# Predicting Prosumers, Rebounds and (Pro-) Environmental Spillovers: The Case of Residential Photovoltaic Systems

Patrick Bigler, University of Bern, patrick.bigler@kpm.unibe.ch
Benedikt Janzen, University of Bern, benedikt.janzen@kpm.unibe.ch

## Overview

Electricity accounts for roughly 18% of global total energy usage and still, nowadays, almost 2 out of 3 kWh are produced from fossil sources. Switzerland's share of electricity in total energy usage is higher with 25%, while the carbon intensity is much lower at around 5%. With growing demand from other economic sectors such as transport, electricity usage is bound to increase further in the coming years. Distributed energy is regarded as an important contributor to increasing renewable electricity's production share. Even though photovoltaic instalations (PV) are increasing, the deviance between actual production and potential is still large, as the Swiss federal institute of energy estimates PV potential to be 40 times higher than actual production in 2019.

Private household's PV adoption and the state's role in promoting this technology has been a topic of increasing academic relevance. In the beginning, most empirical papers have mainly focused on the identification of factors driving the adoption (i.e. Kwan, 2012 or Rai et al., 2016). Another central part of the policy discussion concerning renewable, more efficient electricity production is related to so-called rebound effects. Specifically, in the context of solar panels, if solar users' electricity consumption is unaffected by their decision to install residential photovoltaic systems, any PV generated electricity should reduce conventional electricity generation 1:1. A growing number of empirical studies analyzes the impact of residential PV adoption on domestic electricity consumption in Australia (e.g. La Nauze, 2019), the United States (e.g., Qiu et al., 2019) as well as in European countries (i.e. Frondel et al., 2020). Estimates of solar rebound effects are fairly consistent across studies and range between 15%-21%.

We add to this literature in multiple ways. First, most of the literature has focused on either aggregate data and/or survey data. In this paper, we rely on detailed household-level panel data to investigate solar panel adoption patterns. Second, we apply state-of-the-art machine learning techniques to analyze the adoption patterns of solar modules, which allows us to prevent overfitting and compare out-of sample predictive power. Third, to our knowledge we are the first to estimate the solar rebound effect for Switzerland.

Furthermore, we also consider the impact of residential solar panel adoption on peers' environmental behavior. The causal influence of social norms on energy consumption behavior has been found to exist (Allcott, 2011). In this paper, we draw on a salient piece of information, namely the presence of solar panels on neighboring roofs, to investigate peer effects in environmental contributions. The presence of solar panels on neighboring roofs can enact bahvior through multiple channels. It could make climate change more visible thus enacting pro-environmental behavior. However, it could also signal readily availability of electricity and thus enacting higher consumption. A broad literature body documents the role of social influence in the diffusion of solar panels (e.g., Bollinger & Gillingham, 2012), however, surprisingly little research has been carried out on potential PV adoption social spillovers on other environmental behavior (Wolske, 2020). The research closest to our work is La Nauze (2021), who investigates how installing solar panels affect neighbors' purchases of green power. This paper provides further evidence on the impact of residential solar panel adoption on peers' environmental behaviour.

## Methods

We use a high-resolution panel data set of 165,000 individual households in the canton of Bern, Switzerland spanning from 2008 to 2017. The data set has only been previously employed by Feger et al. (2021) to infer tariff and subsidy designs for policymakers to incentivize solar panel adoption. We combine electricity consumption and price as well as information on PV installation from energy utilities with socio-demographic information from tax fillings. Moreover, we add information on buildings, weather data as well as estimated PV potential. For PV owners, utilities provide us additionally with feed-in electricity data ($ef_t$). Since PV owners not only consume grid electricity at time t ($eg_t$), but also self-consume part of their PV electricity ($es_t$). The information on $ef_t$ is crucial to estimate rebound effects, as otherwise consumption of solar household's would be underestimated. The annual solar production is estimated based on radiation data, panel size and efficiency.

We proceed in three steps: It is likely that a households' decision to adopt a solar panel and its electricity consumption level are related. To overcome this potential source of treatment assignment bias we adopt a matching approach. For each PV household, we match a similar household who has not installed a solar panel. To estimate adoption probabilities we use our extensive micro-data and apply state-of-the-art machine learning techniques such as penalized logistic regression. The estimated propensity scores are used in a radius matching algorithm to match a suitable control for every solar household.

Next we follow Qiu et al. (2019) and examine the causal impact of solar electricity generation on households` own electricity consumption by estimating the following equation for our matched sample:

$$ec_{it} = \partial ep_{it} + p_t + HDD_{it} + CDD_{it} + \mu_{it} + \epsilon_{it},$$

where the dependent variable $ec_{it}$ measures electricity consumption of household i in year t, $ep_{it}$ is solar electricity production of household i in year t, and $\mu_{it}$ are household-year fixed effects that control for time-variant unobservables. HDD and CDD control for weather related electricity consumption (heating and cooling). Therefore the coefficient of interest $\partial$ measures the potential solar rebound effect.

In a third step, we are interested in potential spillover effects from adopting a solar panel. In particular, we are interested whether the adoption decision of neighbors impacts a households' willingness to take private environmentally friendly actions. To do so we estimate fixed effects regression of PV presence in the neighbourhood on electricity consumption, propensity to purchase green electricity and propensity to install a PV.

## Results

We present pre-eliminary results of our machine learning application in the following. Our models' predictive performance is evaluated based on sensitivity, specificity, precision, and false positive rate. Comparing the machine learning approaches to a baseline logistic regression shows that all models perform comparably well in terms of specificity. Lasso estimates outperform Ridge and convential logistic regression in terms of false positive rate and precision, while logistic regression is superior in truly predicting adopters. This implies that the Lasso model predicts a positive outcome too seldom, but if it does it is remarkably precise and almost exclusively right.

Results for the solar rebound and potential environmental spillover effects will be available by the conference's time.

## Conclusions

This paper contributes to the understanding of solar panel diffusion by applying machine learning techniques to a detailed panel data set of 165,000 households in the canton of Bern, Switzerland. Although the improvement in predictive performance using machine learning techniques is marginal, policy makers can still learn something from the results as prediciting solar panel adoption is a difficult task due to its rare occurence. While it does not drastically improve predictive performance, using machine learning does help to further shape the covariates used to explain adoption and helps improving external validity by preventing overfitting.

We provide first evidence on the impact of solar panels on consumer electricity consumption behaviors in Switzerland as well as potential spillover effects to neighboring households. When evaluating the impacts of distributed solar panel adoption, ignoring rebound effects can lead to overestimation of environmental benefits. On the other hand, ignoring potential spillover effects (e.g., positive effect on individual mitigation actions) might lead to underestimation of environmental benefits. Therefore, from the perspective of the policy maker, it is important to have detailed information on behavioral effects of solar panel adoption to inform the discussion on climate change mitigation.

## References (Selection)


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