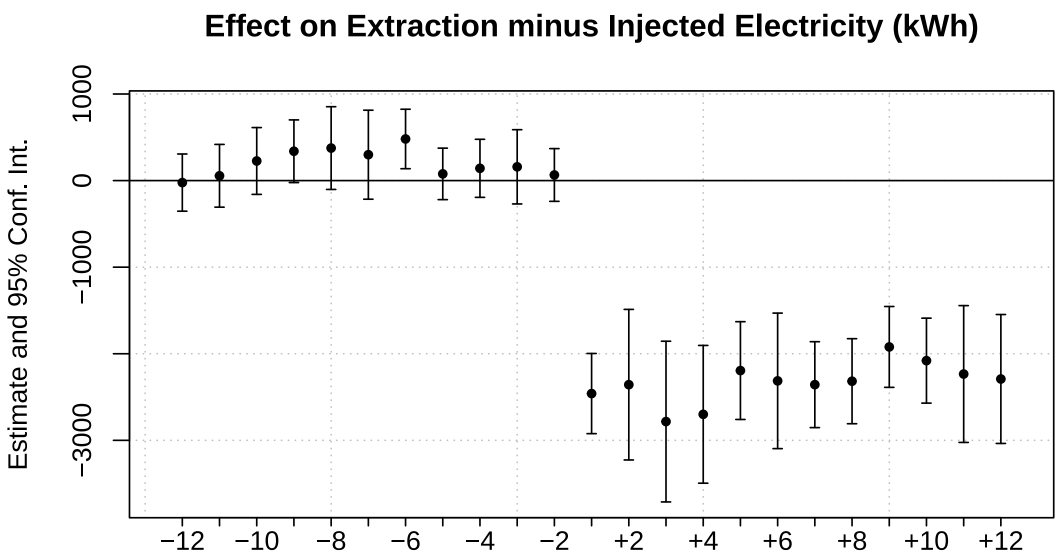


Figure A.2: Event study plot - Net effect.

Notes: This figure shows the event study plot of the net effect, defined (extractions − injections) from the grid. Using 12 leads/lags before/after the solar panel installation, controlling for ID + month fixed effects.

A.6 Change in the Policy

In this section, we study whether the change in the policy has an effect on our estimates for electricity extracted from the grid - we lack the data before the policy to see the effect on injection. We find no effect of the policy change, as shown in Table A.5

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

Dependent Variable:	Extraction (kWh)		
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	-1,201.9***	-1,261.4***	-748.1*
	(202.5)	(274.8)	(396.6)
Solar Panel Installation*After 2017	142.1	231.5	-454.8
	(312.5)	(354.7)	(535.0)
ID Fixed Effects	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month ∗ year	N	N	Y
Observations	24,386	24,386	24,386

*This table shows the effect of installing a solar panel on the electricity taken from the grid, using different sets of fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month ∗ year. "After May 2017" takes the value equal to 1 if the agent installs a solar panel after May 2017. Solar panel installation takes a value equal to 1 after installing the solar panel. Solar panel installation ∗ After May 2017, is the interaction. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

A.7 CO_2 emissions factors

As discussed in Section 5.6, the CO_2 emission reduction due to the policy depends on which electricity source is used in the margin. A way to reflect such a relation is by creating hourly CO_2 emission factors.

We create such factors as follows. First, we construct the total CO_2 emissions per month due to electricity production. To calculate this number, we collect monthly data on fuel oil, gas oil, and natural gas consumption for thermal electricity production and then use the IPCC (2006)'s CO_2-emission factors to convert it to monthly CO_2 emissions. Second, we construct the average hourly CO_2 emission factor of the month by dividing the total CO_2 against the total thermal production of the month. Lastly, we would like to reflect that, within a month, the higher the thermal production, the more likely it is that higher CO_2-emission facilities are being used. We would also like that once we multiply the CO_2-emission factor against the thermal production and sum up over the day, the associated CO_2 emissions equals the CO_2 emitted in that day. Thus, we construct a ponderator within hour-of-the-day in two steps. First, we construct a ponderator per hour equivalent to the total thermal production at that hour divided by the total thermal production that day. Then, we re-weight such a ponderator 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 such a re-weight as follows. Denote the average hourly CO_2 emissions α, the hourly thermal production t_{dh}, and the re-weight factor w_d. Then,

$$\begin{aligned} \sum_h t_{dh} \times \alpha = \sum_h \alpha \times t_{dh} \times \frac{t_{dh}}{\sum_h t_{dh}} \times w_d \\ \sum_h t_{dh} = \frac{w_d}{\sum_h t_{dh}} \sum_h t_{dh}^2 \implies \quad w_d = \frac{(\sum_h t_{dh})^2}{\sum_h t_{dh}^2} \end{aligned} \tag{12}$$

A.8 Value to Consumers

Table A.6 and A.7 show the information use to calculate the back-of-the-envelope savings using the net effect and the injection estimations for households and firms, respectively.

For households, there are three rates: peak, off-peak, and plain. Each household faces each rate for 4 hours, 8 hours, and 12 hours, respectively (please check here). The weighted average is calculated as $10.68 * \frac{4}{24} + 2.223 * \frac{8}{24} + 4.875 * \frac{12}{24} = 4.9585$. The exchange rate was collected from here, the real exchange rate with base 2017 was obtained from here. The net effect estimation is presented in Table A.4 Panel (b) column (1). The injection estimation is presented in Table 5 Panel (b) column (1). Therefore, the savings assuming the weighted average rate and the net effect estimation is $\frac{566.31*4.9585*0.937}{38.955} = 68$ USD at the 2017 base.

Table A.6: Value to consumers - Household data

	Household rate			
	Rate (UY/MWh)	Hours	Weight	Weighted Av.
Peak	10.68	4 hrs	$\frac{4}{24}$	
Off-peak	2.223	8 hrs	$\frac{8}{24}$	4.9585
Plain	4.875	12 hrs	$\frac{12}{24}$	
Exchange rate	38.955			
Real exchange rate base 2017	0.937			
Net effect estimation	-566.31			
Injection estimation	455.28			

This table shows the calculations used to find the saving using the net effect estimations and the injections estimations for households

Similarly, for firms, the data used is presented in Table A.7. Each firm also faces each rate for 4 hours, 8 hours, and 12 hours, respectively (please check here). The weighted average is calculated as: $11.531 * \frac{4}{24} + 2.303 * \frac{8}{24} + 5.068 * \frac{12}{24} = 5.2235$. While the exchange rate was collected from here, the real exchange rate with base 2017 was obtained from here. The net effect estimation is presented in Table A.4 Panel (a) column (1). The injection estimation is presented in Table 5 Panel (a) column (1). Therefore, the savings assuming the weighted average rate and the net effect estimation is $\frac{3584.3*5.2235*0.937}{38.955} = 450$ USD at the 2017 base.

Table A.7: Value to consumers - Firms data

	Firms rate			
	Rate (UY/MWh)	Hours	Weight	Weighted Av.
Peak	11.531	4 hrs	$\frac{4}{24}$	
Off-peak	2.303	8 hrs	$\frac{8}{24}$	5.2235
Plain	5.068	12 hrs	$\frac{12}{24}$	
Exchange rate	38.955			
Real exchange rate base 2017	0.937			
Net effect estimation	-3584.3			
Injection estimation	2135.82			

This table shows the calculations used to find the saving using the net effect estimations and the injections estimations for firms

A.9 Robustness Checks

A.9.1 Alternative Cluster

In this section, we run the main regressions cluster at an ID level. Results do not vary and can be found in Table A.8.

Table A.8: Cluster errors at an ID level

Dependent Variable:	Net Effect (kWh)		
Variables			
Solar Panel Installation	-2,565.0***	-2,839.1***	-2,830.7***
	(227.6)	(279.2)	(286.6)
Observations	18,964	18,964	18,964
Dependent Variable:	Injection (kWh)		
Variables			
Solar Panel Installation	1,569.7***	1,708.8***	1,697.8***
	(98.36)	(113.6)	(114.5)
Observations	24,386	24,386	24,386
Dependent Variable:	Injection (kWh)		
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	1,569.7***	1,708.8***	1,697.8***
	(98.36)	(113.6)	(114.5)
Observations	18,964	18,964	18,964
ID F.E	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y

*This table shows the effect of installing a solar panel on the net electricity using different sets of fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month $*$ year. Standard errors are clustered at ID level. Significance levels: ***0.01 **0.05 *0.1.*

Table A.9: Excluding agents with yearly injection greater than yearly extraction

Dependent Variable:	Net Effect (kWh)		
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	-2,476.8***	-2,772.6***	-2,758.0***
	(293.9)	(398.0)	(397.8)
Observations	16,441	16,441	16,441

Dependent Variable:	Extraction (kWh)		
Variables			
Solar Panel Installation	-1,140.8***	-1,102.9***	-1,120.5***
	(81.02)	(149.2)	(142.5)
Observations	21,744	21,744	21,744

Dependent Variable:	Injection (kWh)		
Variables			
Solar Panel Installation	1,438.0***	1,606.5***	1,595.4***
	(116.2)	(132.7)	(129.1)
Observations	16,441	16,441	16,441

ID F.E	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y

*This table shows the effect of installing a solar panel on the net electricity (extractions − injections) taken from the grid, using different sets of fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month∗ year. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

A.9.2 Exclude Agents with Injection Greater than Extraction

In 2017, the net-metering policy changed slightly. From that point onward, agents shall not produce more electricity yearly than the one they produce. In practice, only 137 agents produce more electricity than they consume in a year. We exclude them from the main regressions; the results virtually do not change. A summary of the results can be found in Table A.9.

Table A.10: Excluding 5% tails on electricity extracted from the grid

Dependent Variable:	Net Effect (kWh)		
Model:	(1)	(2)	(3)
Variables			
Solar Panel Installation	-2,295.6***	-2,391.4***	-2,375.5***
	(174.1)	(270.2)	(236.1)
Observations	17,648	17,648	17,648
Dependent Variable:	Extraction (kWh)		
Variables			
Solar Panel Installation	-918.3***	-810.7***	-836.6***
	(67.99)	(147.6)	(147.3)
Observations	22,278	22,278	22,278
Dependent Variable:	Injection (kWh)		
Variables			
Solar Panel Installation	1,480.3***	1,602.7***	1,596.0***
	(104.4)	(116.8)	(105.4)
Observations	17,648	17,648	17,648
ID F.E	Y	Y	Y
month	Y	Y	N
year	N	Y	N
month $*$ year	N	N	Y

*This table shows the effect of installing a solar panel on the net electricity (extractions − injections) taken from the grid, using different sets of fixed effects. Column (1) uses ID + month fixed effects; column (2) uses ID + month +year fixed effects; finally, column (3) uses ID + month$*$year. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*

A.9.3 Exclude Tails of Agents' Extraction from the Grid

Our results may also be driven by agents with very high or low electricity extraction from the grid. We exclude the 5% with the highest and lowest total electricity extraction from the grid to check whether this is true. The results do not change qualitatively. A summary of the results can be found in Table A.10.

A.9.4 Sun and Abraham (2021) Estimation Approach

In this section, we present the estimation results using the Sun and Abraham (2021) approach. The results are unchanged and presented in Table A.11.

Table A.11: Sun and Abraham (2021) estimation approach

	Net effect (kWh)	Extraction (kWh)	Injections (kWh)
Solar panel installation	-2488.46***	-891.69***	1532.81***
	(298.47)	(169.31)	(90.39)
ID F.E	Y	Y	Y
Month F.E	Y	Y	Y
N	18,963	24,386	18,963

*This table shows the effect of installing a solar panel on the electricity taken from the grid using ID + month fixed effect. Column (1) shows the net effect, i.e, the electricity extracted − injected into the grid; column (2) shows the electricity taken from the grid; finally, column (3) shows the electricity injected into the grid. Standard errors are clustered at state level. Significance levels: ***0.01 **0.05 *0.1.*