

Power Move: Solar Adoption Among Firms

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PRELIMINARY: DO NOT CIRCULATE

Abstract

Fossil fuel consumption for electricity generation remains a major contributor to global emissions, yet firm adoption of renewable energy has been slower than necessary to achieve climate goals. This paper investigates what drives firm-level adoption of distributed solar generation by leveraging unique microdata on solar panel installations across firms. To identify the causal effects of economic incentives on adoption decisions, I exploit variation generated by an energy price subsidy that differentially affected firms' cost-benefit calculations for solar investment, finding evidence of a positive substitution effect. To quantify the relative importance of different price and cost channels, I estimate a discrete-continuous choice model that jointly captures both the adoption decision and the capacity choice. I find that while energy price subsidies did account for a significant increase in solar adoption, firms appear to be more sensitive to high upfront investment costs. Under an equivalent-cost comparison, an installation cost subsidy would add twice as many adopters and more than double additional installed capacity compared to the baseline energy price subsidy. I calculate that installation subsidies achieve carbon abatement at US\$12 per ton CO₂ — twelve times more cost-effectively than energy price subsidies and well below prevailing carbon prices in international markets — demonstrating that policies targeting upfront investment barriers can deliver emissions reductions at substantially lower cost per ton abated.

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I Introduction

Fossil fuel consumption for electricity and heat generation accounts for a third of global emissions, where firms alone contribute over 80% through coal, oil and natural gas ([InfluenceMap, 2025](#)). To face the challenges of and mitigate the environmental effects on climate change, the adoption of renewable energy has become increasingly essential. Adopting renewable sources can lead to competitive advantages as well as foster innovation, promoting sustainable economic growth ([Cohen & Tubb, 2018](#)). Distributed renewable generation¹, in this setting, has additional advantages to provide a fast and scalable avenue for the expansion of clean energy. Self-generation can improve firms' climate resilience by reducing exposure to energy price fluctuations and energy supply shocks, which have become more frequent in recent years, whereas firms that fail to adapt may face significant economic and environmental risks ([Fetzer et al., 2024](#)). Nevertheless, adoption has been lower than anticipated and slower than necessary to guarantee the reduction of greenhouse gas emissions in time to achieve global warming goals ([IPCC, 2018](#)). The goal of this paper is to shed light on the underinvestment into renewable energy, by focusing on the question of what drives firm-level adoption of distributed solar generation.

To answer this question, I look at the case of Brazil. Solar power is due to overtake hydro generation in Brazil in the next 20 to 30 years, and public policy has attempted to lay the groundwork for this transition. Forecasts indicate that small scale solar generation will be responsible for the majority of solar power installed capacity in the country by 2050 ([Bloomberg, 2021](#)). However, increasing instability in hydro generation due to more frequent and more severe droughts has renewed policymakers' commitment to investing in fossil fuel energy sources². This shift is particularly concerning given that solar has already become the second largest source of electricity in Brazil as of 2025, being responsible for 11% of the energy matrix, with distributed solar generation representing over 70% of all solar capacity in the country. Understanding what drives firms to adopt distributed solar generation — and what barriers prevent wider adoption — is therefore critical for designing effective policies to accelerate the energy transition.

Distributed renewable generation in Brazil has benefited from subsidies since 2012 aimed at reducing the cost of energy for adopters via a net metering scheme. This subsidy provided heterogeneous incentives for adoption, which varied widely across the country due to differences in the structure of energy pricing. Specifically, the subsidy exempted adopters from paying a variable component of their energy tariffs on their net grid consumption after adoption. Since price components vary substantially across Brazil's 110+ energy distributors, the subsidy created differential treatment intensity across locations. This institutional feature, combined with rich micro-data covering the universe of firms and adopters, provides a unique opportunity to identify how different price mechanisms — grid energy prices, solar panel costs, and subsidy benefits — interact to shape

¹Distributed generation can be defined as any type of small scale generation that is meant for local consumption, as opposed to utility-scale generation that is meant to supply large transmission and distribution networks for widespread consumption.

²"Termelétricas novas dominam projetos cadastrados para o leilão de reserva de capacidade", *eixos*, March 2025.

firms' adoption decisions.

This paper provides both reduced-form evidence on the pattern of small scale solar adoption by firms in Brazil, and a structural analysis of firms' adoption choices, focusing on the role of different price mechanisms for industrial and commercial establishments that have installed photovoltaic (PV) panels over the past decade. I leverage one main source of heterogeneity to identify the mechanisms behind solar adoption patterns, and carry out my empirical analysis for the State of São Paulo. The existence of heterogeneous energy prices across granular locations, which vary considerably across the state's distribution utilities, creates differential incentives for adoption. As the existing subsidy scheme affects only one component of energy prices, this variation in the cost of electricity provides varying levels of treatment from the subsidy policy. This variation allows me to identify the relevance of multiple price mechanisms affecting PV adoption: substitution between grid and solar energy, demand-side effects through energy intensity, and direct subsidy effects.

The reduced-form analysis yield three key findings. First, I document a strong positive relationship between grid energy prices and firm adoption of solar generation. Using a two-way fixed-effects specification that exploits within-location variation in energy prices over time, I estimate an elasticity of adoption probability with respect to the usage price component of 0.45, implying that a 10% increase in usage prices is associated with an 4.5% increase in the probability of adoption. This result is consistent with firms substituting away from grid-supplied energy toward self-generation when the cost of the outside option increases. Second, I find that the distribution price component — which determines the magnitude of subsidy benefits under the net metering policy — also positively affects adoption, though the effect is smaller in magnitude. This suggests that both the substitution channel and the direct subsidy benefit channel matter for firms' decisions. Third, I document that technology suitability, as measured by solar irradiance, has a positive effect on adoption in the early years of the sample period, but this effect diminishes over time as panel costs decline and adoption becomes more widespread. This pattern suggests that as solar technology became more cost-competitive, generation efficiency became less critical as a determinant of adoption.

To address endogeneity concerns — specifically, that utilities might adjust prices in response to adoption — I implement several robustness checks. First, I examine whether there is differential entry of firms into locations with higher energy prices, which could confound the interpretation of my results. I find no evidence of such entry effects once location fixed effects are included, supporting the interpretation that firms are price-takers in their local energy markets. Second, I implement a spatial differences design that compares adoption rates in neighbouring zip codes served by different utilities and therefore facing different energy prices. The spatial estimates confirm the main results, showing that locations with higher energy price differentials relative to their neighbours experience higher adoption rates. These robustness checks strengthen the causal interpretation of the reduced-form estimates.

While the reduced-form analysis provides evidence of how energy prices affect adoption de-

cisions, it cannot fully decompose the relative importance of different cost and benefit channels, nor does it permit the evaluation of counterfactual policy scenarios. To address these questions, I develop and estimate a structural discrete-continuous choice model of firms' solar adoption decisions. The model jointly captures firms' decisions at both the extensive margin (whether to adopt) and the intensive margin (how much capacity to install), while accounting for multiple price channels: grid energy prices, solar panel installation costs, subsidy benefits, and operational costs. Intuitively, the model allows firms to compare the expected value of adoption to the expected value of the outside option - staying in the grid. Additionally, the expected value of adoption is a function of the optimal capacity for a given firm. Estimating the model parameters with a maximum likelihood approach, to match observed adoption probabilities and the distribution of observed capacity, the model yields several important insights. First, the estimated weight on the net present value of adoption in the utility function indicates that while financial considerations are important, firms also value other factors such as exposure to local adoption patterns and firm-specific characteristics. Second, the structural estimates reveal that firms face substantial capacity choice errors, pointing to potential behavioural biases or information frictions in firms' intensive margin choices. Third, the model estimates imply reasonable payback periods for adopters, which are consistent with industry benchmarks and support the validity of the structural estimates.

Subsequently, I use the estimated model to conduct three main counterfactual policy experiments. First, I simulate adoption absent any energy price subsidy, setting the subsidy benefit to zero while holding all other factors constant. This exercise reveals that the existing subsidy policy increased adoption rates from 2.29% to 2.71% — an 18.3% increase or 0.42 percentage points. While baseline adoption rates are quite low, this finding indicates that the policy had a meaningful positive impact on firms' decisions. The implied additionality suggests that a substantial minority of observed adopters would not have adopted absent the subsidy.

Second, I consider an alternative policy design in which the subsidy is homogeneous across locations rather than proportional to the distribution price. Specifically, I simulate adoption under a lump-sum subsidy set at the mean distribution price across São Paulo State. This counterfactual reveals that a homogeneous price subsidy would have achieved only about half the additional adoption observed under the heterogeneous subsidy — a 0.2 percentage point increase compared to the no-subsidy baseline. This result highlights the importance of subsidy design: the heterogeneous subsidy implicitly provided larger incentives in locations where subsidy benefits were higher, leading to greater overall adoption.

Third, I simulate adoption under an installation cost subsidy rather than an energy price subsidy. Holding the subsidy rate fixed at 5% of panel costs, I find that this alternative policy design would increase adoption rates by 11.8% relative to the baseline energy price subsidy, from 2.71% to 3.03% — a 0.3 percentage point increase. Moreover, total installed capacity would increase by 54.6% under this policy, indicating that while the effect on the extensive margin (number of adopters) is modest, the effect on the intensive margin (capacity per adopter) is substantial. This finding indicates that upfront investment costs constitute a more binding constraint than ongoing

operational and energy costs.

To enable a more direct comparison between the two subsidy types, I conduct an additional counterfactual in which I calibrate the installation cost subsidy to have the same total budgetary cost as the energy price subsidy over a 20-year horizon. Iterating over possible subsidy rates, I find that a 7% installation cost subsidy would have equivalent cost to the baseline energy price subsidy. Under this equivalent-cost scenario, adoption would increase by 19.2% — nearly double the increase achieved by the baseline policy — from 2.71% to 3.23%, representing a 0.52 percentage point gain. Furthermore, total installed capacity would more than double, increasing by 103% compared to the baseline. Under the installation cost subsidy, mean installed capacity rises from 38.7 kW per firm in the baseline to 59 kW, indicating that this policy design encourages both more extensive adoption and larger system sizes among adopters.

These counterfactual results have important implications for climate policy design. The findings indicate that while energy price subsidies can increase renewable energy adoption, they are less cost-effective than direct subsidies to installation costs. The superior performance of installation cost subsidies reflects the relative importance of upfront investment barriers compared to ongoing operational considerations in firms' adoption decisions. From a policy perspective, this suggests that governments seeking to maximize renewable energy deployment per dollar of subsidy spending can prioritise reducing upfront costs through rebates, tax credits, or direct capital subsidies, rather than reducing ongoing energy costs through mechanisms like net metering or feed-in tariffs.

Beyond their differential effects on adoption rates and installed capacity, the two policy designs also differ substantially in their cost-effectiveness at reducing carbon emissions. I calculate the carbon abatement cost — the subsidy expenditure per ton of CO₂ avoided — for each policy by accounting for the energy generated by adopted solar capacity over a 25-year system lifetime and the emission intensity of Brazil's electricity grid. The baseline energy price subsidy achieves carbon abatement at a cost of approximately US\$148 per ton of CO₂, which exceeds prevailing carbon prices in major international markets such as the EU Emissions Trading System and falls at the upper end of social cost of carbon estimates (between US\$50 and US\$100 per ton). In contrast, the equivalent-cost installation subsidy achieves abatement at merely US\$12 per ton CO₂ — a twelve-fold improvement in cost-effectiveness. This stark difference reflects both the higher adoption rates and larger system sizes induced by installation subsidies, resulting in substantially more emissions displaced per dollar of public expenditure. These findings suggest that policies targeting upfront investment barriers can deliver emissions reductions at costs well below those of alternative subsidy settings, with important implications for climate policy design in capital-constrained emerging economies.

The paper is structured as follows. Section II details the institutional background and describes the main data sources, while Section III introduces the theoretical model. Section IV presents the reduced form strategy and results that motivate the model, and Section V presents the model estimation results. Section VI discusses the model counterfactual exercises, while Section VII con-

cludes.

RELATED LITERATURE

This paper contributes to several strands of literature on renewable energy adoption, technology diffusion, and environmental policy. First, it speaks to an increasing literature on PV adoption. Given the rising need for alternative sustainable energy sources, there has been an ever-growing interest in analysing the expansion of these technologies, particularly solar. For the most part, there has been a focus on residential adoption of PV (Hughes & Podolefsky, 2015; Langer & Lemoine, 2018; Feger *et al.*, 2017; De Groote & Verboven, 2019), most likely reflective of the slower uptake from non-residential sectors (Crago & Koegler, 2018). Using the Brazilian setting, this has also been the case, for instance Mejdalani *et al.* (2018) and Montuenga *et al.* (2020) look at the effects of the net metering scheme on residential adoption. Nevertheless, a few recent papers have looked further at commercial adoption. Best & Burke (2023) for one studies non-residential adoption in Australia following the implementation of national targeted policies, and find that earlier adoption by the residential sector is positively correlated with larger investments from firms later on. Speaking on price mechanisms more broadly, Kiso *et al.* (2022) also look at the effect of how energy prices affect PV adoption, using a natural experiment in Japan, and show how energy price increases led to more investment in retrofit household solar installations. This paper makes several contributions to the PV adoption literature. First, while most existing work focuses on residential adoption, I provide comprehensive analysis of non-residential solar adoption using firm-level micro-data covering the universe of installations. Second, I extend the subsidy evaluation framework to examine multiple interacting price mechanisms simultaneously, such as grid energy prices, solar panel costs, and government subsidies.

Second, the paper is also closely related to a large literature on technology diffusion, particularly green technology adoption. While diffusion itself has been a topic of interest for decades (see Stokey 2021 for a recent survey), the diffusion of green technologies has recently become an increasingly important subject of research within economics. A large body of work has looked at green adoption via models of directed technical change (Acemoglu *et al.*, 2012; Lennox & Witajewski-Baltvilks, 2017). For example, Verdolini *et al.* (2018) looks at the complementarity of different energy sources and finds that investment in modern fossil-based technologies can support the decarbonisation process as it acts as back-up capacity to variable sustainable sources, such as wind and solar. Another area of work within this literature has focused on identifying firm characteristics that can determine faster adoption of green technologies (Arvanitis & Ley, 2013; Sui & Gao, 2023). Hötte (2020) for instance finds that firms' knowledge stocks act as barriers to diffusion and decrease the effectiveness of environmental policies, and that subsidies are important policies that can allow for earlier adoption in cases where firms lack capabilities. This paper aims to contribute to these strands of the literature by identifying how technology suitability and policies, as well as structural characteristics of firms that might be relevant factors in technology adoption, can impact diffusion. Lastly, this paper is also related to a growing theoretical literature that has attempted

to model green diffusion (Zeppini, 2015; Dhami, 2023), particularly by modelling and estimating input choice between different energy sources.

Additionally, by evaluating the effect of a subsidy policy on green technology adoption, this paper is also related to a growing literature that has intended to understand the effects of environmental regulation. Studies that make use of micro-data to examine industrial responses to environmental policies often employ one of two approaches: long-run analyses of a single industry, such as cement or electricity, over a significant period of time (Fowlie *et al.*, 2016; Meng, 2016; Clay *et al.*, 2021); or static models that investigate the contemporaneous effects across multiple industries (Shapiro & Walker, 2018; Calel, 2020). This paper aims to bridge these two strands, firstly by providing evidence of a subsidy policy targeted towards early adoption that had long-term effects on the costs of adoption by reducing the lifetime cost of electricity to adopters. Second, the paper aims to identify the dynamics of responses to such policies, by investigating time-varying adoption patterns and considering forward looking agents who might optimise based on expected prices. Methodologically, I contribute by combining reduced-form analysis of subsidy impacts with a structural model of technology choice, allowing to both estimate causal effects of the policy and simulate counterfactual scenarios under alternative policy designs. The use of data covering the universe of firms allows for the identification of these effects across multiple industries and locations. Moreover, by including the possibility of heterogeneous technological efficiency, I also provide further contributions to this literature by being able to identify if environmental policies have heterogeneous effects across different degrees of technology suitability.

Finally, there has been a large body of research aimed at understanding technological lock-in (Kehoe & Atkeson, 1999), and some recent evidence has attempted to shed light on how such lock-in arises, particularly when it comes to energy use (Hawkins-Pierot & Wagner, 2022; Acemoglu *et al.*, 2019). Investigating the factors that determine green technology adoption is a crucial step to informing policy that aims to have any significant impact on emissions reduction and on the energy transition away from fossil fuels. This paper is related to the literature on technology lock-in, particularly relating to “path dependence” in technology use and the resistance in the adoption of green technologies by firms. As a kind of technology lock-in, carbon lock-in has been researched across fields, however quantitative assessments of its causes and its policy implications have been limited (Seto *et al.*, 2016). This paper connects to models of capital investment by looking at investment decisions into green technologies (Kehoe & Atkeson, 1999; De Groote & Verboven, 2019). In this sense, both evaluating the relevance of price mechanisms as well as estimating technology choice models can provide further contributions to how we understand “path dependence” in energy sources.

II Institutional Setting and Data

A. INSTITUTIONAL BACKGROUND AND EMPIRICAL SETTING

The Brazilian retail energy market operates in three stages. First, distribution utilities (hence-

forth referred to as “utilities”) purchase electricity from large-scale generators through centralised auctions, regulated by the National Electric Power Agency (*Agência Nacional de Energia Elétrica - ANEEL*) and operationalised by the Chamber of Electricity and Energy Commercialisation (CCEE). These auctions determine long-term contracts, ranging from 5 to 30 years, which specify the quantity and price of energy provided from generators to utilities. If facing unexpected shortages or excess in demand, utilities can also participate in one-year auctions to accommodate supply for the following year (MME, 2019).

At a second stage, utilities then provide energy to final consumers - firms and households - through the Regulated Procurement Environment (ACR). In this market, each utility covers a concession zone defined by law, with no overlaps and rare changes to geographical boundaries³. Therefore, consumers in a given location (for instance, a given zip-code) have a fixed utility provider and are thus price-takers in the energy market, conditional on their location. At the ACR level, energy prices for final consumers are comprised of two components: the “Usage Price” and the “Distribution Price”, each charged from the consumer per kWh of consumption. The former is defined so as to cover the actual cost of energy procured by the utilities and sold to final consumers. Utilities define Usage Prices at 100% pass-through rates, adjusted yearly by the regulator ANEEL based on auction contracts’ pre-set revisions, inflation rates, and cost adjustments. Hence, utilities are meant to be simply a representative transactor on behalf of consumers with no profit derived from energy supplied by generators. The Distribution Price, on the other hand, is meant to recover fixed costs of the distribution network for the utility, including financial returns on investments into infrastructure and service delivery. This component is also adjusted yearly for inflation and cost adjustments (Ramos *et al.*, 2012).

Finally, at the last stage, final consumers can opt into distributed renewable generation. The focus of this paper will be on Photovoltaic Distributed Generation (PVDG), which represents over 97% of capacity installed in distributed renewable generation by firms in my sample period⁴. The main instrument which regulated distributed generation was implemented in 2012 by ANEEL, establishing a net-metering policy for mini and micro-generation through a Normative Resolution. Mini and micro-generation was defined as any generating operation with an installed capacity up to 5MW, and which generates power from a renewable source, such as solar, wind, biomass or hydro (ANEEL, 2012). The resolution also put in place the first subsidy policy for PVDG: consumers who adopted PVDG would not contribute the Distribution Price on their net grid consumption (ANEEL, 2012). Essentially, net consumers would only pay the Usage Tariff component of the energy tariff for their net energy consumed, and net suppliers received energy credits (in kWh) which could be claimed for up to 5 years.

In 2015 ANEEL published a second Normative Resolution, which regulated three additional

³During the sample period considered in this paper, there were no major changes to concession zones within the State of São Paulo, only shareholder transfers, such as the privatisation of Eletropaulo to ENEL (“Enel reaches a 93.3% stake in Eletropaulo”, July 2018) and the incorporation of Elektro into Neoenergia (“Neoenergia incorporates Elektro”, August 2017).

⁴Appendix Figure A1 shows the yearly shares of total installed capacity for the four sources supported by the net metering scheme - solar, wind, biomass and hydro - between 2013 and 2021.

systems for renewable generation: shared generation, multiple consuming units and remote self-consumption (ANEEL, 2015). These schemes were seen as essential mechanisms to increase public interest in solar generation⁵. Both resolutions were replaced by the Distributed Generation Legal Framework, passed by Congress in January 2022, and which established legal regulatory benchmarks for the subsidy of sustainable energy generation. In my main analysis, I will focus on the period of 2015 to 2020, before these changes were made to the structure of the subsidy.

B. DATA

In my empirical analysis and model estimation, I combine data from a variety of sources, including administrative records, regulatory data, and industry surveys. I describe all data sources next.

ANEEL. I obtain three main datasets from the National Electricity Agency (ANEEL), the public regulator for the Brazilian energy market. The first is the System of Distributed Generation (SISGD) dataset, the registry of all locations with distributed generation connected to the electricity grid. This registry includes all formal firm establishments with net-metering of solar generation since 2012, containing information on which utility the establishment is connected to, location, start date of connection, quantity installed in kW, and establishments' unique identifier. Using this identifier I can also determine whether firms update their installations, when and by how much. The second dataset from ANEEL records effective energy tariffs applied by all utilities since 2010, which includes publicly approved tariffs that were in place as well as the exact dates when they were applied. These tariffs are reported by price component, tariff scheme, and type of supply. Appendix B describes in more detail how these variables are handled to create the final energy tariff variables. The final dataset taken from ANEEL is the *Base de Dados Geográfica da Distribuidora* (Geographical Distributor Database - BDGD), an administrative database that records utilities' assets at granular geographic locations. I use the BDGD to match firms to utilities by zip-code.

RAIS. For firm-level outcomes, I use the administrative dataset of matched employee-employer data from the Ministry of Labour, RAIS (*Relação Anual de Informações Sociais*), which includes information from all formal labour contracts on both workers and firms. Firm-level data include characteristics such as firm size, sector and product, year of entry and year of exit, location at the zip-code level, and a unique establishment-level identifier. I use worker-level data to also obtain firm-level characteristics such as average hourly wages and wage dispersion. I also use both datasets to build zip-code-level characteristics such as average local wages, average construction wages, average solar panel installer wages, local labour force size, and local market size. Using the establishment identifier I can merge firms to the ANEEL distributed generation dataset to match to PVDG adopting firms. With this matched dataset I also construct a zip-code-level solar diffusion

⁵Shared generation is defined when more than one consumer, within the same concession area, uses the solar generated power through a consortium. Multiple consuming units is the system through which consumption is individualised but generation is managed by a local administration, such as a condominium board. Finally, remote self-consumption is characterised by a consuming unit that generates power in a different location to the unit that will consume the energy generated - as long as they are located within the same distribution area.

measure, given as the share of adopting firms in a given zip-code. My main sample spans 2015 to 2020, before major changes to the PVDG schemes (see Section IV.A for details on sample selection).

EPE. For the cost of solar investments, I use the Data Panel on Distributed Generation from the Energy Research Enterprise (*Empresa de Pesquisa Energética - EPE*). This panel is built jointly with ANEEL, and provides yearly municipal-level data on total capacity installed and total value of investment, from 2013 to 2021. From these, I back out the average cost of investment per kW by municipality-year, which I merge with the RAIS firm-level data. I also use the Monthly Energy Consumption dataset from EPE to obtain annual energy use by commercial and industrial sectors, which I then draw on to construct the measure of estimated mean energy demand for the model estimation⁶.

INPE. The National Institute for Spatial Research (INPE) provides data on solar powered generation suitability for 10km by 10km grids of the entire national territory. Through their Atlas for Solar Energy (Pereira *et al.*, 2017), the Laboratory for Modelling and Renewable Resources Studies (LABREN) calculates a solar suitability measure, given in Wh per square meter. These measures are constant over time, and were estimated based on data collected between 1970 and 2015. I match solar irradiance to each firm by identifying the closest coordinate in the Atlas to firms' coordinate locations.

IBGE. I complement RAIS with the Annual Industry Survey (PIA) from the Brazilian Institute of Geography and Statistics (IBGE). This dataset includes total costs, production costs and energy expenses by industry and product code, with which I match to RAIS' firm-level data. The energy expenditure share is then used along with the EPE energy use data to estimate average energy demand⁷.

Table 1 reports some summary statistics for the zip-code and firm-level data. For the former, Panel A presents statistics on the number of firms and formal employees in a given zip-code, the number of adopting firms, average hourly wages, solar irradiance and both energy tariff components. Zip-codes have on average 24 firms operating and 291 employees working in a given year, and on average there are no adopters. Panels B and C report statistics on number of employees, age, average hourly wages and energy prices for all firms and adopting firms only, respectively. Adopting firms are, on average, larger - with a mean 53 employees versus 11 in the full sample - and older - with mean age of 20 against mean 14 for all firms. Nevertheless, mean wages follow similar moments across adopters and the full sample of firms.

To compare the level of solar panel costs with benefit gains from the energy price subsidy, Table 2 reports statistics on installation costs and subsidy gains during the sample period. Panel A shows that on average PV systems cost 7,930 BRL per kW of installed capacity⁸, although the large standard deviation and wide range from the 1st to 99th percentile indicates considerable heterogeneity in installation costs across locations and time, likely driven by differences in installer availability, local labor costs, and economies of scale for larger installations. Using the observed

⁶See Appendix B for details on the construction of these variables.

⁷See Appendix B for details on the construction of these variables.

⁸Approximately 1,500 USD, using the mean 2020 USD/BRL exchange rate.

installed capacity, I can calculate that the average investment by firms into PVDG during my sample period was of 236 thousand BRL⁹. On the other hand, Panel B reports the Distribution Price across locations, which is precisely the subsidy gains associated with adoption. Using lower and upper bounds on the efficiency of installed PV panels in the State of São Paulo, estimated in [Pereira et al. \(2017\)](#), I can then calculate the subsidy benefits for a given adopting firm once they adopt, $p^D \times k \times \rho$ - where ρ is the efficiency parameter¹⁰ and k is installed capacity. The estimated benefits range from 7,640 to 9,410 BRL¹¹.

III Choice Model of Solar Adoption

The model represents a firm's joint decision at both the intensive and extensive margin of adoption. That is, it models the discrete choice of whether or not to switch from grid-supplied energy and adopt distributed solar generation, as well as the continuous choice of the optimal capacity to install. The model resembles the recent literature in discrete-continuous choice models, such as [Benetton et al. \(2025\)](#), by estimating both decisions jointly to avoid any selection bias at the continuous choice. In this section I will set out the main components of the model and discuss the possible interpretations of the final set of parameters to be estimated. I discuss the estimation strategy and report results in Section V.

A. MODEL SET UP

In each year t , in location i , there is a mass of firms I_{it} that can opt into solar generation. Each firm $i \in I_{it}$ makes an entry decision at some point in time $s < t$, including the choice of location l which implies a choice of utility d that will be their energy provider. This is an ex-ante decision, which is taken as given at the moment at which the firm chooses or not to adopt solar generation. At each year t , the firm chooses or not to adopt:

$$j = \begin{cases} 1 & \text{if adopt} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

For each choice, the firm has an expected value, which reflects their conditional profit functions as a function of quantities, energy consumption and energy prices.

Outside option value. Firm i 's expected value of the outside option at year t , in location l , is given by:

$$V_{i0lt} = \varepsilon_{i0lt} \quad (2)$$

⁹Approximately 44 thousand USD, using the mean 2020 USD/BRL exchange rate.

¹⁰[Pereira et al. \(2017\)](#) estimate that the range of efficiency for the State of São Paulo is between 1300-1600 kWh per kWp of installed capacity, which is what I consider for the lower and upper bound ρ .

¹¹Approximately 1,445 and 1,780 USD, using the mean 2020 USD/BRL exchange rate.

Adoption value. Firm i 's expected value of adoption at year t , in location l , is given by:

$$V_{ilt}(k^*) = \lambda NPV_{ilt}(k^*) + \delta_{ilt} + \varepsilon_{ilt} \quad (3)$$

where $NPV_{ilt}(k^*)$ represents the net present value of adoption, and δ_{ilt} represents the mean option value of adoption. The latter is meant to incorporate any idiosyncratic gains that firms may have for adopting, that are not included in the other components, such as green preferences, or increased salience of solar adoption in their location, and is defined as:

$$\delta_{ilt} = \alpha_o + \alpha_1 \times w_{ilt} + \alpha_2 \times n_{ilt} + \alpha_3 \times s_{lt}^{SOLAR} + \zeta_{ilt} \quad (4)$$

where n_{ilt} is firm size; s_{lt}^{SOLAR} is a measure of local solar diffusion; and w_{ilt} is firm i 's mean wages.

Optimal capacity choice. Firm i 's optimal capacity choice k^* is given by the maximisation of the net present value of adoption:

$$k^* = \max_k \sum_{s \geq t} \beta^s \pi_{ils}(k) - C_{ilt}(k) \quad (5)$$

where π_{ils} reflects profit gain from adoption, and C_{ilt} reflects installation costs at the moment of adoption. They are given by:

$$\pi_{ilt}(k) = \theta_1 p_{lt}^{DIST} \times k - \theta_2 k - \theta_3 k^2 + \theta_4 e_{ilt} \times k \quad (6)$$

$$C_{ilt}(k) = c_0 + c_1 c_{lt}^{SOLAR} \times k + c_2 k^2 \quad (7)$$

where p^{DIST} is the Distribution Price of the energy tariff; e_{ilt} measures energy intensity as the share of production costs allocated to energy expenses; and c_{lt}^{SOLAR} is the average PV cost by kW in location l in year t .

Obtaining a closed-form solution requires convex installation and maintenance costs (see Appendix C for the model derivation and sufficient conditions). Solving for k^* :

$$k_{ilt}^*(\cdot | \Theta) = \max \left\{ 0, \left[\frac{\theta_1 \Psi(\beta p_{ilt}^{DIST}) + \bar{\beta} \theta_4 e_{ilt} - \bar{\beta} \theta_2 - c_1 c_{lt}^{SOLAR}}{2(\bar{\beta} \theta_3 + c_2)} \right] \right\} \quad (8)$$

where $\Psi(p_{ilt}^{DIST}, \beta)$ is the expected present value of energy prices and $\bar{\beta} = \sum_{s \geq t} \beta^s$. Interpreting this result: optimal capacity is increasing in both Distribution Price and energy intensity, and decreasing in local solar panel costs.

Probability of adoption. Given optimal capacity k^* for firm i , their probability of adoption will be given by $\mathbb{P}(j = 1 | E_{ilt}, \Theta) = \mathbb{P}(V_{i1lt} > V_{i0lt})$. Under the assumption that $\varepsilon_{i1lt} - \varepsilon_{i0lt} \sim \text{Logistic}(0, 1)$, we can arrive at a closed form solution for the probabilities of adoption $\mathbb{P}(j = 1 | E_{ilt}, \Theta)$. Appendix C derives these probabilities. Given the Logistic assumption, we know they

will the following functional form:

$$\mathbb{P}(j = 1|E_{ilt}, \Theta) = \frac{\exp(U_{i1lt})}{1 + \exp(U_{i1lt})} \quad (9)$$

where $U_{i1lt} = \lambda NPV_{ilt}(k^*) + \delta_{i1lt}$.

We assume firms choose optimal capacity k^* with error¹², such that $k_{ilt}^{observed} - k_{ilt}^* = \varepsilon_{ilt}^k$. Assuming $\varepsilon_{ilt}^k \sim N(0, \sigma_k)$, we define the likelihood function as:

$$\mathcal{L}(\Theta) = \prod_i \{\mathbb{P}(j_i = 1|\Theta, X_i) \times f(k|j_i = 1, \Theta, X_i)\}^{j_i} \times \{\mathbb{P}(j_i = 0|\Theta, X_i)\}^{1-j_i} \quad (10)$$

where: $\Theta = (\beta, \alpha_0, \alpha_1, \alpha_2, \alpha_3, c_0, c_1, c_2, \theta_1, \theta_2, \theta_3, \theta_4, \sigma_k)$ is the parameter set.

IV Reduced-Form Analysis

To motivate the estimation of the model, and provide some initial suggestive evidence on the effects of energy prices on adoption, I present in this section a reduced-form analysis using both firm and zip-code level specifications.

A. SAMPLE SELECTION

The main sample for my analysis includes all formal firms within the State of São Paulo, from 2015 to 2020. During this period, there were no major changes to the regulatory framework behind the PVDG net-metering policy and subsidy, and no large-scale policies for credit lines to firms adopting solar generation through the PVDG. I restrict my sample to the State of São Paulo for two reasons. First, regional components of energy tariffs, such as taxes, vary across states. Second, a majority of other states will only have one utility providing energy to final consumers, whereas São Paulo State has 19 different utilities with somewhat idiosyncratic geographical boundaries. Using the State of São Paulo allows me to observe potential adopters within the same institutional setting facing a heterogeneous energy market.

For the model estimation, I restrict my sample in two ways: I keep manufacturing firms only and I drop adopters with capacity installed above 250kW. I do so to take advantage of the Annual Industrial Survey data on energy expenses by product code, which are only available for manufacturing sectors, and to avoid outliers which may bias the model estimation. The latter represents around 0.6% of all adopters. Appendix Table A1 presents summary statistics comparing this model sample to the full sample used in the reduced-form analysis¹³.

¹²This assumption is as standard in the literature, where a closed-form solution that is deterministic leads to an over-identification issue. The error assumption therefore allows for agents to have some idiosyncratic shock which permits for observed choices diverging from the deterministic closed-form solution, where this shock has mean zero and the variance is an estimated parameter (Benetton *et al.*, 2025).

¹³Appendix Table A3 replicates the main specification estimation results with the subsample of manufacturing firms used for the model estimation. While the standard errors become larger due to the smaller sample size, the point estimate for the Usage Price is the essentially identical to the one with the full sample regression, indicating the economic effects remains similar and does not undermine the link between the reduced-form analysis and the structural model.

B. IDENTIFICATION AND ESTIMATING EQUATIONS

To identify the effects of energy prices and the energy price subsidy on firms' adoption of PVDG, I exploit the large variation in energy prices across the 19 utilities in the State of São Paulo. Figure 1 maps the distribution of utilities across the state and the spatial variation in energy prices, in Panels A and B, respectively¹⁴. Figure 2 plots the distribution of Usage and Distribution Prices in the state across the sample period¹⁵. The identification strategy relies on the assumption that variation in energy prices across utilities and over time is uncorrelated with unobserved determinants of adoption. That is, variation in prices across utilities and over time identifies the effect on adoption. The main threat to identification is a positive simultaneity bias, where utilities adjust prices upward in response to higher adoption rates among contributing consumers. While this is a concern which has been highlighted in this literature and particularly in this setting, existing estimates of the potential effects with the observed adoption rates during my sample period and under observed prices would be less than a 1% increase on the actual energy tariffs (MME, 2019).

There are other attenuating factors for potential endogeneity concerns of energy prices. First, firms choose location ex-ante to adoption¹⁶, indicating they are price-takers in their local energy market and are unlikely to self-select into locations with higher prices. Second, firms rarely update their own installed capacity (only 2% of observed adopters), which supports the hypothesis that there are no dynamic responses in adoption. Finally, there are two channels for how utilities adjust prices in response to adoption. Through the Usage Price, this adjustment is mechanical through reduced demand and the need to sell excess contracted energy at lower prices in the short-term market. As discussed before, the estimated expected effect of this channel is relatively low in my sample period (MME, 2019). Through the Distribution Price, this adjustment can happen in a more discretionary way by utilities, as their contributing consumer base decreases and thus costs are passed through to fewer consumers. However, these discretionary increases are only considered by the regulator in periodical tariff reviews which only occur every 3 to 5 years. Therefore we expect that the potential positive bias would appear with some lag (MME, 2019). Nevertheless, I run additional robustness exercises to overcome these potential biases, discussed in Section IV.D.

Estimating equations. To identify the effects of energy prices on firms' adoption decisions, I use my firm-level dataset to estimate the following two-way fixed-effects specification:

$$y_{ilt} = \alpha_t + \alpha_l + \beta_U \times \log(p_{lt}^{Usage}) + \beta_D \times \log(p_{lt}^{Dist}) + X_{ilt}\delta + W_{lt}\gamma + \epsilon_{ilt} \quad (11)$$

where y_{ilt} is a dummy variable indicating whether or not a firm has adopted solar; α_t and α_l are year and location fixed-effects, respectively; p_{lt}^{Usage} and p_{lt}^{Dist} are Usage and Distribution Prices in location l in year t , respectively¹⁷; X_{ilt} includes firm-level controls such as firm size, age, and

¹⁴Appendix Figure A2 maps both the Usage and Distribution Prices across the state, and Appendix Figure A4 shows the distribution of the subsidised share of the energy tariffs for the country and for the State of São Paulo in the sample period.

¹⁵Figure A5 plots the same price components for all utilities in Brazil, in the same period.

¹⁶Almost 98% of firms will adopt at least 2 years after entering the market, and adopt at their initial location.

¹⁷In this section, I report the results with this dummy-log specification. Appendix A2 also reports the same results

average wages; W_{lt} includes zip-code-level characteristics that are not fixed over time, such as local market size and local average wages. The key identification assumption here is that over-time variation in energy prices within zip-codes can identify the effects of energy prices p^{Usage} and p^{Dist} on adoption. The coefficients capturing these effects are β_U and β_D .

The estimated coefficients admit the following interpretation: β_U captures substitution effects between grid supply and PVDG, where we expect that higher substitute prices will lead to higher adoption probabilities. On the other hand, β_D can capture both a substitution effect (as it also comprises the total energy price of the outside option), as well as the subsidy effect. In this case, we also expect that higher Distribution Prices reflect higher gains from the subsidy in case of adoption, and thus higher probability of adoption.

I also run a complementary specification, by aggregating adoption at the zip-code-level as the share of all adopting firms in a given zip-code-year. I estimate this specification also as a two-way fixed-effect regression:

$$y_{lt} = \alpha_t + \alpha_l + \beta_U \times \log(p_{lt}^{Usage}) + \beta_D \times \log(p_{lt}^{Dist}) + W_{lt}\gamma + \epsilon_{lt} \quad (12)$$

where the energy price variables are the same as in the previous specifications, and the zip-code-level controls W_{lt} also includes mean wages, mean firm size, mean firm age, number of employees working in location l in year t , and total number of firms operating in location l in year t . Similarly to Equation 11, we expect β_U to capture positive substitution effects, where a higher price of the outside option is correlated with higher adoption, and for β_D to capture both a positive substitution and positive subsidy effects.

Finally, I also consider the potential effects of technology suitability. To capture how solar generation efficiency can affect adoption, I use solar irradiance measure of Photovoltaic Active Radiation (PAR) from INPE and estimate the following firm-level specification:

$$y_{il} = \alpha_0 + \beta_R \times R_l + X_{il}\delta + W_l\gamma + \epsilon_{il} \quad (13)$$

where R_l is the PAR measure in location l ; X_{il} includes firm-level characteristics such as firm size and age; W_l includes location characteristics such as average local wages, solar panel costs, and total number of firms. Since PAR measures are constant over time, I estimate Equation 13 for each year of my sample. If technology suitability is relevant for adoption, we expect β_R to be positive. Since R_l is measured at the location level, zip-code fixed-effects cannot be included in the regression, therefore it might be the case that β_R will capture other differences across zip-codes that might also be correlated with adoption. Nevertheless, solar irradiance is higher in more rural areas and areas further away from the richest urban centres, as shown in Appendix Figure A3, such that it's not clear which location characteristics could be captured by β_R .

tables using a dummy-level specification, as well as both results using non-deflated energy prices. My preferred specifications use deflated prices so that any variation over time should capture unexpected increases in prices that should not have been accounted for.

C. RESULTS

Table 3 reports the results from estimating Equation 11¹⁸. Consistent with the substitution hypothesis, both price coefficients are positive and statistically significant, indicating a positive substitution effect between grid supply and distributed generation adoption. Comparing Columns (2) and (4), the estimated coefficient for the Usage Price decreases by an order of magnitude when including zip-code fixed-effects. This result indicates a possible ex-ante sorting where firms' locations is correlated with higher prices, which is not unexpected since firms tend to be connected to higher tension grid networks where prices are inherently higher (Ramos *et al.*, 2012). Taking the estimated $\hat{\beta}_U$, I calculate an elasticity of the adoption probability with respect to the Usage Price of 0.45 - a 10% increase in the Usage Price of the energy tariff can be associated with an 4.5% increase in the probability of adoption. With a baseline of 0.66, this is an equivalent increase of 0.03 percentage points.

Table 4 reports the results from estimating Equation 12. Similarly to the firm-level results, the estimated coefficients for the Usage and Distribution Prices are positive and significant, and in the same magnitude. Again we also find evidence of sorting, where β_U is an order of magnitude larger before including zip-code fixed-effects. Figure 3 reports the estimated coefficients of solar irradiation in Equation 13, for each year in the sample. The estimated coefficients are positive and significant for every year, but they become significantly smaller over time. One possible interpretation of this result is that when solar was less prevalent and adoption much less widespread - such as in the first few years of the sample period - technology suitability was more relevant for adoption. Once PV panels became less expensive, and adoption expanded, generation suitability wasn't as critical for adoption decisions.

While the reduced-form estimates provide causal evidence that energy prices affect adoption decisions through substitution mechanisms, they leave several questions unanswered. First, the estimated elasticities cannot separate the direct substitution effect of usage prices from the indirect subsidy effect of distribution prices. Second, reduced-form estimates do not permit quantification of how firms would respond to alternative policy designs, such as installation cost subsidies rather than operational cost subsidies. Third, the reduced form cannot identify whether observed adoption patterns reflect rational optimization or behavioral frictions in capacity choices. To address these limitations, I estimate the structural discrete-continuous choice model presented in Section III, that jointly captures both the adoption decision (extensive margin) and capacity choice (intensive margin), allowing for counterfactual policy evaluation.

D. ROBUSTNESS EXERCISES

Considering the previous discussion on the possible validity concerns and possible threats to identification, I consider potential confounders and run robustness checks with alternative specifications for the estimating equations.

¹⁸Appendix Table A5 reports the estimated coefficients for all variables, including controls.

Entry of firms. One possible concern with the previous results would be that adoption in certain locations with higher prices would be driven by entry of firms who are choosing to enter to adopt in that location. To check for possible entry effects, I estimate the following regressions:

$$\Delta n_{lt} = \alpha_t + \alpha_l + \beta \Delta(p_{lt}^{Usage} + p_{lt}^{Dist}) + \gamma \Delta X_{lt} + \varepsilon_{lt} \quad (14)$$

$$\Delta n_{lt} = \alpha_t + \alpha_l + \beta \Delta p_{lt}^{Dist} + \gamma \Delta X_{lt} + \varepsilon_{lt} \quad (15)$$

where the dependent variable Δn_{lt} is the change from year $t - 1$ to year t in the number of firms in zip-code l ; X_{lt} includes zip-code-level controls such as number of firms in $t - 1$, the change in mean wages, the change in mean firm size and the change in total number of employees. If we expect there to be some effect of entry from firms seeking higher energy price subsidies, β would be positive in estimated Equations 14 and 15. The results are reported in Table 6. Without including location fixed effects, we find that energy prices are positively correlated with more entry of firms, indicating that market growth happens where prices are also rising. However, when including zip-code fixed-effects - Column (2) - the effects become not statistically significant. Column (3) reports the estimated coefficient β for Equation 15. The negative estimate suggests instead that there is less entry with Distribution Price increases, which supports the hypothesis that there is no entry effect of firms seeking higher prices for adoption.

Spatial Differences. To overcome possible positive simultaneity bias in price adjustments and firms' adoption decisions, I consider a spatial specification that matches zip-codes to "control" locations and estimates the effects of differential energy prices on differential adoption rate. Specifically, I identify, for each zip-code, the 10 closest neighbouring zip-codes which are serviced by different utilities, and therefore face different energy prices. I then use the mean characteristics in these locations as the comparison group for each zip-code. This strategy follows closely to other spatial boundary specifications in the literature, as in Holmes (1998) and Gibbons *et al.* (2013). The estimating equations are:

$$\tilde{y}_{lt} = y_{lt} - \bar{y}_{mt} = \alpha_t + \alpha_l + \beta_U \times \tilde{p}_{lt}^{Usage} + \beta_D \times \tilde{p}_{lt}^{Dist} + \tilde{W}_{lt}\gamma + \varepsilon_{lt} \quad (16)$$

where $\tilde{y}_{lt}$ denotes the differences value between outcomes in zip-code l and mean outcomes in the comparison group of m neighbouring zip-codes. The interpretation of the parameters of interest, β_U and β_D follow a simple intuition. When neighbouring locations face larger energy price differences, we expect differential adoption rates to be higher. Using the two-way fixed effects also helps to control for potential shifts across all locations, for example sharp declines in PV costs in a given year, which happens to be the case throughout my sample period. Additionally, the zip-code fixed effects captures specificities of each location which might also affect cross-sectional differences across zip-codes. Nevertheless, using zip-code fixed effects might generate the same issue as before, where identification comes exclusively from over-time changes in energy prices. I report estimates for the specification with and without these fixed-effects.

Table 5 reports the estimates for Equation 16. The first two columns report the results without location fixed-effects, and the final two report the results with location fixed-effects. As expected, the addition of the fixed-effects does not change the magnitude of the estimates as in the main specification presented in Section IV.B. The estimated β_U suggests an increase of one standard deviation in the differential Usage Price between locations is associated with 0.25 percentage point higher adoption rates.

V Model Estimation and Results

A. ESTIMATION STRATEGY

The model estimation follows a standard maximum likelihood approach, where the ML algorithm identifies the estimated parameter set $\hat{\Theta}$ as the set that maximises the log-likelihood function, which is defined as:

$$l(\Theta|X_i, k_i) = \sum_{i \in j(1)} \log\{\mathbb{P}(j_i = 1|\Theta, X_i)\} + \sum_{i \in j(0)} \log\{1 - \mathbb{P}(j_i = 1|\Theta, X_i)\} + \sum_{i \in j(1)} \phi(k_i|j_i = 1, \Theta, X_i) \quad (17)$$

where $j(1)$ and $j(0)$ are the set of observed adopters and non-adopters, respectively.

B. ESTIMATION RESULTS

Table 7 details the parameter set, interpretations of each parameter and the variables used for identification. There are some key points to highlight. First, due to the structure of the model, the parameters λ , α_0 , θ_3 and c_2 are calibrated, so that the remaining parameters can be just identified with the observed variance in the data. Second, the discount rate is exogenously set at $\beta = 0.95$, following in other models of the literature (De Groote & Verboven, 2019) - Appendix C reports robustness tests to the counterfactual exercises with alternative values of the discount rate. Finally, the second column shows what are the expected signs for each parameter, although I do not explicitly bound the estimation to match these expected signs. Overall, it would be in line with the reduced-form results that larger firms and firms with higher average wages are more likely to adopt, and that local diffusion also has a positive effect on adoption probability. On the Net Present Value (NPV) parameters, there should be positive gains from the subsidy and an energy intensity bonus - $\theta_1 > 0$ and $\theta_4 > 0$ - as well as increasing costs for installation - $c_0 > 0$ and $c_1 > 0$.

The estimated values for the remaining parameter set are reported in Table 8. The estimates reveal positive effects of firm size and average wages on adoption probability, given by α_1 and α_2 . Additionally, local diffusion of solar also has an estimated positive effect on the likelihood on adoption, per the estimated α_3 parameter, suggesting strong peer effects or information spillovers. All the NPV estimates are also in line with the expected signs. The fixed connection cost c_0 aligns

closely with regulatory connection fees stipulated by distributors [ANEEL \(2015\)](#), while the installation cost pass-through c_1 indicates that each BRL (Brazilian Reals) of panel cost translates to just over two BRL in total system cost - which can account for installation, inverters, and other balance-of-system components. Finally, the capacity error estimate σ_k indicates that firms choose with quite large errors - the estimate of 10.65 is 37% of the mean observed capacity of 38.7kW. This points to potential behavioural bias or information constraints, where there are significant optimisation frictions in the intensive margin choice of firms.

The model fits overall option rates well, predicting 2.71% of adoption against 2.31% in the observed data, and matched mean installed capacity at 38.7kW for adopters. Table 9 reports these results, as well as potential interpretations for the estimated parameters of the NPV. The estimated θ_1 can be interpreted as gains per kW of installed capacity, for each Brazilian Real (BRL) of subsidy received. For instance, a Distribution Price of 100 BRL leads to 595 BRL annual gains per kW installed, which could reflect both reductions in energy bills from the subsidy, but also gains from substitution away from grid supply - those associated to the Distribution Price alone. The estimated O&M cost θ_2 of 302 BRL per kW is of the same magnitude, therefore suggesting that the model captures well the cost-benefit structure of the capacity choice.

Table 9 also reports some model fit analyses that suggest the model does a reasonable job at capturing the trade-offs between costs and benefits of adoption¹⁹. First, the model predicts small but modest annual net benefits for adoption, at 2 BRL per year, per kW installed. For observed adopters, the model predicts positive optimal capacity where the estimated annual benefits are larger and more significant, at 416 BRL per year per kW. Moreover, for observed non-adopters where the model still predicts some positive optimal capacity, the model also identifies that net annual benefit is negative on average, correctly confirming that these firms would not adopt. Finally, I use the model estimates to calculate average payback periods for all firms and for adopters only. The mean payback period of adopters is 10.4, much lower than the overall mean of 13 years for all firms. These estimates are also reassuring, since recent industry reports in Brazil put payback periods at 5 to 6 years today, after panel prices have fallen over 40% since the end of my sample period ([EPE, 2025](#)).

VI Model Counterfactuals

There has been an increased interest in many countries for policies that aim to incentivise PVDG adoption ([Feger et al., 2022](#); [Schetinger & de Lucena, 2025](#)). The estimated model here can provide some insight into alternative policy designs for firm adoption in a setting with a relevant subsidy policy already in place. To do so, I conduct three counterfactual policy experiments to evaluate alternative subsidy designs. Finally, using the equivalent-cost installation subsidy counterfactual, I calculate and compare abatement costs of emissions across the two policy alternatives - the baseline energy price subsidy and the installation cost subsidy.

¹⁹Appendix C reports additional model fit checks.

A. COUNTERFACTUAL POLICIES

The estimated model enables evaluation of three counterfactual policy scenarios, each designed to answer a specific policy question. First, what is the additionality of the existing energy price subsidy? That is, how many firms would have adopted absent the policy? To answer this, I consider a no energy subsidy scenario, where firms continue to pay the same energy price after adoption, $p^U + p^D$. That is, I set $\theta_1 = 0$, where there is no explicit financial benefit from adoption in the form of lower energy prices. This counterfactual exercise can provide the implied additionality of the energy price subsidy to adoption by identifying adopters who would not have adopted in the absence of the subsidy policy. The results for this counterfactual are compared to the baseline energy price subsidy scenario, showing the estimated effect of the subsidy policy. Second, does the heterogeneous subsidy structure matter? Since the policy creates varying incentives across locations due to differential distribution prices, I compare outcomes under a homogeneous subsidy set at the mean distribution price. This exercise provides a realistic counterfactual that could be implemented as a lump-sum transfer based on your chosen installed capacity, replacing p^{DIST} in the flow of benefits for firms. I compare these results to both the baseline subsidy and the no subsidy scenario, to compare how adoption would have taken place in each one. Finally, would an alternative subsidy targeting installation costs be more cost-effective? For instance, if the government chose to instate a 5% subsidy on photovoltaic panel prices, how would it affect adoption rates and total capacity when compared to the baseline energy price subsidy? Another possibility to interpret this exercise is the effects of potential decreases in the cost of solar panels. Realistically, panel prices have fallen considerably since the beginning of my sample period in 2015²⁰, and have continued to fall since 2020. Thus, this exercise can also provide insight into how this decreasing input price can also have impacted adoption. I compare the results of this counterfactual exercise to the baseline policy scenario, and evaluate how subsidies that affected cost-benefits differently would have affected adoption differentially.

Figure 4 compares the estimated total adoption rates for each counterfactual exercise. I find that, compared to the no policy scenario, the energy price subsidy increase adoption rates from 2.29% to 2.71%, an 18.1% increase of 0.42 percentage points. While baseline adoption is quite low, this indicates that the policy still had a positive impact on firms' adoption decisions. I also find that a homogeneous price subsidy would have achieved about half (a 0.2 percentage points increase) of the additional adoption observed under the fully heterogeneous energy price subsidy. Finally, I consider the 5% installation cost subsidy instead of the energy price subsidy, and find that adoption rates would have been 0.3 percentage points higher, a 11.8% increase, when compared to the baseline policy. I also find that total capacity under this policy scenario would increase by 54.6%, indicating that although the effect on the number of adopting firms is lot large, the effect on total installed capacity is quite significant.

I run an additional counterfactual exercise, to identify an installation cost subsidy that could have been implemented with the same annual cost - as a one time subsidy - as the energy price

²⁰See Appendix Figure A6.

subsidy costs over a fixed time horizon²¹ I iterate over all possible subsidy rates and estimate the predicted adoption rates and installed capacities of adopters, to calculate the cost of the installation subsidy in a given year. I find that an equivalent cost subsidy would subsidise 7% of panel costs. I then compare the predicted adoption rates for this 7% cost subsidy against the baseline policy scenario, and I find that the new policy would increase adoption by 19.2%, a 0.52 percentage point increase (shown in Figure 5). This result shows that subsidising investment costs could have increased adoption by twice as much as the baseline policy²². Finally, I also find that installed capacity would have increased by 103% when compared to the baseline policy. While mean installed capacity in the baseline scenario was of 38.7kW per firm, the installation cost subsidy estimates mean capacity would increase to 59kW, indicating that not only do more firms choose to adopt, but all adopting firms also choose higher optimal capacity - Figure 6 shows how total installed capacity grows with cost subsidy rates, and Figure 7 shows how both total and mean capacity compare across the baseline policy and the cost-equivalent installation subsidy.

B. ABATEMENT COST ANALYSIS

To evaluate the climate policy implications of these subsidy designs, I calculate the carbon abatement costs — the cost per ton of CO₂ emissions avoided — for both the baseline energy price subsidy and the equivalent-cost installation subsidy. Table 10 presents these calculations, which account for the total subsidy expenditure, the electricity generated by adopted solar capacity over a 25-year system lifetime, and the emission intensity of Brazil’s electricity grid. The reported calculation rely on two main assumptions. First, the efficiency of installed capacity, which I take from [Pereira et al. \(2017\)](#) at 16.5%²³. Second, the emissions intensity of the Brazilian energy grid, which I take as 0.12 kg CO₂/kWh ([MCTI, 2021](#); [SEEG, 2024](#))²⁴.

Under the baseline energy price subsidy, the government achieves carbon abatement at a cost of 741 BRL per ton of CO₂ (approximately US\$148 at the 2020 mean exchange rate). In contrast, the equivalent-cost installation subsidy achieves abatement at merely 62 BRL per ton of CO₂ (US\$12 per ton), representing a twelve-fold improvement in cost-effectiveness. This stark difference arises from two factors: first, the installation subsidy induces nearly double the adoption rate increase (3.23% versus 2.71%), and second, adopters under the installation subsidy choose substantially larger system sizes (mean capacity increases from 39 kW to 59 kW), resulting in nearly double total installed capacity and thus more emissions displaced per dollar of subsidy spent.

²¹In this exercise, I consider a 20-year time horizon where firms still take advantage of the energy price subsidy, which is in line with expected lifetime duration of photovoltaic systems ([Frischknecht et al., 2023](#)).

²²Appendix Figure A7 shows adoption rates and the total policy costs for different installation cost subsidy rates. For instance, achieving just 15% of adoption rates would require around 35% of installation cost subsidies, leading to a 10-fold increase in the total policy cost. This results stems from the mechanism of the cost subsidy, where firms react in both the extensive and intensive margin - more firms adopt and adopting firms choose higher optimal quantity, thus leading to a convex subsidy cost curve.

²³This rate translates to approximately 1445kWh generated per kWp of installed capacity, which sits in the middle range of the efficiency bounds used for Table 2.

²⁴Brazil’s grid is substantially cleaner than the global average of 0.475 kg CO₂/kWh - estimated by the International Energy Agency (IEA) - due to the predominance of hydroelectric generation.

Comparing these estimates to international carbon pricing benchmarks provides important context for evaluating policy effectiveness. The baseline energy price subsidy’s abatement cost of US\$148 per ton of CO₂ substantially exceeds prevailing carbon prices in most established markets. As of 2025, the European Union Emissions Trading System (EU ETS) — the world’s largest carbon market — prices carbon at approximately 70-90 EUR per ton (US\$75-95/ton), while California’s cap-and-trade system prices carbon around US\$35-40/ton. The Intergovernmental Panel on Climate Change (IPCC) estimates the social cost of carbon—representing the economic damages from an additional ton of CO₂ emissions—at US\$50-100/ton in 2025, with higher estimates reaching US\$150-200/ton when accounting for climate tipping points and equity considerations. The baseline energy price subsidy thus falls at the upper end or slightly above these benchmarks, suggesting limited cost-effectiveness relative to other climate mitigation strategies. In contrast, the installation subsidy’s abatement cost of US\$12/ton CO₂ is well below all major carbon pricing mechanisms and social cost estimates, indicating that this policy design could deliver emissions reductions at a fraction of the cost incurred by other abatement technologies or carbon pricing schemes.

These findings carry significant implications for climate policy design in emerging economies, where capital constraints and limited access to financing pose particular barriers to green technology adoption. The installation subsidy’s superior cost-effectiveness suggests that policies targeting upfront investment barriers can unlock substantial emissions reductions at relatively low cost per ton abated. Moreover, the abatement costs calculated here likely represent upper bounds, as the analysis does not account for additional co-benefits such as improved air quality, reduced transmission losses from distributed generation, enhanced energy security, or learning spillovers that reduce future installation costs. The results also highlight an important trade-off in subsidy design: while energy price subsidies provide ongoing benefits that may be more politically sustainable, they achieve emissions reductions at substantially higher cost per ton than policies that address the binding constraint of high upfront capital requirements. For countries with limited fiscal resources seeking to maximize emissions reductions per unit of public expenditure, these findings suggest that installation cost subsidies—implemented through mechanisms such as rebates, low-interest loans, or direct capital grants—represent a more cost-effective approach to accelerating the renewable energy transition.

VII Conclusion

This paper investigates the drivers of firm-level adoption of distributed solar generation in Brazil, focusing on how different price mechanisms shape firms’ investment decisions. Using comprehensive micro-data covering the universe of solar installations by firms, I exploit variation in energy prices across utilities and over time to identify the causal effects of economic incentives on adoption. I find that firms respond to grid energy prices through a substitution mechanism, where higher electricity costs increase the attractiveness of self-generation, but also through the subsidy

price. Additionally, technology suitability plays a role in early adoption patterns, though its importance diminishes as solar technology costs decline and the technology becomes more widely accessible.

To quantify the relative importance of different cost and benefit channels and evaluate alternative policy designs, I develop and estimate a structural discrete-continuous choice model of solar adoption. The model jointly captures firms' decisions about whether to adopt and how much capacity to install, allowing for a comprehensive assessment of how firms trade off upfront investment costs against future energy savings and subsidy benefits. The counterfactual simulations reveal that the existing energy price subsidy meaningfully increased adoption compared to a no-subsidy baseline, demonstrating policy additionality.

However, comparing across policy instruments shows that an installation cost subsidy would have been substantially more effective than the energy price subsidy at promoting adoption. Under an equivalent-cost comparison, where the installation cost subsidy has the same total budgetary cost as the baseline policy, policy-induced increases to the adoption rate would have nearly doubled, and total installed capacity would have more than doubled. These results indicate that high upfront investment costs constituted a more binding constraint on firm adoption than ongoing energy costs, suggesting that firms face significant liquidity constraints or capital market frictions that prevent them from undertaking such investments.

These findings have important implications for the design of climate policies aimed at accelerating renewable energy adoption among firms. Policymakers seeking to maximize renewable energy deployment per dollar of subsidy spending can prioritise reducing upfront costs through rebates, tax credits, or direct capital subsidies rather than reducing ongoing energy costs through mechanisms like net metering or feed-in tariffs. The superior cost-effectiveness of installation subsidies suggests that liquidity constraints and capital market frictions may be significant barriers to green technology adoption. Furthermore, the results indicate that while technology suitability matters for early adoption, declining equipment costs and learning spillovers can make distributed generation increasingly attractive even in locations with moderate solar resources, suggesting broad geographic potential for policy-induced expansion of firm-level solar adoption.

From a climate policy perspective, the installation subsidy achieves carbon abatement at US\$12 per ton of CO₂ — substantially below the baseline energy price subsidy's cost of US\$148 per ton and well below prevailing carbon prices in international markets — demonstrating that policies targeting upfront investment constraints can deliver emissions reductions at costs competitive with or superior to other climate mitigation strategies. This cost-effectiveness advantage is particularly relevant for emerging economies seeking to maximize emissions reductions under fiscal constraints.

Overall, my paper provides empirical evidence on the different price and cost channels that affect distributed generation adoption by firms. My results support the hypothesis that subsidies targeting upfront investment costs can unlock solar adoption among firms that are ex-ante credit constrained or face capital market frictions — especially in a setting where there might be limited

access to financing, and for firms who would otherwise forgo profitable investments in distributed generation due to high initial capital requirements.

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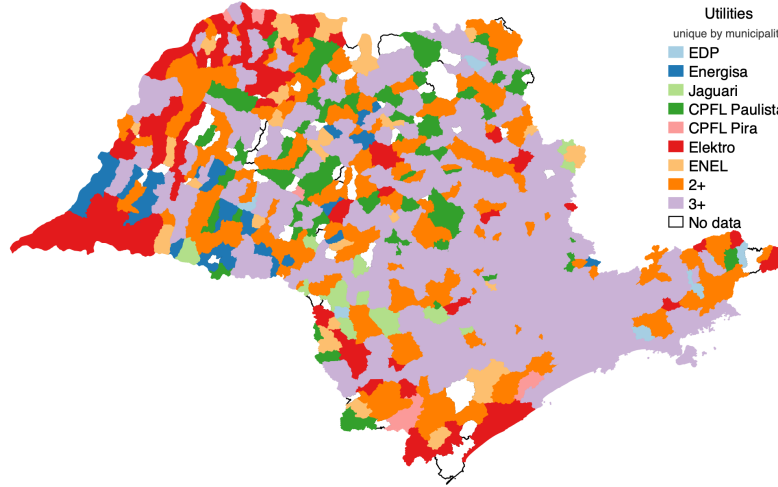
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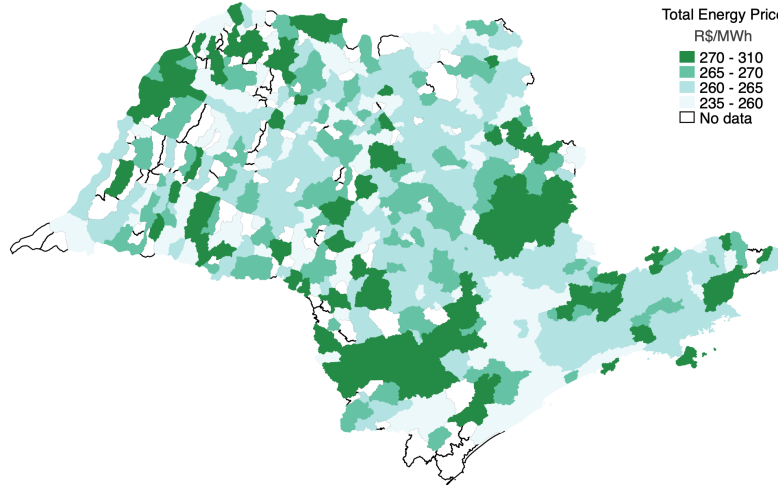
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FIGURE 1: SPATIAL VARIATION IN SÃO PAULO STATE UTILITIES

A. Utilities Spatial Coverage



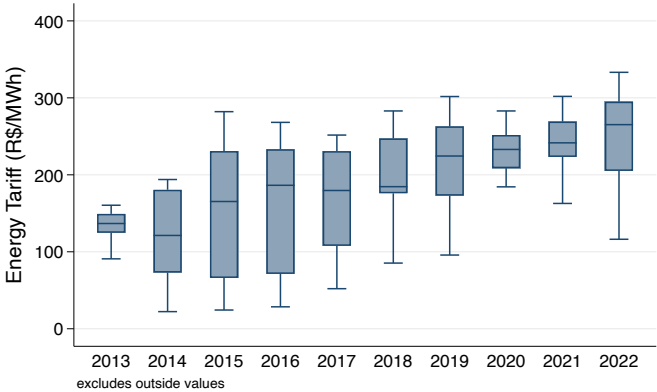
B. Energy Price



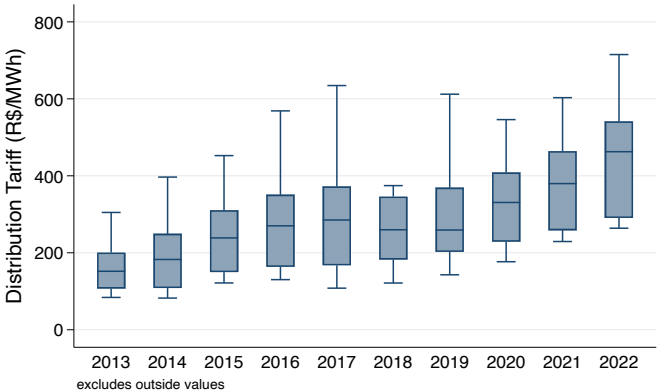
Notes: Energy Prices are aggregated from ≈ 120 thousand zip-codes to 645 municipalities. Missing municipalities are location that are included in the sample due to too few observations or missing data across years.

FIGURE 2: DISTRIBUTION OF ENERGY PRICE COMPONENTS IN SÃO PAULO STATE

A. Usage Price

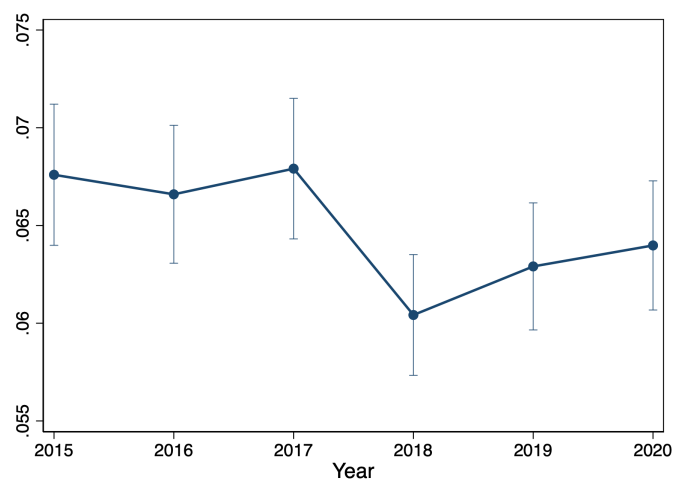


B. Distribution Price



Notes: Price data is nominal energy price components. Outlier observations excluded for better visualisation. Source: ANEEL.

FIGURE 3: SOLAR IRRADIANCE AND FIRM-LEVEL ADOPTION



Notes: Standard errors clustered at the firm and zip-code level. The outcome variable is a dummy for adoption, and each observation is a firm-year. Control variables include firm size, firm age, solar panel costs, mean wages and number of firms in the firm's zip-code.

FIGURE 4: COUNTERFACTUAL TOTAL ADOPTION RATES

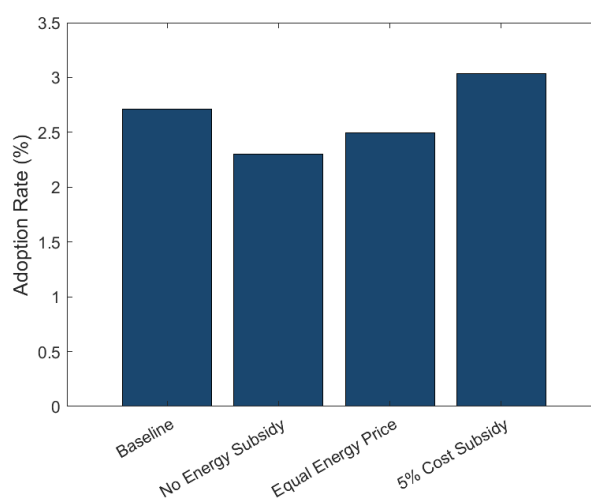


FIGURE 5: EQUIVALENT-COST COUNTERFACTUAL ADOPTION RATES

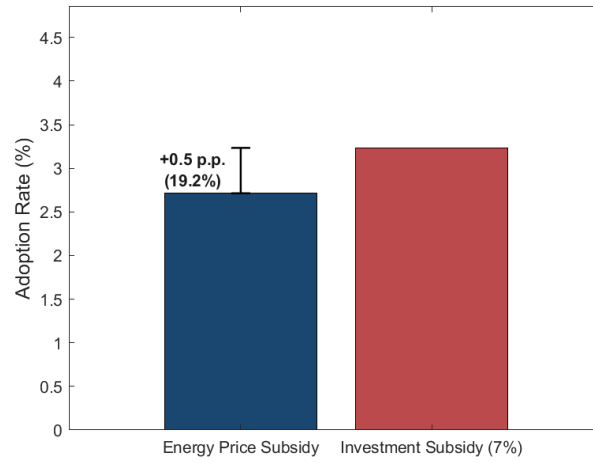


FIGURE 6: CAPACITY BY COST SUBSIDY RATE

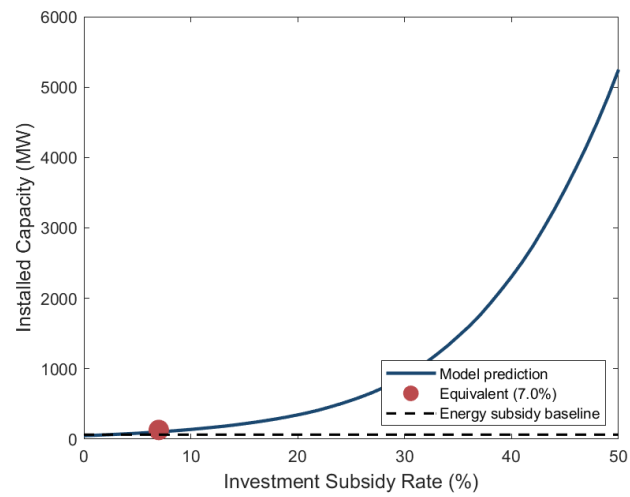
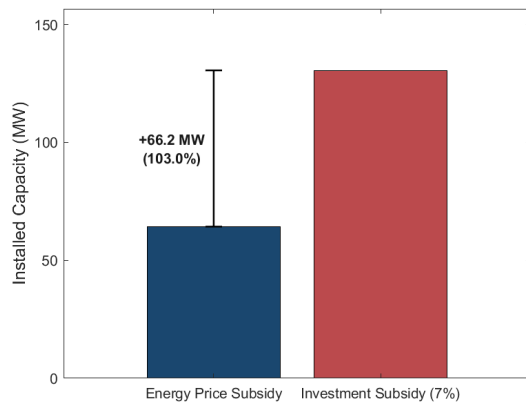


FIGURE 7: CAPACITY INSTALLED: BASELINE VS. EQUIVALENT COST SUBSIDY

A. Total Installed Capacity



A. Mean Installed Capacity

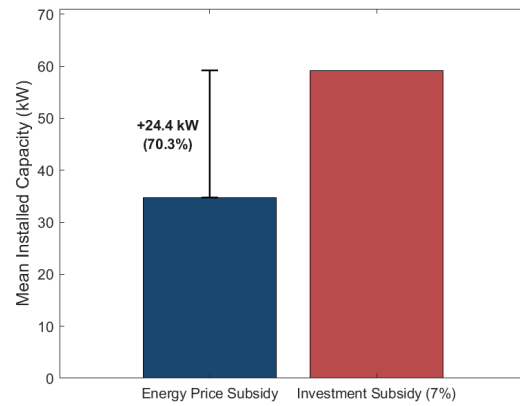


TABLE 1: SUMMARY STATISTICS FOR SÃO PAULO STATE

	Mean	SD	p(1)	p(99)
<i>A. Zip-Code</i>				
# of Firms	24	131	5	201
# of Adopters	0	3	0	3
Labour Force	291	3472	4	3786
Mean Hourly Wage (R\$)	59	31	28	190
Solar Irradiance (kWh/m ² /day)	2	0	2	2
Usage Price (R\$/MWh)	153	7	140	165
Distribution Price (R\$/MWh)	125	14	103	138
N	229129			
<i>B. All Firms</i>				
# of Employees	11	454	0	124
Age in Years	14	12	0	51
Mean Hourly Wage (R\$)	50	40	12	188
Usage Price (R\$/MWh)	153	7	140	165
Distribution Price (R\$/MWh)	126	14	103	138
N	3922043			
<i>B. Adopters</i>				
# of Employees	53	488	0	713
Age in Years	20	13	0	52
Mean Hourly Wage (R\$)	50	31	22	180
Usage Price (R\$/MWh)	162	12	140	184
Distribution Price (R\$/MWh)	102	15	75	138
N	36394			

Notes: Usage and Distribution Prices are calculated as the weighted average of the applied tariffs throughout a given year, averaged across types of supply, where weights are the number of days the tariff was valid during that year. Observations are a zip-code-year and firm-year in Panels A and B, respectively. Labour force is the total number of employees with a formal contract active on December 31st. Hourly wages does not include apprenticeships or internship contracts, only formal contracts of at least 10 weekly hours.

TABLE 2: SOLAR ADOPTION COSTS AND SUBSIDY BENEFITS

	Mean	SD	p(1)	p(99)
<i>A. Installation Costs</i>				
Mean System Cost (R\$/MWp)	7.93	10.71	3.49	68.96
Total System Investment (th R\$)	236.29	1667.88	9.12	2454.27
<i>B. Subsidy Benefits</i>				
Distribution Price (R\$/MWh)	165.65	31.81	107.99	237.25
One-year Subsidy Gain, Low Efficiency (th R\$)	7.64	26.66	0.37	41.95
One-year Subsidy Gain, High Efficiency (th R\$)	9.41	32.81	0.45	51.63
Zip-code-Year N	391253			
Adopter-Year N	36394			

Notes: Mean system cost is calculated by the EPE as the average estimated cost per kWp of installed capacity. Total system investment is the actual estimated investment carried out by observed adopters, that is: mean system cost times installed capacity. Yearly subsidy gains are calculated as: installed capacity times efficiency ratio times Distribution Price. Efficiency ratios reflect how much kWh generation can be achieved by kWp installed, for which I use the lower and upper bound estimated by [Pereira et al. \(2017\)](#). The reported ratios are converted to MWh per kWp installed.

TABLE 3: ENERGY PRICES AND FIRM-LEVEL ADOPTION

	(1)	(2)	(3)	(4)
log(Usage Price)	0.066*** (0.003)	0.065*** (0.003)	0.003*** (0.001)	0.003*** (0.001)
log(Distribution Price)	0.005*** (0.001)	0.005*** (0.001)	0.001** (0.001)	0.002*** (0.001)
CLUSTERED S.E.	Yes	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes	Yes
CONTROLS		Yes		Yes
LOCATION F.E.			Yes	Yes
MEAN DEP. VAR. (%)	0.66	0.66	0.66	0.66
OBSERVATIONS	2960764	2960141	2959833	2959208

Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Notes: Standard errors clustered at the firm and zip-code level. The outcome variable is a dummy for adoption, and each observation is a firm-year. Control variables include firm size, firm age, and number of firms in the firm's zip-code. Appendix Table A5 reports the estimated coefficients for the full specification.

TABLE 4: ENERGY PRICES AND ZIP-CODE ADOPTION RATES

	(1)	(2)	(3)	(4)
log(Usage Price)	0.032*** (0.001)	0.033*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
log(Distribution Price)	0.003*** (0.001)	0.003*** (0.001)	0.004*** (0.001)	0.005*** (0.001)
CLUSTERED S.E.	Yes	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes	Yes
CONTROLS		Yes		Yes
LOCATION F.E.			Yes	Yes
MEAN DEP. VAR. (%)	0.305	0.305	0.312	0.312
OBSERVATIONS	225906	225906	219462	219462

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the zip-code level. The outcome variable is the share of adopting firms, and each observation is a zip-code-year. Control variables include mean firm size, mean firm age, total employees and total number of firms in each zip-code-year. Appendix Table A6 reports the estimated coefficients for the full specification.

TABLE 5: ENERGY PRICES AND ZIP-CODE ADOPTION, SPATIAL DIFFERENCES

	(1)	(2)	(3)	(4)
d(Usage Price)	0.026*** (0.001)	0.013*** (0.002)	0.015*** (0.003)	0.016*** (0.003)
d(Distribution Price)	0.018*** (0.001)	0.021*** (0.001)	0.035*** (0.003)	0.031*** (0.003)
CLUSTERED S.E.	Yes	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes	Yes
CONTROLS		Yes		Yes
LOCATION F.E.			Yes	Yes
MEAN DEP. VAR. (P.P.)	-0.090	-0.090	-0.088	-0.088
OBSERVATIONS	220487	220432	214156	214095

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the zip-code level. The outcome variable is the share of adopting firms, and each observation is a zip-code-year. Control variables include mean firm size, mean firm age, total employees and total number of firms in each zip-code-year. Appendix Table A7 reports the estimated coefficients for the full specification.

TABLE 6: ENERGY PRICES AND FIRM ENTRY

	(1)	(2)	(3)
$\Delta(\text{Energy Tariff})$	0.011*** (0.002)	-0.002 (0.002)	
$\Delta(\text{Distribution Price})$			-0.054*** (0.007)
CLUSTERED S.E.	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes
CONTROLS	Yes	Yes	Yes
LOCATION F.E.		Yes	Yes
MEAN DEP. VAR.	0.310	0.316	0.316
OBSERVATIONS	171236	165542	165542

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the zip-code level. The outcome variable is the year-on-year change in the number of firms in each zip-code, and each observation is a zip-code-year. Control variables include changes in mean firm size, total employees and mean wages in each zip-code-year. Appendix Table A8 reports the estimated coefficients for the full specification.

TABLE 7: MODEL PARAMETERS AND IDENTIFICATION

Variable	Parameter	Value	Identification
Firm Wage Effect	$\alpha_1 > 0$	Estimated	Average firm-level wage (w_{ilt})
Firm Size Effect	$\alpha_2 > 0$	Estimated	Firm Size (n_{ilt})
Diffusion Effect	$\alpha_3 > 0$	Estimated	Local diffusion rate s_{lt}^{SOLAR}
Revenue per kW	$\theta_1 > 0$	Estimated	Distribution Price (p_{lt}^{DIST})
O&M Cost per kW	θ_2	Estimated	Capacity choice (k_{ilt})
Energy Intensity Gains	$\theta_4 > 0$	Estimated	Energy intensity (e_{ilt})
Fixed Install Cost	$c_0 > 0$	Estimated	Observed adoption rate: $\mathbb{P}(j = 1)$
Variable Install Cost	$c_1 > 0$	Estimated	Local panel cost (c_{lt}^{SOLAR})
Capacity Error	$\sigma_k > 0$	Estimated	Capacity choice error ($k_{ilt} - \hat{k}_{ilt}$)
NPV Weight	$\lambda = 0.75$	Calibrated	
Intercept	$\alpha_0 = -500$	Calibrated	
Convex Inefficiency	$\theta_3 = 0.9$	Calibrated	
Convex Install Cost	$c_2 = 0.05$	Calibrated	
Discount Rate	$\beta = 0.95$	Calibrated	

Notes: Estimated parameters are obtained from the estimation of log-likelihood function. Calibrated parameters are obtained from data, and/or set exogenously.

TABLE 8: MODEL ESTIMATION RESULTS

Variable	Parameter	Estimate
Firm Wage Effect	α_1	99.69
Firm Size Effect	α_2	8.99
Diffusion Effect	α_3	121.17
Revenue per kW	θ_1	5.95
O&M Cost per kW	θ_2	302.05
High-Energy Intensity Gains	θ_4	71.12
Fixed Install Cost	c_0	1504.17
Variable Install Cost	c_1	2.01
Capacity Error	σ_k	10.65
N	68,183	

TABLE 9: MODEL RESULTS: INTERPRETING THE NPV

Variable	Parameter	Estimate	Unit
NPV COMPONENTS			
Revenue	θ_1	5.95	per kW-year
O&M cost	θ_2	302.05	R\$/year per kW
Fixed cost	c_0	1504.17	R\$
Installation cost pass-through	c_1	2.01	per R\$
AVERAGE ANNUAL NET BENEFIT			
All firms		2	R\$/year per kW
Adopters		416	R\$/year per kW
Non-adopters		-8	R\$/year per kW
AVERAGE PAYBACK PERIOD			
All firms		13	Years
Adopters		10.4	Years
MOMENT FIT			
Observed adoption rate	$\mathbb{P}(j = 1)$	2.31	%
Model adoption rate		2.71	%
Observed mean capacity	$\bar{k}^{observed}$	38.7	kW
Model mean capacity	$\hat{k}$	38.7	kW
	β	0.95	
	N	68,183	

TABLE 10: ABATEMENT COST ANALYSIS

	Policy	
	Energy Price Subsidy	Installation Cost Subsidy
Total Installed Capacity (MW)	64.29	125.73
CO ₂ Avoided (MMt)	0.278	0.545
Subsidy Cost (M BRL)	206.71	33.88
Abatement Cost (BRL/tCO ₂)	741.47	62.15
Abatement Cost (USD/tCO ₂)	148.29	12.43

Notes: The estimated abatement costs consider: a capacity factor of 16.5%; emissions intensity of the Brazilian energy grid of 0.12 kg/kWh of CO₂; a systems lifetime of 25 years.

A1. Additional Tables

TABLE A1: SUMMARY STATISTICS: ALL VS MANUFACTURING FIRMS

	Mean	SD	p(1)	p(99)
<i>A. All Firms</i>				
# of Employees	11	454	0	124
Age in Years	14	12	0	51
Mean Hourly Wage (R\$)	50	40	12	188
N	3922043			
<i>B. Manufacturing Firms</i>				
# of Employees	21	115	0	316
Age in Years	17	13	0	54
Mean Hourly Wage (R\$)	55	36	13	186
N	358468			

TABLE A2: ADOPTION ACROSS SECTORS

	Entire Sample		Adopters		Share of adopters
	N (1)	Share (2)	N (3)	Share (4)	
Agriculture	35474	0.01	361	0.01	0.01
Arts & Culture	39715	0.01	539	0.01	0.01
Construction	141289	0.04	708	0.02	0.01
Education	108740	0.03	1074	0.03	0.01
Energy	2824	0.00	9	0.00	0.00
Raw materials	3775	0.00	41	0.00	0.01
Financial Services	73324	0.02	370	0.01	0.01
Hospitality	360167	0.09	2935	0.08	0.01
International Organisations	322	0.00	13	0.00	0.04
Health	147265	0.04	1780	0.05	0.01
Industrial	354693	0.09	6571	0.18	0.02
IT	57081	0.01	483	0.01	0.01
Other Services	167626	0.04	2228	0.06	0.01
Public Sector	8257	0.00	398	0.01	0.05
Real Estate	41906	0.01	376	0.01	0.01
Retail	379703	0.10	3398	0.09	0.01
Services	553206	0.14	1971	0.05	0.00
Transportation	182535	0.05	541	0.01	0.00
Water & Waste	11354	0.00	83	0.00	0.01
Wholesale	1252565	0.32	12515	0.34	0.01
Total	3922043	1.00	36394	1.00	

TABLE A3: ENERGY PRICES AND FIRM-LEVEL ADOPTION IN MANUFACTURING

	(1)	(2)	(3)	(4)	(5)
log(Usage Price)	0.125*** (0.010)		0.003 (0.003)	0.124*** (0.010)	
log(Distribution Price)	0.005 (0.005)		-0.001 (0.003)	0.005 (0.005)	
log(Energy Tariff)		0.001 (0.003)			0.001 (0.003)
CLUSTERED S.E.	Yes	Yes	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes	Yes	Yes
CONTROLS				Yes	Yes
LOCATION F.E.		Yes	Yes		Yes
BASELINE %	1.39	1.40	1.40	1.39	1.40
OBSERVATIONS	430477	426326	426326	430422	426273

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the firm and zip-code level. The outcome variable is a dummy for adoption, and each observation is a firm-year. Control variables include firm size, firm age, and number of firms in the firm's zip-code.

TABLE A4: NOMINAL ENERGY PRICES AND FIRM-LEVEL ADOPTION

	(1)	(2)	(3)	(4)
log(Usage Price)	0.066*** (0.003)	0.065*** (0.003)	0.003*** (0.001)	0.003*** (0.001)
log(Distribution Price)	0.005*** (0.001)	0.005*** (0.001)	0.001** (0.001)	0.002*** (0.001)
CLUSTERED S.E.	Yes	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes	Yes
CONTROLS		Yes		Yes
LOCATION F.E.			Yes	Yes
BASELINE %	0.66	0.66	0.66	0.66
OBSERVATIONS	2960764	2960141	2959833	2959208

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the firm and zip-code level. The outcome variable is a dummy for adoption, and each observation is a firm-year. Control variables include firm size, firm age, and number of firms in the firm's zip-code.

TABLE A5: ENERGY PRICES AND FIRM-LEVEL ADOPTION

	(1)	(2)	(3)	(4)
log(Usage Price)	0.066*** (0.003)	0.065*** (0.003)	0.003*** (0.001)	0.003*** (0.001)
log(Distribution Price)	0.005*** (0.001)	0.005*** (0.001)	0.001** (0.001)	0.002*** (0.001)
Firm Size		0.000* (0.000)		0.000* (0.000)
Firm Age		0.000*** (0.000)		0.000*** (0.000)
Local Market Size		-0.000*** (0.000)		0.000*** (0.000)
CLUSTERED S.E.	Yes	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes	Yes
CONTROLS		Yes		Yes
LOCATION F.E.			Yes	Yes
BASELINE %	0.66	0.66	0.66	0.66
OBSERVATIONS	2960764	2960141	2959833	2959208

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the firm and zip-code level. The outcome variable is a dummy for adoption, and each observation is a firm-year. Control variables include firm size, firm age, and number of firms in the firm's zip-code.

TABLE A6: ENERGY PRICES AND ZIP-CODE ADOPTION RATES

	(1)	(2)	(3)	(4)
log(Usage Price)	0.032*** (0.001)	0.033*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
log(Distribution Price)	0.003*** (0.001)	0.003*** (0.001)	0.004*** (0.001)	0.005*** (0.001)
Mean Firm Age		0.000*** (0.000)		0.000*** (0.000)
Mean Firm Size		0.000*** (0.000)		0.000*** (0.000)
Local Labour Market		-0.000 (0.000)		-0.000** (0.000)
Local Market Size		-0.000*** (0.000)		0.000*** (0.000)
Constant	-0.174*** (0.010)	-0.178*** (0.010)	-0.037*** (0.004)	-0.041*** (0.004)
CLUSTERED S.E.	Yes	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes	Yes
CONTROLS		Yes		Yes
LOCATION F.E.			Yes	Yes
BASELINE %	0.305	0.305	0.312	0.312
OBSERVATIONS	225906	225906	219462	219462

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the zip-code level. The outcome variable is the share of adopting firms, and each observation is a zip-code-year. Control variables include mean firm size, mean firm age, total employees and total number of firms in each zip-code-year.

TABLE A7: ENERGY PRICES AND ZIP-CODE ADOPTION, SPATIAL DIFFERENCES

	(1)	(2)	(3)	(4)
d(Usage Price)	0.026*** (0.001)	0.013*** (0.002)	0.015*** (0.003)	0.016*** (0.003)
d(Distribution Price)	0.018*** (0.001)	0.021*** (0.001)	0.035*** (0.003)	0.031*** (0.003)
d(Mean Firm Size)		0.000*** (0.000)		0.000** (0.000)
d(Local Labour Force)		-0.000*** (0.000)		-0.000* (0.000)
d(Municipality GDP Per Capita)		0.000 (0.000)		-0.000*** (0.000)
d(Municipality Population)		-0.000*** (0.000)		-0.000*** (0.000)
d(Mean Wages)		-0.000*** (0.000)		0.000 (0.000)
Constant	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
CLUSTERED S.E.	Yes	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes	Yes
CONTROLS		Yes		Yes
LOCATION F.E.			Yes	Yes
BASELINE %	-0.090	-0.090	-0.088	-0.088
OBSERVATIONS	220487	220432	214156	214095

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the zip-code level. The outcome variable is the difference in share of adopting firms, and each observation is a zip-code-year. Control variables include differences in mean firm size, mean firm wages, total employees, municipality GDP per capita and population, in each zip-code-year.

TABLE A8: ENERGY PRICES AND ZIP-CODE FIRM ENTRY

	(1)	(2)	(3)
$\Delta(\text{Energy Tariff})$	0.011*** (0.002)	-0.002 (0.002)	
$\Delta(\text{Distribution Price})$			-0.054*** (0.007)
$\Delta(\text{Labour Market Size})$	0.002** (0.001)	0.001* (0.001)	0.001* (0.001)
$\Delta(\text{Average Wages})$	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Market Size, $t - 1$	0.079*** (0.004)	-0.303*** (0.013)	-0.302*** (0.013)
$\Delta(\text{Average Firm Size})$	-0.067*** (0.011)	-0.048*** (0.008)	-0.048*** (0.008)
Constant	1.183*** (0.084)	10.132*** (0.300)	10.535*** (0.287)
CLUSTERED S.E.	Yes	Yes	Yes
YEAR F.E.	Yes	Yes	Yes
CONTROLS	Yes	Yes	Yes
LOCATION F.E.		Yes	Yes
BASELINE %	0.310	0.316	0.316
OBSERVATIONS	171236	165542	165542

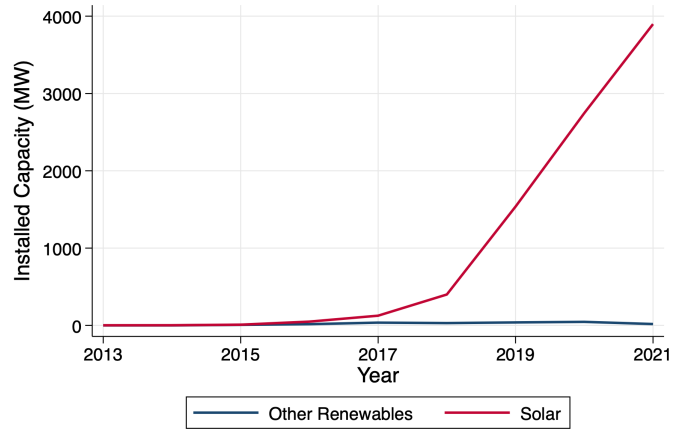
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Standard errors clustered at the zip-code level. The outcome variable is the year-on-year change in the number of firms in each zip-code, and each observation is a zip-code-year. Control variables include changes in mean firm size, total employees and mean wages in each zip-code-year.

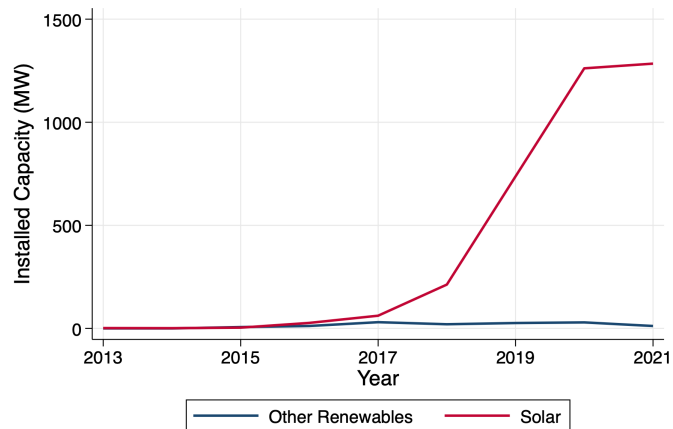
A2. Additional Figures

FIGURE A1: INSTALLED CAPACITY (MW), BY SOURCE AND YEAR

A. All Establishments



B. Firms Only

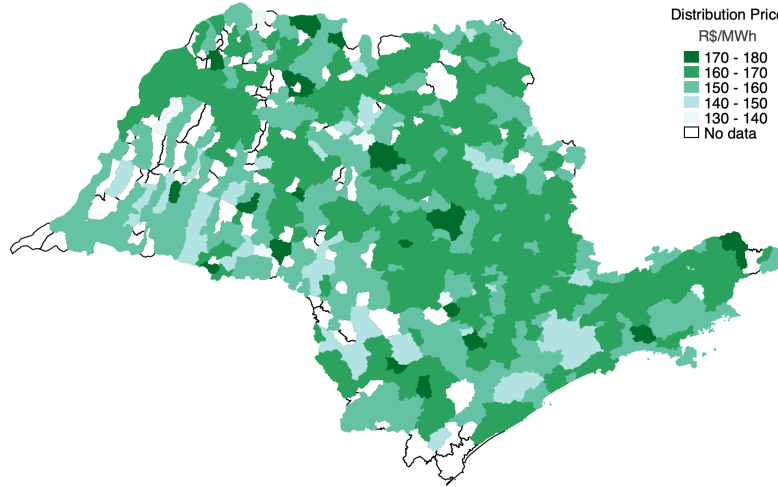


Notes: Values in Panel A include renewable generation by all types of establishments - residential, commercial, industrial, public buildings and rural, while Panel B includes only commercial and industrial establishments.

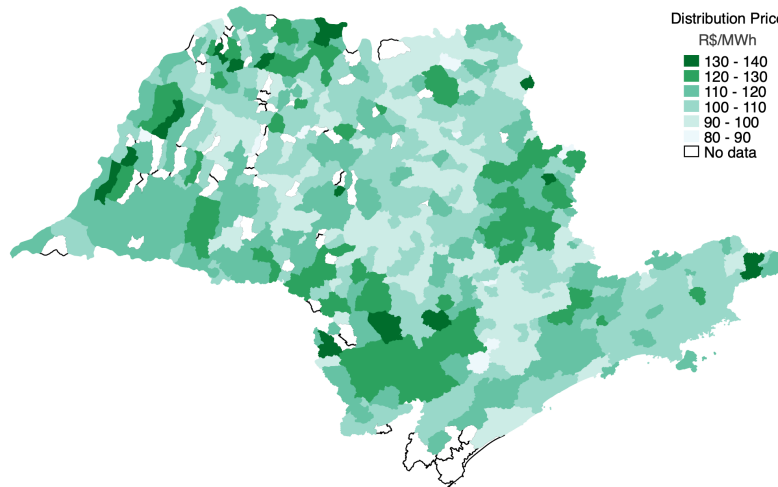
Source: ANEEL.

FIGURE A2: ENERGY PRICE COMPONENTS ACROSS SÃO PAULO STATE

A. Usage Price



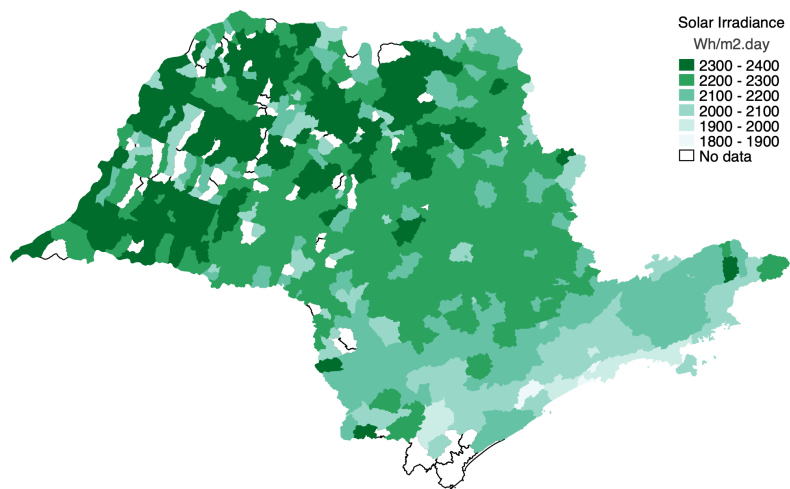
B. Distribution Price



Notes: Energy Prices are aggregated from ≈ 120 thousand zip-codes to 645 municipalities. Both figures map weighted-average deflated energy prices for the year of 2020, in R\$/MWh.

Source: ANEEL.

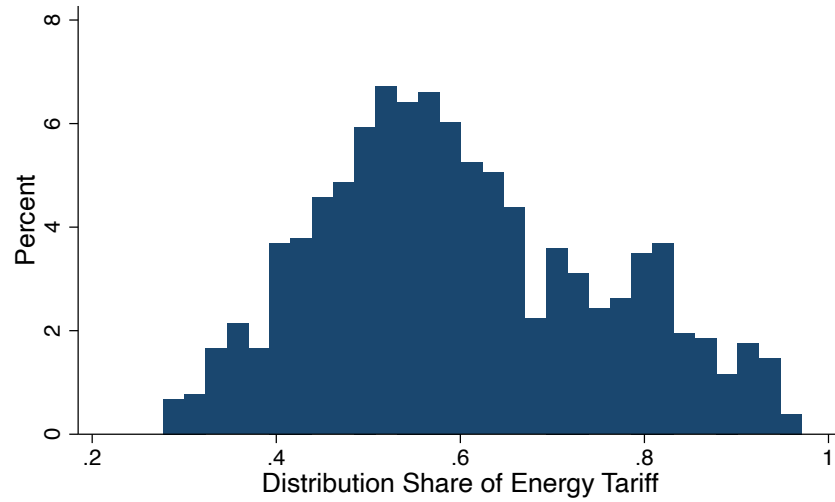
FIGURE A3: SOLAR IRRADIANCE



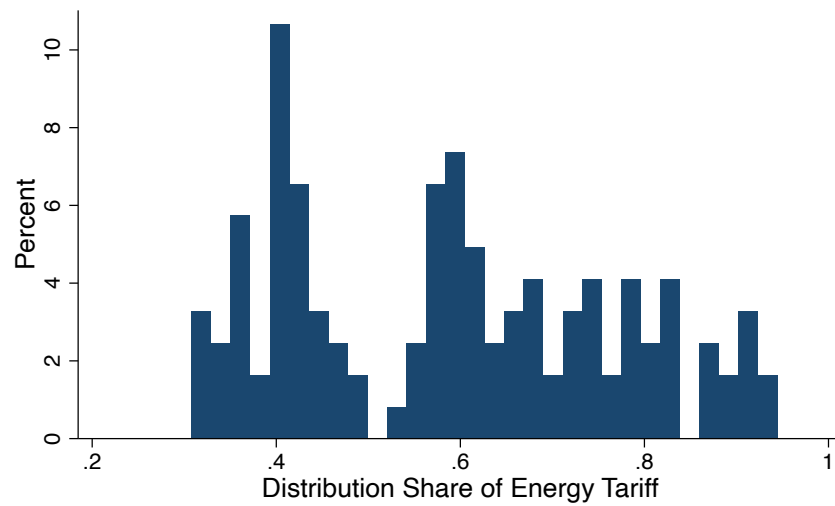
Notes: The figure maps solar irradiance as measured in Wh/m² per day, showing the average irradiance by municipality in the State of São Paulo.
Source: INPE.

FIGURE A4: DISTRIBUTION PRICE SHARE OF THE ENERGY TARIFF

A. Brazil



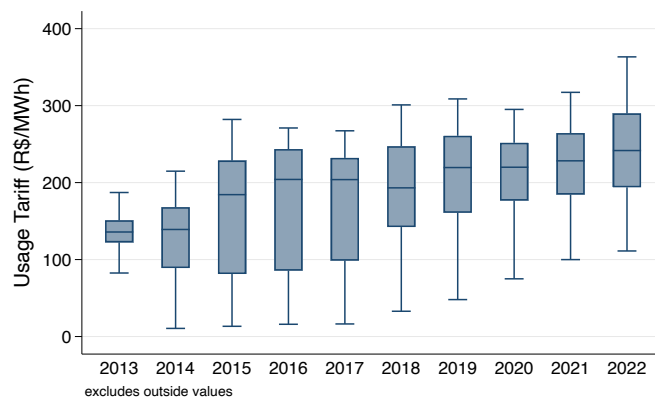
B. São Paulo State



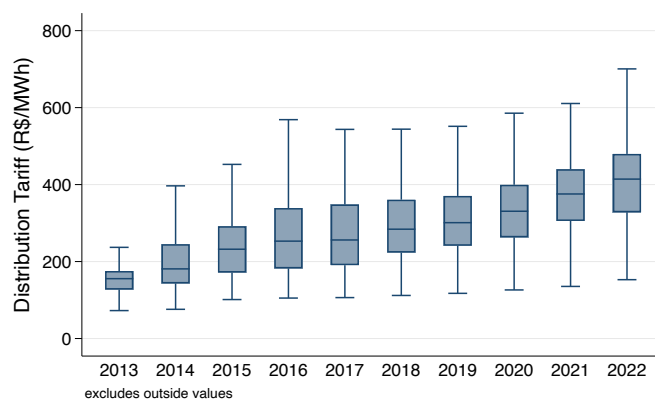
Notes: Both figures use weighted-average yearly deflated energy tariffs for each utility, across the sample period 2015-2020. Panel A includes all utilities operating in Brazil during this period, and Panel B only the utilities operating the State of São Paulo. The share is calculated as $\frac{p^D}{p^D + p^U}$.
Source: ANEEL.

FIGURE A5: DISTRIBUTION OF ENERGY PRICE COMPONENTS IN BRAZIL

A. Usage Price

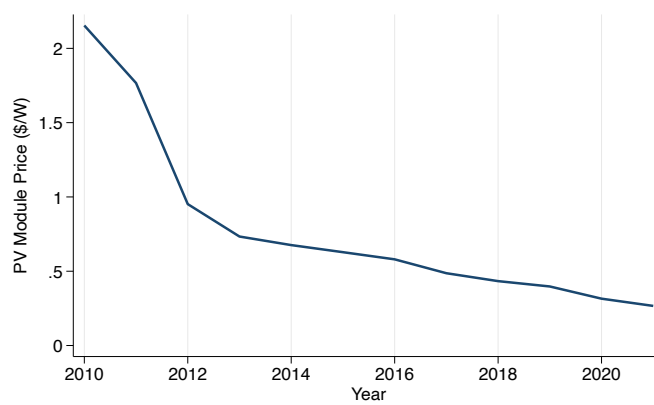


B. Distribution Price



Notes: Both figures use weighted-average yearly nominal energy tariffs for each utility, across the sample period 2015-2020, for all utilities in Brazil.
Source: ANEEL.

FIGURE A6: PHOTOVOLTAIC MODULE PRICES

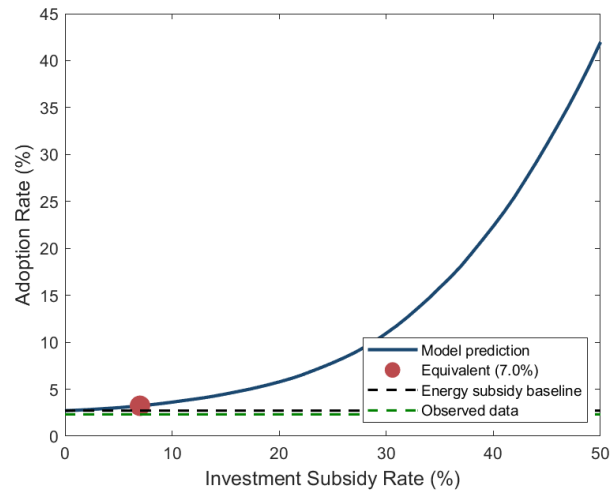


Notes: Values are in 2021 US\$ per Watt.

Source: International Renewable Energy Agency (IRENA).

FIGURE A7: EQUIVALENT-COST COUNTERFACTUAL RESULTS

A. Adoption Rates by Cost Subsidy Rate



B. Total Subsidy Cost by Cost Subsidy Rate

