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Pedro I. Hancevic (CIDE/Universidad Panamericana)

Hector H. Sandoval (Bureau of Economic and Business Research)

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Solar Panel Adoption in SMEs in Emerging Countries

Pedro I. Hancevic[*] Hector H. Sandoval[†]

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Abstract

We analyze the determinants of adoption of distributed solar photovoltaic systems, focusing on small and medium-sized commercial and service firms. We make use of monthly billing data that is perfectly matched with data from the ENCENRE-2019 –a novel survey that gathers data on electricity consumption, stock of electric equipment, and a rich set of firm characteristics in the Metropolitan Area of Aguascalientes, Mexico. Using an econometric model, we find evidence that a set of explanatory variables such as business characteristics, the economic sector, ownership status, stock and usage of equipment and appliances, presence of other solar technologies, and views about the use of renewable energy are important determinants of the probability of adoption of solar panel systems. Furthermore, using machine learning methods to identify the best predictors of solar adoption, we indirectly validate the theory-driven empirical model by assessing a large set of explanatory variables and selecting a subset of these variables. In addition, we investigate relevant cases where a priory solar panel adoption seems to be cost-effective but structural adoption barriers and adoption gaps might coexist for certain groups of electricity users. We also calculate the social cost savings and the avoided CO_2 emissions. Finally, based on our results, we provide several policy implications and recommendations.

JEL classification: D22; O14; Q40; and Q53
Keywords: small and medium-sized enterprises (SMEs), distributed photovoltaic generation, electricity consumption, technology adoption, Mexico

[*]Centro de Investigación y Docencia Económicas (CIDE), Mexico; Universidad Panamericana Campus Bonaterra, Aguascalientes, Mexico; and Red Nacional de Investigadores en Economía (RedNIE), Argentina. E-mail: pedro.hancevic@cide.edu.

[†]Corresponding author. Department of Economics and Bureau of Economic and Business Research (BEBR), University of Florida, Gainesville, FL. E-mail: hsandoval@ufl.edu.
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1 Introduction

In response to global warming, governments around the world have established air pollution emission goals and have committed to specific actions to reduce the effects of human activities on the environment. Among the actions undertaken to reach this goal is the increased use of renewable energy sources such as solar, wind, nuclear, geothermal, and hydropower to produce electricity. The adoption of some of these renewable energy technologies, such as wind and hydropower, is typically the result of large investment projects conducted by government agencies or large private electricity generating firms. On the contrary, during the past fifteen years, technological advances have steadily reduced the cost of solar PV installations and regulatory reforms have eased the connection to the electrical grid, making distributed solar generation more accessible to a broader set of consumers. Therefore, solar PV has the potential to become a reliable alternative for homes, farms, and commercial and service businesses with small and medium-sized electricity needs. However, only a small fraction of the total solar potential has been realized, regardless of the country's development status.[1] Considering the potential benefits of solar PV, it is important to understand the factors that influence the adoption of such technology.

This paper studies the factors influencing the adoption of solar PV systems using data from a novel survey of Non-Residential Electricity Consumption (ENCENRE-2019). The survey contains data on a rich set of characteristics that are matched with monthly billing data for a representative sample of small and medium-sized firms located in the Metropolitan Area of Aguascalientes, Mexico. Notably, Mexico is the 13th largest greenhouse gas (GHG) emitter in the world and the second largest in the Latin America and Caribbean region –behind Brazil.[2] The survey sample includes detailed information concerning firm and building characteristics, electrical equipment, space heating, air conditioning, and lighting, as well as environmental preferences and familiarity with solar technology for both adopters and non-adopters. It is worth noting that firm-level data for adopters and non-adopters are typically not used in the literature due to their lack of availability. Therefore, we are able to study the determinants behind firm-level adoption decisions. Specifically, we use a random utility model and estimate the probability of adoption using linear and logistic regressions. As a separate exercise, we also use machine learning methods to identify the best predictors of solar adoption and increase our understanding of their drivers. Moreover, we calculate net present values, payback periods, and internal rates of return to determine whether non-adopting firms could profit from having installed distributed solar panel systems. The survey

[1] The world solar PV generation in 2020 accounted for 3.7% of total electricity consumption.

[2] Source: USAID, available at https://www.usaid.gov/sites/default/files/2022-05/USAID-Climate-Change-Fact-Sheet-Mexico.pdf

also provides information about the reasons for not installing a PV system within the next year among non-adopters. We use this information to gain a deeper understanding of the determinants of adoption and to shed light on potential policies that may enhance the adoption of this technology. Finally, we estimate the amount of CO_2 emissions reduction annually resulting from the adoption of solar panels by commercial and service SMEs, providing an approximation of the potential impact at the national level.

Our results indicate that business characteristics such operating on weekends, operating in the trade sector, owning the building, durable roof, the presence of electric heating systems, televisions, voltage regulators/stabilizers, or solar water heaters, as well as the regular use of air conditioning and having positive views regarding the use of renewable energy are important determinants that have a positive and significant effect on PV adoption. Moreover, most of these variables are also selected by machine learning methods for the purpose of identifying the best predictors in a separate exercise. In terms of the potential profitability among non-adopters, our results indicate that 87% of them could benefit from installing a solar PV, as they have a positive net present value, with an average payback period of 6.5 years. Among non-adopters, 33.8% consider that renting or borrowing the facilities is the main reasons for not installing a solar panel. It is understandable that non-owners are reluctant to make a sunk investment in a property that does not belong to them. The second reason, cited by 14.2% of non-adopter, is the lack of sufficient information about the price, installation, operation and maintenance, and the process to request the connection to the grid. This suggests that there is a significant percentage of firms that might not invest in solar panels simply because they do not know whether it is a viable option. In third place, there are two reasons tied with 12.3% of non-adopters citing them, one reason is resource and financial constraints, and another is the fact that in their views a solar panel is not required. Finally, our results indicate that the current adoption of solar PV systems accounts for a reduction of approximately 12% of total emissions in our sampled firms. However, when the potential adopters are also included, the emission savings reaches 79% under the current tariff scheme, and between 59% and 98% when prices reflect the social marginal cost of electricity.

While there is a small but growing body of literature examining the determinants of PV adoption, the majority of it has focused on the residential sector. For instance, Kwan (2012) examines the influence of environmental, economic, social, and political factors on the distribution of residential solar PV installations by ZIP code in the U.S., finding that solar insolation, electricity cost, and financial incentives are important factors. Davidson et al. (2014) evaluate additional variables at the ZIP code and census block group levels and find that housing characteristics, such as the number of rooms, heating source, mortgage status, and house age are key indicators of PV adoption. Using a finer aggregation level containing on average 280 households, De Groote et al. (2016) study residential PV adoption in Belgium by including a rich set of socioeconomic and housing variables. They find that local policies have a robust and significant impact on PV adoption, with wealthier households being more likely to adopt it. Other studies on the residential sector have examined the impact of different incentives on the adoption of PV systems, particularly in the U.S. Hughes and Podolefsky (2015) predict that over 50% fewer installations would have occurred without subsidies from the California Solar Initiative (CSI), a state subsidy program aimed at increasing PV adoption. Borenstein (2017) examines the range of incentives to promote residential solar in California and finds that the electricity rate design can influence the economic incentives for adoption. He also shows that the income distribution of solar PV installations in California is heavily skewed toward the wealthy but also that this gap has narrowed in recent years, specially after 2011. Using county-level data, Crago and Chernyakhovskiy (2017) study the effectiveness of several state policy incentives to increase residential PV capacity in the northeastern U.S. Their results show that only rebates have a large and significant effect and that factors affecting the financial returns and indicating pro-environmental preferences are also significant. Kiso et al. (2022) examine the effects of financial incentives, particularly electricity prices, on residential PV installations in Japan and find that higher electricity prices lead to more solar PV installations on existing homes, whereas similar effects are not statistically confirmed for new-build homes. In the context of the Mexican residential sector, Hancevic et al. (2017) show that the subsidized tariff scheme makes it less attractive for residential users to adopt solar energy technologies. In a subsequent article, Hancevic et al. (2022) propose the rebalacing of residential electricity rates in order to increase economic efficiency, improve income redistribution, and reduce the subsidy burden to the government. They also show that removing price distortions encourages residential users to invest in energy efficiency and adopt solar panels.

In contrast, the literature studying the non-residential sector is scarce and has mostly focused on analyzing the factors influencing the size (capacity) of the PV system rather than the determinants of the installation decision. Using U.S. county-level data and a lower bound of 10 kW-capacity and an upper bound of 10 MW-capacity to identify commercial installations, Crago and Koegler (2018) examine the role of state policy incentives in driving the growth of commercial solar PV capacity and find that commercial installations are primarily driven by the promise of financial return. Frey and Mojtahedi (2018), based on non-residential applicants' data from CSI, study the impact of CSI incentives on changes in solar capacity between 2007 and 2014, and find evidence that firms respond to higher solar subsidies by increasing their intensity of solar energy. Cohen et al. (2020) examine the firm's decisions to install solar panels in some state and not other by studying a sample of multi-state companies in U.S. that have adopted solar in at least a few states. They found that the effectiveness of policies in attracting solar energy installation varies and that firms install solar panels where the most solar energy can be generated and the most savings can be realized from avoiding electricity expenses.

Unlike previous studies, this paper uses firm-level data on adopters and non-adopters and makes several key contributions to the literature. First, this is the first paper to study non-residential PV adoption in a developing country. So far, most of the empirical evidence has come from the residential sector in developed countries, primarily from U.S. and to a lesser extent from Europe. In the non-residential sector, empirical evidence is only available from U.S., where policy incentives have played an important role in encouraging the adoption of PV systems. In our context, such policy incentives are unavailable. As such, our findings provide evidence on the adoption decision in the absence of any policy, a common occurrence in developing countries. Second, this paper examines the individual adoption decision, which has not been studied due to data limitations. There is a common lack of detailed data on non-adopters in both residential and non-residential literatures, leading to a focus on studying factors influencing the installation size (capacity) or on studying PV adoption by aggregating the number of PV installations or total installed capacity by some geographical level such as at the ZIP code or county levels. Third, we demonstrate that many a priori profitable solar PV projects are not undertaken by businesses due to an energy-efficiency gap and then go a step further and investigate the reasons explaining this phenomenon, thus providing some guides to policymakers.[3] Our results suggest, as stated in Allcott and Greenstone (2012), that a significant welfare gain can be obtained when public interventions prioritize potential users with investment inefficiencies.

More broadly, our paper contributes to the empirical literature studying other aspects regarding PV adoption such as whether peer effects play a role in the diffusion process of PV (Bollinger and Gillingham, 2012), the role of third-party PV products (Dury et al., 2012), papers studying the barriers and enablers for installing PV system (Zhang et al., 2012; Palm, 2018; Reindl and Palm, 2021), papers studying different price mechanism applicable to the solar panel market (Gillingham et al., 2016; Reguant 2019; and Lian et al, 2020), and papers studying the rebound effect following solar adoption (Beppler et al, 2021; Boccard and Gautier, 2021).

The remainder of the paper is organized as follows. Section 2 discusses solar generation

[3] Broadly speaking we refer to the 'energy efficiency gap' as a sub-optimal investment in energy efficiency or clean energy technologies due to structural and/or market barriers such as misinformation, price distortions, rate uncertainty, credit constraints, supply infrastructure limitations, among other reasons.

in Mexico and provides background information. Section 3 describes the data and provides summary statistics. Section 4 contains empirical results on factors influencing adoption, the best predictors, the profitability of adoption, and the reasons for not adopting. Section 5 calculates the actual and potential reductions in emissions and the associated social costs. Finally, section 6 concludes the paper and provides some policy implications.

2 Background

As a result of the Paris Agreement (COP-21), the Mexican government committed to achieve two environmental goals. The first goal is to cut CO_2 emissions by 50% by the year 2050 with respect to the baseline year 2000. The second goal is to reach a 35% share of clean electricity generation by 2024, and a 43% share by 2030.[4] To put the latter into context, during 2020, only 22.6% of the electricity generated in the country was produced by clean energy sources where hydropower accounted for 7.8%, nuclear power 3.2%, wind 5.7%, solar 3.9%, and biomass and geothermal completed the remaining 2%. The clean-energy goal constitutes a step forward in the decarbonization agenda. However, specialized technical reports estimate that the country has much more potential and could produce more than 80% of its energy with sustainable sources (Cambas et al., 2019; Hancevic et al., 2022b).

Regarding the solar resources, Mexico has an average solar irradiation of 6.36 kWh/m2 per day. With its extensive territory and high irradiation levels, the country has the potential to install more than 1,800 GW of generation capacity in areas with plant factors >20%. That figure is 28 times the total installed capacity in the National Electric System.[5] Therefore, solar PV has the potential of becoming a reliable alternative for small and medium-sized electricity users, such as households, farmers, commercial and service businesses which want to save money on electric bills and also be part of the energy transition phenomenon. In sum, distributed solar PV generation is emerging as an accessible alternative, but surprisingly, its penetration among consumers is still limited. In this paper we focus on SMEs in Aguascalientes, a mid-size metropolitan area representative of the central region of Mexico. As shown in Table 1, Aguascalientes has a similar distribution of businesses by size as the country as a whole, with the vast majority (85.1%) consisting of less than 5 employees.

[4]These nationally determined contributions were ratified in COP-26.

[5]Across its territory, Mexico has resources with plant factors that lie in between 10 and 30 percent.

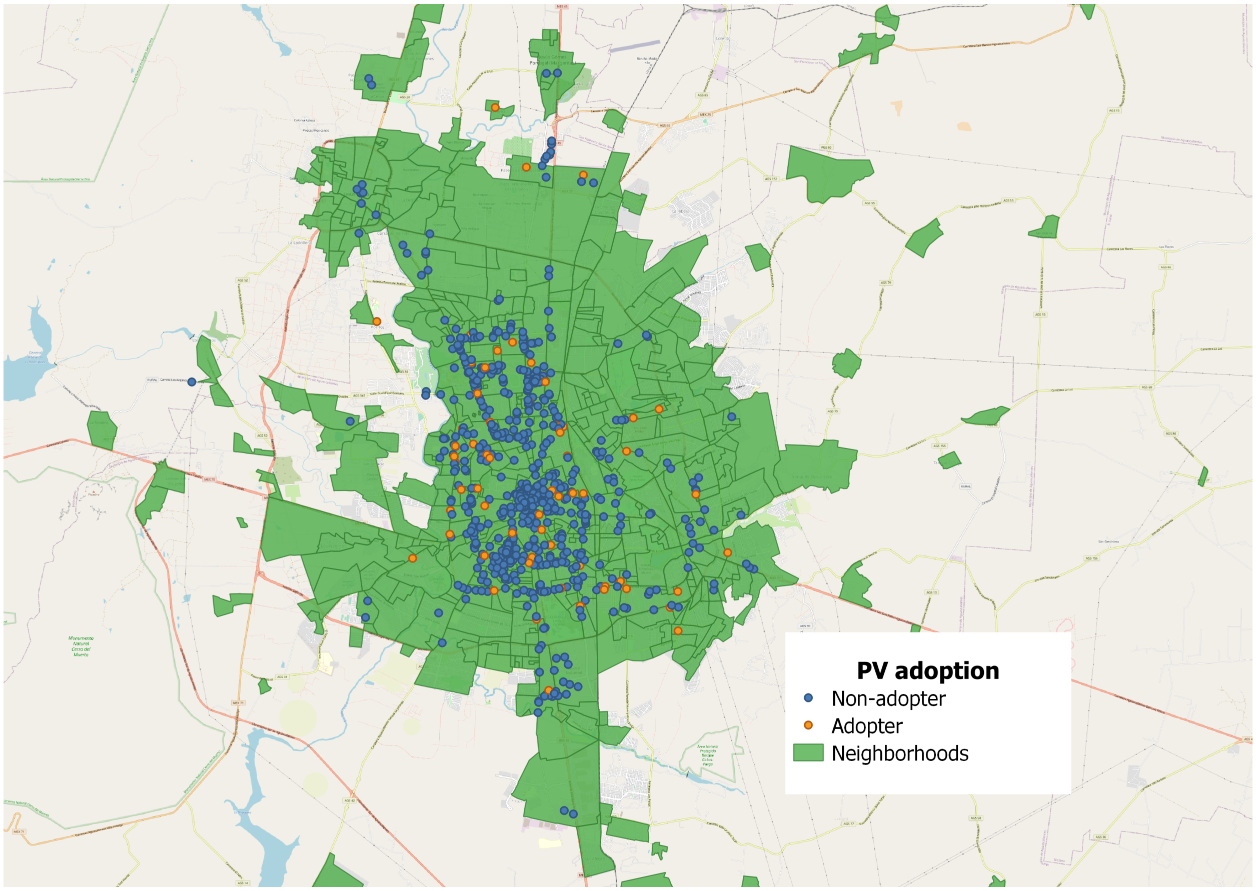
Table 1: Stratification of Business Establishments by Number of Employees

Number of employees	All country Freq.	All country Percent	Aguascalientes MA Freq.	Aguascalientes MA Percent
0 - 5	4,187,047	88.1%	39,151	85.1%
6 - 10	294,086	6.2%	3,612	7.8%
11 - 30	195,437	4.1%	2,382	5.2%
31 a 50	36,523	0.8%	414	0.9%
51 - 100	21,544	0.5%	239	0.5%
101 - 250	12,703	0.3%	161	0.3%
251 or +	5,897	0.1%	55	0.1%
Total	4,753,237	100.0%	46,014	100.0%

Sources: National Statistical Directory of Economic Units (DENUE), prepared by the National Institute of Statistics and Geography (INEGI).

Our sample is representative of the Aguascalientes Metropolitan Area. The majority of the business establishments are located in the central portion of the metropolitan area where there is a greater level of commercial activity. This can be seen in Figure 1, which presents the spatial distribution of firms that have adopted solar panels and those that have not. This map shows neither a clear pattern nor a concentration of adopters in any particular zone. In fact, the location of adopters is in accordance with the usual commercial and business zones.

Figure 1: Spatial Distribution of Adopting and Non-adopting Establishments in Aguascalientes Metropolitan Area



Source: Own elaboration based on ENCENRE-2019 data.

2.1 Investment Costs in Solar Panel Systems

The adoption of distributed generation systems has become economically more attractive since the total cost of installing photovoltaic units have steadily declined during the last decade all over the world. In the case of Mexico, prices have dropped from more than 2.5 USD/Wp in 2010 to approximately 1.5 USD/Wp in 2020.[6] The main reasons behind this declining trend are: increasing market competition, improved productivity, and decreasing input costs. Table 2 shows solar panel investment costs for Aguascalientes which were collected from a sample of local solar PV system vendors and installers.

[6]Similarly, in the United States, prices dropped 66.3% from 2010 to 2018 (Fu et al., 2018).

Table 2: Solar PV System Total Cost in Aguascalientes Metropolitan Area

Year	Exchange rate (MXP/USD)	Investment cost (USD/Wp)
2012	13.17	1.94
2013	12.77	1.80
2014	13.30	1.75
2015	15.85	1.63
2016	18.53	1.62
2017	18.93	1.60
2018	19.24	1.50
2019	19.26	1.45

Sources: Specialized local vendors and installers, IRENA, and Mexican Central Bank. Investment cost includes purchase of the solar panels, the setting-up, and full installation ready-to-operate.

2.2 Electricity Tariffs Contracted by SMEs in Aguascalientes

In this section, we present the different tariff categories that were contracted by the firms in our sample. There are two groups of rates among the surveyed companies. On the one hand, there are firms with the commercial tariff PDBT which corresponds to low demand in low voltage and is the most popular among the establishments. Other commercial/industrial tariffs are GDMTO and GDMTH which stand for large demand in medium voltage with and without peak-load pricing, respectively. On the other hand, some establishments are under the residential tariff 01 and some under the high-demand residential tariff DAC. This fact can be somewhat controversial and even unethical since residential rate 01 is highly subsidized.[7] Table 3 presents the electricity tariffs for the month of October 2019, when data collection for the ENCENRE-2019 ended.

[7] For a precise definition and a complete analysis of residential tariffs in Mexico see Hancevic et al. (2022).

Table 3: Electricity Rates in Aguascalientes for October 2019

A. Residential tariffs

01			Variable			
		(0-150 kWh)	(151-280 kWh)	(+ 281 kWh)		
		0.043	0.052	0.151		
DAC	Fixed	Variable				
	5.637	0.242				

B. Commercial and industrial tariffs

PDBT	Fixed	Variable				
	2.343	0.177				
GDMTO	Fixed	Variable	Capacity	Distribution		
	24.134	0.066	14.203	4.980		
GDMTH			Variable			
	Fixed	Base	Intermediate	Peak	Capacity	Distribution
	23.431	0.048	0.085	0.096	17.577	4.914

This table shows the electricity rates in October 2019. All values are in U.S. Dollars, the exchange rate is 19.25 MXP/USD. Source: State-owned national electric utility (Comisión Federal de Electricidad, CFE).

Tariff 01 is a three-block increasing block pricing scheme with no fixed charge. Users with residential rates are classified by default as 01. In the event that their consumption surpasses the threshold of 3000 kWh per year, they are automatically reclassified as high demand residential customers and are entitled to the DAC tariff. The variable charge in the DAC category is considerably higher than the highest marginal price in the 01 category. Among the 'proper' commercial and industrial electricity tariffs, PDBT is the simplest and is basically a two-part tariff. There are two types of high demand tariffs, GDMTO and GDMTH, which include capacity and distribution charges, and the latter also distinguishes between base, intermediate and peak hours, so variable charges are set accordingly.[8]

3 Data and Descriptive Statistics

Our empirical analysis is based on two main data sources, the Non-Residential Electricity Consumption Survey for the Aguascalientes Metropolitan Area (ENCENRE-2019) and billing data from the state-owned national electric utility (Comisión Federal de Electricidad,

[8] Using the same dataset used in this paper, Bejarano et al. (2022) study this tariff misclassification phenomenon among the different 'proper' commercial rates and residential rates and evaluate the structural winners and losers.

CFE).

3.1 Survey Data

The ENCENRE-2019 is a representative sample of small- and medium-sized enterprises (SMEs) located in the Metropolitan Area of Aguascalientes, Mexico, which was sponsored by the Mexican Ministry of Energy (SENER) and the National Science and Technology Council (CONACYT). This survey was conducted by the Center for Research and Teaching in Economics (CIDE) between May and October of 2019 and contains data from 812 establishments (businesses) in the commercial and service sectors. The primary objective of the survey was to characterize establishments based on several aspects relating to their electricity consumption. Specifically, the survey contains detailed information regarding the firm characteristics related to their economic activity, building characteristics, air conditioning, heating, stock of electrical equipment, as well as energy conservation practices and environmental attitudes. These characteristics are complemented by billing data from the CFE, described below, for the period spanning January 2019 to March 2020. After merging these two datasets and accounting for missing observations, our final working sample contains complete information for 784 establishments.

We selected the variables used in our main empirical analysis of the determinants behind PV adoption based on the literature and they are summarized in Table 4. Except for the number of employees, all of our variables are binary. As shown in this table, the adoption rate is 7.5%. As a point of reference, in the residential sector at the national level only 0.6% of households have solar panels installed by 2018.[9] Furthermore, as expected, the vast majority of the establishments pay the non-residential tariff (90.2%) and are located in one of the three municipalities that comprise the metro area.[10,11]

A number of variables were included in the analysis that described the firm's characteristics. One of these variables is the number of employees. This variable is an indicator of the size of the business, which could have a positive effect on PV adoption, as larger companies with more workers require more equipment and, therefore, consume more electricity. It is possible that this variable may play a similar role to household size in the residential literature, since larger households have a higher electricity consumption. Additionally, variables

[9]Source: National Survey on Energy Consumption in Private Homes (ENCEVI 2018).

[10]In our empirical analysis, we aggregate the tariffs into residential and non-residential categories because there is little variation within these categories. For instance, most establishments in the non-residential category pay the PDBT tariff (84.3%), while most in the residential category pay the 01 tariff (80.5%). The different tariffs are illustrated in Table 3.

[11]The Aguascalientes metropolitan area includes the municipalities: Aguascalientes, Jesús María, and San Francisco de los Romo. The distribution of establishment is 95.4%, 4.2%, and 0.4%, respectively.

such as whether the business is in the trade sector and whether it operates on weekends (Saturdays and/or Sundays) in addition to weekdays are also taken into account. It is possible that the former variable indicates the presence of electric appliances and electronic devices that require high energy consumption, such as air conditioning, which are more likely to be found in commercial establishments. Higher electricity consumption is also associated with the latter variable. A further consideration is whether the building is owned by the company. As documented in the residential literature, renting makes it difficult to adopt new technologies since it is difficult to allocate the benefits and costs between tenants and landlords. In addition, for the particular case of Aguascalientes, the average lifespan of companies is 8.2 years, and only 14.7% survive for more than 20 years.[12] Considering that PV systems typically have payback periods greater than 10 years, firms may be rationally reluctant to invest in these systems. Additionally, the market for used solar panels in Mexico is negligible at present, so relocating and selling a used solar PV unit in order to recover at least a portion of the investment would not be feasible.

We have also incorporated several variables that capture the characteristics of the building. Among the most important characteristics to consider are the rooftops, where most PV systems are installed. Therefore, we included whether the roof material is long-lasting (wood or concrete) and whether the roof and walls are insulated. As for the former, we expect that long-lasting roofing materials will positively influence PV adoption since other common materials, such as palm leaves or galvanized metal sheets, may not be adequate for PV systems or increase installation costs. We also consider whether the building shares walls with others (attached), whether it has an elevator, whether the majority of the space is used for offices, and whether any major renovations have been undertaken since 2000.

While climate conditions in Aguascalientes are pleasant for most people with temperatures typically varying from 39°F to 86°F and rarely below 32°F or above 92°F, we have included several variables capturing heating and cooling systems as business establishments are more likely to have such equipment. As shown in Table 4, around 35% of the establishments are equipped with air-conditioning. This figure contrasts sharply with the residential sector in the Aguascalientes Metro Area where less than 2% of the homes have AC systems.[13] Moreover, we have included variables that reflect whether the A/C unit is used on a regular basis for more than one month per year and whether the temperature is set by a specific norm or policy. Moreover, we have information regarding whether the business has a fan, however, we are unable to determine what type it is (ceiling, window, or pedestal fan).

[12] Source: Mexican National Institute of Statistics and Geography (INEGI). Available at https://www.inegi.org.mx/programas/dn/2019/#Tabulados.

[13] Source: National Survey of Household Income and Expenditure (ENIGH-2018).

For heating, we have included a variable that captures whether the building has an electric heating system. It is noteworthy, however, that less than 10% of establishments have such a system in place.

Further, we have information regarding the stock of electrical equipment, including computer equipment (computers, printers, etc.), refrigeration equipment, and kitchen appliances. Electrical equipment is an important driver of energy consumption, which could encourage the adoption of solar technology in some circumstances. In our analysis, the commercial refrigerator is treated as a separate variable since it consumes more energy than a domestic refrigerator. For our kitchen appliance indicator, we group together the coffee machine, microwave, and domestic refrigerator. Additionally, we consider other relevant equipment such as an electric generator, voltage regulator or stabilizer, water pump, and motion sensor lights for indoor and outdoor use. Among these variables, we anticipate that the presence of an electric generator might discourage the adoption of PV systems, while the presence of a voltage regulator or stabilizer might increase it since they may indicate better understanding of the electricity consumption. Another related variable we included is whether there is an intention to replace electric equipment to save energy because saving energy can also be related to the adoption of PV systems. An interesting variable is whether the establishment already uses a solar water heater, which is an indication of familiarity with and preference for solar technology.

Two additional variables that we have included are whether the business uses gasoline or diesel as part of their regular business activities and whether the respondent has knowledge of the energy consumption (or the amount billed).

Lastly, two variables are used to capture information regarding environmental attitudes. One is whether the respondent mentioned that clean energy can be purchased easily. The other one, whether the respondent mentioned solar panels in response to the open question, "*In your opinion, what are the most effective actions that Mexico's residents could do to save electricity?*"

Table 4: Survey Data: Summary Statistics

	Mean	Std. Dev.	N
PV installation	0.075	(0.264)	784
Residential tariff	0.098	(0.298)	784
Non-residential tariff	0.902	(0.298)	784
Aguascalientes municipality	0.954	(0.209)	784
# of employees	14.726	(32.934)	784
Operating on weekends	0.628	(0.484)	784
Trade sector	0.492	(0.500)	784
Ownership	0.323	(0.468)	784
Durable roof	0.828	(0.378)	784
Elevator	0.056	(0.230)	784
Attached building	0.938	(0.242)	784
Space primarily for offices	0.210	(0.408)	784
Roof & walls insulation	0.093	(0.291)	784
Renovations since 2000	0.124	(0.329)	784
A/C	0.352	(0.478)	784
A/C used regularly	0.264	(0.441)	784
A/C temperature set	0.112	(0.316)	784
Fan	0.601	(0.490)	784
Electric heating system	0.082	(0.274)	784
Desktop/laptop computer	0.865	(0.342)	784
Printer, scanner, copier	0.800	(0.400)	784
Server	0.366	(0.482)	784
Televisions	0.448	(0.498)	784
Kitchen appliance	0.392	(0.488)	784
Commercial refrigerator	0.233	(0.423)	784
Electric generator	0.042	(0.201)	784
Voltage regulator/stabilizer	0.390	(0.488)	784
Water pump	0.523	(0.500)	784
Motion sensor lights	0.240	(0.427)	784
Gasoline/diesel usage	0.583	(0.493)	784
Intentions to replace equipment	0.154	(0.362)	784
Awareness of consumption	0.844	(0.363)	784
Solar water heater	0.032	(0.176)	784
Clean energy is easy to buy	0.399	(0.490)	779
PV: energy-saving solution	0.209	(0.407)	784

The table reports descriptive statistics of the main variables. Except for the number of employees, all variables are binary. Source: ENCENRE-2019.

3.2 Billing Data

For the vast majority of the firms in the ENCENRE-2019 sample, we have either monthly or bimonthly billing data, depending on the tariff category that each firm contracted. This data covers the period from January 2019 to March 2020, right before the COVID-19 pandemic affected the economic activity in Mexico. As the ENCENRE-2019 data collection period was from May to October 2019, the electricity consumption data are representative. Table 5 presents consumption by tariff category. Panel A shows consumption in kWh per billing period, whereas panel B shows consumption as a percentage of average annual consumption. Although there is some seasonality in consumption, this is not pronounced except for firms with industrial electricity rates (GDMO and GDMTH).

In our sample, all adopting firms are under the net-metering scheme. Due to this, the electric bill for users with solar PV systems contains two pieces of information: the kWh supplied to the grid and the kWh drawn from the grid. However, we do not observe the total electricity generated by the solar panel systems and therefore we are unable to accurately account for the total electricity consumed by adopting firms (i.e., electricity produced by the solar panels and directly consumed by the firm plus electricity supplied by the electric utility). We also do not observe energy consumption before the adopting firms installed their solar panels. For these reasons we do not use consumption as one of the explanatory variables when studying the determinants of adoption in the next section. Instead we use the billing data to compute profitability measures for non-adopting establishments in Section 4.3.

Table 5: Billing Data: Electricity Consumption of SMEs in Aguascalientes by Tariff Category

A. Consumption of electricity (in kWh)

Billing period	Tariff category: 01 (n=64)		DAC (n=15)		PDBT (n=608)		GDMTO (n=97)		GDMTH (n=19)	
January	225.1	(175.8)	804.7	(492.5)	1,050.5	(1,441.0)	4,924.0	(5,412.6)	17,522.7	(19,904.8)
February							5,507.3	(6,567.3)	17,668.8	(20,901.6)
March	214.8	(137.8)	874.6	(469.5)	1,095.0	(1,528.3)	5,900.6	(6,654.7)	20,925.8	(26,574.7)
April							6,184.2	(7,325.5)	24,482.1	(25,351.8)
May	251.9	(181.9)	937.4	(513.2)	1,264.9	(1,821.6)	6,702.1	(7,884.5)	27,483.5	(28,872.2)
June							6,906.7	(7,855.7)	24,259.6	(28,656.3)
July	248.9	(150.5)	885.1	(548.2)	1,263.9	(1,894.7)	7,389.3	(8,601.3)	23,967.8	(28,455.3)
August							6,668.2	(7,910.9)	23,615.0	(28,469.6)
September	223.7	(148.0)	822.4	(541.4)	1,179.6	(1,862.3)	7,169.2	(7,567.1)	21,104.7	(26,846.6)
October							6,710.6	(7,718.3)	21,309.3	(26,470.5)
November	226.3	(155.5)	781.4	(341.4)	1,191.0	(1,677.5)	5,786.9	(6,733.2)	19,212.2	(22,600.3)
December							5,258.4	(5,360.7)	17,704.5	(19,678.2)
Total	230.5	(157.5)	855.1	(486.0)	1,172.4	(1,708.8)	6,251.8	(7,206.7)	21,596.3	(25,073.5)

B. Consumption of electricity as a percentage of the average annual consumption

Billing period	Tariff category: 01 (n=64)	DAC (n=15)	PDBT (n=608)	GDMTO (n=97)	GDMTH (n=19)
January	98%	94%	90%	79%	81%
February				88%	82%
March	93%	102%	93%	94%	97%
April				99%	113%
May	109%	110%	108%	107%	127%
June				110%	112%
July	108%	104%	108%	118%	111%
August				107%	109%
September	97%	96%	101%	115%	98%
October				107%	99%
November	98%	91%	102%	93%	89%
December				84%	82%

This table presents the electricity consumption of sampled firms in kWh per billing period, distinguishing among the different tariffs. See subsection 2.2 for more details about the tariff categories. Source: CFE billing data.

4 Empirical Results

This section begins by examining the determinants of PV adoption. We then use machine learning methods to identify the best predictors of solar adoption. Following this, we discuss the cost of adoption and its profitability for non-adopting businesses. Finally, we discuss their reasons for not adopting.

4.1 Determinants of Solar Adoption

Our study examines the factors influencing PV adoption using a random utility model. The model assumes that each firm has the option of buying, installing, and connecting a solar PV system to the electricity grid ($j = 1$) (i.e., adopting a solar PV system) or not adopting a solar PV system ($j = 0$). The preferences of each firm over these two alternatives are described by a utility (profit) function, and each firm chooses the alternative that provides the highest utility. Formally, let the random utility of alternative j for firm i be

$$u_{j,i} = \mathbf{x}_{j,i}\beta + \epsilon_{j,i} \tag{1}$$

where $\mathbf{x}_{j,i}$ is a row vector of observed attributes or characteristics of alternative j and firm i, β is a conformable vector of parameters, and the random term $\epsilon_{j,i}$ is the effect that unobserved attributes of the alternative j have on firm i's preferences.[14] Assuming that $\epsilon_i^\intercal = (\epsilon_{0,i}, \epsilon_{1,i})$ are independently and identically distributed (i.i.d.) as a type 1 extreme value random variable, the probability that the individual i chooses alternative 1 is given by

$$\Pr(j = 1|\mathbf{x}_i) = \frac{exp\,(\mathbf{x}_{1,i}\beta)}{1 + exp\,(\mathbf{x}_{1,i}\beta)} \tag{2}$$

Equation (2) corresponds to a logistic (logit) model. We estimate the parameters of this model, β, using maximum likelihood estimation (MLE). In addition, we estimate the probability of adoption using ordinary least squares (OLS).[15] We use robust standard errors in both cases. The set of variables included in $\mathbf{x}$ are presented in Table 4. These variables capture firm and building characteristics, space heating and cooling, the stock of electrical equipment, as well as behavioral variables related to energy consumption practices, preference for solar technology, and environmental attitudes. In our results, we also present the marginal effects associated to the logit coefficients.

Table 6 contains our main results regarding the determinants behind the adoption of

[14] See Train (2009) for a complete discussion of the theory of random utility modeling and its empirical applications.

[15] In this case, we consider the linear probability model, $\Pr(j = 1|\mathbf{x}_i) = E[j = 1|\mathbf{x}_i] = \mathbf{x}\beta$.

PV. Columns (1) to (3) provide results based on a logit model with different specifications. Column (3) contains our most comprehensive specification, while columns (4) and (5) report its corresponding marginal effects and OLS estimates, respectively.

In column (1), which contains our basic specification, we begin the analysis by including a dummy variable for the non-residential tariff, along with a set of variables capturing firm and building characteristics, as well as variables related to the availability of heating and cooling systems. As expected, the non-residential tariff has a positive effect on the probability of adoption since more expensive energy implies greater potential savings on electric bills for prospective PV adopters. The effect, however, is not statistically significant, likely due to insufficient variation since more than 90% of establishments pay this tariff. Firm characteristics such as whether the business operates on weekends in addition to weekdays have a positive and significant effect on PV adoption. A business that operates also on weekends is expected to consume more energy than one operating only during weekdays. This is the case due to the additional use of its electrical equipment, indoor lighting, and heating and cooling systems during the weekend. This higher energy consumption is likely responsible for the decision to install a PV system. Similarly, whether the building is owned by the company has a positive and significant effect. This confirms that ownership status is an important determinant since it may be risky for non-owners to undertake this type of infrastructure investment in a rented or borrowed facility. This result is consistent with the residential literature, which finds that homeownership status has a positive effect on PV adoption (De Groote et al., 2016). The number of employees and whether the business is in the trade sector both have a positive but insignificant effect. Building characteristics such as whether the building is attached, has an elevator, and whether most of the space is used for offices do not have a significant effect on PV adoption. Furthermore, although the durability of the rooftop has a positive effect, it is also not statistically significant in this specification. In contrast, roof and wall insulation and whether the building has undergone major renovations since 2000, both have a positive and significant effect. Regarding the heating and cooling systems, having an electric heating system has a positive and significant effect on solar adoption, while having an air-conditioning system has a positive but not significant effect.

In column (2), we extend the basic specification by including a rich set of variables related to the stock of electrical equipment, and variables regarding the intention to replace electrical equipment to save energy, and fuel usage. The set of electrical equipment includes office equipment, kitchen appliances, refrigeration equipment, and other relevant equipment such as an electric generator, voltage regulator or stabilizer, water pump, and motion sensor lights. Among all these variables, only televisions, voltage regulator or stabilizer, and commercial refrigerator have a positive and significant effect. Despite the fact that our results show that most electrical equipment does not influence PV adoption, including the number of electrical equipment instead, such as the number of computers or servers, could produce a different result.[16] As expected, the presence of a voltage regulator or stabilizer increases the probability of adoption, while the presence of an electric generator has the opposite effect, although the latter effect is not statistically significant. The variables that capture intentions to replace equipment to save energy and the use of gasoline or diesel in the business both have a positive but not statistically significant effect. The inclusion of the additional variables in column (2) alters the significance of some of the firm and building characteristics variables in the basic specification (column 1). Specifically, insulation on the roof and walls, and whether the building has undergone renovations since 2000, are no longer statistically significant, while rooftop durability is now significant and positive. The latter is consistent with the expectation that a higher quality roof will require a lower investment. Additionally, whether the business is in the trade sector now has a significant and positive effect. Since commercial establishments typically have electric appliances and electronic devices that consume high amounts of energy, this effect was expected.

In column (3), we further extend the model specification by including a set of behavioral variables related to energy consumption practices, familiarity with and preference for solar technology, and environmental attitudes. First, the use of air conditioning regularly and setting the temperature according to a specific norm both have positive effects on PV adoption, however only the former is statistically significant. Since cooling is one of the primary drivers of energy consumption, the positive effect regarding the regular use of the A/C is expected. Setting the A/C temperature according to a specific norm may indicate knowledge of the factors driving energy consumption, and therefore of the potential benefits of PV systems. However, awareness of energy consumption alone has an insignificant effect. Second, the presence of a solar water heater, which indicates familiarity with and preference for solar technology, has a positive and significant effect as expected. In section 4.4, we show that lack of information regarding solar panels is the primary reason why owners do not intend to invest in this technology. Thus, familiarity with this technology can be viewed as an indication of a predisposition to adopt solar-related technologies. Third, the two variables that capture environmental attitudes are also positive and significant, as expected. Finally, the inclusion of this final set of variables only alters the significance of commercial refrigerators in the previous specification (column 2).

Overall, characteristics such as operating also on weekends, operating in the trade sector,

[16] The survey collects information on the number of equipment, however many of these entries have a large number of missing values, making it difficult to conduct the analysis.

building ownership, the durability of the roof, the presence of electric heating systems, televisions, voltage regulators/stabilizers, or solar water heaters, as well as the regular use of air conditioning and positive environmental attitudes regarding renewable energy are important determinants that have a positive and significant effect on PV adoption. Looking at the marginal effects reported in column (4), the presence of solar water heater, the regular use of A/C, ownership status, and a voltage regulator/stabilizer have the largest marginal effects on the predicted probability of adoption, when setting all variables to their means. Finally, the OLS estimates (column 5) are in line with the previous results and indicate that these variables have a positive and significant effect.

Table 6: Estimation Results of the Determinants of PV Adoption

	(1)		(2)		(3)		(4)		(5)	
	Logit-M1		Logit-M2		Logit-M3		dydx-M3		OLS-M3	
Non-residential tariff	0.865	(0.708)	0.673	(0.744)	0.915	(0.701)	0.029	(0.023)	0.022	(0.021)
Aguascalientes municipality	0.646	(0.716)	0.501	(0.815)	0.393	(0.810)	0.012	(0.025)	0.031	(0.039)
# of employees (log)	0.249	(0.188)	0.022	(0.210)	0.154	(0.213)	0.005	(0.007)	0.005	(0.013)
Operating on weekends	0.917***	(0.341)	0.848**	(0.365)	0.685*	(0.364)	0.022**	(0.011)	0.032*	(0.017)
Trade sector	0.429	(0.313)	0.734**	(0.346)	0.803**	(0.374)	0.025**	(0.011)	0.040*	(0.021)
Ownership	1.024***	(0.305)	1.041***	(0.325)	0.977***	(0.332)	0.031***	(0.011)	0.060***	(0.023)
Elevator	-0.410	(0.607)	-0.452	(0.641)	-0.916	(0.799)	-0.029	(0.025)	-0.045	(0.043)
Attached building	1.218	(0.871)	1.279	(0.947)	1.468	(1.075)	0.047	(0.032)	0.067**	(0.034)
Space primarily for offices	-0.014	(0.398)	0.156	(0.411)	0.157	(0.430)	0.005	(0.013)	0.007	(0.022)
Roof & walls insulation	0.774*	(0.399)	0.596	(0.408)	0.426	(0.457)	0.014	(0.015)	0.055	(0.044)
Durable roof	0.522	(0.399)	0.765*	(0.407)	0.723*	(0.438)	0.023*	(0.014)	0.043*	(0.023)
Renovations since 2000	0.648*	(0.393)	0.516	(0.410)	0.387	(0.461)	0.012	(0.015)	0.042	(0.039)
A/C	0.506	(0.341)	0.613	(0.389)	-0.961	(0.715)	-0.030	(0.023)	-0.052*	(0.031)
Electric heating	0.983**	(0.442)	0.846*	(0.491)	0.893*	(0.467)	0.028*	(0.016)	0.083*	(0.045)
Fan			0.515	(0.349)	0.415	(0.339)	0.013	(0.011)	0.033*	(0.020)
Desktop/laptop computer			-0.331	(0.732)	-0.208	(0.784)	-0.007	(0.025)	-0.019	(0.039)
Printer, scanner, copier			0.001	(0.604)	-0.122	(0.659)	-0.004	(0.021)	0.005	(0.033)
Server			0.055	(0.339)	0.077	(0.364)	0.002	(0.012)	0.007	(0.022)
Televisions			0.641*	(0.337)	0.693**	(0.335)	0.022**	(0.011)	0.035*	(0.020)
Electric generator			-0.738	(0.834)	-0.730	(0.866)	-0.023	(0.027)	-0.043	(0.054)
Voltage regulator/stabilizer			0.857**	(0.359)	0.950**	(0.384)	0.030**	(0.012)	0.054**	(0.021)
Water pump			0.369	(0.349)	0.295	(0.362)	0.009	(0.011)	0.009	(0.020)
Commercial refrigerator			0.732**	(0.371)	0.568	(0.383)	0.018	(0.012)	0.033	(0.028)
Kitchen appliance			-0.063	(0.314)	0.033	(0.348)	0.001	(0.011)	0.000	(0.020)
Motion sensor lights			0.297	(0.352)	0.308	(0.378)	0.010	(0.012)	0.029	(0.025)
Gasoline/diesel usage			0.302	(0.355)	0.338	(0.381)	0.011	(0.012)	0.018	(0.019)
Intentions to replace equip.			0.019	(0.397)	-0.027	(0.415)	-0.001	(0.013)	0.000	(0.028)
A/C used regularly					1.293**	(0.615)	0.041**	(0.020)	0.074**	(0.030)
A/C temperature set					0.745	(0.516)	0.024	(0.016)	0.047	(0.041)
Awareness of consumption					0.651	(0.460)	0.021	(0.015)	0.030	(0.021)
Solar water heater					1.296**	(0.624)	0.041*	(0.022)	0.193**	(0.097)
Clean energy is easy to buy					0.848**	(0.334)	0.027***	(0.010)	0.057***	(0.021)
PV: energy-saving solution					0.585*	(0.320)	0.019*	(0.010)	0.037	(0.025)
Constant	-7.942***	(1.670)	-9.017***	(1.972)	-10.526***	(2.268)			-0.302***	(0.082)
Observations	784		784		779		779		779	
R^2									0.141	
% Correctly classified	92.5		92.6		92.9					

The table reports coefficient estimates of the determinants of PV adoption. Robust standard errors are in parentheses. Except for the number of employees, all variables are binary. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: ENCENRE-2019.

4.2 Best Predictors of Solar Adoption

In the previous section, we followed the theory and the literature in constructing the variables used to examine the determinants behind the probability of PV adoption. For this purpose, we constructed 33 different independent variables (determinants). In this section, we follow a data-driven approach instead and use machine learning methods to obtain the best predictors of PV adoption. The sole purpose of this exercise is to build a model that is capable of making good predictions and increase our understanding of the potential drivers of PV adoption. To accomplish this, we construct a wider set of variables that capture the same concepts as before. For example, previously we used a variable to capture whether a business operates on weekends in addition to weekdays (operating on weekends). In studying the determinants of PV adoption, we used this variable because we believe that the distinction between weekdays and weekends is more relevant since businesses that operate only on weekdays differ from those that operate also on weekends in meaningful ways. In this section, in addition to this variable, we include whether the business operates four days a week or less, only on weekdays, or seven days a week. The rest of the independent variables were treated in a similar way. As a result, we expanded our set of independent variables to 58. It should be noted that many of these variables are redundant and highly correlated since they capture similar concepts.

Using this extended set of variables, we fitted linear and logistic models using cross-validation (CV) lasso, adaptive lasso, and elastic net for prediction, that is, for selecting variables that correlate with the outcome in one dataset and testing whether the same variables predict the outcome in another dataset.[17] Therefore, since we want to evaluate our predictions on a sample that was not used to fit the models, we first randomly split our sample into a training (75%) and validation (25%) samples. Next, we fit the models on the training sample and test their predictions on the validation sample. More specifically, we test the goodness of fit and compare their out-of-sample predictive ability.

In addition, we also perform variable selection for linear regression using the leaps-and-bounds algorithm (Furnival and Wilson, 1974; Lindsey and Sheather, 2010) which solves

[17] CV lasso selects λ^*, the lasso penalty parameter, and finds the model that minimizes an out-of-sample prediction error, also known as the CV function. We use the default grid of 100 λ's which are uniformly spaced. Adaptive lasso consists of multiple lassos with each lasso step using CV to select a λ^*. After each lasso, variables with zero coefficients are removed and remaining variables are given penalty weights designed to drive small coefficients to zero. We use the default of two lassos, since typically the selected λ^* does not change after the second lasso. The elastic net extends the lasso by using a more general penalty term that is a mixture of the absolute-value penalty used by lasso and the squared penalty used by ridge regression, making coefficient estimates more robust to the presence of highly correlated covariates (Zou and Hastie, 2005). To fit the model, we specify $(0.2, 0.4, 0.6, 0.8)$ as the set of candidate α's and the default grid of λ values. CV is performed on the combined set of (α, λ) values and the pair that minimizes the CV function is selected.

for the most predictive subset of variables based on information criteria. However, the algorithm's main property does not apply for out-of-sample model selection problems (Gluzmann and Panigo, 2015). We include this procedure as part of our results for comparison as it has been used before in the residential literature (see Davidson et al, 2015).

Table 7 contains the results obtained by each procedure. Since the main goal is to build a model that is good for prediction, as it is usually the case, we report only the variables selected by each method, and provide no coefficients or p-values. The most important question to consider is which model performed better for out-of-sample prediction. The bottom part of the table reports the in-sample (training sample) and out-of-sample (validation sample) prediction performance from the three lasso methods. We focus on using the out-of-sample mean squared error (MSE) and deviance as measures of predictive ability for the linear and nonlinear models, respectively. For the linear models, we use the post-selection coefficient estimates to calculate goodness of fit, while for the logit models we use the penalized coefficient estimates.[18]

As shown in the table, the three lasso methods produce very similar out-of-sample MSE and deviance values. The linear models exhibit differences in MSE until the fourth decimal place, while nonlinear models exhibit differences in deviance until the second decimal place. Regardless of the model used, the adaptive lasso has the highest out-of-sample MSE and deviance, and therefore performs the worst, whereas the elastic net, with the lowest MSE and deviance, performs the best.

Among the linear models, the elastic net selects the greatest number of variables, 20 in total. CV lasso selects a subset of these variables (18 variables) and adaptive lasso selects a subset of this subset (14 variables). It is not surprising that the elastic net picks more variables than the CV lasso since some of the variables are redundant and therefore highly correlated.[19] For instance, the elastic net selected the variables operating on weekends, operating Monday-Friday, and operating Monday-Sunday, while CV lasso selected only the first one. It is also expected that the adaptive lasso will select a subset of the CV lasso variables because it applies a second step CV lasso, thus removing more variables. A similar pattern is observed for the nonlinear model. The elastic net selects the largest number of

[18]The post-selection coefficients are estimated by taking the covariates selected by lasso and reestimating the coefficients using an unpenalized estimator (e.g., OLS or logistic regression). The penalized coefficients are those estimated by lasso with shrinkage. In linear models, post-selection coefficients are theoretically better for prediction than the penalized coefficients in most cases (Belloni and Chernozhukov, 2013; Belloni et al.,2012). However, there are no theoretical grounds for using them with non-linear models. Therefore, we use the penalized coefficients in the logit models. Nevertheless, our main results remain unchanged if we use the post-selection coefficients.

[19]The elastic net combines ridge regression and lasso. When variables are highly correlated with each other, the lasso penalty will drop many of these correlated variables, while the ridge penalty will shrink the coefficients of correlated variables toward each other (Cameron and Trivedi, 2022).

variables, CV lasso selects a subset of these variables, and the adaptive lasso selects a subset of this subset. In this case, however, the elastic net selects a much larger number of variables, a total of 28.

The last column in Table 7 reports the best subset of variables according to the leaps and bounds method based on the AIC criterion. This method selects 15 variables, and with the exception of two variables (micro enterprise and A/C used regularly), these variables overlap with those selected by the other three methods that employ a linear model.

Interestingly, the four procedures tend to select at least one variable from each of our main categories: firm characteristics, building characteristics, heating system, stock of electrical equipment, and from our set of behavioral variables and variables related to attitudes. That is, there is no single category of variables that dominates the selection, indicating that the decision to adopt a PV system is more complex since multiple aspects of the business must be considered.

Finally, while the group of variables as a whole is what matters for prediction, it is worth noting that most of the variables selected by the data-driven methods are consistent with those chosen based on the literature in the previous section to study the determinants of PV adoption. This overlap provides us with further confidence in our results regarding these determinants. In particular, building ownership status, operating also on weekends, operating in the trade sector, and the presence of electric heating systems, televisions, voltage regulators/stabilizers, and solar water heaters are variables that are selected by machine learning methods and which, as indicated in the previous subsection, have a significant and positive effect on PV adoption.

Table 7: Best Predictors of PV Adoption

	Cross-Validation		Adaptive Lasso		Elastic Net		Leaps &
	Logit	Linear	Logit	Linear	Logit	Linear	Bounds
Non-residential tariff					x		
# of employees (log)					x		
Micro enterprise					x		x
Small enterprise	x	x	x	x	x	x	x
Ownership	x	x	x	x	x	x	x
Retail trade	x	x	x	x	x	x	x
Operating on weekends	x	x	x	x	x	x	
Operating Monday-Friday					x	x	
Operating Monday-Sunday					x	x	x
Roof insulation	x	x		x	x	x	x
Window insulation					x		
Electric heating	x	x	x	x	x	x	x
Heating system					x		
Motion sensor lights	x	x			x	x	
Motion sensor lights (indoors)	x	x	x	x	x	x	x
Electric generator					x		
Voltage regulator/stabilizer	x	x	x	x	x	x	x
Fan	x	x	x	x	x	x	x
Televisions	x	x	x	x	x	x	x
Water pump	x	x	x	x	x	x	
Gasoline/diesel usage	x	x			x	x	
Awareness of consumption (kWh)					x		
Awareness of consumption ($)	x	x			x	x	
A/C used regularly					x		x
Solar water heater	x	x	x	x	x	x	x
Clean energy is easy to buy	x	x		x	x	x	x
PV: energy-saving solution		x			x	x	x
Constant	x	x	x	x	x	x	
# Variables	17	18	12	14	28	20	15
Training sample (75%)							
Deviance	0.4198		0.4011		0.4172		
Deviance ratio (D^2)	0.146		0.178		0.152		
MSE		0.0552		0.0554		0.0551	
R-squared		0.117		0.113		0.118	
Obs.	582	582	588	582	582	582	
Validation sample (25%)							
Deviance	0.5909		0.5930		0.5842		
Deviance ratio (D^2)	0.104		0.100		0.114		
MSE		0.0805		0.0809		0.0802	
R-squared		0.121		0.117		0.125	
Obs.	196	196	196	196	196	196	

The table reports the variables selected by CV lasso, adaptive lasso, elastic net, and the leaps-and-bounds algorithm based on the AIC criterion. For the first three procedures, the sample was randomly split in training and validation samples (75% and 25%, respectively) and the table reports the goodness of fit on these samples. Source: ENCENRE-2019.

4.3 Investment Costs and Profitability of Solar Adoption

Using data on installation and maintenance costs, billing data, electricity rates, and the estimated annual solar PV generation capacity (required to meet each firm energy consumption), we identify the number of non-adopting businesses that would profit from having installed solar PV systems. For this purpose, we compute three complementary measures of profitability: the Net Present Value (NPV), the Internal Rate of Return (IRR), and the (undiscounted) Payback Period (PP).[20] We assume a discount rate of 10% and a lifespan of 25 years for all Solar PV systems. Details regarding the simulation used for this exercise can be found in Appendix A.

Table 8 shows the distribution of potential adopters by tariff category. The businesses that should adopt are those with a positive NPV. First, it would be unprofitable for a business to invest in solar panels under the highly subsidized residential tariff 01. Due to the very low price of electricity purchased from the electric utility, investing in solar panels does not result in a positive return on investment. In contrast, distributed photovoltaic systems are ideal for businesses with high residential consumption rates (DAC).[21] Second, for the remaining tariffs –i.e., the proper commercial tariffs: PDBT, GDMTO, and GDMTH– the vast majority of business establishments would benefit from solar panel adoption. Overall, our calculations indicate that 87.1% of the businesses have a positive net present value, and therefore would benefit from the installation of a PV system. We would like to point out that our simulations do not take into account the feasibility of the installation or the amount of space available on the rooftop to support the panels. The results presented here are therefore an upper bound of the adoption potential of this technology.

[20] NPV is defined as the difference between the present value of cash inflows and the present value of cash outflows over a period of time, in our exercise 25 years –i.e., the assumed lifetime of a solar PV system. The IRR is the discount rate that makes the NPV of all cash flows equal to zero. The PP is the amount of time it takes to recover the cost of an investment, or simply the length of time an investment reaches a break-even point, without considering the time value of money.

$$NPV = \sum_{t=0}^{25} \frac{C_t}{(1+r)^t}$$

where C_t is the cash flow of year t and r is the discount rate.

[21] These findings are similar to those reported by Hancevic et al. (2022) who examined households under tariffs 01 and DAC in several states of Mexico.

Table 8: Non-adopters: Potential Adopters by Tariff Categories

Tariff category		Should adopt PV system? No	Yes	Total
Residential tariffs:	01	61	0	61
	DAC	0	15	15
Business tariffs:	PDBT	11	524	535
	GDMTO	20	66	86
	GDMTH	0	18	18
	Total	92	623	715
		12.9%	87.1%	100%

The table reports the number of non-adopters with positive net present values by electricity tariff category. Source: Own calculations using ENCENRE-2019 and CFE billing data.

Table 9 reports summary statistics of the three profitability measures for those non-adopters with positive net present values (87.1% of all non-adopters). Our calculations show that the average internal rate of return is 15.8% and the average payback period is 6.5 years. Notably, for the latter, the number of years ranges between one and ten. As mentioned earlier, the average lifespan of a company in Aguascalientes is approximately 8.2 years before the company is bought, acquired or liquidated, and only 14.7% of them reach 20 years operating. Given that solar PV systems have a life-span of approximately 25 years, but only a small fraction of businesses will survive that long, firms may be reluctant to invest in this technology.

Table 9: Profitability Measures for Non-adopting Establishments

	Mean	Std. Dev.	Min	Max
Net present value ($)	109,157	158,511	709	1,681,353
Internal rate of return (%)	15.8%	5.4%	8.8%	80.5%
Gross Payback Period (years)	6.5	1.3	1.2	10.0

The table reports some potential profitability measures for those non-adopters with positive net present values (87.1% of all non-adopters). Source: Own calculations using ENCENRE-2019 and CFE billing data.

4.4 Reasons for not Adopting Solar Panels

From the group of 725 non-adopters, only 131 firms (18.1%) reported that they planned to install solar panels within the next year at the time they responded to the survey. Since we are able to follow the subsequent energy consumption of the firms in our sample up to one year later after the survey was conducted, and since it is explicitly marked in the energy bills whether or not they have or have not installed a solar PV system, we are able to identify which firms succeeded in putting solar panels in place within the next 12 months. Out of 131 firms planning to install a PV system, only 13 (9.9%) did, while 12 out of 593 (2%) that did not plan to install ended up adopting a PV system.

Considering the non-adopters who are *not planning on investing* in solar panels within the next 12 months. Table 10 presents the main reasons for not adopting. As observed in the main regression results (see Table 6), ownership increases the likelihood of a firm having solar panels installed, but it is also indicative of potential adoption. The fact that premises are rented or borrowed is the main reason for not adopting (33.8%). It is understandable that non-owners are reluctant to make a sunk investment in a property that does not belong to them, unless some contractual advantages are conceded in the corresponding rental agreements. The second reason for not installing PV systems is the insufficient information about the price, installation, operation and maintenance, the procedures to request the connection to the grid, etc., so as to make an informed investment decision (14.2%). This is indicative that there is a significant percentage of firms that might not consider investing in solar panels simply because they do not know whether it is a viable option to cut on electricity spending. Resource and financial constraints are also relevant (12.3%) and a similar percentage of users still think they do not need a solar panel system (12.3%). Other users highlight that the equipment, installation, and/or maintenance are very expensive (9.3%). And a small number of businesses consider solar panels cannot be purchased nearby (1.2%).

Table 10: Non-adopters: Main Reasons for not Installing Solar Panels within the Next 12 Months.

Reasons	Freq.	Percent
The premises are rented or borrowed	200	33.8%
Insufficient information about price, installation, and operation	84	14.2%
Lacks financial resources or access to financing	73	12.3%
Solar panels are not required	73	12.3%
The equipment, installation, and/or maintenance are very expensive	55	9.3%
Solar panels cannot be purchased nearby	7	1.2%
Other reasons	43	7.3%
Does not know / No response	58	9.8%
Total	593	100.0%

The table reports the main reasons given by non-adopters for not installing solar panels. The sample consists of 593 establishments that did not have a PV system installed and did not intend to install one within the next year. Source: ENCENRE-2019.

To put our results into context, Palm (2018) explores the barriers to and enablers of residential solar PV adoption in Sweden in 2008-2009 and 2014-2016. During the period 2008-2009, most users invested in solar panels for environmental reasons, whereas economic considerations, such as profitability, became more important during the period 2014-2016. The financial cost, however, has been a persistent barrier over both periods examined. Additionally, the steadily declining prices of solar panels, together with the adoption subsidies, have facilitated adoption in Sweden. Reindl & Palm (2021) analyze the responses of a sample of non-residential property owners. Main reasons for not adopting include: economic barriers, taxation, insufficient subsidies, regulatory barriers, administrative/organizational barriers, design barriers, maintenance barriers, and building construction barriers. As a second group of reasons that are mentioned moderately often, the authors identify: information/knowledge barriers, technological barriers, security and insurance, lack of electricity storage, and tenants' electricity supply contracts.

In line with these studies, the reasons cited by SMEs in Aguascalientes are more concerned with economic profitability and financing, as well as with lack of information. Among the sampled businesses, environmental issues do not appear to be as prevalent. The comparative benefit of our study is that we interviewed both owners and non-owners of the commercial facilities, which provided a broader understanding of the real situation of small and medium-sized businesses in Mexico.

5 Potential Environmental Impacts

The purpose of this section is to quantify the environmental impact of solar panels. This is done by estimating the savings in electricity consumption coming from the network as well as the reduction in associated emissions. Then, the observed savings are compared with the potential savings that would occur if all companies for which adopting solar panels is profitable did so. Additionally, we calculate the savings in monetary terms, using current electricity rates as well as different social marginal costs to correct existing distortions in retail pricing. From a social perspective, the marginal price paid by electricity users may be well below or above the social marginal cost and different factors contribute to these distortions. Distribution and commercialization segments of the market offer economies of scale. In addition, time-invariant regulated tariffs do not match production costs. Also, electricity tariffs do not fully account for the externality costs of air pollution during the generation process. Each of these aspects of electricity pricing works in a different direction and can sometimes even offset one another. The social marginal cost of electricity in this paper is based on a similar approach to Borenstein and Bushnell (2022) and Hancevic and Sandoval (2022), in that the social marginal cost includes three main components: the private marginal cost of electricity (nodal prices), the externality cost associated with air pollution, and the distribution and commercialization costs.[22]

In Table 11, line 1, we show the annual reduction in tons of CO_2 equivalent emissions and in percentage of total emissions of the sampled firms. Column (I) presents the reduction attributed to observed adopters. Columns (II) to (IV) also include potential adopters – i.e., those non-adopting firms that would profited from investing in solar panels. Specifically, column (II) considers the profitable adoption under the current tariff scheme, whereas column (III) and (IV) consider the social costs of electricity incorporating a carbon tax of 50 and 100 USD per tCO_2e, respectively. On line 2 of table 11, we show the associated cost savings in monetary terms. In particular, columns (III) and (IV) which compute the social cost savings consider the local marginal prices (i.e., nodal prices), the distribution costs, and the externality cost of emissions.

Table 11: Environmental impact and social cost savings

		Adopters plus Potential Adopters		
	Adopters (I)	Current tariffs (II)	50 USD/tCO_2e (III)	100 USD/tCO_2e (IV)
1. Emissions reduction				
tCO_2e/year	824.3	5,477.3	4,101.0	6,746.3
% of total emissions of firms in the sample	11.9%	79.1%	59.4%	97.7%
2. Monetary savings				
Mexican Pesos/year	5,151,175	45,450,949	29,070,462	54,817,691

This table shows the environmental impact of solar panel adoption in terms of emissions reduction and monetary (private and social) cost savings. Scenario I includes only observed adopters; II includes adopters plus potential adopters under the current tariff scheme; III includes adopters plus potential adopters using social costs that correct for externalities, including a carbon tax of 50 USD per tCO_2e; and IV is similar to III but including a carbon tax of 100 USD per tCO_2e. Source: own elaboration using CENACE Nodal Prices, CFE tariffs and billing data, and the ENCENRE-2019.

The current adoption of solar PV systems accounts for a reduction of approximately 12% of total emissions in our sampled firms. When the potential adopters are also included, the emission savings could reach 79% under the current tariff scheme, and between 59% and 98% when prices reflect the social marginal cost of electricity. Social savings in monetary terms account for approximately 5 million pesos per year (column I). Once again, columns (II)-(IV) consider the potential adopters as well. Under the current tariff scheme, the private savings

[22] The nodal prices are available at the National Center for Energy Control (CENACE) https://www.cenace.gob.mx/Paginas/SIM/Reportes/PreEnerServConMTR.aspx.

could reach more than 45 million pesos per year, whereas the social cost savings could be between 29 and 55 million pesos per year. As shown in Table 1, our sample is representative of the commercial and service SME sector at the country level. Therefore, controlling for climatic differences and some regional particularities, the results presented here could be easily extrapolated to the rest of the country.

6 Conclusions and Policy Implications

Since the cost of solar PV installations has steadily declined over the last fifteen years, distributed solar generation has become a more attractive and reliable alternative. Despite this, solar PV generation only accounts for 3.7% of the total energy consumed worldwide in 2020. The use of solar PV has the potential to facilitate the transition to renewable energy, reduce greenhouse gas emissions, and mitigate climate change; therefore, it is important to understand the factors that influence residential and non-residential adoption. However, the empirical evidence is lacking, particularly for the non-residential sector and even more so in the context of developing countries. In this paper, we fill this gap by using business level data from a novel survey (ENCENRE-2019) to study solar PV adoption in the context of small and medium-sized businesses in Mexico, an emerging economy.

We found that businesses operating on weekends, operating within the trade sector, owning the facilities where the business operates, having a durable roof, and having electric heating systems and voltage regulators/stabilizers are likely to install a PV system. In addition, businesses with solar water heaters, which indicate a preference and familiarity with solar technology, and businesses with positive attitudes toward renewable energy are also more likely to adopt solar PV systems. Interestingly, most of these characteristics are also considered the best predictors of solar adoption when using different machine learning methods for variable selection. Additionally, our results indicate that the vast majority of businesses without solar panels in our sample (87%) could benefit from installing them and can expect to recoup the investment in 6.5 years on average. Moreover, we also found that among non-adopters, the three major reasons for not installing solar panels were, first, the lack of ownership of the facilities, second, insufficient information regarding the price, the installation and maintenance, and process of requesting a grid connection, and third, the lack of financial resources or access to financing. Lastly, our findings indicate that the current adoption of solar PV systems results in a reduction of approximately 12% of total emissions in the sampled firms. When potential adopters are also taken into account, emission savings reach 79% under current tariffs, and between 59% and 98% when prices reflect social marginal costs.

There are several policy implications that can be drawn from our results. Most public policies that seek to accelerate the adoption of solar panels combine financial incentives and accessible credit lines, such as rebates, sales tax exemptions, and loan programs with interest rates below the market. Some of these policies aim to reduce the upfront installation cost, however, our findings indicate that the most important factor in preventing businesses from adopting solar PV is ownership of the building in which the business operates. Renting makes it difficult to adopt new technologies because it is more challenging to allocate the benefits and costs between tenants and landlords. Therefore, policies that mitigate this split incentive problem, such as minimum standards on new rental units or realigning the incentives in lease documents, can lead to a greater adoption of solar panels. Moreover, our results show that the second main reason for non-adoption is the lack of information about the price, installation costs, operation and maintenance details of solar panels. Hence, information campaigns that both raise awareness about the benefits of solar PV systems but also provide this information could also be helpful in promoting their adoption. In addition, our results confirm that subsidized financing, tax incentives, and other factors that directly influence the return on investment should help accelerate the growth of solar PV. Finally, given the lifespan of small businesses, policies that can assist in the establishment of a secondary market for used solar PV units may also be beneficial.

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A Solar Panel Adoption Simulation for Non-adopting Firms

We follow Hancevic et al. (2022) and adapt the methodology to run a simulation for the set of non-adopters in our sample.[23] We assume all connections to the grid are done under a net metering scheme and firms minimize the annualized cost of electricity (including the distributed PV investment cost, the PV operating and maintenance costs, and the electricity bill). The PV prices we use in the objective function are based upon information of a typical meteorological year and a standard investment cost of US$1.60 per WDC. In addition, we assume the annual operation and maintenance costs are linear and amount to US$4 per kW of installed capacity. The optimization problem for the firm i who seeks to minimize the total cost of electricity, TC_i, is

$$\begin{aligned} \min_{\{q_{i,\text{pv}};q_{i,\text{cfe}}\}} TC_i \quad &= I(q_{i,\text{pv}}) + \beta\left[C(q_{i,\text{pv}}) + T(q_{i,\text{cfe}})\right] \\ &\text{subject to} \\ &0 < \bar{q}_i \leq q_{i,\text{pv}} + q_{i,\text{cfe}} \\ &q_{i,\text{pv}} \leq q_{i,\text{pv}}^{\max} \\ &q_{i,\text{pv}}, q_{i,\text{cfe}} \geq 0 \end{aligned} \tag{3}$$

where $q_{i,\text{cfe}}$ is the electricity purchased from the grid and $q_{i,\text{pv}}$ is the quantity generated by the PV system. $T(\cdot)$ is the electricity tariff –i.e., 01, DAC, PDBT, GDMTO, or GDMTH. $I(\cdot)$ and $C(\cdot)$ are the investment cost, and the operating and maintenance costs of the solar panels, respectively.

The objective function is subject to the following two constraints: i) the sum of conventional and DPV consumption must be greater than or equal to the consumption $\bar{q}_i$, and ii) distributed PV consumption has to be less than or equal to the maximum production capacity in each business establishment, $q_{i,\text{pv}}^{\max}$.

[23] We also exclude 19 firms that are non-adopters in the ENCENRE-2019 but adopted soon after they were interviewed.

To calculate the maximum generation capacity, we simulate the performance of typical PV system and consider the system has one single orientation ($\angle 190$ azimuth and $\angle 5$ inclination), 1:1 DC-AC conversion efficiency, 1.6% inverter efficiency, and 0.5% performance degradation per year.