Essays in the Economics of Decarbonization

Evidence on Direct and Indirect Effects of Transportation and Solar Photovoltaic Policy in Switzerland

Patrick Bigler

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To my parents - Thank you for fostering my curiosity!

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Introduction

"The strongest governments on earth cannot clean up pollution by themselves. They must rely on each ordinary person, like you and me, on our choices, and on our will."

Chai Jing

* * *

It is scientifically undisputed that climate change is pre-dominantly caused by increased greenhouse gas emissions originating mainly in the combustion of fossil energy sources. Without immediate increased mitigation efforts, global warming will likely exceed $1.5°C$ and there remains a significant gap between trajectories and national pledges to limit warming below $2°C$ (IPCC, 2023). Globally, the main source of greenhouse gas emissions is the power generation sector, closely followed by industrial processes and transportation. There is, however, significant heterogeneity between countries and areas. For instance, in Europe, transportation and electricity production together account for around 60% of total emissions and have a comparable relative share (IEA, 2022). While many developed economies have put some policies in place to reduce future emissions, projected abatement will not be sufficient to reach targets. Sometimes the implementation of further policies was denied through the political process or met with protests. For instance, in Switzerland two recent votes on increased carbon pricing and changes in vehicle taxation did not pass a public referendum (Soguel, 2022; Swissinfo, 2022). Nevertheless, as the Chinese journalist and producer Chai Jing put it so powerfully, individual reactions to and actions supporting such policies are necessary to reach climate targets ratified in international agreements.

In the last decade, technological improvement and rapid cost decline has made renewable electricity generation and individual transport electrification both attainable and financially competitive (IRENA, 2023; Ritchie, 2021). The electrification of the transport sector, however, increases the relative importance of the power generation sector in decarbonizing global economies. The environmental impact of electric vehicles is directly linked to the environmental friendliness of the marginal electricity capacity (Gillingham et al., 2021; Holland et al., 2016). At the same time, several support measures such as feed-in tariffs, subsidy schemes or tax reductions have been employed to increase the uptake of both renewable electricity generation technologies and electric vehicles. However, as indicated above, public support for decarbonization policies is not uniform and financial resources are scarce. It is thus vital to implement policies as effectively as possible and understand the consequences of such policies on choices and actions of humans.

This dissertation illustrates both direct and indirect effects of policies supporting the uptake of electric vehicles and solar photovoltaic systems. Its primary objective is to demonstrate how policy evaluation, guided by an understanding of human behavior, is an essential process required to most efficiently decarbonize the economy while still receiving sufficient public support. The dissertation comprises three distinct research papers, each employing data from the Swiss canton of Bern. However, I also aim to illustrate the generalization and wider applicability of the results. The first paper presented in chapter 2 focuses on the individual uptake of electric vehicles and its interplay with supporting policy measures both from an environmental and a distributional point of view. The second and third paper illustrate direct and indirect effects of increased solar photovoltaic diffusion on both neighboring households' energy behavior (chapter 1) and the household's own electricity consumption (chapter 3). In the following paragraphs, I provide a short overview of each paper's content and findings.

In the first paper 'Environmental, Redistributive and Revenue Effects of Policies Promoting Fuel Efficient and Electric Vehicles', co-authored with Doina Radulescu, we study determinants of vehicle purchases and the impact of policies promoting fuel-efficiency. Switzerland, like many developed countries, supports the uptake of fuel-efficient vehicles through vehicle tax reductions, fuel taxation and, in some cases, upfront price subsidies. Most public revenue generated through the taxation of transport activities is stipulated as a benefits tax with the goal to finance road infrastructure. Increases in fuel-efficiency in general, and replacement of internal combustion vehicles through electric vehicles in particular, lead to the erosion of infrastructure investment funds. Additionally, implementation of support policies, such as electric vehicle subsidies, require additional public spending. We account for these public budget implications while also looking at consumer surplus and environmental outcomes, as well as distributional concerns in simulating potential policy alternatives. Our results document that households react more strongly to policy measures that incentivize fuel-efficiency in the form of upfront price subsidies than through vehicle taxation. We then proceed to study optimal policy combinations of rebate and penalty schemes on vehicle taxes, as well as upfront price subsidies with three simultaneous policy goals: reach a certain share of electric vehicle registrations while keeping (wealth-weighted) consumer surplus changes and public budget at similar levels. We illustrate a politically feasible pathway for policymakers to more efficiently organize public outlays to support the uptake of fuel-efficient vehicles and generate environmental benefits without decreasing consumer welfare and accounting for distributional concerns.

The second chapter, 'Green Spills: Peer Effects of Solar Photovoltaic Adoption on Energy Behaviors' illustrates indirect effects of increased solar photovoltaic diffusion. My co-author, Benedikt Janzen, and I study if households become more 'green' after their neighbor(s) install a solar photovoltaic system. We theorize that a household's increased contributions to climate change mitigation results from social norm based conditional cooperation: following the observation of their peers' increased efforts, signaled through the installation of solar photovoltaic systems, we expect neighbors to adopt more environmentally-friendly behaviors. We show that agents adjust their energy behavior in different ways and based on their specific constraints. They are, on average, reducing their electricity consumption and increasing their own adoption of environmentally-friendly technologies, such as electric vehicles and solar photovoltaic. Electricity conservation efforts are stronger for households living in dwellings with relatively poor solar photovoltaic potential, while households with relatively higher potential are more likely to act through the purchase of durable goods. Peer effects are generally stronger for households with higher income status, living outside the city center and owning their home. Accounting for these indirect effects significantly improves the cost-benefit calculation of solar photovoltaic subsidies.

The third chapter, 'Extent and Anatomy of the Solar Photovoltaic Rebound: Evidence from Swiss Households' focuses on changes in electricity consumption of households after installing a solar photovoltaic system. I study the behavioral change induced through the role change from electricity consumer to electricity producer and consumer, a 'prosumer'. Owners of solar photovoltaic installations receive financial remuneration for excess electricity that they did not consume themselves and thus fed into the electricity grid. However, this return is generally lower than electricity prices, and thus locally produced solar photovoltaic electricity decreases both their marginal and average costs of electricity consumption, which could cause increased consumption levels. I provide first evidence for a solar photovoltaic rebound effect in Switzerland, which is at comparable levels to other European countries, but decompose this effect into different parts. My results illustrate that parts of the rebound effect are driven by the co-adoption of electricity-intensive durable goods, such as electric vehicles, and thus the additional electricity consumption induced by the solar photovoltaic installation is (partially) an energy substitution and not an expansion. This result has important implications for both the evaluation of solar photovoltaic support measures, as well as the planning and forecast of future electricity load requirements.

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Chapter 1

Environmental, Redistributive and Revenue Effects of Policies Promoting Fuel Efficient and Electric Vehicles

Patrick Bigler Doina Radulescu

Abstract

We analyze welfare implications of policies promoting environmentally-friendly vehicles, employing rich, Swiss micro-data on 23,000 newly purchased cars and their buyers, and random coefficients choice models. We compute price elasticities and car adoption probabilities across wealth quartiles. Using our estimated random coefficient logit parameters, we compute optimal combinations of subsidies and vehicle tax 'feebate' schemes that safeguard road infrastructure financing, while both meeting a pre-specified electric vehicle share, and taking equity considerations into account. In our setting, CO_2 emissions of the new car fleet can be substantially decreased without jeopardizing road infrastructure revenue, if the social planner switches from the current regime to a policy mix of upfront price subsidies coupled with additional vehicle tax penalties on fuel inefficient vehicles.

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1.1. Introduction

According to the International Energy Agency (IEA), the transport sector accounted for 21% of global CO_2 emissions in 2021, representing an increase of 32.5% since 2000. At the same time, nearly three-quarters or 3.5 Gt CO_2 of road related transport emissions can be attributed to cars and vans (IEA, 2022). To achieve a significant decarbonization of the road transport sector, the IEA forecasts that electric vehicle (EV) sales need to represent 60% of global car sales by 2030 (from 5% in 2020). The European Union also aims to have an 80% share of EVs in 2050. To achieve these targets, measures to promote energy efficient technologies for vehicles and the fuels that drive them will need to be deployed. Policymakers have designed ambitious policies to combat emissions in the car sector. These policies should be assessed, however, not only with regards to their impact on environmental outcomes, but also with respect to their potential redistributive implications, which requires an in-depth analysis of policy effects on vehicle choices across socioeconomic groups (e.g. Durrmeyer (2021)).

In this paper, we estimate a stylized car choice model and address the welfare implications of various counterfactual policy scenarios overall and for different population groups. In many countries, revenue raised from fuel and motor vehicle taxation is used to fund road transport infrastructure. EVs, and more fuel efficient cars in general, are subject to preferential tax and tariff treatment. Although this policy is meant to incentivize fuel-efficiency, it also raises equity and public budget concerns. Widespread adoption of fuel-efficient cars, although desirable from an environmental perspective, may come at the cost of lower revenues to finance road infrastructure (Davis and Sallee, 2020). At the same time, generous support mechanisms, such as upfront price subsidies, require even more public spending. It is thus important that a comprehensive welfare analysis accounts for additional dimensions beyond the change in consumer surplus, namely impacts on public finances and effects on emissions. Accounting for impacts along the wealth distribution allows us to address potential equity concerns. We first analyze the effects of two instruments: a 'feebate' on annual vehicle registration taxes that combines rebates for environmentally friendly cars with additional fees for inefficient vehicles, and an upfront price subsidy for EVs. In a second step, we compute the optimal subsidy-'feebate' combination from a social planner perspective under different constraints.

To conduct our counterfactual exercises, we first estimate a discrete choice model with a control function approach, following Petrin and Train (2010), in order to estimate households' preferences for new vehicles in the Swiss canton of Bern, observing all private new car purchases from January 2017 to June 2019. The perfect match between household and car ownership micro-data allows us to account for a large number of car- as well as household-specific attributes. In addition to unobserved heterogeneity through random coefficients, we can also control for observed heterogeneity in the valuation of certain car-specific characteristics. We estimate average own-price elasticities of around 2.46 and find heterogeneity in different wealth groups' price sensitivity, with an estimated average elasticity of 2.56 (2.47) for households in the lowest (highest) wealth quartile. Agents slightly undervalue future variable costs in comparison to upfront prices. Moreover, poorer households are less likely to adopt EVs, and this is only partially explained by observables such as budget constraints, public and private charging availability and driving heterogeneity; while a household in the lowest wealth group has a 0.5% probability to purchase an EV, agents in the highest income quartile are almost 3 percentage points - or 6 times - more likely to do so.

Our policy experiments reveal that the introduction of additional penalties on the annual vehicle tax for relatively 'dirty' vehicles, in addition to the already existing rebates for efficient cars, is regressive and only leads to small emission reductions. While EV price subsidies lead to a significant increase in EV uptake, they have distributional implications, as the majority of subsidy payments go to higher-income households. Additionally, the negative impact of EV subsidies on public budget is greater than their benefits in terms of consumer surplus and the social value of carbon emission reductions. We address this trade-off in our final counterfactual exercise. We take the perspective of a social planner seeking the optimal policy mix of vehicle tax 'feebate' schedules and EV subsidies, which minimizes shortfalls in public revenue while achieving a pre-defined EV market share, and maintains or even increases consumer welfare. Our results show that a combination of relatively high subsidies (CHF 7,200)[1] and a vehicle tax schedule featuring low tax rebates for environmentally friendly vehicles and no additional fees for inefficient vehicles attains balanced consumer welfare, increased EV uptake and simultaneously requires only small additional public outlays. If, for the sake of equity, the social planner places a greater weight on the utility of lower wealth households, the optimal subsidy is lower and the adjustments in tax scheme are more pronounced, with lower annual vehicle tax rates for relatively efficient vehicles, and additional annual fees on relatively inefficient vehicles. Results are similar if we allow households to adjust their annual mileage consumption based on higher annual operating costs. However, in this case, the additional fees on vehicle taxes for fuel inefficient cars are also levied if the social planer does not cater to equity concerns. This optimal policy mix illustrates two major points: both subsidies and tax rebates lead to lower public revenue, but upfront subsidies have stronger effects on the electrification of the new car fleet and thus on the reduction of emissions. Furthermore, transport policy leads to a more substantial emission reduction if households adjust their mileage consumption. Our optimal policy mix leads to substantial increases of 41-46% in the EV share with relatively small additional public outlays of CHF 1.5 to 1.7 million, expenses which are partially self-financed through higher annual vehicle taxes on relatively less efficient, newly registered cars. While this illustrates how policymakers can substantially increase EV uptake at little to no additional costs, it highlights potential concerns about road transport policy's distributional impacts: despite our optimal policy mix catering to equity concerns, a substantially higher share of EV subsidies is paid to the wealthiest (48%) as compared to the least wealthy (9%) households. Nevertheless, this difference is substantially lower in our setting than estimated numbers for the US (Borenstein and Davis, 2016).

Related literature includes papers focusing on the demand estimation of the car market in general (e.g. Berry et al. (1995)) and agents' preferences for EVs and hybrid vehicles (HVs) in particular (Xing et al., 2021). Our work is methodologically closely related to Huse and Koptyug (2022). A few recent studies question whether an energy paradox in the valuation of future expected fuel or variable costs exists, and find only slight undervaluation in Europe (Grigolon et al., 2018), and substantial consumer myopia in a quasi-experimental setting using US data (Gillingham, Houde, et al., 2021). Similarly, Huse and Koptyug (2022) find that both future fuel costs and vehicle taxes are undervalued in comparison to upfront costs, with vehicle taxes representing the

[1] 100 CHF ≈ 100 USD in our time frame

stronger undervaluation and the salience of rebates to vehicle taxes being postulated as the likely explanation for this discrepancy. Other empirical work on this topic shows mild to moderate undervaluation, if any at all (e.g. Allcott and Wozny (2014)).

A broader literature base has focused on the impact of government policies, such as subsidies, tax credits, fuel taxes and emission standards, on the car market and emission abatement (e.g. d'Haultfoeuille et al. (2014) and Li et al. (2013)), as well as the specific market outcomes of policies promoting fuel efficient vehicles. Most studies find that government interventions support the uptake of more fuel-efficient vehicles, albeit at relatively high costs. Muehlegger and Rapson (2023), for example, estimate the costs of legislating California's 2025 EV adoption goals to be USD 12-18 billion. Other studies highlight potential consumer windfall gains from subsidies and tax credits, as these may promote vehicle purchases by households that already intended to buy an environmentally friendly vehicle (Xing et al., 2021). Closely related is the analysis of the distributional impact of fossil fuel taxes and vehicle subsidies (e.g. Bento et al. (2009)). Most papers find that subsidies are completely passed through to consumers but redistribute between income groups. Borenstein and Davis (2016) find that 90% of vehicle income tax credits were granted to the highest income quintile, whereas Durrmeyer (2021) finds that middle-income households benefit the most from the French 'feebate' policy.

We contribute to and expand on this literature in the following way: first, we estimate optimal combinations of two relatively prominent policies promoting fuel efficient vehicles while taking into account the trade-off between road infrastructure finances and environmental targets in the new vehicle market. We find that a combination of vehicle tax 'feebate' schemes and EV upfront price subsidies achieves substantially higher EV adoption rates at relatively low additional costs and net-positive aggregate consumer surplus. This illustrates that the currently employed policy mix is not efficient and the same environmental outcome could be achieved at lower costs. Our detailed data allows us to compute an optimal policy mix in the presence of equity concerns, wherein the government places a greater welfare weight on the utility of low wealth households, addressing potential environmental justice concerns at a relatively early stage of EV market penetration.[2] Second, we estimate preferences for fuel-efficient, especially battery electric vehicles, on a micro level and thus further illustrate potential adoption barriers and preference distributions for particular vehicles. We show that poorer households are substantially less likely to purchase EVs, a finding that can only partially be attributed to observables such as lower availability of private charging (moderated by lower home ownership rates and lower photovoltaic diffusion among less wealthy households) or price sensitivity. Our result illustrates potential knowledge or preference gaps between socioeconomic groups which could be explained by financial literacy or technology awareness and sentiment. Third, we find undervaluation parameters for future variable costs at around a ratio of 0.7, which is in line with previous literature from the US and Europe, and very close to estimated parameters from Sweden (Huse and Koptyug, 2022). We are unable to disentangle myopia and salience in our effect, but survey evidence from Cerruti, Daminato, et al. (2019) suggests

[2]Although the EV market development during our time of observation is at an earlier stage, the actual registration shares are close to global averages in 2021. EV registration shares in Europe sharply increased during 2021 and 2022. This was driven by a combination of support policies and increasing product variety.

that many households are unaware of rebate incentives in vehicle taxes. This implies that introducing such vehicle tax 'feebates' should be accompanied by measures to increase public awareness.

The paper is structured as follows. Section 1.2 provides an overview of the institutional background, and in Section 1.3 we present the empirical strategy. Section 1.4 provides an overview of the data and some descriptive statistics. Section 1.5 presents the regression results and is followed by a welfare analysis in Section 1.6. Finally, Section 1.7 concludes.

1.2. Background and Institutional Setting

Our empirical analysis relies on data and information on car registrations in the Swiss canton of Bern which, with an area of 6,000 km^2, and just over 1 million inhabitants, is the second-largest canton by both area and population. Switzerland is a federal state with 26 cantons whose political responsibilities, by default, lie with the cantons, unless they were granted to the federal level. As a consequence various regional transport-related regulations exist. Taxes, levies and support schemes have two main goals; on the one hand, they should address the various driving-related externalities, such as emissions, congestion, and accident risks. On the other hand, they are designed as benefit taxes, meaning that the beneficiaries of the publicly provided infrastructure should bear the main share of its costs. This section details two policy instruments designed at the cantonal level that we analyze in our counterfactual scenarios. Further national level road transport policies are described in subsection 1.A.4.

The annually owed vehicle tax is a means to finance the local road infrastructure. In our setting the tax is a function of both the vehicle weight and emission category. Furthermore, battery electric vehicles are subject to a reduced base tax (50%). The adoption of cleaner vehicles is incentivized through tax rate reductions granted in the year of registration and the following three years. EVs get a further reduction of 60% while category A and B vehicles receive rebates of 40% and 20% respectively.[3] Vehicle owners are billed annually based on registration data and rebates are automatically granted.

Other cantons use similar measures to promote fuel-efficiency. While the baseline tax in most cantons is either a function of weight, engine size or power, some feature complete tax exemptions for EVs and higher bonuses on the annual tax payments. Some cantons also implement a malus on vehicles with relatively high emissions. This 'feebate' system is also encountered in other countries such as Sweden. Similarly, France, Singapore and New Zealand employ a 'feebate' system for the initial vehicle registration instead of the annual tax (Wappelhorst, 2023).

Even though tax rebates are quite generous, in recent years, transport sector emission targets were not met. Some regions have thus introduced additional measures and started promoting EVs with upfront purchase price subsidies. Private EV subsidies were introduced in 4 out of 26 cantons and

[3] The vehicle categories are based on relative fuel-efficiency. The regulator calculates for every car a fuel-efficiency rating measured in liters of gasoline equivalents required per 100 kilometers driven. Every vehicle is assigned to a group. The efficiency categories ranges from A to G, but we additionally define EV as separate category as they often get more preferential treatment.

reach a maximum of CHF 4,000 in the canton of Ticino. They are paid directly to consumers once they register their EV with the cantonal road traffic offices. No direct payments are made to car dealerships or vehicle importers. We simulate different combinations of these two policies in our counterfactual and optimal policy scenarios.

1.3. Empirical Analysis

We employ a unique dataset matching household-specific characteristics with detailed information on car ownership and car-specific attributes. Hence, we are not only able to infer the effect of car-specific characteristics on household utility, but we can also estimate how the valuation of these characteristics interacts with agent-specific attributes.

Starting with the seminal work of Berry et al. (1995), most empirical studies estimating automobile market demand, employ a random coefficients logit demand model (e.g., Grigolon et al. (2018)). However, due to lack of access to individual-level data, these models usually aggregate individual decisions into market shares. One of our main advantages is the extensive information on household characteristics, which allows us to control for a large number of observables. Previous research also incorporated household characteristics based on random draws from population surveys into a model with market shares. For example, the Micro-BLP model (Berry et al., 2004) employs individual-level decisions of car buyers and their reported second-choice data to improve the estimation of substitution patterns. They thereby draw on information on the population distribution of certain socioeconomic factors, such as age and income.

Because we do not observe second choices, and observe 'only' one market, we resort to a standard discrete choice model based on an aggregated choice set and individual-level socioeconomic data. We, thus, directly model a utility function and choice probabilities instead of aggregated market shares.

Utility specification - We define the conditional indirect utility of household i, purchasing vehicle type j as:

$$u_{ij} = \beta_i^x x_j + \beta^z z_i x_j + \alpha_i (p_j + \gamma(G_{ij} + T_j)) + \sum_{l=2-4} \phi_l p_j d_i^l + \varepsilon_{ij} \tag{1.1}$$

x_j is a vector of car-specific characteristics, such as engine power, height, weight and size and β_i^x is a vector of coefficients that captures the (individual) valuations of those attributes. The household-specific characteristics are summarized by the vector z_i, including age, household size and location-specific characteristics. We interact household attributes with car specific characteristics to capture observed heterogeneity preference patterns based on population groups. p_j denotes the price of vehicle type j, and d_i^l is a dummy variable indicating whether household i belongs to wealth quartile l ($l \in [\,2, 3, 4\,]$). Thus, we allow for heterogeneity in the marginal utility of income based on wealth levels with α_1 measuring the baseline price sensitivity of the least wealthy households, and ϕ_l measuring each wealth quartile's average deviation from the baseline price sensitivity. We follow Grigolon et al. (2018) and model the variable costs as present value of lifetime costs. G_{ij} represents the present value of future fuel costs, including fuel taxes, and T_j the present value of future vehicle taxes. γ denotes the valuation of these costs. It indicates whether a household pays full attention to future costs associated with a purchase of a certain car type or whether a future pay-off - for example in the form of a better fuel economy - is undervalued. We define the present value of expected vehicle taxes and the present value of expected fuel costs as:

$$T_j = E\left[\sum_{s=0}^{S} \frac{t_{js}}{(1+r)^s}\right] \tag{1.2}$$

$$G_{ij} = E\left[\sum_{s=0}^{S} \frac{m_i[e_j g_{js}]}{(1+r)^s}\right] \tag{1.3}$$

S is a household's time horizon (i.e. the expected holding period) and r denotes the discount rate. In Equation 1.2, t_{js} represents the annual vehicle taxes that are levied based on a car's weight and fuel efficiency.[4] EVs are subject to lower rates and both EVs as well as fuel-efficient vehicles benefit from further reductions after initial registration. Hence, the net present value of vehicle tax payments can be defined the following way:

$$T_j = \sum_{s=0}^{3} \frac{t_j \sum_{k=EV}^{G} (1+F_k) \mathbb{1}_{EC=k}}{(1+r)^s} + \sum_{s=4}^{S} \frac{t_j}{(1+r)^s} \tag{1.4}$$

with k the relative fuel-efficiency category of vehicle j and F_k the respective bonus / malus for a given efficiency class (EC).

In terms of driving costs m_i represents the annual kilometers driven. We allow for consumer-specific km driven, but assume mileage to be inelastic with respect to fuel economy, which is in line with previous research (e.g., Bento et al. (2009)).[5] e_j denotes the fuel economy of the car type (l or kWh per km), g_{js} is the expected price for a unit of car type j's fuel in period s.[6] We model a household's expectation about future fuel prices to depend solely on today's fuel price. In a similar vein, we assume that households do not anticipate, or do not have expectations, about future tax system changes and consider only the current system when deciding on their car purchase. Following Grigolon et al. (2018), we define a capitalization factor as

$$\rho = \sum_{s=0}^{S} \frac{1}{(1+r)^s} \tag{1.5}$$

which allows us to simplify the lifetime fuel costs G_{ij} as:

$$G_{ij} = \rho m_i [e_j g_j] \tag{1.6}$$

[4] The formal definition of the tax rate is given in subsection 1.A.4

[5] subsection 1.A.5 further discusses this assumption and empirical evidence for it.

[6] At the moment, Switzerland imposes a fuel tax on gasoline and diesel. These taxes are paid by the importing companies, and we assume these taxes and the VAT are part of the fuel price g_{js} used to calculate the driving costs.

We define the deterministic part V_{ij} of the utility function and substitute Equation 1.6 and Equation 1.4 into Equation 1.1 and derive the utility of household i from purchasing car type j as:

$$u_{ij} = V_{ij} + \varepsilon_{ij} \tag{1.7}$$

with

$$V_{ij} = \alpha_i(p_j + \gamma \left[\rho m_i e_j g_j + \left(\sum_{s=0}^{3} \frac{t_j \sum_{k=EV}^{G}(1+F_k)\mathbb{1}_{EC=k}}{(1+r)^s} + \sum_{s=4}^{S} \frac{t_j}{(1+r)^s}\right)\right]) + \beta_i^x x_j + \beta^z z_i x_j + \sum_{l=2-4} \phi_l p_j d_i^l \tag{1.8}$$

Estimation - Inferring the choice probabilities allows us to investigate how households value certain car characteristics, and later to enact a number of counterfactual scenarios. We specify a likelihood function based on each household's probability to choose a certain vehicle type. This likelihood function allows us to estimate these discrete choice models with individual-level data and an exhaustive choice set. Assuming the non-deterministic utility component ε_{ij} to be independent and identically distributed with a type 1 extreme value distribution, facilitates the derivation of standard logit functional forms for the choice probabilities. These models imply independence of irrelevant alternatives (IIA). In other words, the relative odds of two cars being chosen remain the same, independent of the availability of another option. As Berry et al. (1995) point out, the car market is unlikely to follow such restrictive substitution patterns.

To overcome this assumption, we specify the utility function more flexibly by introducing random coefficients. We thereby allow for agents' heterogeneous valuations of certain car characteristics. The mixing distribution f(β;θ) is specified for a number of coefficients with $\beta = (\beta_i^x, \alpha_i)$ and θ being mean and variance parameters to be estimated. This relaxes the independence assumption for the ε_{ij}'s and allows us to denote the probability of household i choosing vehicle type j as (McFadden and Train, 2000):

$$P_{ij} \equiv \int \frac{e^{V_{ij}}}{\sum_j e^{V_{ij}}} f(\beta|\theta)d\beta \tag{1.9}$$

We assume a normal mixing distribution and estimate each random coefficient's mean and standard deviation, but no covariance terms between them. Many mixed logit applications use normally distributed coefficients, and the heterogeneity in valuation is generally picked up comparably well. [7] We maximize the log likelihood function, consisting of the sum of each household's log probability to purchase each vehicle type, using simulated maximum likelihood estimation. To estimate the random coefficients we use 200 Halton draws.

[7] A notable exception are bi- or multimodal preference distributions (e.g. Bansal et al. (2018)). We control for observed heterogeneity patterns such as, for example, age dependent engine power valuation. Thus we think that potential bi-modal coefficient distributions are already captured.

Identification - In addition to the random deviations, the car market - as a differentiated product market - likely exhibits unobserved car-specific characteristics correlated with a household's derived utility. Those would be subsumed into ε_{ij} and lead to biased price coefficients, given that researchers can expect car dealerships to observe such preference patterns. Thus, part of the error term is observed by both, consumers and producers, but not by the econometrician. Assuming that car manufacturers charge higher markups if they observe their products to have sought-after characteristics, prices will be correlated with these unobserved product characteristics. Therefore, price sensitivity estimates are upward biased. Berry et al. (1995) suggest an instrumental variable approach and Petrin and Train (2010) implement a control function approach to correct biased estimates. We use different strategies to deal with these potential endogeneity concerns. On the one hand, we use indicator variables to control for car-specific characteristics. First, we control for varying car type preferences by estimating separate parameters for different vehicle categories (e.g. SUV, mini-van, small car, luxury car...). Second, we estimate coefficients for brand specific indicator variables. The observed variation in our data does not allow us to estimate a different parameter for each observed brand. We estimate a brand-specific parameter for the top 10 brands (e.g. VW, Ford, BMW) and subsume the remaining 27 brands into 6 region-specific indicator variables (e.g. Asia for KIA).[8] Hence we identify our parameters based on variation within brand and vehicle type, thus controlling for unobserved brand or type specific preferences on an aggregated level.[9]

To control for further potential price endogeneity due to unobserved preferences for certain within brand vehicles, we use BLP style instruments. Formally we split the error terms into two components: $\varepsilon_{ij} = \varepsilon^1_{ij} + \varepsilon^2_{ij}$. In this setting, ε^1_{ij} is correlated with the price based on characteristics unobserved by the researcher while ε^2_{ij} is i.i.d extreme value. In a first step, we estimate a linear pricing equation of the following form

$$p_j = \beta x_j + \lambda c_j + \xi_j \tag{1.10}$$

where x_j denotes, as above, the car characteristics of vehicle j, and c_j is a vector of marginal cost shifters. ξ_j are the unobserved error terms in the pricing equation. The predicted residuals from this pricing function $\hat{\xi}_j$ are used as an additional term in the utility function to control for the potential correlation between prices and ε^1_{ij}. All cars sold in Switzerland are imported and thus globally produced. As a small open economy, Swiss consumers' demand is not expected to affect global conglomerates' vehicle portfolios. Most brands have either a subsidiary company or a unique partner acting as general importer. Thus, we use, as marginal cost shifters, the classic BLP-style instruments, which are constructed as the sum of characteristics from competitors' vehicle fleet

[8]The six regions are defined as the three neighboring countries France, Italy and Germany as well as USA, Asia and Europe.

[9]The classic BLP approach estimates product-specific constants. In our setting with many observed products (i.e. around 400 options), pre-dominantly cross-sectional variation in product characteristics and individual level observations from one market the estimation of product specific constants is not feasible.

and the sum of characteristics from the own vehicle fleet excluding this particular vehicle.[10]

Sample and choice set - We model the purchase decision of households conditional on buying a new car and thus abstract from both an outside good and secondary vehicle markets (Xing et al., 2021). We follow a common procedure in the literature (e.g. Bento et al. (2009)), and calculate average car characteristics on a level of make-model fuel-type combination (e.g. VW Golf diesel).[11] Our final choice set includes 489 distinct cars after excluding a few exotic options.[12]

1.4. Data

We draw on unique data comprising car registration information from the canton Bern's Road Traffic Office, observing a cross-section of car ownership information as of June 2019. We match socioeconomics such as income, wealth, household size, age and home ownership status provided by the Bern Tax Office. However, we cannot use the within individual variation in socioeconomics because it is unlikely - especially for older cars - that the current owner would also be the initial purchaser, and we want to model households' decision to purchase new vehicles.[13] Hence, we use a sub sample and restrict the analysis to newly registered vehicles between 2017 and 2019, as we are unable to model potential secondary market sales, due to data restrictions.[14] Socioeconomic data is matched as average income and wealth as well as age and household size at purchase time. We observe in total around 23,000 households purchasing a new car.[15]

We collect additional vehicle characteristics from the Swiss Federal Road office, such as fuel economy, engine power and size (i.e. length times width). In addition, price data is retrieved from Eurotax, a company that collects historical suggested retail prices.[16] We assume that the suggested retail price includes the 4% automobile tariffs levied upon import. We view this full pass-through assumption as justified, due to the following reasons: Import tariffs are charged to the importing

[10]We use in total 8 instruments, the sum of characteristics from the brands own vehicle fleet as well as the sum of characteristics from competing brands vehicle fleet. Characteristics are: Car size, car height, weight and engine power.

[11]To compute these average values we use actual registration data from all of Switzerland as weights for different vehicle types within the category and collapse the data on an annual basis.

[12]We exclude cars of brands with fewer than five registrations during our observed time frame overall, as well as make-model-fuel combinations with two or fewer registrations in any given year. The options excluded are mainly high-priced cars of luxury brands such as Ferrari or Bentley.

[13]We focus on new vehicles, as we intend to understand preferences for electric vehicles in particular and analyze policies that specifically address new vehicle purchases.

[14]We assume that the same person owning the vehicle is the original purchaser in the last 30 months, which is substantially lower than survey estimates of mean holding periods of 6 years for newly purchased vehicles as well as average leasing contracts lasting for 57 months. On average, 40% of cars were leased in 2020.

[15]No household purchased multiple new vehicles over this 2.5 year period.

[16]We observe market availability and price information for around 48,000 distinct vehicles. Because the car type record in the observed choice data is not always so distinct, we employ a weighted string match algorithm to match registration with the closest price data available. By employing this weighted score and using a rather high match threshold we ensure that the actual price in the data is as close as possible to the actual valid price on the market.

company which usually is a brand specific subsidiary while regional car dealerships ultimately sell the vehicles to the consumers.[17]

We briefly describe here how we calculate the net present value of expected variable costs. Further details are available in subsection 1.A.3 and subsection 1.A.4. Each vehicle's net present value of vehicle taxes is calculated as described in Equation 1.4. We assume a car longevity of 10 years[18] and compute the present discounted value of annual vehicle taxes. We follow the literature (e.g. Allcott and Wozny (2014) and assume a discount rate of 6%. Present value of vehicle tax payments varies between CHF 840 and CHF 5,462 , with a higher average value of CHF 3,312 for conventional cars and a much lower value of around CHF 1,357 CHF for EVs. We define a car's fuel economy as the costs per 100km driven. Fuel efficiency is retrieved from the Swiss Federal Roads Office's TARGA dataset, and based on both laboratory as well as driving tests. Fuel prices are measured as the annual average in the year of registration gathered from the Swiss Statistical Office. The car registration data also includes the number of kilometers driven for some cars.[19] For households that lack observations of odometer readings, we use observed odometer readings of their previous cars or from different households and estimate a mileage consumption function to impute the average expected annual distance driven. This procedure allows us to calculate the present value of future driving costs based on mileage, efficiency and average fuel costs.[20]

In Table 1.1 we summarize car characteristics based on three different samples. First, we present the choice set available to households. Roughly 50% are gasoline-driven. More environmentally friendly cars, such as EVs and hybrids,[21] are less often encountered with 20 and 54 make-model combinations respectively. Taxes and driving costs are lower for EVs, whereas prices are, on average, similar across categories. The second panel presents the actually observed choices. Almost 70% of registrations are gasoline-driven cars. EVs and hybrids exhibit relatively low market shares. Gasoline cars show below average prices, weights, engine powers and sizes. In contrast, EVs are, on average, CHF 20,000 more expensive than corresponding gasoline vehicles. EVs and hybrids feature considerably lower variable costs. The final panel presents the most frequently purchased vehicle in each fuel category. The gasoline-driven VW Polo was the most popular vehicle, with 419 total registrations. With a below-average price as well as relatively high fuel efficiency and low annual taxes within the category of gasoline-driven cars, it appears to be an attractive option. In terms of hybrids and EVs the most popular choices are the Toyota Yaris and Renault Zoe.
In addition, we control for the availability of EV charging stations. Several previous studies found that the availability of public charging affects the diffusion of EVs (e.g. Egbue and Long (2012)). We derive geocoded data for all public charging stations from LEMNET and count each station within a household's 5km radius. Additionally, we compute the distance to the closest EV to control for potential peer effects (e.g. Jansson et al. (2017)). The left panel of Figure 1.1 plots the

[17] If individuals decide to purchase their vehicles and import it, they have to pay the same tariff as well as potential emission standard levies.

[18] This is at the lower end of Eurostat estimates but Swiss household's average holding period is six years for newly purchased cars and five years in general based on questionnaire results.

[19] kilometer demand is recorded at the regular car inspection, which is required every 2-3 years.

[20] We conduct various robustness checks for these assumptions in subsection 1.A.6.

[21] Our dataset does not allow us to distinguish between plug-in hybrid cars and standard hybrid vehicles and we thus aggregate them into one category called hybrids.

Table 1.1. CHOICE SET

	N	Price	Tax	Engine Power	Weight	Height	Size	Fuel costs
Choice set								
Total	489	47	400	136	2,077	1.55	8.17	9.17
Gasoline	242	44	415	143	1,957	1.53	7.96	10.38
Diesel	173	45	420	123	2,202	1.59	8.43	8.52
Electric	20	48	90	145	2,020	1.55	7.44	3.6
Hybrid	54	62	384	142	2,232	1.52	8.55	7.87
Observed choices								
Total	23,074	35	382	112	1,929	1.55	7.83	8.94
Gasoline	16,005	31	372	108	1,815	1.53	7.59	9.28
Diesel	5,601	43	445	122	2,237	1.62	8.5	8.71
Electric	380	53	96	195	2,197	1.53	8.17	3.8
Hybrid	1,088	40	305	97	1,921	1.54	7.79	6.82
Most frequent choice								
VW Polo (gas)	419	23	226	80	1,608	1.43	7.09	7.78
Ford Kuga (diesel)	291	31	490	109	2,246	1.68	8.32	8.18
Renault Zoe (EV)	79	31	88	100	1,976	1.56	7.07	4.04
Toyota Yaris (Hybrid)	230	26	222	54	1,565	1.51	6.69	5.34

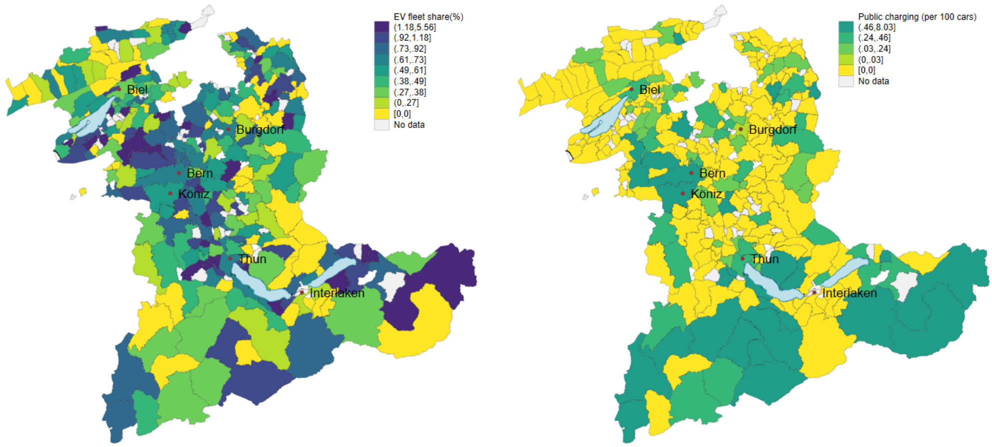
Note: This table presents car characteristics from three different panels. Characteristics are vehicle price in thousands CHF, annual vehicle tax in CHF, the engine power measured in KW, vehicle weight in kilograms, vehicle height measured in meters and the vehicle size in square meters, which is the multiplication of car length and width. Fuel costs are measured as CHF per 100km driven and thus a function of the observed average fuel price and the fuel-efficiency of the vehicle. The first panel presents the summary statistics of the theoretically available choice set for each household. N denotes the number of cars per category, whereas the other columns represent the average car characteristics. In the second panel, the same variables are presented, but in terms of actually observed choices. The final panel presents the most frequently observed choice. Here, the first column presents the number of households that choose this particular car and the reported car characteristics are the actual values.

share of EVs in total car registrations, whereas the number of charging stations per 100 registered vehicles per municipality is presented in the right panel. This facilitates a graphic assessment of clustering patterns, as well as correlation between charging station diffusion and EV adoption. There is heterogeneity in terms of EV registration shares between the different municipalities. Public charging stations are most prevalent in the urban centers (e.g. Bern city) as well as in the touristic regions in the south of the canton (e.g. Grindelwald or Gstaad).[22] Furthermore, we illustrate the distribution of households owning EVs and hybrid cars in Figure 1.A.1. The distribution is fairly similar to population distribution, as southern regions with lower numbers of observed registrations also feature a lower population density.

Table 1.2 presents the summary statistics for some socioeconomic and car characteristics for our final sample of 23,074 households. The equivalent information for different subsamples divided

[22]This appears plausible for public charging stations with availability in spaces where private parking is scarce (cities) and where daily or tourist visits are frequent.

Figure 1.1. EV AND CHARGING STATION DIFFUSION



Note: The left map shows the EV diffusion normalized by number of registered cars on a community level. The right map shows the number of public charging stations per 100 registered cars on a community level. Both maps were computed by the authors based on data from the Road Traffic Office of Bern as well as charging station data downloaded from LEMNET.

by fuel type category is presented in Table 1.A.1. Average household income amounts to CHF 114,000, and the mean vehicle price lies at around CHF 35,000. Most variables show considerable variation; for instance, vehicle prices range from CHF 8,000 to CHF 210,000. As described in Table 1.A.1, mean household income of EV owners is around 50% higher than overall average income. On average, agents drive 12,300 kilometers which is in line with previous estimates for Switzerland (i.e. Alberini and Bareit (2019)). Exhaust pipe CO_2 emissions are 0 for EVs but can vary between 88g/km and 359 g/km for gasoline-driven cars. Previous research has shown that an electric vehicle's environmental benefit depends heavily on local factors of electricity production, particularly the energy mix (Holland et al., 2016). While we acknowledge that, in our setting, zero emissions from EVs are an optimistic assumption, we decide to focus on pipe emissions solely for the following reasons. Switzerland has one of the cleanest electricity grids in Europe and relies almost entirely on non-fossil fuel electricity production (e.g. hydropower).[23] Furthermore, we argue that accounting for carbon emissions caused in the electricity production would require to also account for carbon emissions embedded in both gasoline and diesel.[24]

[23]The three main providers in the canton of Bern actually guarantee their customers a certain electricity mix, that contains no fossil fuel-based electricity.

[24]Switzerland does not have its own natural resources and thus both gasoline and diesel are based on oil extracted abroad, transported, refined (either locally or in Europe) and again transported to the points of sale. Current estimates illustrate that this process is significantly more carbon intensive than both average and marginal electricity production in Switzerland (Frischknecht, 2022).

Table 1.2. Summary Statistics - Overall Sample

	N	Mean	SD	Min.	Median	Max.
Household income (TCHF)	23,074	114	467	0	94	68,364
Household wealth (TCHF)	23,074	691	5,046	0	322	648,887
Age (main income source)	23,074	55	15	21	56	119
Suggested car price (TCHF)	23,074	35	20	8	32	210
Distance driven (KM/year)	23,074	12,342	2,875	4,132	11,961	29,715
Fuel Economy (CHF/100km)	23,074	9	2	3	9	25
CO_2 emission (g/km)	23,074	132	32	0	129	359
Distance to EV charging station (m)	23,074	1,320	1,300	1	789	9,679
Household size	23,074	2.1	1.11	1	2	5

Note: Author's calculation. Data sources described in text of Section 1.4

1.5. Regression Results

We present our estimates in Table 1.3. Column (1) to (3) depict the baseline conditional logit (CL) results. In column (4)-(6) we estimate random coefficient logit models. Preference heterogeneity is allowed for four variables; car price, variable costs, height and weight.[25] Both the estimated standard deviations and the log likelihood values indicate that the random deviations add little additional explanatory power. Column (1) and column (4) are the same baseline model where we estimate preferences for observables, but do not interact vehicle characteristics with demographic information. Column (2) and Column (5) add the aforementioned interaction terms between certain vehicle specific characteristics and socioeconomic variables. Interaction terms are informed by expectations and previous studies such as, for example, bigger households preferring larger cars or wealthier households being less price-sensitive. Column (3) and column (6) represent our preferred specifications, where we address potential price endogeneity through the control function approach, as described in Section 1.3.[26] Price coefficients become more negative, thus suggesting that our IV approach addresses the expected direction of the bias.[27] All specifications

[25] This is for the following two reasons: First, price and variable costs are our main variables of interest in the counterfactual scenarios. Second, height and weight are the two main vehicle characteristics, for which we do not allow for preference heterogeneity based on observables. We do not control for household characteristics interaction terms and thus control for potential unobserved deviations. Specifications with different random coefficients have been estimated, but were similar and are thus not further discussed.

[26] Estimated parameters for the predicted residuals are not presented but statistically significant and positive. First stage results are depicted in Table 1.A.2 - the relevance test for all instruments jointly is highly statistically significant.

[27] The reported standard errors correspond to the square root of the diagonal of the inverse Hessian matrix. As elaborated by Petrin and Train (2010) the control function approach - and thus the double usage of the data in estimation - would require that the standard errors be corrected. We re-estimate column (6) with bootstrapped standard errors based on 100 random subsample draws with replacement. Due to computational limitations a larger sample draw or further replications appear infeasible. Results of the

include brand specific dummies as well as vehicle type dummies.[28] Coefficients for these categorical variables are not displayed, but are mostly significant, which suggests that there are certain brand-specific or car-type specific preference patterns.

Both the upfront price, as well as the future variable costs, display a negative and highly significant coefficient. Moreover, reaction to vehicle price is more pronounced, which is in line with recent findings on myopic car drivers (e.g. (Gillingham, Houde, et al., 2021; Huse and Koptyug, 2022)). The discrepancy between upfront cost valuation and future variable cost valuation is only present, if we control for price endogeneity. On average, our car owners value CHF 100 in upfront costs as much as CHF 71 in future variable costs when discounting at 6%. There is quite substantial variation between the different wealth groups. Lowest wealth quartile households, on average, value CHF 100 in upfront cost savings at CHF 62 in future variable costs, while the highest wealth quartile households value CHF 100 in upfront cost at CHF 95 in future variable costs. We should note, however, that we examine only a subsample of the population, namely new car buyers; thus, in contrast to the aforementioned papers, we cannot draw conclusions about general consumer myopia. Additionally, we control for not only fuel costs but also for vehicle taxes; thus, cost salience may be another potential explanation. Such salience effects have been found in Sweden (Huse and Koptyug, 2022), the UK (Cerruti, Alberini, et al., 2019) and Germany (Andor et al., 2020). Vehicle tax reductions are not publicly advertised and households may not be perfectly aware of them. Additionally, taxes are charged once per year in retrospective and new vehicle buyers may not be aware of potential cost savings. Differences between upfront cost and future expected variable cost valuations may also stem from the fact that households anticipate policy changes over the vehicle's lifetime, such as a future expiration of the tax reduction. Thus, the undervaluation of variable costs may be a combination of several factors such as salience, inattention and future policy or price expectations but also myopia or financial literacy. For example, Cerruti, Daminato, et al. (2019) find that roughly 50% of Swiss consumers are aware of tax reductions in their respective canton, further supporting the explanation that the stronger reaction to upfront prices in comparison to the variable costs may not only be consumers acting myopic, but also consumers being unaware.

We control for observed preference heterogeneity by estimating interaction terms between household and car characteristics. We find significant heterogeneity in terms of price sensitivity based on wealth levels. The interaction terms coefficients between price and wealth groups are positive and increase with higher wealth status; this translates into lower price sensitivities for households in higher wealth brackets. In our opinion, this could be a sign of lower budgetary constraints for wealthier households. Furthermore, we also find that larger households value bigger cars to a greater extent and younger agents prefer more powerful cars. Moreover, we also estimate various interaction effects of socioeconomic characteristics with EV dummies, seeking to gain a better understanding of EV adoption patterns. We control for the density of charging stations, and find that households living in areas with higher public charging density have higher EV adoption rates.[29] Home ownership and solar panel ownership also feature positive and significant coefficients. This

bootstrapped standard errors are available upon request and not further discussed, given that the main results are consistent.

[28]We include a brand dummy for the top-10 brands and subsume the other cars into country of origin dummies. If we explicitly control for each of the top-12 or top-15 brands, the results remain the same.

[29]This effect, however, is a correlation and we can not comment on the direction of causality.

indicates three potential barriers to adoption. First, in order to acquire an EV, an agent needs access to a charging point. With an improved public charging infrastructure availability, we observe higher EV adoption rates, which is in line with previous research (e.g. Springel (2021)). Second, the availability of charging infrastructure is not only a public but also a private issue. Households living in their own dwelling can easily install a charging point in their own garage, and thus depend to a lower extent on public charging networks. Third, households owning solar PV are significantly more likely to adopt an EV as well. In our opinion, potential synergies between cost efficient self-produced electricity and EV ownership, or the EV battery as potential storage device, are the likely explanation for this pattern. We find no evidence for peer effects or urbanity patterns in terms of EV adoption. We furthermore observe that the general disutility from EVs, as indicated by the negative coefficient for EVs, is lower for wealthier people, as the interaction terms between wealth quartile indicators and the EV dummy variable are positive and increasing. This suggests that less wealthy households are generally less likely to adopt EVs conditional on controlling for the aforementioned potential explanations. This has important implications for distributional concerns, but we can only speculate on explanations. General technology skepticism in poorer households or lower educational status and financial literacy could be potential explanations. In addition to observed heterogeneity, we allow unobserved consumer heterogeneity through random coefficients. Most estimates are quite centered with relatively low estimated standard deviations except for the price coefficients.

To assess whether our results depend on model specification or assumptions, we conduct a number of robustness checks, which focus mainly on the calculation of future variable costs. For instance, we apply a lower discount rate of 2%, a shorter time horizon of six years, and constant annual kilometers driven. In addition, we conduct further robustness checks for potential model misspecification. We introduce different random coefficient, omit certain interaction terms, or control for additional interaction terms. For instance, we allow for heterogeneous price sensitivity based on income instead of wealth groups. Results are mainly unchanged and consistent in terms of significance sign and magnitude and discussed in detail in subsection 1.A.6.

To evaluate how well our preferred specification (Column (6) in Table 1.3) fits the data, we conduct certain tests. We estimate predicted market shares presented in Table 1.4. Results indicate that 70% of chosen cars are gasoline driven. The share of electric and hybrid vehicles is comparably low: 1.64% and 4.7% respectively. Furthermore, wealthiest households are 7 percentage points less likely to buy a gasoline driven car compared to a household in the lowest bracket. In contrast, poorest households display a 3 percentage point lower probability of acquiring an EV compared to the highest wealth quartile.[30]

In addition, we compute mean own and cross-price elasticities overall, as well as for each wealth group separately. This allows us to compare our results to the relevant literature, and to better understand substitution patterns among the different vehicles and fuel categories. Table 1.5 presents the overall elasticities. The estimated average own-price elasticity accounts to -2.46. It is important to note that initial probabilities of the four fuel types are quite heterogeneous. Furthermore, the number of options within one fuel type differs as well. For instance, households can choose

[30]We also conduct a chi-square goodness of fit test. The results are presented in Table 1.A.5.

Table 1.3. REGRESSION RESULTS

	Conditional logit			Random Coefficient logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Car price (TCHF)	−0.0125***	−0.0239***	−0.0620***	−0.018***	−0.0239***	−0.0665***
	(0.0011)	(0.0014)	(0.0030)	(0.0015)	(0.0014)	(0.0031)
Variable costs (TCHF)	−0.0079	−0.0371***	−0.0378***	−0.0128***	−0.0349***	−0.0412***
	(0.0069)	(0.0069)	(0.0069)	(0.007)	(0.0069)	(0.0069)
Engine power (KW)	0.0013***	0.0074***	0.0175***	0.017***	0.0072***	0.0178***
Car height	0.4877***	0.3863***	0.4118***	0.127	0.2330+	0.2211
Car weight	−0.0005***	−0.0004***	0.0000	−0.0003***	−0.0003***	0.0001
Hybrid engine	−0.5745***	−0.4513**	0.0348	−0.5295***	−0.4120**	0.0458
Electric engine	−0.7415***	−2.6532***	−2.5457***	−0.7368***	−2.650***	−2.512***
Diesel engine	−0.5774***	−0.6105***	−0.4941***	−0.5645***	−0.5920***	−0.4941***
Car size	0.0849***	−0.0858***	0.0335	0.0745***	0.0933**	0.0247
Environmentally friendly	0.0555*	0.127***	0.0576*	0.1189***	0.1720***	0.0717**
Price heterogeneity						
2nd wealth quartile		0.0033**	0.0033**		0.0033**	0.0033**
		(0.0011)	(0.0011)		(0.001)	(0.0011)
3rd wealth quartile		0.0057***	0.0056***		0.0057***	0.0056***
		(0.0012)	(0.0012)		(0.0012)	(0.0012)
4th wealth quartile		0.0234***	0.0233***		0.0234***	0.0233***
		(0.0011)	(0.0011)		(0.0012)	(0.0012)
EV effects						
EV agglomeration		0.1256	0.1271		0.1270	0.1222
EV rural		−0.102	−0.101		−0.1000	−0.1077
Distance to EV		−0.0267	−0.0263		−0.0266	−0.0264
Nb. Charging (5km)		0.0072*	0.0071*		0.0070*	0.0069*
EV - Homeowner		0.3924*	0.3897*		0.3960*	0.3801*
EV - Solar panel HH		2.2408***	2.2379***		2.2420***	2.2534***
EV 2nd wealth quartile		0.879***	0.8778***		0.8760***	0.8797***
EV 3rd wealth quartile		0.7158***	0.7141***		0.7100**	0.7252**
EV 4th wealth quartile		1.4866***	1.4769***		1.4800***	1.4860***
Rand. Coefficients						
Car Price				0.0110***	0.0000	0.0104***
Height				0.0074	0.0000	0.0036
Weight				0.0000	0.0000	0.0000
Variable costs				0.0011	0.0000	0.0000
Estimated average γ	0.632	2.34	0.701	0.7111	2.21	0.705
Observations	9, 816, 000	9, 816, 000	9, 816, 000	9, 816, 000	9, 816, 000	9, 816, 000
Nr. of cases	23, 074	23, 074	23, 074	23, 074	23, 074	23, 074
Log Likelihood	−134, 349.13	−133, 215.01	−133, 106.89	−134, 334.26	−133, 256.2	133, 096.55
Car type dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Car brand dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Car-size - HH-size interactions	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
KW-Age-Group interactions	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
EV trend	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Control function	*No*	*No*	*Yes*	*No*	*No*	*Yes*

Note: Coefficients based on estimated mixed logit models. Estimated standard errors in parentheses for selected coefficients, but mainly suppressed to save space in the table. Model (1) - (3) features no random coefficients. Coefficients in Models (4), (5) and (6) allow for random coefficients. Model (3) and Model (6) control for potential price endogeneity using the control function approach as described in Section 1.3. Suppressed coefficients that are part of the model but not presented in the table include: categorical variable for brand identifier, categorical variable for vehicle type, interaction terms between car size and household size category, interaction term between age group and engine power, interaction term between registration year 2018/2019 and EV category.
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

between more than 200 gasoline-driven cars, whereas the choice set contains only 20 EVs. The elasticities reflect the relative substitution patterns. For instance, a 1% price increase leads to a 2.3% decrease in adoption probability for gasoline-driven cars, compared to 3.1% for Hybrids. Furthermore, relative substitution between the fuel types appears to be quite similar, albeit of small magnitude. These values are slightly lower than corresponding values from the literature. For example, Xing et al. (2021) estimate an own-price elasticity of -2.67, and Muehlegger and Rapson (2023) find EV own-price elasticities of -3.2 to -3.4. With respect to cross-price elasticities, Xing

Table 1.4. Predicted probabilities

	Overall	1st wealth quartile	2nd wealth quartile	3rd wealth quartile	4th wealth quartile
Gasoline	69.41	72.1	70.56	69.62	65.36
Diesel	24.25	23.1	23.75	24.48	25.66
Electric	1.64	.5	1.28	1.35	3.44
Hybrid	4.7	4.3	4.42	4.54	5.53

Note: 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3.

et al. (2021) estimate a gasoline to EV (to gasoline) average cross-price elasticity of 0.028 (0.029), whereas our estimates are smaller: 0.005 (0.005). Nevertheless, in line with Xing et al. (2021), we also find that EV buyers tend to have a distinct preference for EVs and thus display a substantially higher cross-price elasticity to other EVs relative than to different fuel types. These differences in both own- and cross-price elasticity estimates have a number of potential explanations. First, our analysis focuses on new car buyers in a relatively higher-income environment in Switzerland. Furthermore, we use newer data from 2019 and thus believe that interchangeability among the different fuel types has further grown during more recent years. Range anxiety has also decreased over time and is less of a concern in Switzerland, where public charging network density is relatively high and average daily travel distance is relatively low.[31]

We calculate the own- and cross-price elasticities differentiated by wealth quartile, which is an important feature of our data. These results are depicted in Table 1.A.3. We find substantial differences with an average own-price elasticity of -2.56 (-2.47) for the lowest (highest) wealth quartile agents.[32] Lower wealth groups are substantially more price elastic with respect to combustion engine vehicles and less elastic for alternative fuel vehicles (EVs and hybrids), whereas for higher wealth groups own-price elasticity is higher for EVs than for fossil fuel-driven vehicles. The pattern of EV buyers having relatively persistent preferences, and mainly substituting to other EVs, is observed for all groups with higher cross-price elasticity estimates for EV-EV substitution. The exception are lowest wealth households, who generally exhibit a strong distaste for EVs.

[31] Survey estimates from 2015 predict average daily distance traveled to be 24 km.

[32] The difference between wealth groups is even more pronounced if we compare groups based on median price elasticity instead of average. The median own-price elasticity for the least wealthy households is -2.35 whereas for the wealthiest households it is -1.76.

Table 1.5. IMPLIED SUBSTITUTION PATTERNS AND ELASTICITIES

	Own	Cross Gasoline	Cross Diesel	Cross Electric	Cross Hybrid
Gasoline	-2.341	.005	.005	.005	.005
Diesel	-2.444	.003	.003	.003	.003
Electric	-2.35	.002	.002	.007	.002
Hybrid	-3.132	.002	.002	.002	.002

Note: Estimations based on sample and specification (6) of Table 1.3. The table presents the estimated elasticities based on a 1% price increase, which corresponds to the mean own and cross-price elasticities. All measures are in percentages.

1.6. Welfare and Counterfactuals

We simulate two policy changes based on the estimated coefficients. These two policies - namely an introduction of a vehicle tax malus for relatively 'dirty' cars and an upfront price subsidy for EVs - are common instruments in various countries and Swiss cantons. They allow policy makers to address the negative environmental externalities arising from the road transport sector. However, these policies not only affect emission intensity, but also have heterogeneous effects across socioeconomic groups, as well as implications for public revenue. We assume that the annual number of private registered cars amounts to 9,230 in the canton of Bern[33], and assess the changes in tax revenue, emissions and consumer welfare for each policy scenario. A major concern related to the spread of fuel-efficient cars in general, and EVs in particular, relates to the shortfall in tax revenue. This is because fuel-efficient cars and EVs benefit from generous vehicle tax reductions (Davis and Sallee, 2020) and also pay lower (or none) fossil fuel taxes. These missing revenues to cover infrastructure costs should be taken into account in the welfare assessment of road transport related policy scenarios.

We assume no choice set adjustments and inelastic annual mileage with respect to the vehicle tax changes, as they are independent of driving (e.g., West et al. (2017)).[34] We furthermore assume the market size and number of purchased vehicles remains the same.[35] To assess the overall welfare impact we first calculate the net present value of the annual emission savings. Second, we sum the

[33]This corresponds to the average annual registrations in our timeframe.

[34]Even if households were not perfectly inelastic in their mileage demand, the effects of the simulated policies still occur. Similar to Grigolon et al. (2018) we argue that our approach is an estimate of an upper bound in terms of revenue and a lower bound in terms of CO_2 reduction.

[35]Since we abstract from an outside good and model the purchase decision conditional on buying a new car, this assumption only changes results in terms of scale and not in terms of effect direction. It is unlikely that our policy changes would shift consumers from not buying a new vehicle at all to buying an electric car

monetary equivalents of the three welfare components: consumer surplus, change in emissions and public revenue.[36] We account for potential benefits due to misoptimization in our consumer surplus measure, and calculate both decision consumer surplus and changes in belief error (Allcott, 2013).[37] Public revenue is defined as the net present value of fossil fuel tax, vehicle tax and vehicle tariffs less subsidy expenses. Carbon emission reductions are expressed in monetary terms using a social cost of carbon (SCC) of CHF 175.[38]

1.6.1. Vehicle tax 'feebate'

In this counterfactual we simulate the introduction of maluses of 40% and 20% for efficiency categories G and F respectively, which complements the already existing bonuses of 40% and 20% for the efficiency categories A and B.[39] These additional fees would also apply in the year of initial registration and the following three years, and hence affect the new vehicle market only.

Table 1.6 presents the changes in adoption probabilities for the four fuel categories and the distribution across the wealth quartiles. On average, individuals substitute away from gasoline to mainly diesel driven cars, however, the overall response is quite low. Wealthier households react to a stronger degree and are overall more likely to substitute.

In Table 1.7 we summarize the welfare implications. The additional levies on the two least-efficient vehicle categories in the first 4 years of registration, lead to an overall decline in experienced consumer surplus of CHF 702,141 in absolute terms, which corresponds to 0.023% relative to the status quo. As this policy increases variable costs, and households are either not perfectly aware or perfectly optimizing, they actually exhibit higher deviations in perceived and experienced running costs, which manifests in positive changes in belief error. Annual vehicle tax revenue increases by about CHF 193,000 while fossil fuel tax and vehicle tariff revenue slightly decrease, as consumers shift to relatively more efficient and cheaper models. The registration tax is regressive, as illustrated by the vehicle tax incidence. Less wealthy households pay a higher share of their income, even though in absolute terms wealthier households bear a bigger amount of the vehicle tax. The policy change leads to a very small (0.14%) drop in the new car fleet's annual CO_2 emissions. The decrease is most pronounced among wealthier and the least wealthy households. Overall, the welfare effect of the policy change is slightly negative with an estimated NPV of around CHF 56,000 and thus

and thus expand the market. We provide some suggestive evidence for this assumption in subsection 1.A.5 which is further supported by previous empirical studies (e.g. Huse and Lucinda (2014))

[36] We acknowledge that a complete welfare assessment would also require to account for producer surplus in the car industry, particular for car dealers. We abstract from this in our welfare measure, due to data availability. For the lack of better term we abuse terminology and define as welfare the sum of consumer surplus, emission savings and public revenue.

[37] We further discuss definitions and formulas in subsection 1.A.2.

[38] We acknowledge that this is a comparably high value. For instance US policy currently employs USD 52 as SCC. We base our value on newest empirical evidence (Rennert et al., 2022) and suggested values from Swiss road traffic (CHF 132.8 in 2015) (for Spatial Development, 2022) and Germany (EUR 228 in 2020) (Umweltbundesamt, 2023).

[39] We also simulate how different changes in the composition of the bonus / malus scheme affect vehicle registrations. The results of these simulations are discussed in subsection 1.A.7.

Table 1.6. VEHICLE TAX 'FEEBATE' - PERCENTAGE CHANGE IN PROBABILITIES

	Overall	1st wealth quartile	2nd wealth quartile	3rd wealth quartile	4th wealth quartile
Gasoline	-.05	-.0434	-.0433	-.0424	-.0709
Diesel	.0326	.032	.0294	.0282	.0407
Electric	.0061	.0017	.0041	.0042	.0145
Hybrid	.0113	.0098	.0098	.01	.0156

Note: 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3. These numbers reflect percentage point changes.

also the change in welfare as a share of income (incidence) is negligible. The overall effect stems from the fact that additional tax revenue and reductions in experienced consumer surplus roughly balance each other out.

Table 1.7. VEHICLE TAX 'FEEBATE' - WELFARE

	1st wealth quartile	2nd wealth quartile	3rd wealth quartile	4th wealth quartile	Overall
Δ Cons. surplus (decision) (TCHF)	-114.455	-114.881	-118.123	-248.712	-596.171
Δ Belief error (TCHF)	46.461	40.156	36.439	-16.915	106.141
Δ Cons. surplus (experienced) (%)	-.028	-.024	-.022	-.021	-.023
Δ Vehicle taxes (CHF p.a)	45,927.4	43,780.3	43,215.4	60,426.1	193,398
Vehicle tax incidence (%)	.667	.452	.342	.212	.35
Δ Fuel levy (CHF p.a)	-1,750.69	-1,513.99	-1,416.78	-1,880.07	-6,632.3
Δ Vehicle tariffs (CHF)	-7,405.66	-6,854.76	-6,562.07	-11,616.1	-32,445.5
ΔCO_2 (t p.a.)	-5.497	-4.765	-4.464	-5.913	-20.862
ΔCO_2 (%)	-.13	-.125	-.122	-.179	-.139
ΔCO_2 (CHF)	962.048	833.79	781.265	1,034.74	3,650.83
Overall Welfare effect (TCHF)	-7.78	-8.355	-9.309	-30.913	-56.422
Welfare incidence (%)	-.001	-.001	0	-.001	-.001

Note: 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3. Consumer surplus based on Equation 1.20. Welfare impact assumes a vehicle lifetime of 10 years and discount rate of 6% to calculate the NPV of public revenue changes and emission reductions, which are measured in tons of CO_2. Global social cost of carbon applied is CHF 175 per t CO_2.

This analysis illustrates that increasing vehicle tax rates for relatively inefficient vehicles is a viable way to secure road infrastructure financing. However, such a policy has little impact on the new car fleet's carbon emissions, and if reductions in vehicle tax rates for relatively efficient vehicles are maintained, the policy exhibits overall negative welfare impacts.

1.6.2. Subsidy

In this counterfactual, we simulate the effects of an EV upfront price subsidy that could complement the existing support mechanisms in the canton of Bern. We use, as baseline scenario, the most generous observed subsidy of CHF 4,000.[40] We assume full pass-through of subsidies to vehicle prices. This is, in our opinion, justified by the following facts: Subsidies are paid out directly to consumers upon vehicle registration, neither car dealerships nor importers receive any payments, Switzerland is a relatively small, integrated market with short distances[41] and there is empirical evidence for almost full pass-through (Muehlegger and Rapson, 2023).

As Table 1.8 illustrates, the likelihood to acquire an EV increases by 0.35 percentage points, whereas all other fuel types are less likely chosen. The substitution mainly stems from gasoline-driven vehicles. Wealthier households are more likely to switch to an EV, while they already have substantially higher initial probability to adopt EVs. Although this is a relatively weak reaction, it is important to keep in mind the low base level of EV adoption. Our model predicts an average probability of 1.64%. An increase of 0.36 percentage points translates into an average predicted probability of 2.0%, which corresponds to an EV market share increase of 22%.

Table 1.8. EV SUBSIDY - PERCENTAGE CHANGE IN PROBABILITIES

	Overall	1st wealth quartile	2nd wealth quartile	3rd wealth quartile	4th wealth quartile
Gasoline	-.254	-.1108	-.2557	-.253	-.3967
Diesel	-.0842	-.0323	-.0791	-.0816	-.1438
Electric	.3561	.1495	.3506	.3508	.5736
Hybrid	-.0179	-.0065	-.0158	-.0163	-.0332

Note: 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3. All changes depicted in percentage points.

Table 1.9 presents the counterfactual welfare effects. The subsidy leads to a slight increase in experienced consumer surplus of 0.02%, and the majority of realized decision consumer surplus changes is concentrated in the top wealth quartile. The subsidy can be considered a negative product tax and similar to Allcott, 2013, we find that the subsidy alleviates consumer mistakes. Hence, it incorporates an internality into the decision making process, by lowering the belief error. Overall, the subsidy costs around CHF 738,000 with a fairly heterogenous distribution among the wealth quartiles. Agents in the highest wealth quartile receive more than six times the subsidy

[40] Further simulation results using subsidy values up to CHF 10,000 are depicted in subsection 1.A.7.

[41] For instance, households living in the city of Bern can reach up to 8 other cantons by driving less than 100km. If, for example, retail car dealers in Bern would adjust prices as reaction to EV subsidies, households could purchase vehicles at car dealers in different cantons and still receive the subsidy by registering with Bern's road authorities.

payments compared to those in the lowest group. At the same time, the changed composition of the hypothetical new car fleet decreases all public revenue. Annual CO_2 emissions are 54.7 tons or 0.36% lower, with a greater decrease observed in the higher wealth groups. The overall impact amounts to CHF -180,000. Thus, public revenue changes in this scenario dominate overall welfare effects.

Table 1.9. EV SUBSIDY - WELFARE

	1st wealth quartile	2nd wealth quartile	3rd wealth quartile	4th wealth quartile	Overall
Δ Cons. surplus (Decision) (TCHF)	53.091	133.494	140.277	343.22	670.082
Δ Belief error (TCHF)	-10.409	-20.941	-19.073	-3.017	-53.44
Δ Change Cons. surplus (experienced) (%)	.011	.024	.022	.031	.022
Total subsidy (TCHF)	60.251	150.451	157.023	370.448	738.208
Δ Fuel levy (CHF p.a)	-1,991.47	-4,231.23	-4,080.35	-6,121.69	-17,052.1
Δ Car registration taxes (CHF p.a)	-995.397	-2,343.02	-2,361.16	-4,050.49	-9,750.9
Δ Vehicle tariffs (CHF)	-4,590.48	-10,732.7	-10,744.3	-20,218.8	-46,290
Δ CO_2 (t p.a.)	-6.374	-13.558	-13.082	-19.674	-54.705
Δ CO_2 (%)	-.151	-.356	-.356	-.594	-.364
Δ CO_2 (CHF)	1,115.46	2,372.59	2,289.27	3,442.86	9,573.45
Overall Welfare effect (TCHF)	-14.331	-35.894	-37.213	-90.71	-180.21
Welfare incidence (%)	-.001	-.002	-.002	-.003	-.002

Note: 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3. Consumer surplus based on Equation 1.20. Welfare impact assumes a vehicle lifetime of 10 years and discount rate of 6% to calculate the NPV of public revenue changes and emission reductions, which are measured in tons of CO_2. Global social cost of carbon applied is CHF 175 per t CO_2.

The subsidy is relatively more effective in terms of emission reduction. For instance, the carbon emission reduction caused by the additional fee on category F and G vehicles is as high as the one achieved by a CHF 1,600 EV upfront price subsidy. Nevertheless, subsidies require additional government outlays and come at relatively high costs. Abatement costs amount to CHF 1,833 per t CO_2 if only emission reductions are taken into account. If all welfare changes are accounted for, the abatement costs are considerably lower at CHF 487, which is slightly lower than comparable income tax credit costs in California (Xing et al., 2021), but still substantially higher than for example EU ETS prices.[42] Furthermore, subsidies have redistributive implications, as wealthier households are the main beneficiaries, due to their higher initial propensity for EV adoption.

1.6.3. Optimal policy under constraints

The two instruments involve trade-offs with regard to achieving emission reductions, safeguarding road infrastructure financing, and accounting for equity concerns. Thus, we estimate the optimal policy mix of vehicle tax schemes and EV subsidies from the perspective of a social planner. We account for three relevant policy objectives: an environmental target, the public budget and

[42] In 2019 the average EU ETS price was around CHF 28.

consumer welfare.[43] The social planner seeks to safeguard public revenues while achieving both a pre-defined EV market share, and maintaining consumer welfare levels.[44] Swiss road transport policy is formulated to secure stable road infrastructure financing through benefit taxation. Since we allow the social planner to specifically target more environmentally friendly vehicles, we want to safeguard against the erosion of public revenues. Moreover, we want to ensure political feasibility and achieve relatively high public acceptance. In other words, the social planner minimizes absolute public revenue changes, while achieving a stipulated EV market share, and (experienced) consumer surplus changes are non-negative. Furthermore, we also account for potential equity concerns by assigning higher welfare weights to lower wealth household's consumer surplus changes. The following constrained minimization problem is solved:

$$\min_{t_j, \eta_j^g} |\Delta R_s| = |R_s^1 - R_s^0| \tag{1.11}$$

with

$$R_s^c = \sum_{i=1}^{N} \sum_{j=1}^{K} P_{ij} \{-\eta_j^g \mathbb{1}_{g=EV} + \mathbb{1}_{g \neq EV} p_j \tau_j^{imp} + T_j + \rho [m_{ij} e_j \tau_j^g]\} \tag{1.12}$$

Formally, ΔR_s represents the difference between the net present value of public revenue in the presence of subsidies and potentially changed vehicle tax regimes (R_s^1) and the status quo (R_s^0). P_{ij} represents household i's predicted probability to purchase vehicle j. η_j^g, τ_j^{imp} and τ_j^g denote the EV subsidy, vehicle import tariff and the fossil fuel levy. T_j is the present value of vehicle taxes while t_j denotes the annual vehicle tax for vehicle j. $\mathbb{1}$ is an indicator function and is equal to 1 if the respective condition is met and zero otherwise. This is important, because only EVs benefit from subsidies and they are also exempt from the import tariff. The discount factor ρ is defined in Equation 1.5 and translates annual levy payments into the corresponding net present value. Both policy instruments t_j and η_j^g are constrained at natural or set boundaries. These range constraints ensure that we do not extrapolate out of the support of observed cost variation and stipulate realistic policy boundaries. Additionally, two formal constraints represent policy targets and restrict the set of potential optimal policy combinations. The simulation process is further described in subsection 1.A.7.

In contrast to the previous section, we also allow for non-zero mileage elasticities in one scenario. Even though the vehicle tax is independent of annual mileage consumption, one could argue that agents may adapt their driving behavior as variable costs increase. In our baseline scenario households do not adapt their driving behavior due to changes in vehicle tax rates. In our opinion this is the most realistic case, since registration tax payments are independent of mileage consumption, but only vary between car types j. In the second scenario, we use an estimated driving elasticity of 0.3 (Gillingham, Rapson, et al., 2020) and allow households to adjust their driving behavior.

[43]We abstract from companies' profits, as we are unable to estimate profits and markups from car dealerships due to data availability.

[44]This exercise could also be formulated as minimizing abatement costs. Results would remain mainly the same.

The following two additional targets apply. First, we ensure that consumers do not experience a reduction in consumer surplus compared to the status quo:

$$\sum_{i=1}^{N} \left(\frac{1}{y_i}\right)^{\kappa} \Delta CS_i - \Delta CS_i^b \geq 0 \tag{1.13}$$

where CS_i is consumer i's decision consumer surplus as defined in Equation 1.20 and CS_i^b is consumer i's belief error as defined in Equation 1.25. As illustrated by Allcott (2013), it is important to account for potential misperception in households' annual driving expenditures. Hence, we define experienced consumer surplus, as the difference between decision consumer surplus and changes in belief error.[45] y_i is household i's wealth and $\kappa \in [0;1]$ indicates whether the social planner cares about redistribution ($\kappa = 1$) or not ($\kappa = 0$) (Saez, 2002). We constrain the (un-)weighted sum of consumer surplus changes of all households N. Experienced consumer surplus changes are a function of the subsidy η_j^g and the registration tax t_j, in comparison to the status quo (state 0), where both parameters (η_j^g, t_j) are at their current level.

Second, we characterize an environmental target as an EV market share, which corresponds to commonly stipulated policy milestones. The share of electric vehicles in new car registrations for a given year s is a function of vehicle type adoption probabilities P_{ij}. Thus,

$$S_s^{EV} = \frac{1}{N} \sum_{i=1}^{N} \sum_{j}^{K} \mathbb{1}_{g=EV} P_{ij} \tag{1.14}$$

N denotes the sample size and $\mathbb{1}_{g=EV}$ is equal to 1 for EVs and zero otherwise. K denotes the set of available vehicles (j).

The Swiss 'Roadmap Elektromobilität' stipulates that in 2022, 15% of newly registered vehicles should be EVs.[46] This target also includes plug-in hybrids while our subsidies will only be implemented for battery EVs. Thus, the target amounts to 8.25%.[47] Such a BEV registration share in 2022 is attainable with an annual registration share growth rate of 0.43. However, in most recent years, growth has been smaller. Thus, to attain the 2022 policy goal and assuming a constant growth rate,[48] the target of EVs in newly registered cars is set to 2.31% for the year 2018. In other words, if the share of EVs in newly registered cars was 0.0231 in 2018, and registration shares continued to grow at the observed average growth rate of 0.375, the goal of 8.25% share of BEVs in annual registrations is met in 2022. Formally, the first constraint stipulates that:

$$S_{2018}^{EV^1} \geq 0.0231 \tag{1.15}$$

Table 1.10 presents the results of the optimization exercise. The table distinguishes between the case of elastic mileage and inelastic mileage and the two consumer welfare constraints of weighted

[45] Further details and formal definitions are presented in subsection 1.A.2.

[46] More information can be found here: für Energie und Umwelt (2020)

[47] Assuming that BEVs continue to represent 55% (average) of the newly registered electric vehicles (BEVs + plug-in's) as has been the case in Switzerland during 2016-2018.

[48] We set the growth rate to 0.375 which corresponds to the observed values for 2013 to 2018.

Table 1.10. Optimal policy outcomes

		3 year feebate (incl. mileage)		3 year feebate - elastic(0.3)	
	$\kappa = 0$	$\kappa = 0$	$\kappa = 1$	$\kappa = 0$	$\kappa = 1$
Overall effects					
Subsidy level (TCHF)	7,200	7,200	6,800	7,600	7,000
Feebate (EV / A / B / E / F / G)	(0/0/0/0/0/0)	(-0.3/-0.1/0/0/0/0)	(-0.7/-0.5/-0.3/0.1/0.3/0.5)	(-0.7/0/0/0.1/0.3/0.5)	(-0.5/-0.3/-0.1/0/0.1/0.3)
Δ Decision Consumer Surplus (TCHF)	45.46	298.52	662.78	287.69	867.18
Δ Belief error (TCHF)	381.50	287.38	-58.09	225.38	9.49
Δ Experienced Consumer Surplus (TCHF)	-336.04	11.14	720.87	62.31	857.69
CO_2 reduction (t p.a.)	79.91	87.51	136.73	377.57	196.60
CO_2 reduction (% p.a.)	0.53	0.58	0.91	2.51	1.31
Δ public revenue (TCHF)	-154.96	-539.31	-1,430.30	1.56	-1,174
Δ tax (TCHF)	455.94	362.57	148.65	743.69	253.54
Subsidy paid (TCHF)	1,538.34	1,551.29	1,452.73	1,690.36	1,500.97
EV share (%)	2.31	2.33	2.31	2.41	2.32
Abatement costs (CHF / t CO_2)	834.8	820.00	704.96	-23.98	218.61
Distributive effects					
Subsidy share 1st wealth quartile (%)	8.58	8.59	8.53	8.64	8.56
Subsidy share 4th wealth quartile (%)	48.44	48.44	48.70	48.24	48.56
Tax share 1st wealth quartile (%)	24.94	24.98	24.87	25.01	24.93
Tax share 4th wealth quartile (%)	25.32	25.30	25.96	25.48	25.62

Note: 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3. Results of constrained minimization of Equation 1.11 with Equation 1.15 and Equation 1.13 as constraints. Decision consumer surplus as defined in Equation 1.20 and belief errors as in Equation 1.25. Experienced consumer surplus is the difference between these two measures. We assume a vehicle lifetime of 10 years and a discount rate of 6% to calculate the NPV of public revenue changes. κ indicates whether welfare function is income weighted (=1) or not (=0). Abatement costs measure the sum of experienced consumer surplus changes and public revenue changes divided by the net present value of emission reductions.

($\kappa = 1$) or unweighted ($\kappa = 0$) changes in (experienced) consumer surplus. Overall, a pattern of high subsidies, and balanced vehicle tax schedules emerges. In our baseline scenario (column 1) the social planner only considers decision consumer surplus. The optimal policy mix is to replace existing vehicle tax reductions with upfront price subsidies. This requires some additional public outlays of around CHF 150,000 in net present value today but allows to attain the EV target while ensuring positive decision consumer surplus changes. Taking into account the experienced consumer surplus rather than decision consumer surplus makes the additional condition more binding. In this scenario, it is optimal to keep some reductions in vehicle tax rates on EVs, as well as the most fuel efficient category, to safeguard consumers from increased belief errors. The optimal subsidy level remains at CHF 7,200. The net present value of additional public outlays in this scenario is higher at CHF 500,000, but abatement costs are slightly lower at CHF 820 to CHF 834.[49] If we account for distributional concerns ($\kappa = 1$) and assign a higher welfare weight to poorer households, the optimal policy mix features increased vehicle tax reductions for EVs (-0.7), as well as efficient vehicles (-0.5 for A and -0.3 for B vehicles), and additional levies on the least efficient vehicles (0.1 for E, 0.3 for F and 0.5 for G cars). Optimal subsidies are slightly lower at CHF 6,800. While the absolute deviation in form of net present value of public revenue is substantially larger at CHF 1.4 million, the actual abatement costs are the lowest in this case at

[49] Abatement costs are calculated in the following way: $C = \frac{\Delta CS^E + \Delta R_s}{\rho \Delta |CO_2|}$ where ΔCS^E is the aggregate change in consumer surplus, ΔR_s is the aggregate change in public revenue (which is negative with increased outlays) and $\rho \Delta |CO_2|$ is the absolute net present value of emission changes.

CHF 705, and the CO_2 emission reductions are the highest at 136 tons.

Allowing for an elastic driving behavior has two consequences. On one hand, emission reductions are substantially larger, as households can now react through two channels: they can either purchase more fuel efficient cars, or they can reduce their driving as a reaction to increased vehicle tax payments. On the other hand, fuel tax revenue declines further, requiring additional revenue to be generated through vehicle taxes. The optimal policy mix absent equity concerns ($\kappa = 0$) includes a slightly higher EV subsidy at CHF 7,600, but additional penalties on less fuel-efficient vehicles. In this scenario, the deviation from public budget and consumer surplus changes are both positive, which leads to negative abatement costs. This scenario decreases emissions at no additional public or private costs, but abstracts from potential disutility from reduced driving.[50] This effect is driven by consumer's adjustments in driving behavior conditional on the purchased vehicle. The additional levies' negative impact in the consumer surplus calculation is slightly muted. If the policy maker caters to equity concerns ($\kappa = 1$) and households are allowed to adjust their driving behavior, the optimal solution is again a more balanced policy mix. This features slightly lower subsidies at CHF 7,000, additional levies on the least fuel efficient vehicles, and additional tax rebates on more fuel efficient vehicles. Compared to the case with inelastic driving behavior, the optimal 'feebate' scheme is more balanced with additional reductions (levies) of 0.5 vs. 0.7 (0.3 vs. 0.5) on the most (least) fuel-efficient cars. In column (5), the drop in public revenue is more pronounced compared to the case of elastic mileage and no equity concerns (column 4), which translates into lower annual emission reductions at 196 tons. Nevertheless, emission reduction is higher and abatement costs lower, compared to the scenario with equity concerns and inelastic driving behavior.

In all scenarios, the EV target is slightly surpassed, as the estimated EV share lies between 2.31% to 2.41%. These results illustrate that a combination of high subsidies for battery EVs and vehicle tax penalties for inefficient cars, is better suited to attain emission reductions, without heavily jeopardizing revenues required to finance road infrastructure. If the social planner caters to equity concerns, optimal subsidies and vehicle tax incentives are more fine-tuned, with reductions for efficient vehicles, and penalties for inefficient ones. However, we should bear in mind that, even if we account for equity in the calculation of aggregate consumer surplus, a substantial share of subsidy payments flows to the wealthiest individuals (around 48%). Almost no subsidies are paid out to the lowest wealth quartile. At the same time, there is small variation in tax payment shares between individuals, as both highest and lowest wealth groups pay close to 25%. This may further exacerbate distributional concerns. Hence, while the optimal policy mix delivers on the promise of higher EV diffusion, while safeguarding road infrastructure finances, and maintaining consumer welfare, additional policy measures to alleviate distributional implications might be required.

1.7. Conclusion

We provide evidence for substantial differences in price sensitivity between wealth groups and modest to slight undervaluation of expected future variable costs, which could be caused by myopia but

[50] Reduced driving, however, could also have benefits in the form of reduced congestion or traffic accidents. Similar to the disutility such benefits are also abstracted from.

also salience of tax reductions. We document revealed preferences for EVs and find that wealthiest households are 6 times likelier than the poorest households to purchase EVs. This discrepancy is only partially explained by observables such as lower price sensitivity, charging infrastructure access and potentially cheaper electricity (moderated by homeownership and solar PV ownership).

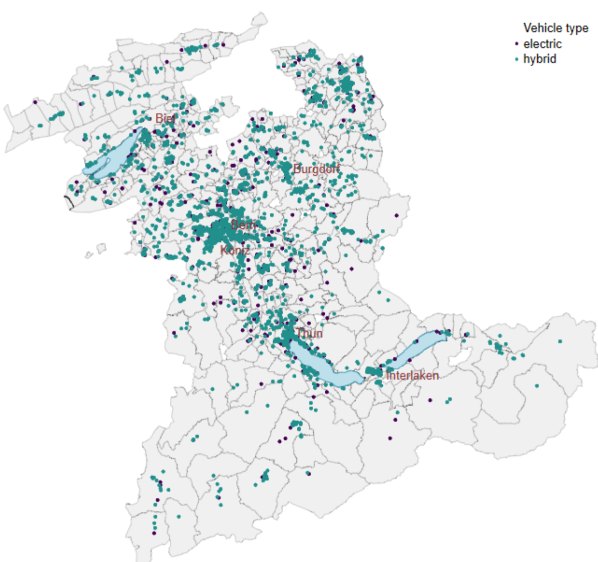
Our counterfactual policy analysis suggests two main takeaways. First, we show that the currently employed policy mix of vehicle tax rebates and no upfront price subsidies, can be revamped to achieve policy goals in a more efficient manner. Currently, tax rebates account for around CHF 0.5 million annually. If these funds were instead used as upfront price subsidies, the EV share in new car registrations would increase by 0.6 percentage points and carbon emissions would decline by around 70 tons annually. Additional vehicle tax penalties for inefficient cars allow for further increases in subsidies, and emission reductions, without jeopardizing road infrastructure financing. Second, tax instruments usually exhibit regressive features, imposing higher relative costs on poorer households. Subsidies exacerbate such concerns and are often coupled with potential inframarginal gains for relatively richer households. Even if we account for such equity concerns, the optimal policy mix still constitutes high upfront price subsidies paired with vehicle tax 'feebates', which substantially increases EV registrations with low additional public outlays.

Our analysis comes with a few caveats. We focus only on new car registrations, thus ignoring policy impacts on second-hand vehicle markets. Since poorer individuals are less likely to be active on new vehicle markets, distributional consequences might be underestimated. Furthermore, we focus on only one small market within Switzerland. However, we argue that our employed policy mix is representative for Switzerland, Western Europe (Wallbox, 2023) and several US states (Igleheart, 2022). Most countries in Western Europe were employing a policy mix of annual tax reductions for fuel-efficient cars. In recent years, several countries such as Germany, Italy, Spain and Sweden have moved towards introducing upfront price subsidies while either keeping vehicle tax rebates in place or fading them out. Hence, our estimates indicate potential hurdles, as well as avenues to higher EV adoption and reductions in private road transport carbon emissions while taking both redistribution and public finance concerns into account. We illustrate a path for policy makers to accommodate the trade-off between environmental and equity concerns without jeopardizing the financing of road infrastructure.

1.A Appendix

1.A.1. Additional Tables and Graphs

Figure 1.A.1. MAP OF ELECTRIC AND HYBRID CARS



Note: This map depicts the location of all registered electric and hybrid vehicles that are part of our study sample.

Table 1.A.1. Summary Statistics - by fuel type

(a) Gasoline

	N	Mean	SD	Min.	Median	Max.
Household income (TCHF)	16,005	111	556	0	90	68,364
Household wealth (TCHF)	16,005	680	5,825	0	311	648,887
Age (main income source)	16,005	55	16	21	57	99
Suggested car price (TCHF)	16,005	31	20	8	28	210
Distance driven (KM/year)	16,005	11,259	2,084	4,132	11,183	29,715
Fuel Economy (CHF/100km)	16,005	9	2	6	9	25
CO_2 emission (g/km)	16,005	135	27	88	129	359
Distance to EV charging station (m)	16,005	1,317	1,292	1	787	9,679
Household size	16,005	2	1.05	1	2	5

(b) Diesel

	N	Mean	SD	Min.	Median	Max.
Household income (TCHF)	5,601	117	95	0	101	3,698
Household wealth (TCHF)	5,601	618	2,456	0	303	144,041
Age (main income source)	5,601	52	13	21	52	94
Suggested car price (TCHF)	5,601	43	15	12	41	115
Distance driven (KM/year)	5,601	15,717	2,322	4,498	15,695	28,872
Fuel Economy (CHF/100km)	5,601	9	1	5	9	16
CO_2emission (g/km)	5,601	138	21	86	137	244
Distance to EV charging station (m)	5,601	1,323	1,328	3	784	9,296
Household size	5,601	2.38	1.23	1	2	5

(c) Hybrid

	N	Mean	SD	Min.	Median	Max.
Household income (TCHF)	1,088	129	106	3	105	1,395
Household wealth (TCHF)	1,088	963	2,101	0	491	28,973
Age (main income source)	1,088	60	13	22	61	90
Suggested car price (TCHF)	1,088	40	20	18	35	160
Distance driven (KM/year)	1,088	11,418	2,125	6,337	11,228	27,692
Fuel Economy (CHF/100km)	1,088	7	2	4	6	15
CO_2 emission (g/km)	1,088	91	28	33	87	221
Distance to EV charging station (m)	1,088	1,352	1,282	7	829	6,617
Household size	1,088	2.06	1.01	1	2	5

(d) Electric

	N	Mean	SD	Min.	Median	Max.
Household income (TCHF)	380	170	141	7	138	1,092
Household wealth (TCHF)	380	1,495	3,844	0	711	63,082
Age (main income source)	380	55	13	22	54	119
Suggested car price (TCHF)	380	53	25	24	46	104
Distance driven (KM/year)	380	10,838	2,181	4,466	10,663	23,351
Fuel Economy (CHF/100km)	380	4	1	3	4	6
CO_2 emission (g/km)	380	0	0	0	0	0
Distance to EV charging station (m)	380	1,313	1,310	37	791	7,482
Household size	380	2.47	1.2	1	2	5

Note: Author's calculation. Data sources described in text of Section 1.4

Table 1.A.2. Control functions

	(1) price	(2) price	(3) price	(4) price	(5) price
Car weight	0.022 * **	0.022 * **	0.022 * **	0.022 * **	0.022 * **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Engine power (KW)	0.207 * **	0.207 * **	0.207 * **	0.207 * **	0.207 * **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Electric engine	4.200 * **	4.196 * **	4.217 * **	4.134 * **	4.185 * **
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hybrid engine	11.836 * **	11.836 * **	11.835 * **	11.827 * **	11.837 * **
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Diesel engine	3.358 * **	3.358 * **	3.360 * **	3.352 * **	3.357 * **
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Car size	5.506 * **	5.506 * **	5.506 * **	5.514 * **	5.506 * **
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Efficiency category A, B or C	−2.356 * **	−2.360 * **	−2.334 * **	−2.412 * **	−2.375 * **
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Own brand size	−0.001 * **	−0.001 * **	−0.001 * **	−0.001 * **	−0.001 * **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Other brand size	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Own brand KW	−0.065 * **	−0.065 * **	−0.065 * **	−0.065 * **	−0.065 * **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Other brand KW	−0.049 * **	−0.049 * **	−0.049 * **	−0.049 * **	−0.049 * **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Own brand height	−3.656 * **	−3.660 * **	−3.638 * **	−3.655 * **	−3.672 * **
	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)
Other brand height	−1.745 * **	−1.749 * **	−1.727 * **	−1.746 * **	−1.762 * **
	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)
Own brand weight	0.022 * **	0.022 * **	0.022 * **	0.022 * **	0.022 * **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Other brand weight	0.017 * **	0.017 * **	0.017 * **	0.017 * **	0.017 * **
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	9, 816, 000	9, 816, 000	9, 816, 000	9, 816, 000	9, 816, 000
R^2	0.89	0.89	0.89	0.89	0.89
Brand dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Car type dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
F-stat (First-stage relevance)	115, 103.731	115, 110.358	115, 070.876	115, 159.948	115, 132.036

Note: Coefficients based on OLS regression of vehicle prices on car characteristics and the instruments sum of car characteristics of own and competing brand portfolios and the characteristics car size, engine power, height and weight. Column (1) corresponds to the main specification. Column (2) with lower discount rate of 2%, column (3) with shorter time horizon of six years, column (4) with constant kilometer consumption and column (5) with the longer time horizon of 15 years.
+p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 1.A.3. IMPLIED ELASTICITIES - BY WEALTH GROUP

(a) Mean Elasticities - 1st wealth quartile

	Own	Cross Gasoline	Cross Diesel	Cross Electric	Cross Hybrid
Gasoline	-2.639	.006	.006	.002	.005
Diesel	-2.533	.003	.003	.001	.003
Electric	-.917	.001	.001	0	.001
Hybrid	-2.921	.002	.002	.001	.002

(b) Mean Elasticities - 2nd wealth quartile

	Own	Cross Gasoline	Cross Diesel	Cross Electric	Cross Hybrid
Gasoline	-2.356	.006	.005	.004	.005
Diesel	-2.488	.003	.003	.002	.003
Electric	-2.141	.002	.002	.003	.002
Hybrid	-2.861	.002	.002	.002	.002

(c) Mean Elasticities - 3rd wealth quartile

	Own	Cross Gasoline	Cross Diesel	Cross Electric	Cross Hybrid
Gasoline	-2.189	.005	.005	.004	.005
Diesel	-2.494	.003	.003	.002	.003
Electric	-2.135	.002	.002	.005	.002
Hybrid	-2.943	.002	.002	.002	.002

(d) Mean Elasticities - 4th wealth quartile

	Own	Cross Gasoline	Cross Diesel	Cross Electric	Cross Hybrid
Gasoline	-2.18	.004	.004	.008	.005
Diesel	-2.261	.002	.003	.005	.003
Electric	-4.208	.003	.003	.02	.004
Hybrid	-3.802	.002	.002	.005	.003

Note: Estimations based on sample and specification (6) of Table 1.3. All elasticities are mean own- and cross-price elasticities presented in percent. Results based on simulated price increase of 1%. Sample distinguished into 4 wealth groups. 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF.

1.A.2. Welfare measures

According to Allcott (2013), one should differentiate between decision consumer surplus, experienced consumer surplus and belief error, in the welfare evaluation of potential policies in a setting where agents are prone to making errors in cost valuation. We should account for potential positive internalities from increased product taxation, if households underestimate future variable cost savings (i.e. $\gamma < 1$). Individual $i's$ experienced consumer surplus is the difference between decision surplus and belief error. Or more formally:

$$CS_i^* = CS_i - CS_i^b \tag{1.16}$$

Following Small and Rosen (1981), we define decision consumer surplus as:

$$CS_i = \frac{1}{a_i} \max_j u_{ij} \tag{1.17}$$

where a_i is the marginal utility of income for household i (Train, 2009). The researcher observes only the deterministic aspect of utility V_{ij} and thus expected decision consumer surplus can be defined as:

$$E(CS_i) = \frac{1}{a_i} E[\max_j (V_{ij} + {}_{ij})] \tag{1.18}$$

Assuming an iid Type 1 extreme value distribution of the error term, Small and Rosen (1981) have shown that the expected consumer surplus can be computed as:

$$E(CS_i) = \frac{1}{a_i} \log(\sum_{j=1}^{J} e^{V_{ij}}) + C \tag{1.19}$$

with C representing an unknown constant. Because we allow for heterogeneous deviations from the mean valuation of certain characteristics, the above formula is slightly adapted because the unobserved random terms are integrated out (Train, 2015). The change in decision consumer surplus following a policy change can be expressed as

$$\Delta E(CS_i) = \int \frac{1}{a_i} [\log(\sum_{j=1}^{J^1} e^{V_{ij}^1}) - \log(\sum_{j=1}^{J^0} e^{V_{ij}^0})] f(\alpha, \beta) d\alpha d\beta \tag{1.20}$$

where 1 and 0 represent the time period after and before the policy change respectively. The estimated price coefficient is usually employed as an estimate for the marginal utility of income, based on the assumption that an increase in the price leads to a decrease in the consumer's available income for purchasing other goods (Train, 2009). We allow for heterogeneity in the price sensitivity based on a households wealth level, as described in Section 1.3; thus, the marginal utility of income is:

$$a_i = -\frac{\partial u_{ij}}{\partial p_j} = \alpha_i + \sum_{l=2-4} \phi_l d_i^l \tag{1.21}$$

where $l \in [2, 3, 4]$ and d_i^l is a dummy variable indicating whether a household belongs to a particular wealth quartile.

The belief error is formally defined as (Allcott, 2013):

$$CS_i^b = \sum_{j=1}^{K} P_{ij}(G_{ij} + T_{ij} - \gamma_i(G_{ij} + T_{ij})) \tag{1.22}$$

which is the probability weighted sum of the difference between experienced future variable costs and perceived future variable costs. γ_i is defined as the ratio of the variable cost parameter and price sensitivity and thus again differs depending on wealth groups. More formally we define the estimated variable cost parameter as $b_i = \gamma(\alpha_i + \sum_{l=2-4} \phi_l d_i^l)$ and can thus recover γ_i the following way:

$$\gamma_i = \frac{b_i}{a_i} \tag{1.23}$$

$$\gamma_i = \frac{\gamma(\alpha_i + \sum_{l=2-4} \phi_l d_i^l)}{\alpha_i + \sum_{l=2-4} \phi_l d_i^l} \tag{1.24}$$

Accordingly, the change in belief error based on our policy simulations is the following:

$$\Delta E(CS_i^b) = \int [\sum_{j=1}^{K} P_{ij}^1(G_{ij}^1 + T_{ij}^1 - \gamma_i(G_{ij}^1 + T_{ij}^1)) - \sum_{j=1}^{K} P_{ij}^0(G_{ij}^0 + T_{ij}^0 - \gamma_i(G_{ij}^0 + T_{ij}^0))] f(\alpha, \beta) d\alpha d\beta \tag{1.25}$$

And the expected change in experienced consumer surplus is the difference between the expected change in consumer surplus and the expected change in belief error as defined in Equation 1.20 and Equation 1.25 respectively.

1.A.3. Details on Data and Variable Calculation

As indicated in subsection 1.A.4 as well as Section 1.4 we use different sources of data as well as variation to estimate preference parameters for car characteristics. In this section we further describe the data sources and the variation we exploit.

Vehicle prices We have access to proprietary data from Eurotax, which provides suggested retail prices and market availability (i.e. time frame when vehicle model was imported) for various car models and different European markets. Data is available on a monthly basis and very granular vehicle type classification (i.e. Ford Fiesta 1.5 SCTI front wheel diesel). We match this detailed vehicle data to observed registrations in the entire country using a string-matching algorithm. Based on this matched sample we compute weighted average suggested retail prices on the year-make-model-fuel type level for each vehicle in our choice set. We assume that tariffs, levies and taxes faced by the importers are fully passed through and part of the suggested retail price. This assumption is in our opinion justified, as for each brand there is generally one importer and individuals need to pay these fees as well if they decide to directly import the cars instead. We only account for direct vehicle tariffs and abstract from VAT and fuel economy standard penalties, as the latter are harder to account for on a per-vehicle basis.

Car characteristics Similarly, we also aggregate other vehicle characteristics such as height, weight, size, engine power as well as fuel usage and carbon emissions. Each vehicle registered in Switzerland has a specific license and unique identifier. This identifier is observed in both the registration data as well as the vehicle characteristic database. We again calculate weighted average characteristics using Swiss-wide registration data to get average characteristics on a year-make-model-fuel type level. Fuel types are directly observed in the registration data and differentiated into four categories. We define as gasoline and diesel cars, vehicles that use the respective fossil fuel only to accelerate. As EV we define electric vehicles, that solely rely on electricity and have no secondary energy source. The literature often refers to these cars as battery electric vehicles or BEV. Hybrid cars consist of both plug-in hybrids which have two separate engines and can potentially be driven on electricity or fossil fuel only and classic hybrids which are usually fossil fuel operated but have a small electric support engine that mainly is charged through recovered energy while driving. Our choice set consists of 54 hybrid options, which are equally split into plug-in hybrids and classic hybrids. However, in our sample only 1 out of 4 registered hybrid cars is a plug-in. Furthermore, we use brand dummies for the ten most observed brands as well as the region of origin for the remaining brands. Region is defined based on brand association and not on currently observed ownership structures. For instance, Peugeot is considered French, although they are now part of a larger conglomerate with European headquarters situated in Amsterdam. We use car type dummies according to classical market segmentation (e.g. SUV, Micro-class, Minivan...).

Variable costs We subsume the net present value of annual vehicle taxes and annual expected driving costs under expected variable costs and in the following describe how we estimate the different cost components. Annual vehicle taxes are calculated as described in Equation 1.27 and parameters weight, fuel type and energy efficiency class are observed in the vehicle characteristics database. Hence, vehicle taxes are calculated using the given formula and the net present value is calculated according to the description in Section 1.3.

The annual expected driving costs are a function of a vehicle's fuel efficiency, the expected fuel costs and the number of kilometers driven (VMT) as formally defined in Equation 1.6. We describe data gathering and calculation of these three components in more detail. A vehicle's fuel efficiency is gathered from the vehicle licensing data, where extensive laboratory and driving tests assess the fuel usage of each vehicle allowed to be driven on Swiss roads. Fuel usage is denoted in liters / 100km for fossil fuels and kWh / 100km for EVs. Hybrid vehicles fuel usage, which can consist of both fossil fuels and electricity, are assessed based on observed average usage of the different fuels, and directly indicated as such in the data. We use the fuel usage provided by the license data and assume that plug-in hybrid vehicle drivers will use their vehicles according to observed averages.

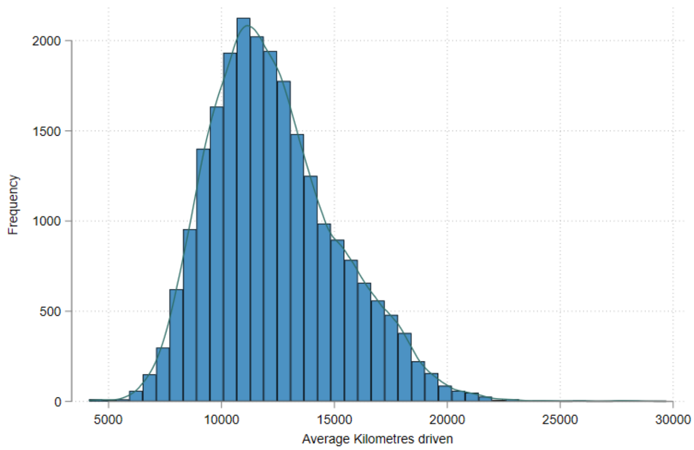
We use annual average gasoline, diesel and electricity prices as measured in the official Swiss price indices and communicated by the Federal Statistical Office. More granular data for gasoline and diesel prices is unfortunately not publicly available. Fossil fuel taxes are levied on gasoline and diesel upon import at the border. The majority of fossil fuels are produced abroad and directly imported and distributed to the different gas station operators. There are two small production sites that import oil and produce gasoline in Switzerland. However, the same tariff and levies apply as imported crude oil with the purpose of producing fossil fuels similarly needs to be declared. Tariffs, taxes and levies are directly charged to the importing companies and we assume full cost pass-through to customers.

Annual kilometers driven or VMT is imputed based on observed odometer readings from previous years. For a small fraction of households we can directly observe their annual VMT from odometer readings (less than 1%). For the remaining households we use observed odometer readings based on bi-annual vehicle inspections to impute annual vehicle miles travelled based on socioeconomic and car specific characteristics. Formally we estimate the following regression:

$$\log(VMT_{ij}) = \alpha + \beta x_j + \gamma z_i + \nu_{ij} \tag{1.26}$$

with x_j and z_i, as before, are a vector of observed vehicle characteristics (i.e. fuel type, car category, engine power and so on) and a vector of observed socioeconomic characteristics (i.e. age group, wealth, income, urban-rural classification...) respectively. We estimate the model using observed odometer reading data of around 60,000 household-vehicle combinations. This estimation is then used to impute the expected annual VMT for each household. We use the car characteristics of the actually chosen option to impute the expected driving distance and use it as a household specific variable. Hence, we assume households do not adjust their driving behavior with respect to fuel economy. Further details to this assumption are discussed in subsection 1.A.5. We present the expected VMT distribution in Figure 1.A.2. The distribution of predicted annual distance driven quite closely resembles the distribution used in Grigolon et al. (2018) based on an UK travel survey, even though at slightly lower numbers. We assume households drive on average 12,300 Km per year, which is fairly close to survey results from Switzerland as documented in Alberini and Bareit (2019).

Figure 1.A.2. Predicted annual kilometers driven



Note: This graph depicts the distribution of the imputed annual vehicle kilometers driven. Values are imputed based on observed odometer readings and a regression of kilometer demand on various car specific and socioeconomic characteristics.

1.A.4. Swiss Road Transport Policy

As indicated in Section 1.2, Swiss road transport policy varies on many jurisdictional levels. Here we want to provide further background on the cantonal vehicle tax and further national policies. Vehicle taxes are an important means for cantonal governments to generate revenue to finance the local road infrastructure. Each of the 26 Swiss cantons levies such a tax. Most cantons employ a model based on either weight or vehicle power. Some cantons also account for carbon emissions or efficiency categories in the calculation of the tax. Most cantons feature incentives for more efficient vehicles in the form of reductions or complete waiver of these levies. The canton of Bern currently employs the following calculation scheme:

$$t_j = \frac{1}{2}\mathbb{1}^{g=EV} \begin{cases} w_j\tau^w & \text{if } w_j \leq 1 \\ \tau^w + (w_j - 1)0.86\tau^w & \text{if } 1 < w_j \leq 2 \\ 1.86\tau^w + (w_j - 2)0.86^2\tau^w & \text{if } 2 < w_j \leq 3 \\ 2.5996\tau^w + (w_j - 3)0.86^3\tau^w & \text{if } 3 < w_j \leq 4 \end{cases} \tag{1.27}$$

w_j denotes vehicle weight in tons, τ^w the base tax rate in CHF per t, which is currently set at CHF 240, and CHF 120 for EVs.[51]

A number of additional policies are in place at the national level. As a small open economy, Switzerland does not have any domestic car manufacturers; each vehicle registered here is imported at some point in time. Thus, vehicles are subject to a 4% import tariff. In order to promote EV adoption, the federal government exempts fully electric vehicles from this tariff. The tariff is directly levied at the border crossing and must be paid by the importing company. Most vehicles are brought to Switzerland by a general importer that is either a direct subsidiary (i.e. BMW Switzerland AG) or a general importer with a brand-specific contract (e.g. Emil Frey AG for Toyota). Tariffs are directly levied when products cross the border.

Furthermore, Switzerland has implemented a fuel tax per litre of fossil fuel, which is aimed at both financing road infrastructure as well as internalizing pollution externalities. Currently, the rate is set at around CHF 85 per 100 liters of fossil fuel with a slightly higher tax rate for diesel compared to gasoline. This tax is directly levied at importing or producing companies and thus included in the end fossil fuel price. In our welfare evaluation we take the changed public revenue from vehicle taxes, vehicle tariffs and fossil fuel taxation into account. Other smaller or harder to quantify policies are abstracted from.

For completeness we still list these additional policies that might affect the advertised sale prices, as well as decisions of households to purchase vehicles, but are abstracted in our welfare and public revenue evaluation. Each imported car is subject to an attribute-based fuel economy standard, which is a function of carbon emissions and weight. Most car brands are represented by general importers that bring the majority of cars into Switzerland.[52] The penalty is calculated based on the individual or fleet-wide fuel economy and assessed retrospectively, based on last year's imports, in comparison to other vehicle importers, and a fleet-specific emission target. If emissions are

[51] $\mathbb{1}^{g=EV}$ indicates if vehicle j belongs to the vehicle type group (g) of EVs

[52] Less than 1% of cars were imported by individuals in 2019.

lower than the vehicle specific emission goal no bonuses are paid out and the penalty is set to zero. Unlike individual importers, general importers would benefit from importing cleaner vehicles than the emission goal, as they average out the relatively 'dirtier' vehicles and a fleet's emission standard is calculated based on the *average* emissions and the *average* weight. Nevertheless, if the threshold is surpassed, the same penalty applies and is multiplied with the number of vehicles imported. In recent years, penalties have substantially risen and peaked at CHF 132 million in 2020, which corresponds to CHF 550 per imported car. In addition, fossil fuel-selling companies are subject to a carbon compensation scheme and are required to offset parts of their emissions. This rate is increased on an annual basis and amounts to 12% as of this writing. Regulations cap the amount of costs that can be passed through to consumers via the fuel price. Lastly, highway access requires the annual purchase of a vignette that needs to be visibly placed on the vehicle and amounts to CHF 40.

1.A.5. Elasticities

Our analysis and the derived results hinge upon the assumed values for three main elasticities. The goal of this section is to provide more background on these three elasticities, further insights into our assumed values and a short discussion of the relevant literature.

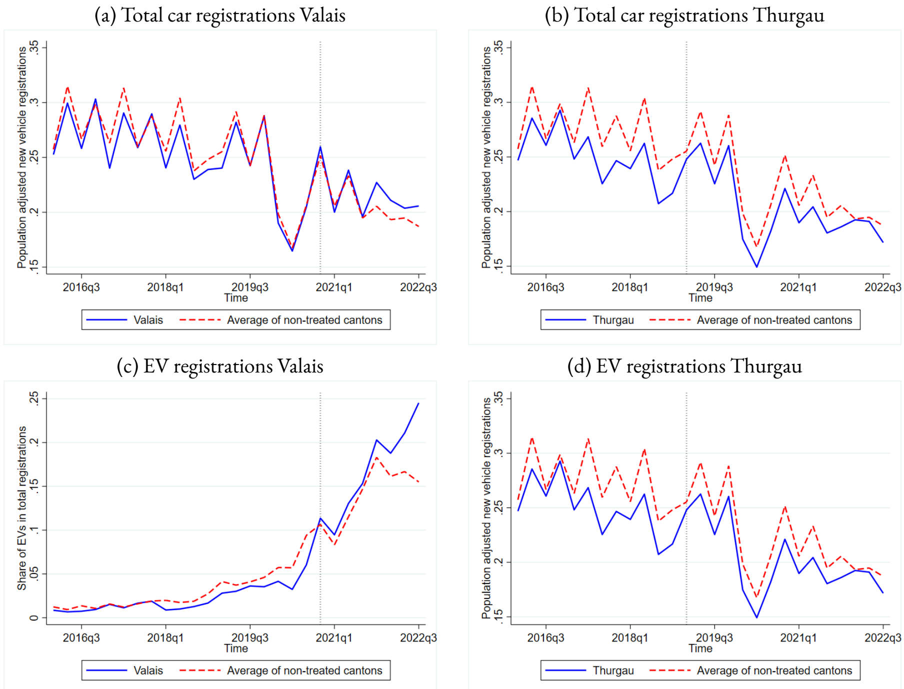
First, *the elasticity of vehicle miles travelled (VMT) with respect to fuel economy*. This elasticity measures whether or not households adapt their driving behavior if their vehicle was more fuel efficient. We assume this elasticity to be zero in the short-run and thus use annual mileage consumption as a household specific, choice-independent variable in the estimation of the car adoption probabilities. This assumption may contrast with the vast literature on energy efficiency rebound effects. However, as Gillingham, Rapson, et al. (2020) point out, it is important to distinguish between driving elasticity with respect to *fuel costs* or with respect to *energy efficiency*. Most empirical estimates of rebound effects identify the effects based on variation in fuel prices. However, as emphasized by Linn (2016), these estimates require one of three assumptions if VMT elasticity with respect to fuel economy shall be estimated based on fuel price-variations. He relaxes this assumption and finds significant elasticities of -0.2 to -0.4. In contrast, other studies provide evidence for the driving elasticity with respect to fuel-efficiency in the US to be low or close to zero (e.g. Bento et al. (2009)). Hence, in our opinion, the assumption is justified, since we assume that households form expectations about their required mileage consumption and choose a car depending on their expectation and the observed fuel-efficiency. Hence, the driving demand is taken into account in the car choice decision but not adjusted conditional on the decision. This assumption is furthermore supported by quasi-experimental evidence from Texas showing that households that, due to policy constraints, purchase a more efficient vehicle than anticipated, did not adapt their driving demand (West et al., 2017).

Second, a closely related elasticity is the *VMT elasticity with respect to the fuel-price*. As discussed above it is important to distinguish these two. Andersson (2019) illustrates that it is vital to distinguish between fuel-policy and fuel-price elasticities as households might perceive changes in gasoline price policy, mainly caused by fuel taxation, as more persistent and thus adapt their behavior more strongly. We however do not employ policy measures that directly affect the fuel costs or the fuel economy of a vehicle. The vehicle tax in our example is independent of mileage consumption and thus we expect agents to not reduce their driving as fuel consumption costs are not affected by the policy. Nevertheless, we employ as a robustness check in the optimal policy section an average fuel price elasticity of -0.3 to account for a potential reaction in terms of reduced driving if households were to budget for vehicle operation costs per year that would increase based on the new vehicle tax regime.

Third, *new vehicle purchase elasticity with respect to car prices*. Again we assume this elasticity to be zero, meaning that the amount of newly purchased vehicles or the market size for new vehicles does not significantly expand if price incentives for cars are provided. We follow Huse and Lucinda (2014) and argue that the market share of the subsidized vehicles (EV) is relatively small during the sample period. Furthermore, EVs in our time frame of observation tend to be relatively more expensive than other cars in the same segment and subsidies, while generous, still account for a small share of the upfront vehicle price. For this reason, we argue that it is unlikely that households that did not purchase a new car, would decide to buy a new vehicle, especially an EV. The aforementioned papers provide further empirical evidence, that this assumption is justified. We graphically depict the evolution of new vehicle registrations in the two cantons of Thurgau and Valais, that, in recent years, had generous subsidies in place. Figure 1.A.3 depicts quarterly new vehicle registrations, adjusted by population, for the treated cantons in comparison to the average of other Swiss cantons, who did not have a subsidy policy in place.[53] This suggestive evidence further supports the assumption that the subsidies led to more EV registrations, but not more car purchases in general. Hence, subsidies should not affect market expansion.

[53]Towards the end of the sample period in the canton of Valais, the market does seem to expand slightly. In our opinion, this is likely driven by the specific policy and not necessarily an increased market. The EV subsidy was announced in December 2021 as an extension of the already in place subsidy for EVs and PHEVs but with both a cost cap as well as a time cap up until September 2022. Hence, we argue that the increased registrations are pre-eliminary purchases of households that were planning on buying a new vehicle relatively soon and now did so earlier in order to benefit. Our suggested EV subsidy would however not be limited in time and thus not have this problem. The canton of Thurgau also depicted in the graph never announced such a time constraint and there the market appears to not have expanded.

Figure 1.A.3. MARKET SIZE ELASTICITY WITH RESPECT TO SUBSIDY



Note: The graphs present the population adjusted quarterly new vehicle registrations for the cantons Valais and Thurgau in comparison to the Swiss-wide average of non-treated cantons. Averages were calculated based on registration statistics from the Federal Roads Office. Cantons Ticino, Schaffhausen, Valais and Thurgau were not part of the control group, as they have a similar subsidy policy in place.

1.A.6. Robustness Checks and Model Evaluation

We conduct various robustness checks and sensitivity analysis with respect to model specification.[54] As discussed in Section 1.3 we assume certain values on how we calculate the future variable costs for each household-car-option combination. In our baseline specification we assume a time horizon of 10 years and a discount rate of 6%. In a first step we relax these assumptions and depict the results in Table 1.A.4. First, in column (1) we apply a lower discount rate of 2%, because nominal interest rates were predominantly close to zero or even negative between 2017-2019. Second, in column (2) we assume a shorter time horizon of 6 years[55] and third in column (3) we assume constant annual kilometer consumption instead of the imputed values. We employ mileages of 16,000 km and 12,000 km for diesel and non-diesel cars respectively.[56] The results vary between the different specifications but are largely consistent in terms of significance, sign, and magnitude. Similar to Grigolon et al. (2018), we find that the difference in households' valuation of upfront and future expected variable costs depends on mileage heterogeneity and if mileage is not accounted for, the extent of future variable cost undervaluation is overestimated. [57] In columns (4) to (6) we conduct further robustness checks for potential model misspecification. In column (4) we estimate random coefficients for the dummy variables hybrid and diesel and thus allow for non-observed heterogeneity between households in the preference for these fuel types. We find significant heterogeneity for households valuing hybrids but not for diesel. The overall model fit, parameter estimates and implications to our preferred specification, however, is almost unchanged. In column (5) we present the results of our preferred specification when we omit the interaction terms of EV and wealth quartile indicators to control for potential over fitting. The parameters and implications of the coefficients remains almost unchanged. As a last sensitivity check, we also estimate households' price sensitivity heterogeneity based on income instead of wealth quartiles, since the risk assessment of households that purchase their vehicles through leasing contracts may be conducted on the grounds of income rather than wealth. We find again a similar result as in our preferred specification, namely that higher income households are significantly less price sensitive than lower income households, as the interaction terms feature positive and increasingly higher coefficients. The extent of heterogeneity based on income is slightly stronger than based on wealth. The similarity in the result is not really surprising as the correlation between wealth and income in our sample of new vehicle buyers is strongly positive (around 0.9).

[54] We also test a number of additional technical assumptions. The results, which are largely unchanged, are available upon request. Further estimations include the following: estimation with 400 instead of 200 Halton draws, estimation with shifted and shuffled Halton draws instead of standard Halton draws and estimation with bootstrapped standard errors to correct for the double use of data in the control function approach.

[55] According to recent survey data, this corresponds to the average holding period of new vehicles bought in Switzerland

[56] These values were taken from (Alberini and Bareit, 2019) which are based on survey results for Switzerland

[57] We furthermore conducted robustness checks with longer time horizons of 15 years and 25 years holding periods. Again the results are similar but point in the direction of stronger undervaluation of future variable costs. Results are not further presented nor discussed, but available upon request.

Table 1.A.4. Regression results - Sensitivity

	Variable cost specification			Model specification		
	(1)	(2)	(3)	(4)	(5)	(6)
Car price (TCHF)	−0.0665***	−0.0665***	−0.0665***	−0.0649***	−0.0668***	−0.0743***
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0032)
Variable costs (TCHF)	−0.0362***	−0.0540***	−0.0264***	−0.0408***	−0.0455***	
	(0.0059)	(0.0103)	(0.0040)	(0.0069)	(0.0069)	(0.0069)
Engine power (KW)	0.0179***	0.0177***	0.0179***	0.0172***	0.0178***	0.0187***
Car height	0.2339+	0.2116	0.2362+	0.0962	0.2134	0.2029
Car weight	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001+
Hybrid engine	0.0326	0.0461	0.0406	−0.1561	0.0468	−0.0122
Electric engine	−2.5578***	−2.5106***	−2.5415***	−2.4483***	−1.9438***	−2.5344***
Diesel engine	−0.4959***	−0.4884***	−0.4992***	−0.5028***	−0.4904***	−0.4995***
Car size	0.0251	0.0253	0.0243	0.0007	0.0264	0.0853**
Environmentally friendly	0.0709**	0.0711**	0.0705**	0.0831***	0.0658**	0.0768***
Price heterogeneity						
2nd wealth quartile	0.0033**	0.0033**	0.0033**	0.0033**	0.0035**	
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	
3rd wealth quartile	0.0056***	0.0056***	0.0056***	0.0055***	0.0056***	
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	
4th wealth quartile	0.0233***	0.0234***	0.0233***	0.0233***	0.0237***	
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	
2nd inc. quartile						0.0088***
						(0.0012)
3rd inc. quartile						0.0168***
						(0.0013)
4th inc. quartile						0.0342***
						(0.0012)
EV effects						
EV 2nd wealth quartile	0.8760***	0.8709***	0.8767***	0.9212***		0.8574***
EV 3rd wealth quartile	0.7178**	0.7072**	0.7254**	0.7343**		0.6760**
EV 4th wealth quartile	1.4870***	1.4725***	1.4877***	1.4989***		1.5507***
Rand. Coefficients						
Car Price	0.0102***	0.0101***	0.0104***	0.0108***	0.0101***	0.0078***
Height	0.0031	0.0032	0.0036		0.0029	0.0031
Weight	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Variable costs	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001
Hybrid				0.0120***		
Diesel				0.0125		
Estimated average γ	0.62	0.92	0.45	0.72	0.66	0.77
Observations	9, 816, 000	9, 816, 000	9, 816, 000	9, 816, 000	9, 816, 000	9, 816, 000
Nr. of cases	23, 074	23, 074	23, 074	23, 074	23, 074	23, 074
Log Likelihood	−133, 096.24	−133, 100.53	−133, 093.12	−133, 105.81	−133, 128.53	−132, 874.11
Car type dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Car brand dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Car-size - HH-size interactions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
KW-Age-Group interactions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Add. EV interactions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control function	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: Coefficients based on estimated mixed logit models. Estimated standard errors in parentheses for selected coefficients, but mainly suppressed to save space in the table. Further coefficients included in the model but not presented nor discussed include: Interaction household size category with vehicle size, age group category with engine power, EV dummy with agglomeration indicator, rural indicator, distance to closest EV, public charging station density, homeownership and solar PV ownership indicator as well as purchase year 2018 or 2019 indicator. The first three columns control for different calculations of the future variable costs: (1) corresponds to a discount rate of 2% instead of 6%, (2) to a shorter holding period of 6 years instead of 10 years, (3) to constant mileage consumption of households (12,000 km p.a. for non-diesel households and 16,000 km p.a. for diesel households). Columns (4) to (6) control for other model specification assumptions. (4) controls for different random coefficients by allowing for random deviations in the average preference for hybrid and diesel cars, (5) controls against potential overfitting by omitting the EV wealth quartile interactions and (6) controls for income heterogeneity instead of wealth heterogeneity in the price sensitivity.

+ p<0.1 * p<0.05; ** p<0.01; *** p<0.001

Table 1.A.5. Prediction evaluation

Income	Gas predicted (N)	Gas actual (N)	EV predicted (N)	EV actual (N)
Overall	16,016	16,005	379	380
1st wealth. quartile	4,159	4,141	29	29
2nd inc quartile	4,070	4,001	74	74
3rd inc quartile	4,016	4,043	78	78
4th inc quartile	3,771	3,820	199	198
Income	Diesel predicted (N)	Diesel actual (N)	Hybrid predicted (N)	Hybrid actual (N)
Overall	5,618	5,601	1,086	1,088
1st inc. quartile	1,333	1,458	248	145
2nd inc quartile	1,370	1,436	255	252
3rd inc quartile	1,412	1,355	262	295
4th inc quartile	1,480	1,352	319	396
Overall fit χ_3^2	0.031			
Gas by quartile χ_3^2	2.077		EV by quartile χ_3^2	0.005
Diesel by quartile χ_3^2	28.26		HEV by quartile χ_3^2	91.86
All income quartile: χ_{15}^2	122.21			

Note: Predictions based on sample and specification (6) of Table 1.3. 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3. The critical values are 24.996, 7.815 and 3.841 for the χ_{15}^2, χ_3^2 and χ_1^2 with a 95% significance level and 30.578, 11.345 and 6.635 with a 99% significance level respectively.

To evaluate the model fit of our preferred specification we conduct chi-square goodness of fit tests to evaluate how well the model fits the data and compare the model predictions with the observed shares in the data. Table 1.A.5 presents the results. The model fits the data well with a chi-square test statistic of 0.03, if we test the model fit based on fuel types without differentiating between wealth quartiles. Therefore, we cannot reject the null hypothesis that the model prediction is significantly different from the observed shares in the population with 99% confidence. Furthermore, we evaluate how well we predict the fuel types based on the average predicted probabilities for each car combination and each wealth quartile. Our model captures the trend that less wealthy households are more likely to purchase gasoline vehicles quite well: we even slightly overestimate (underestimate) the share of gasoline driven cars in the first (fourth) wealth group. Overall, we cannot reject the null hypothesis that predicted numbers and observed numbers are significantly different from each other at the 1% level for gasoline cars. The model fit is even better for EVs and we can again not reject the null hypothesis that predicted and observed numbers of EVs are different when accounting for wealth groups. However, our model fits the data slightly less well for Diesel and hybrid vehicles. For hybrid cars we predict the difference in adoption rates between wealthiest and least wealthy households to be bigger while for diesel cars we predict a reverse pattern of increasing adoption while the observed shares actually decrease similar to gasoline vehicles but to a lesser extent.

1.A.7. Counterfactual process and simulation

We base the two counterfactuals on existing cantonal road transport policy. In the main text we present the policy scenarios of additional fees on relatively dirty vehicles levied through the annual vehicle tax and the introduction of an upfront EV subsidy. We furthermore present optimal policy mix simulations. This section describes the simulation process and the employed values and further discusses the implications of varying levels of EV subsidies as well as different 'feebate' scenarios that we also simulate to better illustrate the implications.

For the vehicle tax, we simulate different 'feebate' scenarios where on one hand, we either increase or remove the existing rebates on the annual tax payments in the first 3 years of registration, or we increase the tax for vehicles in the least efficient categories. Table 1.A.6 describes the different scenarios. We formalize additional penalties and reductions with F_k where k denotes the fuel-efficiency category. These scenarios depict the simulation in Figure 1.A.4, with scenario 10 corresponding to the counterfactual discussed in more detail in Section 1.6.

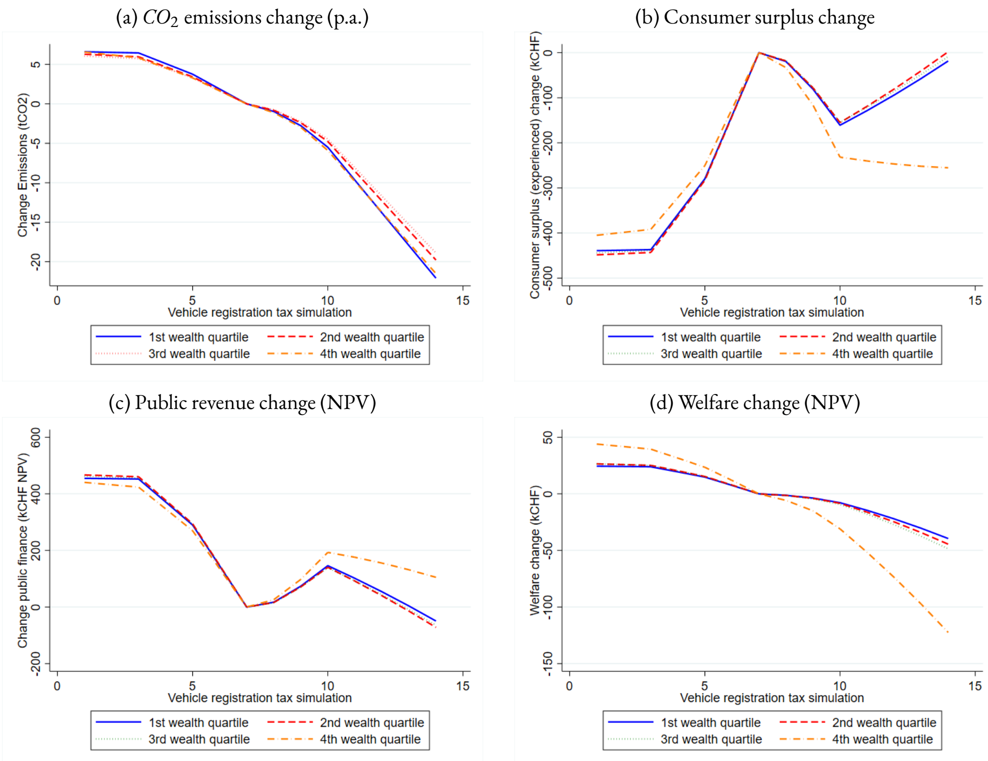
Table 1.A.6. Vehicle tax 'feebate' - Scenarios

scenario	F_{EV}	F_A	F_B	F_E	F_F	F_G
1	0	0	0	0	0	0
2	-0.1	0	0	0	0	0
3	-0.2	0	0	0	0	0
4	-0.3	-0.1	0	0	0	0
5	-0.4	-0.2	0	0	0	0
6	-0.5	-0.3	-0.1	0	0	0
7	-0.6	-0.4	-0.2	0	0	0
8	-0.6	-0.4	-0.2	0	0	0.1
9	-0.6	-0.4	-0.2	0	0.1	0.2
10	-0.6	-0.4	-0.2	0	0.2	0.4
11	-0.7	-0.5	-0.3	0.1	0.3	0.5
12	-0.8	-0.6	-0.4	0.2	0.4	0.6
13	-0.9	-0.7	-0.5	0.3	0.5	0.7
14	-1	-0.8	-0.6	0.4	0.6	0.8

Note: This table illustrates the employed scenarios in the vehicle tax counterfactual.

Different changes in the composition of the bonus / malus scheme affect vehicle registrations differently. We simulate each scenario denoted in Figure 1.A.4 separately. First, we assume no bonus or malus scheme is in place. Subsequently, we reintroduce the bonus step by step. Once we reach the current policy level, we introduce additional rebates for the more efficient vehicles and additional levies for the less efficient vehicles. The results of these scenarios aggregated by wealth

Figure 1.A.4. Vehicle tax 'feebate' - Welfare simulation



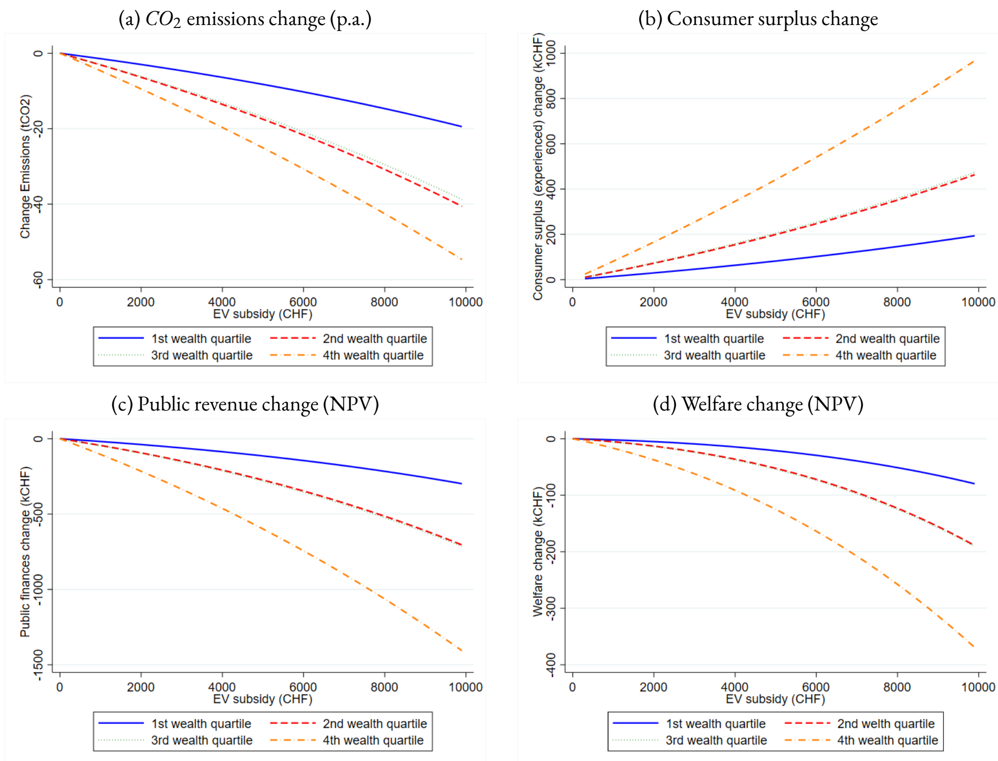
Note: 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3. Consumer surplus based on Equation 1.20. Welfare impact assumes a vehicle lifetime of 10 years and discount rate of 6% to calculate the NPV of public revenue changes and emission reductions. Global social cost of carbon applied is CHF 175 per t CO_2. The x-axis depicts the relevant simulation scenario, where either granted bonus payments on the more efficient vehicle categories is taken away or increased and additional malus payments on the least-efficient cars are levied. Detailed scenarios are described in Table 1.A.6.

quartiles are depicted in Figure 1.A.4. As expected, removing the bonus scheme increases emissions of the new car fleet and decreases (experienced) consumer surplus, but increases public revenues. Introducing malus payments on inefficient cars accompanied by a further reduction in vehicle tax on cleaner automobiles decreases emissions even further, but public revenues also decrease. There is some heterogeneity between population groups, as wealthier households react less strongly to changes in the vehicle tax scheme, and appear to be more likely to have inefficient cars, and thus pay for the higher vehicle tax rates. In terms of welfare, removing bonus schemes is welfare increasing, as the losses in consumer surplus are compensated for by additional public revenues. However, this compensating mechanism disappears when a more specific bonus / malus scheme is in place where relatively efficient cars are incentivized through tax reductions, while relatively inefficient cars are further penalized. In other words, the public revenue generation of additional vehicle taxes dominates the reduction in consumer surplus when fuel efficiency is not further incentivized. When fuel efficiency is further incentivized through more extreme differentiation in tax rates between the different fuel efficiency categories the additionally generated public revenue shrinks and can not be compensated by subsequent increases in consumer surplus.

We complement our analysis of the upfront price subsidy with increasing subsidies. In the process depicted in Figure 1.A.5, we increase the subsidy by steps of CHF 300 starting at zero and ranging to CHF 10,000. With higher subsidies, the emission reductions grow exponentially, suggesting that higher subsidies lead to increasing changes in EV adoption probabilities. Consumer surplus increases non-linearly with a more pronounced reaction for wealthier groups. At the same time, revenues raised from the different taxes decreases non-linearly and at a higher rate for wealthier households. This heterogeneous effect is mainly driven by wealthier households' higher propensity to purchase EVs, which makes them more likely to collect subsidy payments. The lower reduction in public revenues (lower left panel of Figure 1.A.5) for the lower wealth groups, indicates that the contribution to road financing from poorer households changes less, while they simultaneously receive less subsidy payments. Thus, the subsidy also raises redistributive concerns. One should note however, that the contribution of higher wealth agents is still higher in absolute terms, because some of them tend to have more expensive, heavier and less-fuel efficient vehicles, leading to higher overall public revenue contributions. In total, the subsidy features negative welfare effects because the negative repercussions on public revenue outweigh changes in emissions and consumer surplus.

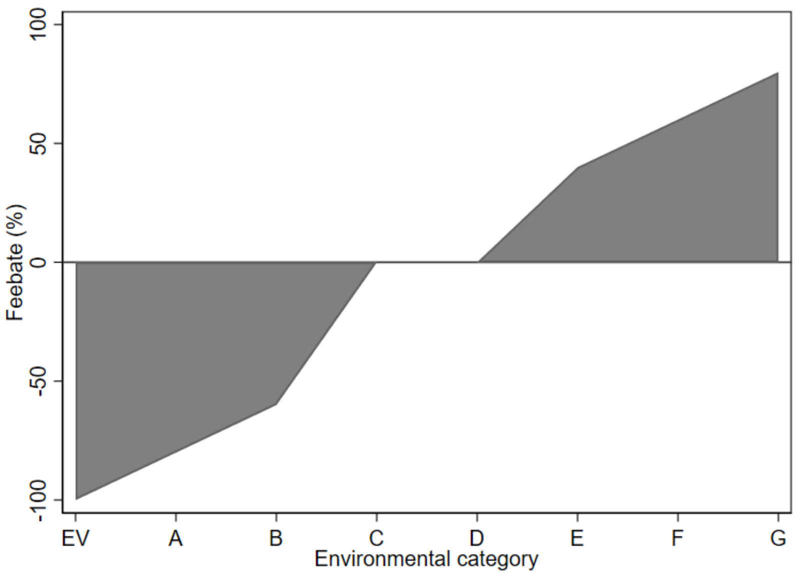
In the optimal policy mix scenario, we expand the range and detail of the two policies even further. The subsidy is bound between 0 and CHF 10,000, to maintain realistic policy boundaries. Increments of CHF 200 are estimated. The vehicle tax 'feebate' is estimated in multiple scenarios. The boundaries of the policy scheme are presented in Figure 1.A.6. The rebates and increased fees follow a clear structure. We simulate rebates on only EVs in increments of 10%. Then penalties on the least efficient category, or rebates on the most efficient category are added. The difference in the absolute value always is 20%. For instance, if the rebate on EV vehicle tax is 50%, the rebate on category A vehicles is 30%, and the fee for category G vehicles is also 30%. Similarly, if also category B (F) vehicles have rebates (fees), the value in absolute terms is again 20% lower than the value for category A (G) vehicles, respectively. Accordingly, category B vehicles would receive a 10% rebate, while category F vehicles would have an additional fee of 10%. The same holds for the difference between fees for category E and category F cars. We also simulate scenarios, in which only rebates or only fees are incorporated, as well as scenarios with, for instance, only fees for category G and rebates for EVs. In total we simulate 68 policy combinations for the vehicle tax 'feebate' schedule with the detailed list being available upon request and 50 subsidy levels which ultimately corresponds to a grid of 3,400 potential policy combinations. The optimum is then determined based on combinations that satisfy both constraints and minimizes the absolute deviations in public revenue from the status quo.

Figure 1.A.5. EV SUBSIDY - WELFARE SIMULATION



Note: 1st quartile: wealth < 38.4 TCHF, 2nd quartile: 38.4<=wealth< 321.9 TCHF, 3rd quartile: 321.9<= wealth<659 TCHF and 4th quartile: wealth >= 659 TCHF. Estimation based on sample and specification (6) of Table 1.3. Consumer surplus based on Equation 1.20. Welfare impact assumes a vehicle lifetime of 10 years and discount rate of 6% to calculate the NPV of public revenue changes and emission reductions. Global social cost of carbon applied is CHF 175 per t CO_2. The x-axis depicts the level of subsidy, which gradually increased from 0 to CHF 10,000.

Figure 1.A.6. VEHICLE TAX 'FEEBATE' - POLICY SCHEME



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Chapter 2

Green Spills: Peer Effects of Solar Photovoltaic Adoption on Energy Behaviors

Patrick Bigler Benedikt Janzen

Abstract

We examine causal peer effects of solar photovoltaic (PV) adoption using geocoded panel data of 260,000 Swiss households (2008-2019) and instrumental variables exploiting variation in rooftop solar PV potential. Peer behavior has a simultaneous impact on a broad spectrum of energy practices. We find that solar PV adoption increases neighbors' electricity conservation efforts. Households reduce their annual electricity consumption by 0.2% for each additional solar PV 100 meters away. We document peer effects between and within markets of pro-environmental durable goods, with an increase in solar PV and electric vehicle adoptions following new solar PVs nearby. Accounting for peer effects increases environmental benefits of solar PV diffusion by one third.

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2.1. Introduction

Various governing bodies have created support mechanisms for renewable energy, ranging from feed-in tariffs to technological subsidies, but also including substantial investments in research and development. For instance, the European Commission, 2022 has committed 19 billion to facilitate the roll out of renewables. Although recent empirical evidence suggests that a carbon price more efficiently addresses the problem of climate change mitigation in electricity production (e.g., Abrell et al., 2019; Gugler et al., 2021), policymakers seem to prefer subsidizing renewable electricity generation to introducing carbon prices (ECA, 2022). However, this result comes with a caveat, as it does not take into account possible effects of increased green technology diffusion on the energy and environmental behavior of peers (e.g., Bollinger and Gillingham, 2012; La Nauze, 2021; Lyu, 2022). These could significantly increase the benefits of subsidizing renewable energy and should be considered in potential cost-benefit analysis of support measures.

If I install a solar photovoltaic system (PV), do my neighbors become greener? In this paper, we investigate this question by examining causal peer effects of solar PV adoption on a range of different energy-related household behaviors. We argue that households perceive the installation of a new solar PV nearby as an indicator of increased peer contribution to climate change mitigation. This consequently motivates them to amplify their own participation in climate mitigation in the form of pro-environmental energy practices. Such behavior is consistent with theories of conditional cooperation, which assume that an individual's contribution to a public good is higher when there is information that many others contribute (Fehr and Schurtenberger, 2018), and which have been thoroughly tested empirically in lab (e.g., Fischbacher et al., 2001) and field experiments (e.g., Frey and Meier, 2004).

To identify peer effects, we employ a geocoded panel data set consisting of around 260,000 individual households in the canton of Bern, Switzerland, observed from 2008 to 2019. The data combines information on household energy behavior, including their electricity consumption, electricity product choice, ownership of solar PVs and electric vehicles (EVs), as well as various socioeconomic and demographic information on the household and the dwelling in which it resides. We enrich this information with administrative data on state-registered solar PVs to obtain the near universe of solar PVs in our study region. To study peer effects of solar PV adoption on neighboring households' energy behavior, we create a continuous measure of solar PV density. We first calculate the exact distance between each household and each solar PV in every given year of our observation period, to then construct a measure of solar PV density for each household-year combination by adding the inverse of these distances.

Our empirical strategy examines how changes in solar PV density affect household energy behavior. To overcome potential econometric challenges when identifying causal peer effects related to self-selection of peers, correlated unobservables, and simultaneity (Brock and Durlauf, 2001; Manski, 1993; Soetevent, 2006), we estimate a fixed effects regression model in which we include the lagged solar PV density, household-level fixed effects, zip-code-by-year fixed effects, and a variety of time-varying characteristics at the household and building level. To address remaining concerns about correlated unobservables that influence both peers' solar PV adoption decision and agents' energy behavior, such as for instance local advertising campaigns, we generate plausibly random variation in solar PV density over time using peer rooftop solar PV potential and its interaction with global solar PV prices as instruments. For rooftop solar PV potential, we use an engineering based measure of average annual solar irradiance per square meter of roof surface that accounts for building location, building geometry, rooftop inclination and orientation, and shading for each individual rooftop area in our study region.

We find evidence for peer effects of solar PV adoption on various energy-related household behaviors that are both visible and not visible to neighbors. First, we document an increase in neighbors' electricity conservation efforts. In our preferred specification, where we instrument for solar PV density, we find that households reduce their annual electricity consumption by 0.2% for each additional solar PV installation 100 m away. This corresponds to an average annual saving of about 10 kWh (or, for example, a reduction in annual laundry usage by twelve loads). Second, we document peer effects between and within markets of pro-environmental durable goods. On average, one additional solar PV adoption at 100 m distance to a household leads to a 0.02 percentage point increase in the probability of solar PV adoption and a 0.01 percentage point increase in the probability of EV adoption. Although the magnitude of these effects appears small, they are relatively large in comparison to the baseline probabilities of 1% for solar PV and 0.44% for EV adoption. Put differently, an additional solar PV installation at 100 m distance to a household leads to a significant increase in both the probability of adopting a solar PV and an EV by 2% and 2.3%, respectively.

Given our rich micro-level data, we are able to study heterogeneity in peer responses across actions and along household characteristics. We provide suggestive evidence that the peer effect manifests itself in different ways contingent upon households' constraints. We show that households with relatively low solar PV potential are more likely to act through the channel of electricity conservation, while households with relatively high solar PV potential respond mainly by adopting pro-environmental durable goods such as solar PVs and EVs. We also find that the peer effect in solar PV diffusion is muted for households that do not own their house and therefore do not have decision-making power to install a solar PV, further suggesting an important role of household constraints. Households thus use both salient and private actions that best suit their constraints to meet their desire for cooperation with increased pro-environmental peer behavior. In addition, we show that peer effects are stronger for higher-income households, living outside the city of Bern, suggesting that the anonymity of urban centers and lower socioeconomic status might (partially) mute the social norm based motivation of conditional cooperation.

Not only are our estimated peer effects statistically significant, but they are also economically meaningful. To illustrate our estimates' economic implications, we run a simulation where we randomly place solar PVs within our study region. Results imply that 100 solar PVs result on average in about 6 additional solar PVs, 4 additional EVs and 310 MWh of annual electricity savings due to peer effects. These additional conservation efforts correspond to the average annual electricity consumption of approximately 60 households and compensate conventional estimates of anticipated solar PV rebound effects (Qiu et al., 2019). Back-of-the-envelope calculation suggests that accounting for peer effects of solar PV diffusion increases social benefits in the form of Greenhouse Gas (GHG) reductions by 1/3, at least for low levels of solar PV adoption. This has important implications for subsidy evaluation. During our study period, the average solar subsidy received was CHF 900/kWp[1], which is higher than the estimated direct benefits at conventional levels for social cost of carbon. Including additional benefits due to peer effects decreases the estimated abatement costs by 20% and pushes them closer to current estimates of social cost of carbon. This applies even in a setting where the average carbon intensity of the grid is already comparatively low (i.e. the benefits of increased solar PV diffusion are likely lower than in countries where marginal electricity generation is predominantly from fossil sources).[2] If future expected GHG reductions are (not) discounted, abatement costs decrease from CHF 309 to CHF 246 per ton of CO_2 eq. (CHF 209 to CHF 166 per ton of CO_2 eq.).

Related Literature and Contribution - This paper contributes to several different strands of the literature. Peer effects on agent behavior have been found across a range of different topics, including education (Duflo, Dupas, et al., 2011; Hoxby, 2000; Sacerdote, 2001), welfare program participation (Dahl et al., 2014; Duflo and Saez, 2003), consumption (Agarwal et al., 2021; De Giorgi et al., 2020; Kuhn et al., 2011; Moretti, 2011), worker productivity (Mas and Moretti, 2009; Waldinger, 2012), and product adoption (Bailey et al., 2022; Björkegren, 2019; Conley and Udry, 2010; Foster and Rosenzweig, 1995; Oster and Thornton, 2012). Within the environmental domain, a broad literature body documents the role of peer effects in the diffusion of pro-environmental durable goods, both within markets for green technologies, such as solar PVs (Baranzini et al., 2017; Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Rode and Weber, 2016) and fuel-efficient vehicles (Heutel and Muehlegger, 2015; Narayanan and Nair, 2013; Tebbe, 2022), as well as between markets for green technologies (Lyu, 2022). In related work, La Nauze, 2021 investigates how installing solar PVs affects interacting agents' purchases of green power. Other related studies include Beattie et al., 2019 and Comin and Rode, 2023, who examine the impact of solar PV adoption on beliefs and voting patterns, respectively. In this paper, we contribute to this literature by considering the influence of peer solar PV adoption on a broad range of agent energy behavior at the micro-level and providing insights into what drives heterogeneity in responses across different actions. We show that peer behavior has a simultaneous impact on a broad spectrum of actions which are both visible and non-visible to interacting agents, and that the peer effect manifests in different ways depending on household constraints. Also, to the best of our knowledge, this is the first paper to study the impact of solar PV adoption on electricity conservation efforts of peers.

A related strand in environmental economics studies the causal influence of social norms on conservation behavior (e.g., Allcott, 2011; Allcott and Rogers, 2014; Bollinger, Burkhardt, et al., 2020; Costa and Kahn, 2013). In this paper, we contribute to that literature by drawing on a visible and salient piece of information to investigate how social norm based messages influence energy use and adoption of durable goods. We document significant and strong reactions to increased social standards in the vein of conditional cooperation. Households are more willing to contribute to climate change mitigation through the adoption of environmentally friendly durable goods and reduced electricity consumption. Increased solar PV uptake, possibly caused by subsidies, substantially influences peers' energy behavior, and these additional indirect effects

[1] During the study period, CHF 1 was approximately equal to USD 1. The subsidies are paid as a share of installation costs (max. 30%).

[2] Switzerland's average carbon intensity of the grid is 75% lower than the EU27 average in 2019 (Scarlat et al., 2022).

can significantly reduce implied abatement costs of solar subsidies. Furthermore, we provide an additional path for policy makers to benefit from these social norm based effects, namely, by installing solar PVs on rooftops under their jurisdiction.

The rest of the paper is organized as follows. Section 2.2 presents a simple conceptual framework of social influence on energy behavior. Section 2.3 introduces the institutional setting as well as data sources, collection procedures and summary statistics. Section 2.4 presents our empirical strategy. Section 2.5 presents the results, discusses the most important findings, and provides further tests of our empirical strategy and Section 2.6 illustrates policy implications. Finally, Section 2.7 concludes.

2.2. Conceptual Framework

There is ample evidence of social influence on household energy behavior (Abrahamse and Steg, 2013; Farrow et al., 2017; Wolske et al., 2020). In discussing why we might observe peer effects of solar PV adoption on interacting agents' energy behaviors, we closely follow Wolske et al., 2020, who suggest that social influence can explain peer effects in household energy behavior by manifesting itself through interpersonal communication, and persuasion (social learning), or through social norms.

Social learning can take place in the form of conversational or observational learning. With regards to solar PV diffusion prior research suggests that word-of-mouth communication about the benefits of solar PVs is an important factor in adoption decisions (Baranzini et al., 2017; Bollinger, Gillingham, Lamp, et al., 2019; Gillingham and Bollinger, 2021), however observational learning seems to be the main driver of solar PV peer effects (Bollinger, Gillingham, Kirkpatrick, et al., 2022; Rode and Müller, 2021). While observational and conversational learning can explain highly localized peer effects in solar PV diffusion, they not necessarily explain peer effects of solar PV adoption on other household energy behaviors. Wolske et al., 2020 propose normative social influence as a complementary explanation. One example of social influence is the social norm of conditional cooperation (Fehr and Schurtenberger, 2018), which has been extensively tested empirically (DellaVigna et al., 2012; Kessler, 2017; Rustagi et al., 2010; Shang and Croson, 2009). It prescribes individuals to contribute to a public good as long as other group members also contribute.

Suppose that there is a social norm that stipulates a common behavior standard, and that people have a desire to adhere to this social norm. Individuals gain disutility from negative deviations from this common standard. Moreover, for simplicity, assume that positive deviation from the common standard has no additional benefit and individual costs of deviation grow with larger deviations from the social norm (Fehr and Schurtenberger, 2018). We can formalize this as:

$$u_i = \begin{cases} x_i - \gamma_i (c^* - c_i)^2 & \text{if} \quad c_i < c^* \\ x_i & \text{if} \quad c_i \geq c^*, \end{cases} \tag{2.1}$$

where u_i is the individual utility, x_i is the individual material payoff (which depends on the decision of all players), c_i is the individual behavior (or individual level of cooperation), γ_i is an individual parameter expressing the strength of the desire to conform with a social norm, and c^* is the social norm. If individuals comply with the social norm (i.e., $c_i \geq c^*$) they receive utility in the form of their own material payoff x_i. However, if they do not adhere to the social norm ($c_i < c^*$) they incur non-conformity costs $\gamma_i(c^* - c_i)^2$. If individuals desire to adhere to the common behavioral standard is sufficiently large, it creates an incentive to increase c_i to reduce costs of non-conformity.

Climate change mitigation is a textbook example of a public goods problem (Stern, 2008). We argue that an increase in the prevalence of solar PVs changes a households' empirical beliefs about the extent to which peers engage in climate change mitigation. Such an increase leaves individuals with a spectrum of options bounded by the following corner solutions: non-compliance at initial level and full compliance with the new social norm. For simplicity, we only discuss these two states. Individuals can fully comply with the social norm, and increase their effort to the new perceived level of public good contribution at the costs of decreased material payoff. Alternatively, they can remain at their initial level of contribution and thus material payoff, but infer disutility through non-compliance. Individuals with a sufficiently large parameter γ_i will increase their effort in order to avoid non-conformity costs, and thus increase their climate change mitigation effort.

2.3. Background and Data

Our study focuses on the Swiss canton of Bern, which with around one million inhabitants and 6,000 km^2 area, is the second largest canton both in terms of size, and population. With around 140,000 inhabitants, the city of Bern is the capital and the largest urban center within the canton. Switzerland is a highly decentralized federal state. Local and regional governments by default legislate many aspects of life. Federal law is only in place if responsibility was ceded from the cantons to the state. We use a high-resolution panel data set of 262,708 unique households spanning from 2008 to 2019.[3] We first discuss the institutional setting and then present data sources and descriptives.

2.3.1. Institutional Setting

Electricity markets are locally organized with monopolistic regional grid operators and power utility companies. Households are assigned to their grid operator, as well as their electricity provider, based on their location. Service areas are defined by community borders and customers have no choice of provider. End-user prices are annually fixed, and independent of electricity consumption. They vary based on the chosen electricity product and tariff.[4]

[3] Our data is not balanced, as we do not observe all households in each period. On average, we observe 183,752 households per year with the minimum of 134,571 in 2019 and the maximum of 201,760 in 2017. The minimum in 2019 is due to the fact, that we observe households served by EWB only from 2008 to 2018. To account for this discrepancy we also estimate all specifications using only the data from either utility separately and discuss these results in the heterogeneity analysis.

[4] Electricity products mostly differ in terms of the type and location of the power sources (e.g., only regional solar PV as power source). In terms of tariff, there is a choice between uniform pricing or peak/off-peak pricing. When registering with the utility, households are assigned uniform prices and the default product consists predominantly of hydropower (blue electricity product).

Switzerland has committed to a growing share of renewable electricity production and a nuclear power phasing out. The generation of renewable energy through residential solar PVs is promoted with various instruments. Early adopters received cost-covering feed-in tariffs (until 2015) and nowadays residential solar PVs are mainly supported with upfront price subsidies. The local utility is required to purchase excess solar production at average annual electricity market prices under the condition that the solar PV is registered with the utility (i.e., connected to the grid). Households have the option to certify their solar PV system and sell local renewable electricity certificates. Similarly, Switzerland has a public support systems in place to combat transport related emissions. In the canton of Bern there is a tax reduction for new EV registrations but no upfront price subsidy.[5]

2.3.2. Data

Data is gathered from various sources. We obtain electricity billing data for individual households from BKW Energie AG (BKW), the largest cantonal and second-largest Swiss utility in terms of turnover, and from Energie Wasser Bern (EWB), the utility serving the city of Bern. The billing data includes annual electricity consumption, electricity product choice, and information about installed solar PVs and their capacity. Figure 2.A.1 illustrates our study region depicted in zip codes. In total the two utilities cover 350 out of 473 zip codes in the canton and around 65% of the population.

This information is augmented with various additional data sources. First, the canton of Bern Tax Administration provides us with annual income and wealth data, as well as various additional demographic household-level information, such as age, household size, and home ownership. Second, we obtain geocoded building-level data from the Swiss Federal Statistical Office (BFS). Building and dwelling characteristics include the type of building (e.g., single-family home), construction year, size of living space, number of rooms, floors, and apartments, as well as the existing heating system. Third, we draw on individual car ownership data from the canton of Bern Road Traffic Office (SVSA Bern), where we observe car ownership, fuel type, and various other car-specific characteristics. Fourth, we gather information on all installed solar PVs in Switzerland from the national inventory operated by Pronovo AG. The register includes all solar PVs that either exceed a capacity of 30 kWp, were supported by public support schemes or are selling local renewable electricity certificates. For each solar PV, we observe the installation date, the capacity, and the geocoded location. We draw a rectangle around the canton of Bern adding 3 km to each of the most northern, most southern, most eastern, and most western coordinate, and include each solar PV within this rectangle in our sample. In addition, to obtain the universe of solar PVs in our study region, we supplement this data with solar PVs that are registered with the two utilities but not included in the registry.[6] Finally, we access data on rooftop solar PV potential for the universe

[5]For a more detailed description see Bigler and Radulescu, 2022.

[6]This adds 131 PV installations, which is less than 0.5% of the total number of solar PVs in our sample.

of rooftops in our study region from the Swiss Federal Office of Energy (BFE)[7] and global annual solar PV prices from Our World in Data.[8]

Our main variables of interest are related to agent energy behavior and include electricity outcomes (i.e., annual electricity consumption and electricity product choice) and durable good adoption (i.e., ownership of solar PV and EV).

Based on the billing data of the two utilities we construct annual household electricity consumption. If a household has more than one electricity meter associated with its customer number, we total the kWh consumed unless the electricity meter belongs to a different building. Electricity meters are usually read once a year, and most reading dates are around the end of the calendar year. If the reading period is shorter than a year, we normalize electricity consumption to 365 days based on observed reading days and drop observations with a reading period of less than 180 days.[9] Since the raw data contains various large and small observations that are not justifiable with a standard household electricity consumption profile, we drop the top and bottom 1% of annual household electricity consumption, in order to ensure that our results are not driven by outliers.[10]

Our second electricity outcome of interest is the decision of households to voluntarily purchase a particular electricity product. As the offered electricity products vary between utilities we subsume different products into three categories - grey, blue, and green. For each of the two utilities, the green electricity product is the most expensive and is marketed as the most environmentally friendly, with a significantly higher share of renewable energy sources. The blue electricity product is the baseline product and contains mainly hydro power. We label the cheapest product, advertised as the least environmentally friendly, and containing mostly electricity from hydro and nuclear power plants, as grey. Customers in the city of Bern (i.e., EWB) had a choice between different electricity products throughout the observation period. BKW did not introduce different electricity products until 2016. Hence, for this utility and outcome, observations before 2016 are dropped.

With respect to durable goods adoption, we define indicator variables for solar PV ownership and EV ownership (hybrid or battery EV) for each household in a given year. For multi-vehicle households it is sufficient for one of the vehicles to be electric, such that the indicator variable is equal to one.

We provide summary statistics for both our outcomes of interest and a selection of household-level characteristics in Table 2.1. Panel (A) shows summary statistics of energy-related household behavior. On average, annual household electricity consumption accumulates to 4,943.21 kWh. The minimum recorded annual electricity consumption is 375 kWh and the maximum is 33,418 kWh. The distribution is right-skewed with a median consumption of 3,228 kWh. On average, 3.72% of households use green electricity, 0.44% own an EV, and 1% have a solar PV. Panel (B) shows summary statistics for a selection of household-level characteristics. The average household

[7] `https://opendata.swiss/de/dataset/solarenergiepotenziale-der-schweizer-gemeinden`.

[8] `https://ourworldindata.org/grapher/solar-pv-prices`. Prices are converted to Swiss francs using CHF / USD exchange rates set at 2021 USD prices from the Penn World tables (Feenstra et al., 2015)

[9] In total, we adjust around 5% of raw observations.

[10] The data is both read by humans from the electricity meters and written to the database.

Table 2.1. Summary Statistics

	N	Mean	Sd	Min	Median	Max
Panel A: Outcomes						
Electricity consumption (kWh)	2,202,709	4,943.21	5,057.45	375.03	3,228.96	33,418
Green mix	1,103,015	.04	.19	0	0	1
EV	2,205,023	0	.07	0	0	1
Solar PV	2,205,023	.01	.1	0	0	1
Panel B: Controls						
Electricity price (CHF/kWh)	2,203,923	.22	.03	.04	.22	1
Household income (TCHF)	2,195,622	93.07	117.61	1	77.02	59,098.2
Household size	2,205,023	1.96	1.1	1	2	5
Homeowner	2,205,023	.41	.49	0	0	1
Age	2,163,147	54.16	16.98	15	53	106
Single-family home	2,205,023	.26	.44	0	0	1
Living space (m^2)	2,201,596	99.13	42.84	0	90	995
Number of vehicles	2,205,023	.2	.42	0	0	5

Note: This table presents summary statistics of our sample and a selection of relevant outcome variables and covariates.

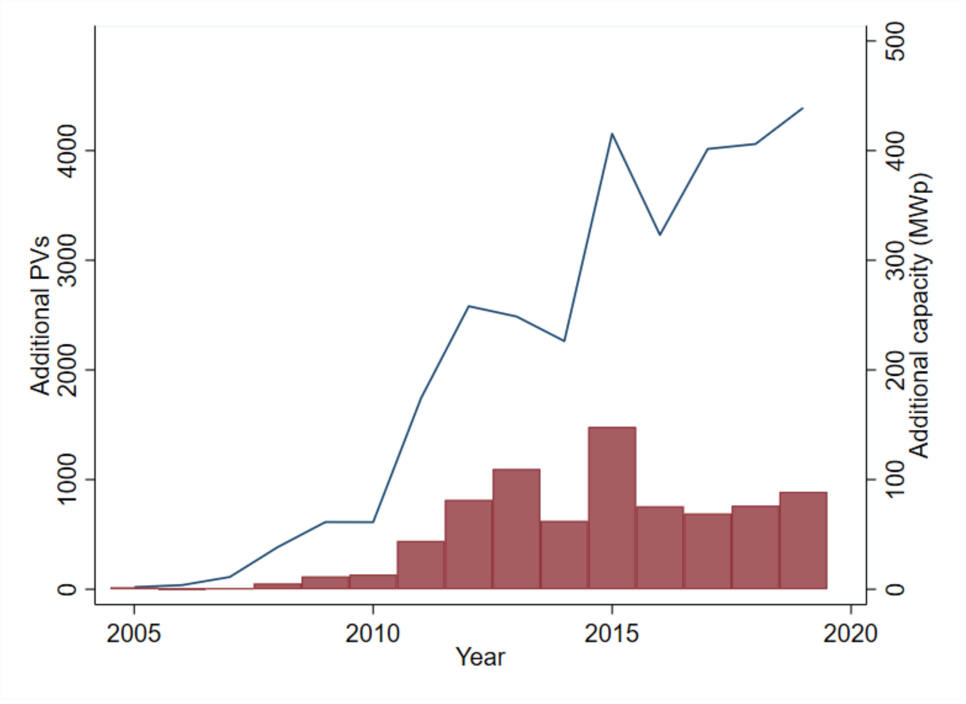
has 1.96 members, earns CHF 93k per year, is 54.2 years old, has a living space of 99.2 m^2, and consumes electricity at a price of CHF 0.22 per kWh. In addition, the average household has a 41% chance of being a homeowner, a 26% chance of living in a single-family home, and owns 0.2 vehicles. Most of the distributions of our covariates are right-skewed, with median values lower than means. For our empirical strategy, we transform most continuous variables by taking the natural logarithm. In Table 2.A.1, we show summary statistics for each of the two utilities separately. There are differences in terms of socioeconomics as well as energy behaviors between the two subgroups. On average, households served by the city utility (i.e., EWB) use less electricity, own fewer EVs and solar PVs, earn less, have fewer household members, are younger, and have less living space.

In Table 2.A.3, we present the relative rate of adoption for our binary outcomes of interest as well as average electricity consumption over time. For all three pro-environmental outcomes, the adoption rate increases over time. While adoption of solar PVs and EVs increases steadily, the uptake of the green electricity product peaks in 2013 and then declines slightly through 2019. Again, it is important to note that for the majority of our sample, electricity product choice is only available and thus observed from 2016 onwards. For annual average electricity consumption we observe a decreasing trend over time with the highest mean annual consumption in the period 2008 - 2010 and then steadily decreasing throughout the observation period.[11] We argue that this pattern is consistent with an increase in energy efficiency investments over time.

Figure 2.1 shows the additional number of new solar PVs installed, and the additional solar PV

[11] In 2019, average annual electricity consumption peaks again. This is due to a higher average annual consumption of BKW households, as households served by EWB are only observed until 2018. We show in our robustness checks and heterogeneity analysis that results are consistent when we use only the data of BKW.

Figure 2.1. Evolution of new solar PV adoptions and new solar PV capacity



Note: The graph shows the additional number of solar PVs installed per year (blue line) and the additional installed solar PV capacity per year (red bars) in our study region. Installations represent the universe of solar PVs within or very close to the canton of Bern.

capacity installed per year. Starting in the year 2008 there is a sharp increase in the number of new annual solar PVs as well as in new annual solar PV capacity. While more installations took place in recent years, the annually added capacity peaked in 2015. One possible explanation for this pattern is the shift from feed-in-tariffs to upfront subsidies, which may have de-incentivized the adoption of large solar PVs. Between 2017 and 2019, more than 4,000 new solar PVs were installed annually. The cumulative number of adopted solar PVs is 30,879 in 2019. Adoption rates vary substantially within our study region. In Figure 2.A.2, we illustrate the number of solar PVs per building at the end of 2019 in each zip code. The lowest adoption rates are observed in the mountainous zip codes in the south of the canton, as well as in urban zip codes. The highest adoption rates are observed in the suburban areas within close commuting distance to the urban centers. These are mostly areas with a higher share of single-family homes, higher incomes, and higher home ownership rates.

2.4. Empirical Strategy

2.4.1. Relationship of Interest

To infer the impact of solar PV adoption on energy-related behavior of neighboring households, we model household energy behavior as a function of household characteristics, building attributes, and a rich set of fixed effects. Our baseline estimation equation reads as follows:

$$y_{it} = \beta \mathrm{PV}_{it-1} + \gamma x_{it-1} + \delta z_{it} + \alpha_i + \omega_{ct} + \varepsilon_{it}, \tag{2.2}$$

where y_{it} is either an indicator of household i's decision to purchase green electricity, adopt a solar PV or an EV, or the natural logarithm of electricity consumption in year t. α_i is a set of household-level fixed effects and ω_{ct} are zip-code-year fixed effects.

To study the impact of solar PV adoption on interacting agents' energy behavior, we create a density measure for peer solar PV installations, for each individual household according to an approach commonly used in urban economics (Ewing and Cervero, 2010). More specifically, our main variable of interest, PV_{it-1}, denotes the lagged, distance-weighted, density of peer solar PV installations, and is defined in the following way:

$$\mathrm{PV}_{it} = \sum_{p=1}^{P} \frac{\mathbb{1}_{ipt}}{\mathrm{dist}_{ipt}}. \tag{2.3}$$

The indicator function $\mathbb{1}_{ipt}$ in the numerator depicts whether household i's peer p at time t has adopted a solar PV. We use the universe of solar PV installations in and close to the canton of Bern to construct our treatment variables. For each solar PV geolocation we calculate the distance to each individual household in a given year. We sum over each peer and discount the impact of an additional installation with the distance between household i and peer p at time t, dist_{ipt}.[12,13] Panel (A) in Table 2.A.4 provides summary statistics of our main variable of interest, solar PV density. On average, solar PV density amounts to 0.51 with a maximum of 1.95 and a minimum of 0.01. We present the distribution of our treatment variable for each year separately in Figure 2.2. There is a steady increase in average solar PV density, reflecting increasing adoption rates over time.[14] β in Equation 2.2 represents our main coefficient of interest, the peer effect, and measures how a change in solar PV density relates to household-level energy behaviors.

In addition to solar PV density, we calculate density measures for the green electricity product and EVs using the same procedure as for solar PVs, and include their lagged values in our baseline regression equation (x_{it-1}). This allows us to control for potential peer effects in green electricity or EV adoption between neighbors. x_{it-1} also includes other lagged energy-related controls, such

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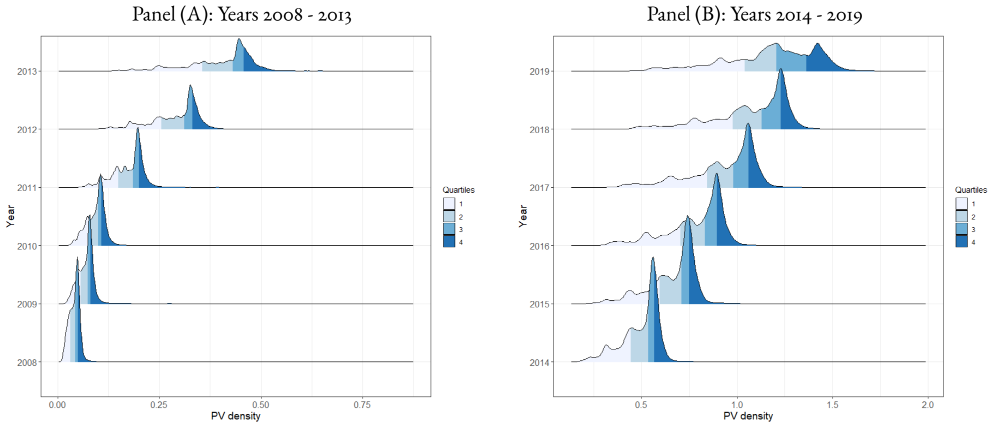
[12] We disregard solar PVs within 0-5 m of a household. This is to ensure that we do not inadvertently use a household's own solar PV for their treatment, as the geocoding in the two data sources may not be completely identical. For instance, the household dataset uses the center of the rooftop, while the solar PV dataset uses the exact location on the rooftop.

[13] Later, we show that the results are robust to changes in the treatment definition, including setting distance thresholds, weighting solar PVs by squared distance, and a ring-based treatment definition.

[14] Note the difference in the scale of the x-axis between Panel (A) and (B).

Figure 2.2. SOLAR PV DENSITY DISTRIBUTION BY YEAR



Note: The plot shows the distribution of solar PV density per year. The entire estimation sample was used to plot the yearly distributions.

as electricity prices or electricity product choice. Depending on the outcome of interest we vary which energy-related control variables are included. For example, for EV adoption, green electricity product adoption and annual electricity consumption as outcomes, we include lagged solar PV adoption as a control variable. z_{it} is a vector of time-varying household and building specific controls, which contains information on age, income, wealth, household size, marital status, size of living space, number of rooms, type of building, age of building, heating system, home ownership, as well as the number and fuel type of household vehicle portfolio. In addition, z_{it} includes a density measure for buildings and apartments.[15]

2.4.2. Identification

We address the three common concerns in identifying peer effects related to self-selection of peers, correlated unobservables, and simultaneity (Brock and Durlauf, 2001; Manski, 1993; Soetevent, 2006) by closely following the recent empirical literature (e.g., Bollinger, Burkhardt, et al., 2020; Bollinger and Gillingham, 2012; Towe and Lawley, 2013).

First, to account for simultaneity (or reflection), we use past rather than concurrent decisions by peers and include the density of solar PV installations in the previous period. Using prior peer group decisions, instead of contemporaneous decisions, should largely address concerns

[15] Building and apartment density is defined as in Equation 2.3 but all buildings and apartments are just one without indicator variable.

about simultaneity.[16] Also, for electricity product choice and electricity consumption we view simultaneity in the behavior of interacting agents to be negligible, as these are private and mostly unobserved actions. We consider it unrealistic that one household's decision to use less electricity will influence another household's decision to adopt a solar PV. Second, to account for endogenous group formation leading to self-selection of peers (or homophily), we include zip-code-year fixed effects, ω_{ct}, as well as household-level fixed effects, α_i, which account for time-invariant household preferences and time-varying selection into peer groups. Not accounting for non-random sorting of households into a neighborhood based on common (unobserved) characteristics would lead to a biased peer effect estimate. Third, concerns about correlated unobservable variables that may affect both peers and individual households should be largely addressed by our time-varying location-specific fixed effects, ω_{ct}. These control for localized supply activities and allow for non-linear preference development between zip codes. An example are localized marketing efforts at different points in time that target households for pro-environmental behavior or lead to local changes in climate change awareness or perception. Increased marketing in a given location would cause unobserved shocks to households' environmental preferences and influence both the solar PV density in that neighborhood, and energy-related behavior of peers.

To further address concerns with regards to sorting or correlated unobservables, we include an unusually rich set of household-level controls, building characteristics (z_{it}), and lagged energy-related controls (x_{it-1}). The set of energy-related control variables (i.e., green electricity product density and EV density) helps to account for sorting on green preferences and to control for potentially correlated local shocks to environmental awareness. In addition, for example, the inclusion of lagged solar PV adoption as a control variable when examining EV adoption or annual electricity consumption helps to account for the potential co-adoption of green technologies, and changes in grid energy consumption due to solar PV adoption. To control for the number of potential peers, as well as possible supply side effects stemming from large real estate development projects, we also include both building and apartment density in z_{it}.[17]

We estimate all regressions using ordinary least squares (OLS). Although the unboundedness of predicted probabilities might be a concern for the three binary outcomes of interest, we prefer OLS because of the well-known incidental parameter problem of non-linear fixed effects models (Chamberlain, 1980; Neyman and Scott, 1948). This is of particular concern, as our baseline regression equation includes household-level fixed effects. To test for potential model misspecification due to the linearity assumption, we also conduct a robustness checks where we estimate a logit fixed effects model. However, as we do not attain convergence with household-level fixed effects, we have to estimate a logit model with zip-code-year fixed effects only.

Instrumental Variable Approach - Although we argue that the estimation of Equation 2.2 addresses most concerns regarding the causal identification of peer effects, we resort to an instrumental variables (IV) approach to tackle remaining concerns regarding correlated unobservables.

[16] Especially since there is an additional time lag between the adoption decision and installation of solar PVs. We use the date of the solar PV's grid connection as adoption date.

[17] In the specification for solar PV adoption as an outcome, we also control for household rooftop solar PV potential, its interaction with global solar PV prices, and size of the rooftop area to control for household i's suitability to install solar PV.

We isolate random variation in solar PV density over time, by using peer rooftop solar PV potential, and its interaction with annual global solar PV prices, as instruments. The instruments have two sources of variation: temporal variation in annual global solar PV prices, and spatial variation across households in terms of peer rooftop solar PV potential.[18] We supplement Equation 2.2 with the following first-stage regression:

$$\mathrm{PV}_{it} = \lambda \mathrm{PVPotential}_{it} + \phi \mathrm{PVPotential}_{it} \times \mathrm{Costs}_t + \gamma x_{it-1} + \delta z_{it} + \alpha_i + \omega_{ct} + \xi_{it}, \qquad (2.4)$$

where $\mathrm{PVPotential}_{it}$ is the distance-weighted peer rooftop solar PV potential, as measured by a rooftop's calculated mean annual irradiance per square meter. The calculated mean annual irradiance per square meter is an engineering based measure of the actual solar irradiance reaching a roof surface. It takes into account the location of the building (e.g., solar irradiance based on longitude and latitude), building geometry (e.g., roof inclination and orientation), terrain (e.g., shading by mountains), vegetation (e.g., shading by trees), and surrounding buildings (e.g., shading by high-rise buildings). The calculated mean annual irradiance per square meter is available for each individual roof surface in Switzerland.[19] To use rooftop solar PV potential as an instrument for solar PV density, we create a density measure for peer rooftop solar PV potential, similar to the procedure for our treatment variable. More specifically, we construct our rooftop solar PV potential instrument in the following way:

$$\mathrm{PVPotential}_{it} = \sum_{p=1}^{P} \frac{\mathrm{kWh/m^2/yr}_{ipt}}{\mathrm{dist}_{ipt}}, \qquad (2.5)$$

where $\mathrm{kWh/m^2/yr}_{ip}$ is the above mentioned calculated mean annual irradiance per square meter of roof surface of household i's peer p. Since buildings have multiple roof surfaces, we select the roof surface with the highest calculated average annual irradiance per square meter for each building.[20] To avoid selecting roof surfaces that are too small for a solar PV, we disregard roof surfaces smaller than 20m^2, which roughly corresponds to a 3 kWp solar PV installation. In addition, we resort to global solar PV prices and include an interaction effect between peer rooftop solar PV potential ($\mathrm{PVPotential}_{it}$) and global solar PV prices (Costs_t) in the first stage regression. Our instruments thus represent rooftop solar PV potential of peers as well as the evolution of the profitability of solar PV installations over time.[21] We show the evolution of global solar PV prices as well as the correlation of peer rooftop solar PV potential and solar PV density in Figure 2.A.4. Furthermore, summary statistics of both our instrumental variables are presented in Panel (B) of Table 2.A.4. The average peer rooftop solar PV potential is 1,309.79 kWh per m^2 of rooftop

[18] There is also time variation in peer rooftop solar PV potential due to construction or renovation of buildings and relocation of households. Some households (i) moved within the service area during the time frame of observation and thus remain within the estimation sample but experience shocks to their solar PV density as well as their solar PV potential density in the year of relocation.

[19] See Klauser, 2016 for a detailed explanation of the methodology used to calculate the solar PV potential of each individual roof area in Switzerland.

[20] In Figure 2.A.3 we provide graphical evidence that solar PVs are actually installed on the roof surface with the highest solar PV potential.

[21] We do not include global solar PV costs separately, as they are collinear with the zip-code-year fixed effects.

area with the median being 1,316.12 kWh per m^2 of rooftop area. Solar PV costs have been steadily decreasing over time starting at 4.5 CHF/W in 2008 and decreasing to roughly 0.40 CHF/W in 2019. Furthermore, we decompose the variance of both instruments into variation over time and variation between individuals. In Table 2.A.5, we show that the variation in solar PV costs relates to the time component of our data while the share of variation in peer rooftop solar PV potential is mainly due to local time-invariant differences.

The main assumption of our approach to establishing a causal relationship between solar PV density and energy-related household behavior depends on the instrumental variable satisfying two conditions. The first is that the instruments, peer rooftop solar PV potential and its interaction with global solar PV prices, should be correlated with solar PV density. We illustrate and test this in the first-stage regressions presented in Table 2.A.6. We also provide some further graphical evidence for the relevance of rooftop solar PV potential. Figure 2.A.5 depicts the average rooftop solar PV potential per zip code. Comparing the figure with Figure 2.A.2 suggests that the highest and lowest adoption rates are observed in zip code areas with the highest and lowest average potential, respectively. This suggests that households are on average aware of their own rooftops' solar PV potential and adoption rates are at least partially driven by natural circumstances, such as shading in mountainous regions. In Figure 2.A.6 we also provide some micro-geographic visual motivation for using peers' rooftop solar PV potential as an instrument for peers' actual solar PV installations. This figure further supports our assumption that zip codes with high (low) rooftop solar PV potential also have high (low) solar PV density. Moreover, it illustrates that there is sufficient within zip code rooftop solar PV potential variation to causally estimate a peer effect, as we rely on within zip code differences for identification. The relevance assumption can be tested using Kleibergen-Paap Wald statistic (Kleibergen and Paap, 2006).

The second condition is that the instrument should affect household energy behavior only through its effect on solar PV density. In other words, something unobserved would need to significantly impact both a neighborhood's average solar PV potential, or profitability, and a household's energy behavior. This assumption can not be tested and we provide arguments why it is, in our opinion, unlikely that such unobserved factors influence both variables. First, peer rooftop solar PV potential is determined by neighboring building's location, geometry, and shading and should be plausibly exogenous to household energy behaviors. Even if we allow for very localized sorting or highly localized shocks to environmental preferences, the majority of buildings (i.e., 97%) has been constructed before our timeframe of observation, which corresponds to the period of increased solar PV diffusion. Hence, it is unlikely that rooftop solar PV potential was taken into account when buildings were constructed. We furthermore argue that we deem it unlikely that households chose their preferred housing location based on rooftop solar PV potential alone, as real estate markets were highly competitive and sorting likely occurred on a community, or neighborhood level, and not on a street level.[22] To further support this argument, we present correlations between rooftop solar PV potential and our observed socioeconomics in Table 2.A.7. The strongest correlation is between solar PV potential density and building period indicators for

[22]For more information the following news article documents certain aspects of housing markets in our timeframe of observation: `https://www.swissinfo.ch/eng/business/home-ownership-remains-a-mirage-for-most-swiss/47884684`

buildings constructed before 1945 (0.07) and after 2000 (-0.08). This correlation is relatively weak in itself and is indicative that the solar PV potential density is, if at all related with the building age, in a direction that further supports our argument. Relatively new (old) buildings are more likely in neighborhoods with comparable low (high) solar PV density. Hence, it is unlikely that our instrument is driven by new constructions built to maximize solar PV potential. We take this as further support that rooftop solar PV potential is likely orthogonal to households' socioeconomic characteristics as well as to location specific characteristics of their homes. One potential threat to identification could be if well-suited rooftops were all located within the same areas within a zip code, for instance, due to equally orientated and constructed rooftops. As documented in Figure 2.A.6, rooftop orientation, suitability, and inclination vary within a zip code and within areas in zip codes. For the second instrument, the global solar PV costs, we argue that our sample in the canton of Bern represents a small share of global solar PV purchases. It is thus unlikely that increased demand for solar PV would impact average global prices.

2.5. Results

We find evidence for highly localized peer effects of increasing solar PV adoption on neighboring household's energy-related behavior. In what follows, we distinguish between electricity behavior and durable goods adoption. We first present the main results, then we explore heterogeneities in peer effects. Next, we perform various robustness checks to assess and discuss the validity of our results.

2.5.1. Main effects

Effects on electricity behavior -Table 2.2 presents the results for household electricity behavior. Odd rows show OLS regression results and even rows represent IV regression results. Columns (1) and (2) depict the results when using the natural logarithm of annual electricity consumption as outcome and columns (3) and (4) present the effect of lagged solar PV density on the probability to voluntarily purchase the green electricity product.

We find a negative and significant effect of an increase in solar PV density on households' electricity consumption. On average, an increase in solar PV density of 0.01, which corresponds to an additional solar PV installation at 100 m distance, leads to a significant decrease in annual electricity consumption between 0.12% and 0.18% depending on the specification. In absolute figures, this means annual electricity savings of about 10 kWh for an average household induced by an additional solar PV 100 m away.[23] We prefer the results of our IV specification as presented in column (2), because it addresses all potential concerns related to the identification of causal peer effects. Our instruments are both relevant, as shown by the high first-stage F-statistic and the significant Kleibergen-Paap test. Moreover, the two instruments pass the Hansen J-test for overidentifying restriction.

To the best of our knowledge there is no prior causal evidence of an increase in electricity conservation efforts after agents observe the adoption of solar PVs by neighboring households. As

[23]This corresponds, for example, to a reduction in monthly laundry usage by one load.

Table 2.2. PEER EFFECTS ON ELECTRICITY BEHAVIOR

Dependent variable:	Elec. consumption		Green mix	
	(1) OLS	(2) IV	(3) OLS	(4) IV
PV density	−0.1188 * **	−0.1756*	0.0072	−0.0091
	(0.0221)	(0.0743)	(0.0125)	(0.0461)
EV HH	0.1501 * **	0.1502 * **	0.0155	0.0153
	(0.0363)	(0.0363)	(0.0184)	(0.0184)
PV HH	−0.0872 * **	−0.0838 * **	0.0059	0.0065
	(0.0088)	(0.0097)	(0.0051)	(0.0055)
N	1, 834, 745	1, 834, 745	928, 821	928, 821
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	*N/A*	1648.2	*N/A*	492.6
p-value Kleibergen-Paap	*N/A*	0	*N/A*	0
p-value Hansen's J	*N/A*	0.537	*N/A*	0.793

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. Odd rows are OLS estimates while even rows are IV regressions. All estimates include individual level control variables as described in Section 2.4.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$.

argued above, we suspect this result to be driven by increased environmental awareness and a higher willingness to contribute to climate change mitigation. While increasing solar PV density is observable, increased efforts in electricity conservation are unobserved, private actions. Similar results of social norms influencing peer behavior have been found in different contexts, such as, water (Bollinger, Burkhardt, et al., 2020) or electricity conservation (Allcott and Rogers, 2014). Moreover, increased willingness for pro-social contributions, in a setting where social norms are observed, has been documented in experimental settings testing for charitable giving or altruistic behavior (e.g., DellaVigna et al., 2012; Frey and Meier, 2004).

We find no evidence of peer effects of solar PV installation on the likelihood that a household chooses a green electricity product. Both the OLS and IV regression estimates are close to zero and insignificant on conventional levels. Our results for the impact of solar PV adoption on peer green power purchases contrast with La Nauze, 2021, who finds that, on average, an increase in the number of solar PVs increases voluntary green power purchases by peers. La Nauze, 2021 shows that in a zip code area, the share of non-solar customers signing new green power contracts increases by 0.002 for every 100 additional solar PVs installed. There are several possible explanations why our result differs from the results of the above study. First, we are using household-level data, while the aforementioned study conducts the analysis on a more aggregate level. Second, we observe only four periods in which the majority of households had the opportunity to choose different electricity products. Third, the choice of electricity product is known to be influenced by default choice (e.g., Ebeling and Lotz, 2015; Liebe et al., 2021), and product choice appears to be quite persistent in our setting, with few households switching during our observation period. Finally, the default product in our sample might already be perceived as environmentally friendly, because it contains mainly hydropower. We test this alternative explanation by estimating whether peer solar PV adoption has an impact on households' decision to opt out of the baseline product to purchase grey electricity, the least environmentally friendly electricity product. The results are depicted in Table 2.A.8. Estimating an OLS regression in which we control for individual and zip-code-year fixed effects and various socioeconomic control variables, we find suggestive evidence that a higher solar PV density is correlated with a decrease in the likelihood that a household chooses the grey electricity product. However, statistical significance vanishes when using our preferred IV specification.

Effects on durable goods adoption - Table 2.3 presents the results for durable goods adoption. Again, odd rows show OLS regression results and even rows depict IV regressions. We use a common procedure in durable good adoption estimation and assume households to exit the market once they decide to adopt (Bollinger, Gillingham, Kirkpatrick, et al., 2022).[24] While column (1) and (2) show the results for EV adoption, columns (3) and (4) present the solar PV adoption results.

With our linear fixed effects regression, we find no significant effect of peers' decision to adopt a solar PV on interacting agents' decision to adopt an EV. Once we instrument for solar PV density, our results show a significant positive effect of solar PV density on the probability to adopt an EV. The IV point estimate is not statistically different from the OLS point estimate. On average,

[24]This means that once a household adopts a solar PV or an EV, we drop subsequent observations of this agent. In terms of solar PV adoption it is relatively unlikely that households adopt multiple times. However, with EVs it is possible that a household purchases more than one electric car. We argue that our procedure is cautious because we observe EV markets at a relatively early stage and adoption rates do not exceed 1% before our last year of observation.

Table 2.3. Peer effects on durable goods adoption

Dependent variable:	EV		Solar PV	
	(1) OLS	(2) IV	(3) OLS	(4) IV
PV density	0.0024	0.0104*	0.0193 * **	0.0219 * **
	(0.0015)	(0.0045)	(0.0023)	(0.0066)
PV HH	0.0065 * **	0.0061 * **		
	(0.0010)	(0.0010)		
EV HH			0.0795 * **	0.0795 * **
			(0.0170)	(0.0170)
N	1, 825, 197	1, 825, 197	1, 765, 332	1, 765, 332
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	*N/A*	1, 565.0	*N/A*	1, 529.3
p-value Kleibergen-Paap	*N/A*	0	*N/A*	0
p-value Hansen's J	*N/A*	0.297	*N/A*	0.168

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. Odd rows are OLS estimates while even rows are IV regressions. All estimates include individual level control variables as described in Section 2.4.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$.

an additional solar installation at 100 m distance of a household leads to a 0.01 percentage point increase in the probability of adopting an EV, an increase of 2.3% over the baseline adoption rate of 0.44%.

Our finding that EV adoption is higher in areas with higher PV diffusion is consistent with the findings of Lyu, 2022, who documents this pattern using zip code-level data from California. Lyu, 2022 finds that in an average zip code, an additional solar PV leads to 0.184 additional EV sales and interprets this increase as co-adoption of solar PV and EV within the same household. Because we are using micro-level data, we can distinguish between co-adoption of solar PV and EV within the same household and an increase of EV adoption by interacting agents due to peer effects. As indicated in Table 2.3, we also control for a households lagged solar PV and EV adoption in our respective specifications. In addition to our causal peer effect, we document suggestive evidence of solar PV to EV co-adoption as well as EV to solar PV co-adoption, as indicated by the respective positive coefficients. However, we caution to interpret this result as causal, since within household EV and solar PV adoption could both be correlated with unobserved factors.[25]

In our preferred IV regression, we find that, on average, an additional solar PV installation at 100 m distance leads to a 0.02 percentage point increase in the probability to adopt a solar PV, which constitutes a 2% increase over the baseline adoption rate of 1%. In this specification linear fixed effects results and IV results are almost identical in terms of magnitude.

There is a large literature documenting the influence of peers in the adoption of solar PVs (Baranzini et al., 2017; Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Rode and Weber, 2016). The magnitude of our estimated peer effect in solar PV adoption is difficult to compare with other studies because they often use different levels of spatial aggregation and/or different treatment definitions. In a similar setting, but with more aggregated data, Baranzini et al., 2017 find that an additional solar PV within 1 km leads to 0.11 additional installations within a zip code. We show in our economic relevance simulation that 100 additional installations on average lead to 6 additional solar PVs.

Although not statistically different from each other, it should be noted that our IV coefficients are consistently larger in magnitude than our OLS coefficients. Given our concerns regarding correlated unobservables, one would expect the opposite to happen. However, as mentioned above, we argue that the estimation of a household-level fixed effects regression already addresses this concern regarding the causal identification of peer effects. One possible explanation could be that the source of the bias addressed by our IV regression is a classic measurement error in our treatment variable (i.e., measurement error in exposure to solar PVs[26]). If this was the case and assuming the classical errors-in-variables assumptions to hold, the OLS-estimator for β would then be attenuated towards zero (Griliches and Hausman, 1986), as documented in our results.

[25] We also estimate solar PV to EV co-adoption using a similar IV strategy employing an agent's own rooftop solar PV suitability (i.e., PV potential, rooftop area and interaction terms with global PV costs) as instruments and find no evidence of solar PV to EV co-adoption. Detailed results are omitted, but available upon request.

[26] This might be due to (unobserved) differences in the visibility of solar PVs or solar PVs that are isolated from the grid and therefore not included in our data.

Local effects - To aid interpretation and increase comparability to other studies, we use our estimated IV coefficients to predict how installing additional solar PVs at a given distance will, on average, affect the energy behavior of interacting agents. We illustrate these results graphically in Figure 2.3. In Panel (A) we depict the percentage change in annual electricity consumption due to the installation of an additional solar PV at distances of 10 m, 25 m, 50 m, 100 m, 200 m, 250 m, and 500 m. Panel (B) and (C) show the average marginal effect of an additional solar PV installation, at the same distances, on the probability of adopting a solar PV or an EV. We present the effects for the durable goods as a percentage point change in the adoption probability.[27] The figures visualize that the estimated peer effects are highly localized and rapidly loose economic significance with increasing distance. For instance, an additional peer solar PV causes an average decrease in annual electricity consumption of 1.76% for households living 10 m away, whereas households living 500 m away decrease their annual electricity consumption on average by 0.03%. The local nature of our effects is similar to previous literature studying peer effects in solar PV diffusion (e.g., Bollinger, Gillingham, Kirkpatrick, et al., 2022).

2.5.2. Robustness Checks

Before discussing the results further, we explore the validity and robustness of our estimated peer effects. To test the validity of our empirical strategy, we conduct a placebo test. We estimate both the linear fixed effects model as well as the IV model using annual household income as outcome variable. Using a placebo test allows us to check for an association that should only be there if our research design is flawed. Along these lines, we argue that solar PV density should not be correlated with annual household income if we properly account for peer self-selection (or homophily). Results of this empirical exercise are depicted in Table 2.A.9. In both the OLS and IV regression we find no statistically significant relationship between solar PV installation density and interacting agents' annual household income. We interpret this as further evidence supporting our empirical strategy and hence the causal interpretation of our estimated peer effects.

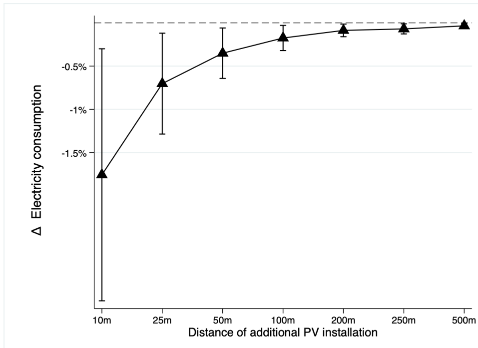
We test the robustness of our results across several dimensions. In a first step, we change our treatment definition from solar PV density to the geospatial count of solar PV installations at a certain distance from the household. Such ring based treatment definitions are the more common approach in the estimation of peer effects in solar PV diffusion (e.g., Bollinger, Gillingham, Kirkpatrick, et al., 2022; Graziano and Gillingham, 2015). We use three different ring sizes, i.e., 5 - 100 m, 5 - 250 m, and 5 - 500 m[28] to explore whether our results of highly localized peer effects on energy-related household behavior hold with an alternative treatment definition. Table 2.A.10 and Table 2.A.11 show the estimated coefficients using the same instrumental variable strategy as in our main results. Estimates are qualitatively similar to our baseline findings. The pattern remains consistent suggesting that an increase in the count of solar PVs close to a household (i.e., 5 - 100 m) increases the probability to adopt a solar PV or an EV and lowers average annual electricity consumption. The estimated peer effects' magnitudes are larger for solar PVs installed in close vicinity to a household and effects fade out with distance.

[27] In the interest of space we do not illustrate our results for green electricity product choice, as they are not statistically significantly different from zero.

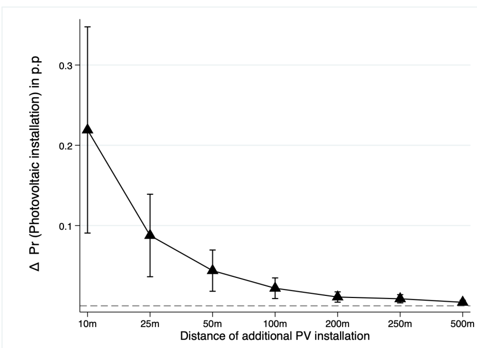
[28] Again, we do not count solar PV installations within 0 - 5 m of a household.

Figure 2.3. Average marginal effects of additional solar PV

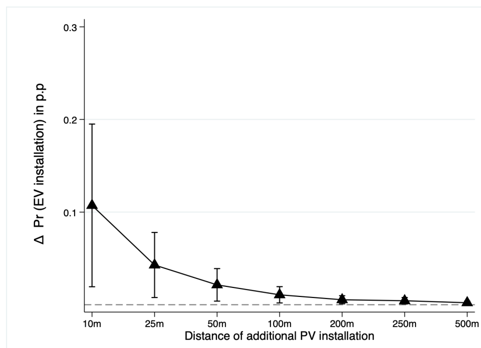
Panel (A): Electricity consumption



Panel (B): Solar PV



Panel (C): EV



Note: These plots show the average estimated changes in the outcome as a result of an additional solar PV in the indicated range of distance. The outcomes of interest are indicated in the plot title. Effects are depicted in changes in percentage points to adopt an EV (B) or a solar PV (C). The effect in plot (A) is in percent changes. Coefficients based on instrumented linear fixed effects regression including various control variables, individual, and zip code-year fixed effects presented in Table 2.2 and Table 2.3. Whiskers denote 95% confidence intervals. Standard errors are clustered at the individual level.

In a next step, we adapt our solar PV density treatment definition by excluding installations after a certain distance. In other words, we define a ring of 10 km around each location in our dataset and calculate the distance to each solar PV within this ring, hence assuming that the effect not only fades out but completely disappears at a certain distance. We define the sum of the inverse of these distances as our cut-off density measure. Results are presented in Table 2.A.12. Again, the results stay consistent with our main estimates. Households with more solar PVs installed closer to their home are more likely to purchase a solar PV, an EV, and, on average, consume less electricity. Point estimates increase in comparison to our baseline estimates, remain statistically significant, and all estimates' 95% confidence intervals overlap with the baseline point estimate.[29]

We conduct further robustness checks with regards to our main specification. In Table 2.A.13 we show the results when not accounting for households' inter-related or co-adoption behavior. The results are similar when we do not include solar PV and/or EV adoption as covariates in our main specifications. Table 2.A.14 shows that the results are unchanged when we control for contemporaneous household adoption decision of EV and solar PV instead of lagged adoption decisions, therefore addressing concerns about our finding of electricity conservation behavior being driven by newly installed solar PVs. Such solar PV installations potentially crowd-out grid electricity consumption with self-produced electricity and could be an alternative explanation to our postulated social norm based electricity conservation effort. In Table 2.A.15 we exclude the density measures of EVs and green electricity product adoption, as potentially bad control variables. Results are similar to that of our baseline specification.

In addition, we test different specifications with regards to our IV strategy. The rooftop solar PV potential instrument has some temporal variation from the construction of new buildings and the relocation of households. There are two potential concerns related to endogeneity of this time-varying component. First, our identification strategy could be compromised if new buildings with high rooftop solar PV potential are strategically built in neighborhoods with environmentally friendly residents. In order to test how this affects our results, we estimate our preferred specification using only rooftop's solar PV potential which were constructed before the beginning of our observation period (i.e., 2008). Most buildings were built before solar PVs were readily available, and therefore rooftop geometry was not specifically set out to maximize the roof surfaces' solar potential.[30] Our results are robust to the exclusion of newly constructed buildings, as shown in Table 2.A.16. Second, estimates might be driven by some households' strategic relocation based on rooftop solar PV potential and unobserved preferences. Although household energy behavior may change after a move (e.g., better appliances, more living space, different insulation, different heating type), we argue that we adequately account for such changes with our various household-level control variables. To ensure that our results are not affected by movers, we exclude relocating households and re-estimate our preferred IV specification using only the non-mover sample. As shown in Table 2.A.17, our results are robust to the exclusion of movers. In Table 2.A.18, we do both and use only the initial rooftop solar PV potential at the beginning of our observation period, and exclude relocating households, thus relying only on cross-sectional variation of rooftop solar PV potential. Results are again qualitatively similar to our baseline results.

Next, we test our results for potential model misspecification. For our three binary outcomes, EV

[29] We perform the same robustness check with ring sizes of 1 km and 5 km, respectively. The results are qualitatively similar, although in some cases with wider confidence intervals. Again, the magnitude of the point estimates increases relative to the baseline estimates. Tables are omitted, but available upon request. We furthermore also conduct a robustness check where we calculate the density as the count of solar PVs discounted at the squared distance. Again, results remain qualitatively similar and are not further presented nor discussed.

[30] More than 70% of our observed households live in buildings constructed before 1980. Less than 10% were built after 2000 and approximately 2% within the last 10 years.

adoption, solar PV adoption, and green electricity product choice, the linear probability model is an approximation of the true underlying data generating process since we model a probabilistic outcome. As discussed in Section 2.4 we prefer OLS, due to the incidental parameter problem of non-linear fixed effects model. Furthermore, our logit fixed effects models only allow us to control for fixed effects at a more aggregated level, as they would otherwise not converge. We apply a control function approach to control for the potential endogeneity of solar PV density in the non-linear models (Wooldridge, 2014). Electricity consumption is a continuous dependent variable bounded at zero. Hence, instead of modelling consumption in a log-linear fixed effect model, we use a control function Poisson-pseudo maximum likelihood (PPML) approach for the electricity consumption to test for potential model misspecification. We depict the results in Table 2.A.19. Average partial effects from logit estimations are similar in extent, direction, and significance to the estimated effects from the corresponding OLS regression.[31] All specifications only control for zip-code-year fixed effects, as convergence with household fixed effects was not attainable.[32] The PPML model is not subject to the incidental parameter problem and here we compare the control function approach with both household and zip-code-year fixed effects to our baseline estimate of the OLS regression using the natural logarithm of annual electricity consumption as an outcome. Again, we find very similar point estimates for the log-linear and the non-linear models.

We furthermore test the robustness of our results to the inclusion of community-year fixed effects instead of zip-code-year fixed effects.[33] This allows us to control for potential policy shocks at the lowest administrative level. However, this comes with the caveat that we group more heterogeneous households into a spatial unit, especially in the bigger[34] or newer[35] communities. We depict the results of our preferred specification but including community-year instead of zip-code-year fixed effects in Table 2.A.20. The results remain qualitatively similar, however, the magnitude and significance of the estimated peer effects changes slightly. The effect of an increase in solar PV density on EV adoption is no longer statistically significant, but the magnitude of the point estimate is almost identical to the estimated peer effect when using zip-code-year fixed effects. The magnitude of the peer effects on solar PV adoption and annual electricity consumption increases and remains statistically significant at conventional levels.

[31] In every specification average partial effects of the logit specifications lie within the 95% confidence interval of the linear fixed effects model.

[32] More detailed local fixed effects interacted with year fixed effects (i.e., 500m^2-grid-cell-year) also converged and results are qualitatively similar. We opt to present the zip-code-year fixed effects specifications for consistency.

[33] While zip codes are historically organized around communities, some larger communities have multiple zip codes while some smaller communities share a zip code together.

[34] Specifically for the cities in our sample it remains true that there are very heterogeneous areas within a community based on building type, rental prices and household's socioeconomic characteristics. Parts of these differences and potential shocks to environmental awareness are likely picked up by our zip code fixed effects, but might be missed by our community fixed effects, as they could be potentially diverging.

[35] There is a trend of community mergers, which puts different villages together into the same community to lower the administrative burden. The new communities might still remain in older territories and boundaries based on agricultural fields or geographical areas between the different villages within a new community might remain

Table 2.A.21 presents the results of our preferred IV specification when we cluster standard errors at the zip code level rather than at the individual level to account for possible spatial correlation in the error terms. Clustering at the zip code level is potentially more conservative than clustering at the individual level, as our sampling is not clustered[36] and treatment assignment occurs at the individual level (Abadie et al., 2023).[37] The estimated peer effect of solar PV density on EV adoption is now significant at the 1% level, as the standard error decreases when clustering on zip code level. The estimated peer effect on annual electricity consumption is significant at the 10% level, but no longer at the 5% level.[38]

2.5.3. Heterogeneous Effects

In a next step, we study heterogeneities in peer effects. We analyze how peer effects vary with peer household's observable characteristics by estimating our preferred IV specification on split samples. We select a subset of relevant household characteristics based on the existing literature. For example, in our study region, dwelling characteristics, urbanity, and income have been shown to play a role in household electricity consumption, as well as in the decision to adopt an EV or a solar PV (Bigler and Radulescu, 2022; Feger et al., 2022). More specifically, we explore potential treatment effect heterogeneity along age and income of the household, living in a single-family home, home ownership status, living in the urban center, and living in a community designated as a mountain area.[39]

Figure 2.4 illustrates the results.[40] Panel (A) depicts estimates when using the natural logarithm of annual electricity consumption as outcome. We find that the magnitude of our estimated pro-environmental peer effect on annual electricity consumption is larger for households with higher incomes and for households living in non-mountainous areas, but outside the city of Bern.[41] However, confidence intervals of the split sample estimates include our baseline point estimate in all specifications indicating that the estimated peer effects are not statistically different from the baseline. Nevertheless, it is interesting to note that high-income and non-urban households seem to be stronger motivated by visible public good contributions than low-income and urban households. This can also be formally confirmed by the z-score test statistics. The two split sample point estimates that are significantly statistically different from each other are the comparison

[36]We observe all households in the service regions of both electricity providers.

[37]Each household has a specific solar PV density as well as a specific peer rooftop solar PV potential depending on the location of their house within a community.

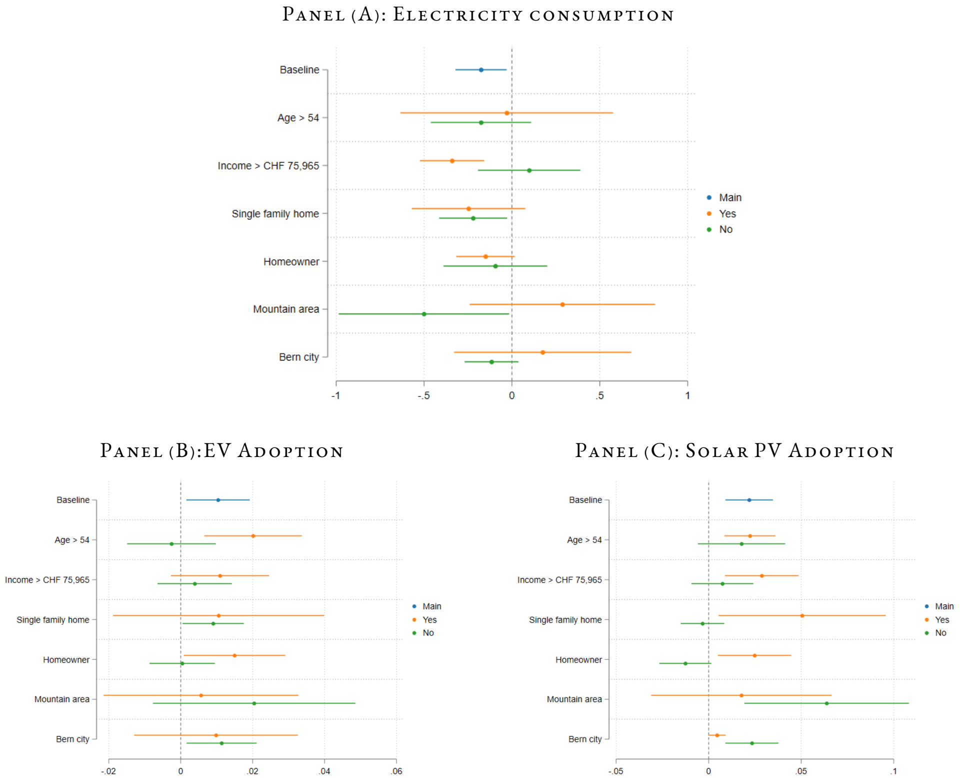
[38]The p-value for the two-sided test of the coefficient being different from zero is 6.4%

[39]We split the sample based on median age and median income. Mountain area designation is based on the majority of the area being either 800 m above sea level on average or that the difference in altitude between the lowest and the highest point at a distance of at least 500 m is more than 225 m, which corresponds to an official measure from the Swiss Federal Office of Statistics (BFS). For urbanity, we split the sample by utility, as EWB only serves customers in the city of Bern.

[40]In line with our baseline estimate, we also find no significant heterogeneous effects of an increase in solar PV density on the probability of a household purchasing a green electricity product. In the interest of space we do not illustrate these results.

[41]To formally test whether the point estimates from the subsample regressions are statistically different from one another we follow the procedure suggested by (Clogg et al., 1995).

Figure 2.4. Effect heterogeneity



Note: This figure shows estimated effects of split sample IV regression based on our preferred specifications presented in Section 2.5. Sample is split based on observable household characteristics. Income and age are split based on median values. Location specific differences based on observed data from building and tax data. A locations' mountain designation is based on official data from the Federal Statistical Office. Area of city of Bern is divided based on the two electric utilities providing us with data.

between households in mountain and non-mountain areas and the comparison between low and high income households. Various explanations are possible for this pattern such as, for instance, budget constraints to invest in more energy efficient appliances or higher anonymity between neighbors in urban settings.

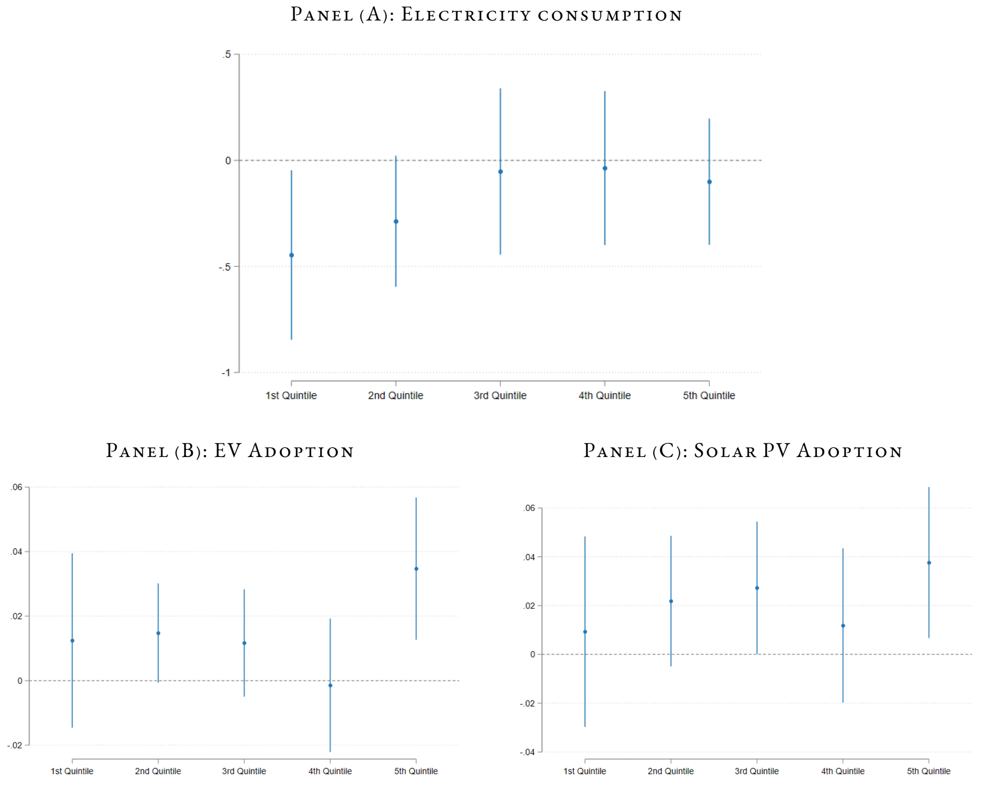
Panel (B) documents heterogeneity in peer effects of solar PV installation on EV adoption. We find that the magnitude of the peer effect is larger for above-median age and homeowners. We document suggestive evidence for stronger effects for high-income households. However, again all confidence intervals include our baseline point estimate, suggesting that the heterogeneity of the treatment effects due to the observed household characteristics is limited. If we test the difference between the split sample point estimates of above and below median households, we can reject the null hypothesis that the two estimates are the same at the 5% confidence level. At the 10% confidence level the hypothesis can also be reject for the heterogeneity based on home ownership status. We speculate that the age effect illustrates older households increased willingness to adopt more sustainable durable goods if they observe their peer's doing so. However, the effect could also be driven by the fact that EVs tend to be new vehicles and older households are more likely to be able to afford new vehicles and thus have a higher initial probability to own an EV. In terms of peer effects in solar PV diffusion (Panel (C)), we find that the peer effect is driven by homeowners and for households living in a single-family home.[42] This suggests that the peer effect only comes into play when a household has the decision-making power to install a solar PV. Furthermore, high-income households seem to be stronger influenced by peer effects in solar PV adoption, thus suggesting that budget constraints could be further reasons for peer effects to be muted. However, the correlation between high-income household and home ownership status is likely high and thus the effect could also depict decision power through home ownership. In addition, we find that peer effects in solar PV diffusion are stronger in non-urban, non-mountain regions, thus confirming previous research suggesting that the built environment influences peer effects in the adoption of solar PVs (Graziano and Gillingham, 2015).

To test whether the heterogeneities are only a feature of the local average treatment effect (LATE) identified by our instrument, we supplement the estimation of LATE through IV regression by estimating the same split sample heterogeneity for our OLS regression. That is, we do not instrument for solar PV density, but only use fixed effects and socioeconomic controls to identify heterogeneity in the effect of changes in solar PV density on agent energy behavior. The estimated coefficients in the OLS split sample regressions reveal a similar picture. Heterogeneity patterns in solar PV diffusion remain qualitatively similar, but peer effects are more accurately estimated. All results are depicted in Figure 2.A.7.

We also estimate heterogeneities in treatment effect based on differences in solar PV potential. We split the sample into five equally sized groups and illustrate the different treatment effects for each quintile separately in Figure 2.5. An interesting pattern emerges. Households with relatively low solar PV potential mainly react to increased solar PV diffusion through the channel of electricity consumption. On the other hand, the reaction in terms of pro-environmental durable goods adoption is reversed. Households in the highest solar PV potential quintile have the strongest reaction to increased solar PV neighborhood diffusion in terms of both EV and solar PV adoption. This suggestive pattern illustrates that households are reacting to the signal of increased contribution to climate change mitigation through different visible and non-visible channels, and do so in a manner that is optimal given their circumstances. Households that have relatively little own solar PV potential are more likely to invest into electricity conservation efforts, either through reduced consumption or more energy efficient appliances. Similarly, households that have higher solar PV potential are more likely to invest into a solar PV or an EV. One potential explanation for

[42] Point estimates for non-owners and residents of multi-unit homes are statistically significantly different from both the baseline estimate as well as the split sample estimate for home owners and single family home residents.

Figure 2.5. Effect heterogeneity - solar PV potential quintiles



Note: This figure shows estimated effects of split sample IV regression. Sample is split based on rooftop solar PV potential. Each household is assigned to a quintile of the distribution based on estimated rooftop solar PV potential of their home. 95% confidence interval for each parameter illustrated based on clustered standard errors on individual level.

the EV effect in the highest solar PV potential households is that they either co-adopt, or anticipate a future investment into a solar PV, and thus already decide to purchase an EV.[43] While these effects are illustrative and suggestive for potential differing behaviors between individuals based on their best-available pro-environmental action, most coefficient are not statistically significantly different from each other using the above mentioned procedure suggested by Clogg et al., 1995.

[43]We still control for all potential confounding variables and thus the estimated solar PV peer effect is still conditional on control variables and estimated using the IV strategy. However, the sample composition between the quintiles might differ and thus the observations we condition on. We assessed this by looking at summary statistics and there appears no clear pattern between potential confounding variables such as wealth, income, home ownership status and so on and the solar PV potential classes. This is also in line with our argument for the validity of the instrument.

We also illustrate further heterogeneity based on wealth and income quintiles in Figure 2.A.8. Similar to the indicative results splitting on median income, we find suggestive evidence that the pro-environmental peer effects (increase in solar PV and EV adoption as well as the decrease in electricity consumption) are predominantly driven by the higher income and wealth groups.

2.6. Economic Relevance

Our results are not only statistically significant, but also economically relevant. To quantify the solar PV peer effect's impact on household energy-related behavior, we run four different hypothetical scenarios. Three of the simulations represent policy scenarios readily available for local authorities' implementation. In the fourth simulation, we randomly place solar PVs in our study region. We depict these results in Table 2.4. First, we run a simulation where we place a solar PV on every public school (main) building in our study region that does not already have a solar PV. In total, an additional 312 hypothetical solar PVs are added to the solar PV installation base. We estimate 15 additional EVs, 19 solar PVs, and annual electricity savings of 1,069 MWh to be caused through peer effects from these additionally installed solar PVs. In a second scenario, we add a solar PV on every (still empty) city hall's rooftop, resulting in 302 additional hypothetical installations. Our simulation implies that these additional solar PVs translate to 11 additional EVs, 14 additional solar PVs, and annual electricity savings of 813 MWh through peer effects. We suspect that the difference in impact is primarily due to the generally more central location of town halls, which may be surrounded by fewer neighbors, while schools tend to be located in residential areas. Our third policy scenario has the largest estimated impact in absolute terms. Here we simulate a hypothetical solar PV mandate for newly constructed buildings beginning in 2017. Apart from the 2,682 solar PVs on the newly constructed buildings, the mandate results in 30 additional EVs, 38 solar PVs and annual electricity savings of 2,337 MWh due to peer effects.[44] It is important to qualify these results in the vein of conditional cooperation as motivation for pro-environmental peer effects. Our treatment, solar PV density, does not differentiate between size and ownership of the solar PV. However, Baranzini et al., 2017 shows that peer effects in solar PV diffusion are stronger between similar agents (i.e. households to households or farmers to farmers). Our estimate is a local average treatment effect, and we do not differentiate between private solar PVs, or industrial solar PVs, but the majority of solar PVs that make up our density measure are private ones. Nevertheless, if household reaction to solar PVs, that are installed due to a mandate or on public buildings, are smaller than reactions to the average (voluntary) installation, our estimates in these three scenarios would constitute an upper-bound.

To partially address these concerns we, in a final scenario, randomly place 100 solar PVs in our study region (on private rooftops) and repeat this process 1,000 times. We show the distribution of estimated impacts across the simulations in Figure 2.6. On average, these 100 additional solar PVs translate to 4 newly adopted EVs, 6 additional solar PVs, and 310 MWh in electricity savings.

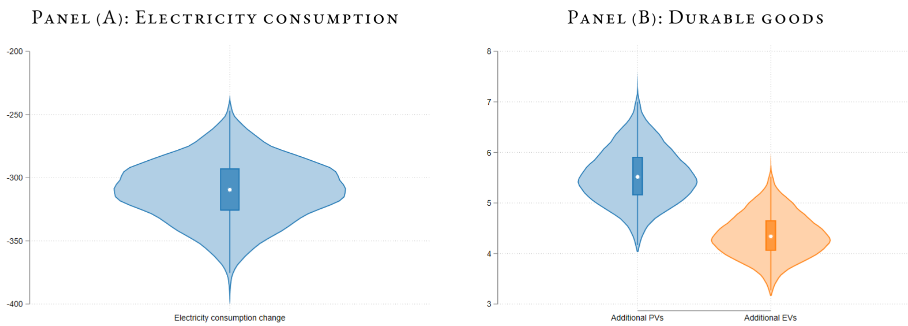
[44] Such mandates were discussed and planned to be implemented starting in 2014 and were nationally implemented as of October 2022. The canton of Bern was one of several cantons that had no mandate in place when the national law overruled (the lack of) cantonal mandates.

Table 2.4. Economic relevance

	Schools	City halls	PV mandate	Random
Panel A: Absolute change				
Electricity consumption (MWh)	-1,069	-813	-2,337	-310
EV (nb.)	15	11	30	4
Solar PV (nb.)	19	14	38	6
Panel B: Relative change				
Electricity consumption (%)	-.157	-.111	-.359	-.045
EV (pp.)	.009	.007	.019	.003
Solar PV (pp.)	.019	.013	.038	.006
Number of additional solar PVs	312	302	2,682	100

Note: This table presents the results of 4 hypothetical simulations. Panel (A) presents the changes in the outcome, while Panel (B) presents the relative changes in percent or percentage points respectively. The four scenarios are PV placements on each school, each city hall, each newly constructed building from 2017 on and random placements of 100 additional PVs.

Figure 2.6. Random placements



Note: These plots show the average estimated changes in the outcome as a result of 100 randomly placed additional solar PVs. Effects are depicted in MWh changes in electricity consumption and additional adoptions of EVs and solar PVs. Plots indicate the distribution of total 1000 simulated random placements.

Based on the 100 randomly placed additional solar PVs, the estimated electricity conservation effect translates to eliminating the average annual consumption of around 63 households.[45]

Both scholars and policy makers often cite the solar PV rebound as a potentially important concern with increasing solar PV diffusion (La Nauze, 2019; Qiu et al., 2019). A simple back-of-the-envelope calculation suggests that, in our setting, the solar PV rebound is compensated by the additional electricity saving efforts of surrounding households. More specifically, solar PV adopters on average

[45]The average annual household electricity consumption is 4943.21 kWh or 4.94 MWh. 310 MWh/4.94 MWh = 62.75.

consumed 9,300 kWh of electricity in the year prior to adoption. If we assume, on average, a 20% rebound effect for new solar PV adopters, we expect their total electricity consumption to increase by 1,860 kWh, which for 100 households corresponds to 186 MWh. Hence, in our setting, the additional electricity conservation effort by peers overcompensates the anticipated and expected rebound effect from solar PV adoption.

Furthermore, we use the effects from the randomly placed solar PVs and provide a back-of-the-envelope calculation for the additional environmental benefits. This corresponds to an indicative assessment of the abatement costs and efficiency of solar PV subsidies. We differentiate between the direct environmental effect, which is the replacement of average grid electricity by solar PV electricity, and the indirect effect which are the aforementioned peer effects in electricity conservation, and durable good adoption, as well as the anticipated solar rebound effect. Further details on the assumptions and sources can be found in Table 2.A.22, while the detailed calculation is presented and discussed in subsection 2.A.4. Accounting for additional behavioral changes, caused by increased solar PV diffusion, increases the societal benefits in the form of GHG abatement by around 33%, and thus significantly impacts cost-benefit evaluations of solar PV subsidies. If expected GHG emission reductions are discounted at 2.75%, the estimated abatement costs are approximately CHF 63 per t of CO_2 eq. lower. This corresponds to a 20% reduction relative to the baseline scenario of CHF 309 per t of CO_2 eq., which only accounts for the direct benefits. If future GHG reductions are not discounted, the abatement costs from solar PV subsidies are even lower at CHF 166 per t of CO_2 eq. if all effects are considered vs. CHF 209 per t of CO_2 eq. if only direct abatement effects are taken into account.

2.7. Conclusion

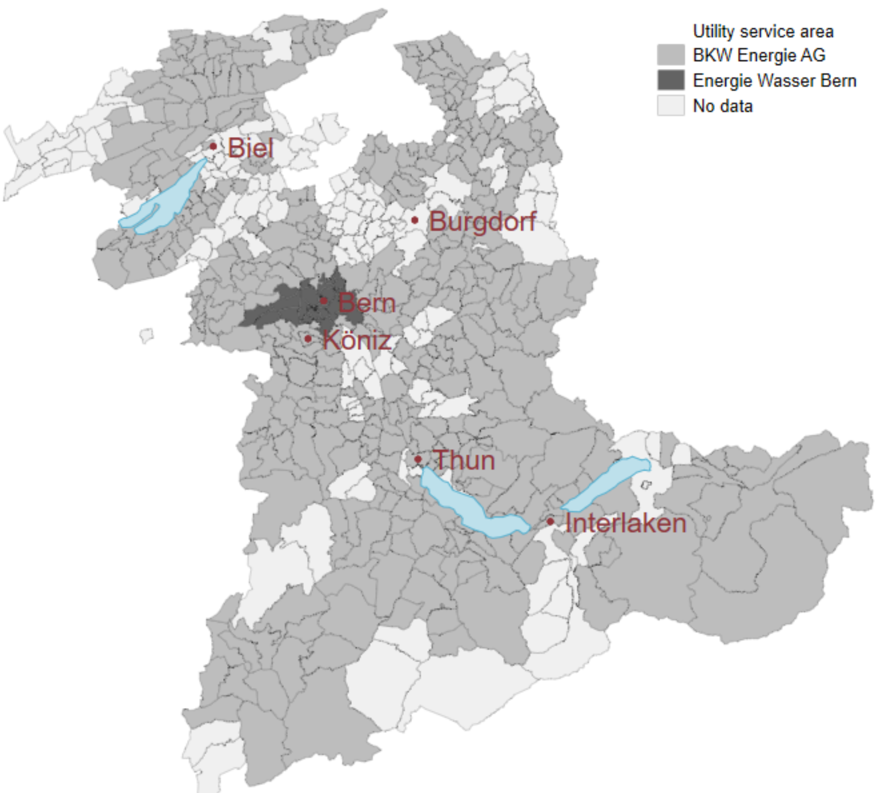
We provide evidence for causal peer effects of solar PV adoption on neighbors' energy-related behaviors. Our results suggest that increased solar PV adoption causes highly localized pro-environmental peer effects on peers' willingness to contribute to climate change mitigation in the form of electricity conservation as well as the adoption of pro-environmental durable goods. While the increased adoption of solar PV by neighbors can be interpreted as a combination between social learning and pro-social behavior, we interpret the private, non-visible actions of increased electricity conservation efforts as social norm based conditional cooperation. These results are important to thoroughly understand and evaluate potential support schemes to increase the uptake of solar PVs.

For example, scholars and policy makers often cite the solar rebound effect (La Nauze, 2019; Qiu et al., 2019) as a potentially undesirable side effect of increasing solar PV diffusion that could justify removing subsidies for solar PVs. Our results suggest that the solar rebound effect is compensated for by a positive pro-environmental peer effect on neighboring households' electricity consumption. Back-of-the-envelope calculation suggests that, in our setting, not accounting for peer effects underestimates social benefits of solar PV diffusion in the form of GHG reductions by about one third and overstates abatement costs of the solar PV subsidy by about 20%.

2.A Appendix

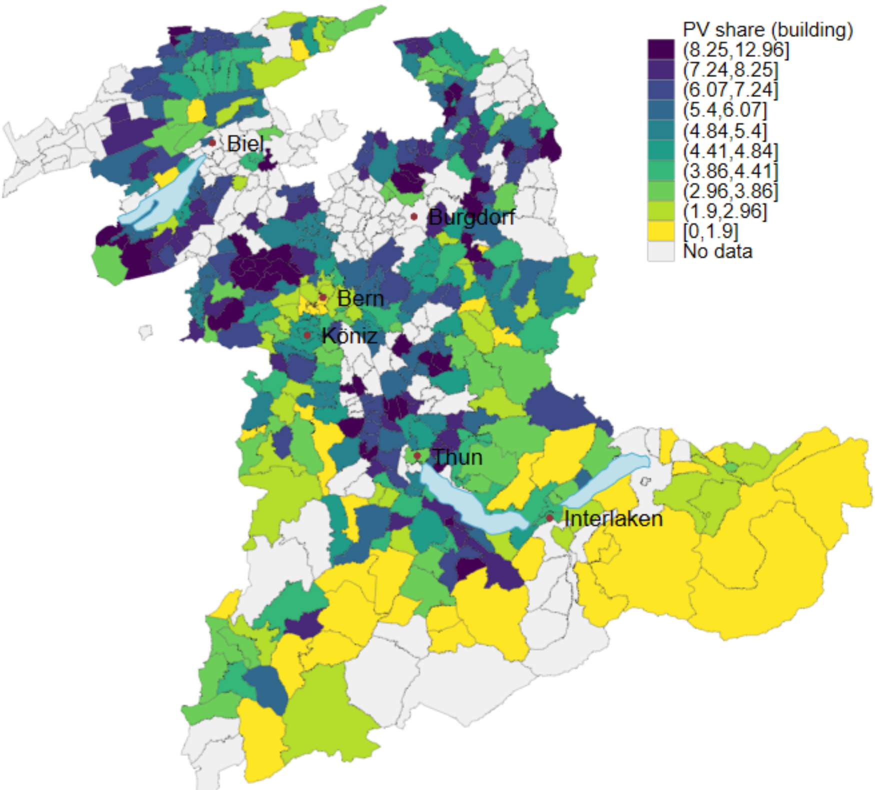
2.A.1. Additional Figures

Figure 2.A.1. Overview of data providers' service area



Note: The map depicts the canton of Bern by zip codes. The darker gray areas represent the two utilities' service area which provided us with data. Light gray illustrates zip codes with different electricity providers we do not observe. White areas within the canton are lakes.

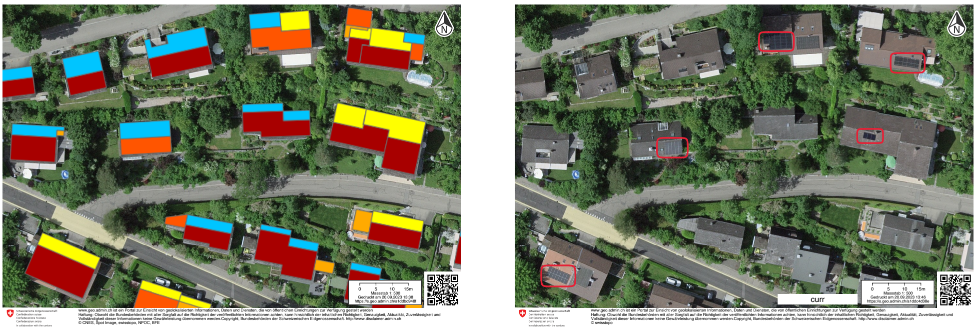
Figure 2.A.2. LOCAL DISTRIBUTION OF SOLAR PV INSTALLATIONS



Note: The map depicts the canton of Bern by zip codes and illustrates the share of buildings with a solar PV at the end of 2019. Deciles of the distribution are illustrated. Data is sourced from Pronovo, BKW and EWB with further details in subsection 2.3.1. We exclude zip codes that are not in the electricity providers' service area for better comparison, even though the raw data contains the entire canton.

Figure 2.A.3. Solar PV placement

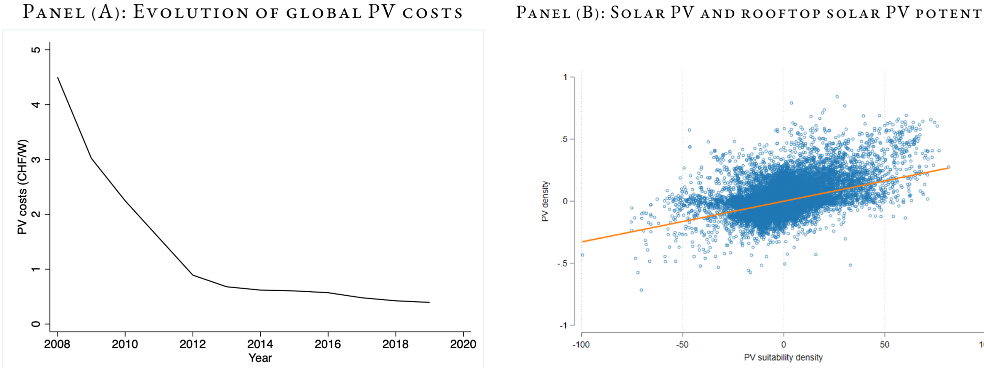
Panel (A): Rooftop Solar PV potential | Panel (B): Actual Solar PV placement



Note: This figure shows (a) rooftop solar PV potential and (b) actual solar PV placements. The colors indicate the rooftop solar PV potential in one of five categories as defined by BFE: Blue: low (< 800 kWh/m^2/yr); yellow: medium (≥ 800 kWh/m^2/yr and < 1000 kWh/m^2/yr); orange: high (≥ 1000 kWh/m^2/yr and < 1200 kWh/m^2/yr); red: very high (≥ 1200 kWh/m^2/yr and < 1400 kWh/m^2/yr); dark red: top (> 1400 kWh/m^2/yr).

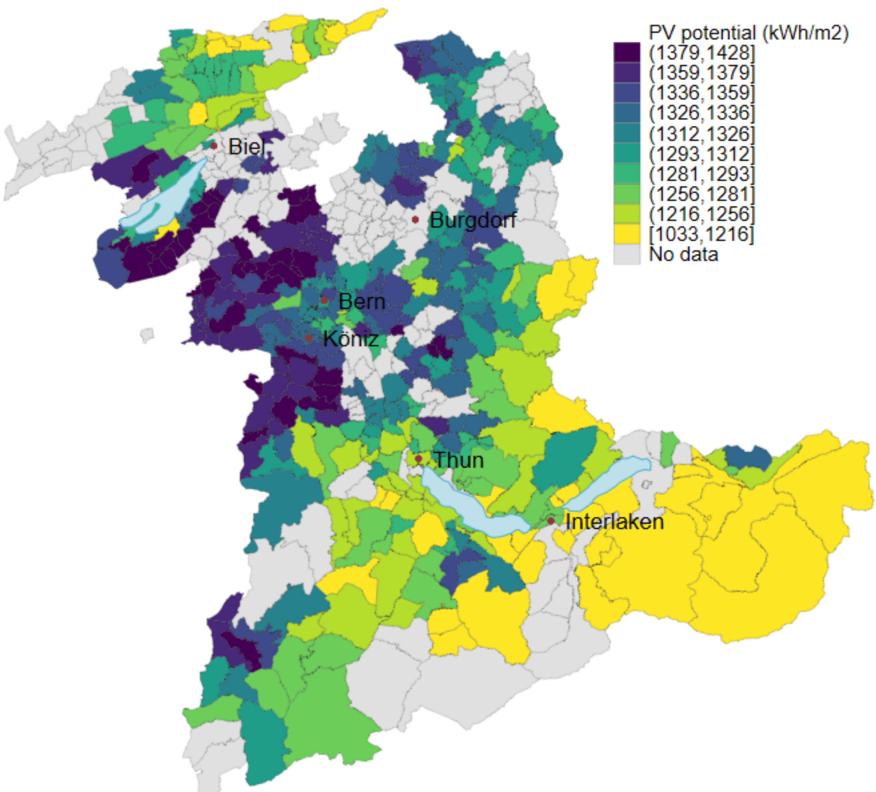
Figure 2.A.4. Suggestive evidence First stage relevance

Panel (A): Evolution of global PV costs | Panel (B): Solar PV and rooftop solar PV potential



Note: This figure presents the evolution and correlation of our instruments. Panel (A) illustrates the evolution of global PV costs transformed into CHF at 2021 USD costs using PP-adjusted exchange rates. Panel (B) presents the linear fit as well as the scatterplot of the average de-meaned PV density and the average de-meaned PV suitability density. We subtract zip-year mean densities from each measure and average them over individuals before illustrating this descriptive first stage relevance. This presents first illustrative correlation between our instrument and treatment of interest.

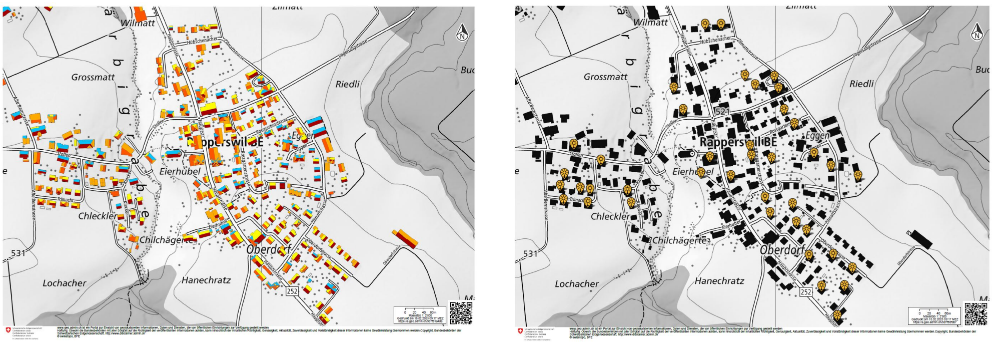
Figure 2.A.5. Local distribution of rooftop solar PV potential



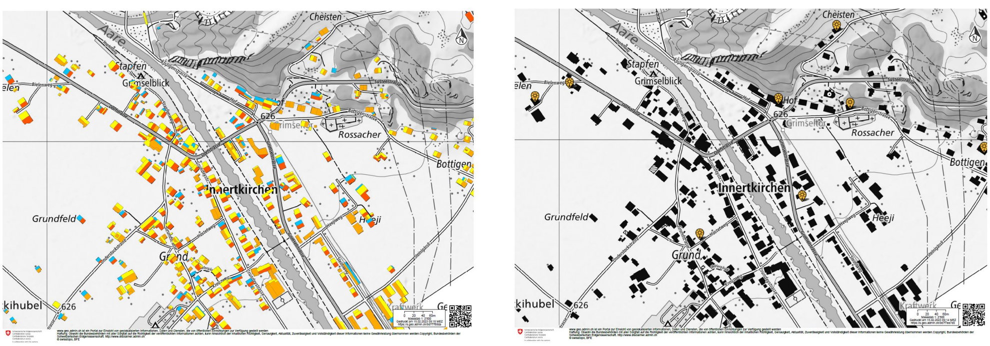
Note: The map depicts the canton of Bern by zip codes and illustrates the average engineering based estimate of rooftop solar PV potential. Only the most suited rooftop with a size above $20m^2$ from each building are taken into consideration. Deciles of the distribution are illustrated. Data is sourced from Pronovo, BKW and EWB with further details in subsection 2.3.1. We exclude zip codes that are not in the electricity providers' service area for better comparison, even though the raw data contains the entire canton.

Figure 2.A.6. Rooftop solar PV potential and actual solar PV installations

Panel (A): Highest average rooftop solar PV potential

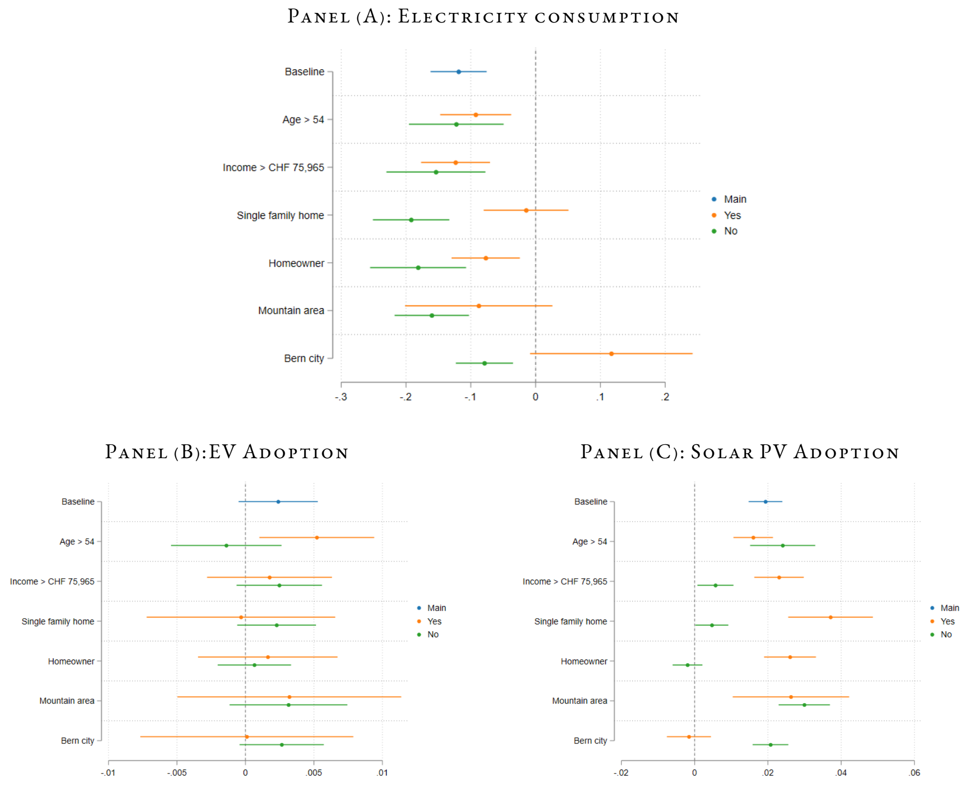


Panel (B): Lowest average rooftop solar PV potential



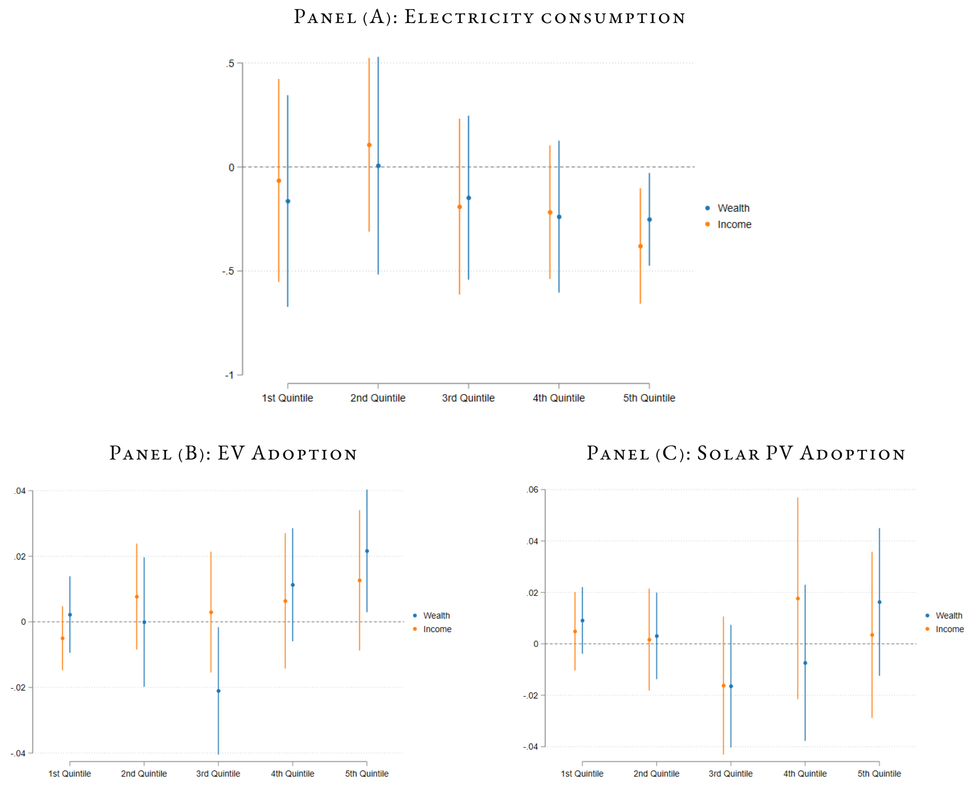
Note: This figure shows partial maps of the zip code areas with (a) the highest average rooftop solar PV potential and (b) the lowest average rooftop solar PV potential in our study region. The left side of the figure shows rooftop solar PV potential. The colors indicate the rooftop solar PV potential in one of five categories as defined by BFE: Blue: low (< 800 kWh/m^2/yr); yellow: medium (≥ 800 kWh/m^2/yr and < 1000 kWh/m^2/yr); orange: high (≥ 1000 kWh/m^2/yr and < 1200 kWh/m^2/yr); red: very high (≥ 1200 kWh/m^2/yr and < 1400 kWh/m^2/yr); dark red: top (> 1400 kWh/m^2/yr). The right side of the figure shows actual solar PV installations at the time this study was conducted. (a): Rapperswil, BE; (b): Innertkirchen, BE.

Figure 2.A.7. Effect heterogeneity - OLS



Note: This figure shows estimated effects of split sample OLS regression. It is to compare the heterogeneity results to our estimated LATEs in Figure 2.4. Sample is split based on observable household characteristics. Income and age are split based on median values. Location specific differences based on observed data from building and tax data. A locations' mountain designation is based on official data from the Federal Statistical Office. Area of city of Bern is divided based on the two electric utilities providing us with data.

Figure 2.A.8. Effect heterogeneity - Wealth and Income quintiles



Note: This figure shows estimated effects of split sample IV regression. Sample is split based on observable household characteristics income and wealth. Each households is assigned to a quintile of the distribution based on average observed income or wealth and each model is estimated separately.

2.A.2. Additional Tables

Table 2.A.1. Summary Statistics by Electricity Provider

(a) BKW

	N	Mean	Sd	Min	Median	Max
Panel A: Outcomes						
Electricity consumption (kWh)	1,679,021	5,562.33	5,410.61	375.08	3,769	33,418
Green mix	579,327	.03	.18	0	0	1
EV	1,681,335	.01	.07	0	0	1
Solar PV	1,681,335	.01	.11	0	0	1
Panel B: Controls						
Electricity price (CHF/kWh)	1,680,235	.23	.03	.11	.23	.6
Household income (TCHF)	1,681,335	95.11	115.59	1	79.18	59,098.2
Household size	1,681,335	2.03	1.12	1	2	5
Homeowner	1,681,335	.48	.5	0	0	1
Age	1,659,080	54.98	16.71	15	55	106
Single family home	1,681,335	.32	.46	0	0	1
Living space (m^2)	1,678,935	104.31	44.38	0	95	995
Number of vehicles	1,681,335	.22	.45	0	0	5

(b) EWB

	N	Mean	Sd	Min	Median	Max
Panel A: Outcomes						
Electricity consumption (kWh)	523,688	2,958.22	2,925.06	375.03	2,140.87	33,406
Green mix	523,688	.04	.2	0	0	1
EV	523,688	0	.05	0	0	1
Solar PV	523,688	0	.01	0	0	1
Panel B: Controls						
Electricity price (CHF/kWh)	523,688	.21	.04	.04	.21	1
Household income (TCHF)	514,287	86.39	123.73	1	70.71	23,599.2
Household size	523,688	1.72	1.01	1	1	5
Homeowner	523,688	.18	.39	0	0	1
Age	504,067	51.47	17.56	16	50	104
Single family home	523,688	.08	.27	0	0	1
Living space (m^2)	522,661	82.47	32.26	0	77	600
Number of vehicles	523,688	.11	.32	0	0	3

Notes: Author's calculation. Data sources described in text of subsection 2.3.1. Sample differentiated based on the two electricity providers, which are part of our sample. Providers are assigned to households based on community borders. EWB serves the city of Bern, BKW the majority of communities in the canton of Bern except for the main city centers and some exceptions.

Table 2.A.3. Outcomes - Evolution

	Green mix	Solar PV	EV	Electricity consumption
2008	1.48	.08	.02	5,158.18
2009	1.55	.15	.06	5,166.56
2010	1.60	.19	.09	5,180.29
2011	1.71	.34	.17	5,024.10
2012	2.01	.58	.24	4,927.70
2013	7.00	.72	.34	5,039.72
2014	6.53	.98	.42	4,732.88
2015	6.20	1.27	.51	4,954.11
2016	4.01	1.48	.63	4,661.74
2017	3.80	1.67	.76	4,606.03
2018	3.75	1.87	.93	4,650.76
2019	3.22	2.92	1.25	5,388.44
Mean	3.72	1.00	.44	4,943.21
N	1,103,015	2,205,023	2,205,023	2,202,709

Note: This table presents the relative adoption share in percent for the three binary outcomes of interest. Households are indicated as adopter if they owned a photovoltaic installation, an electric vehicle or opted in for the most renewable electricity mix (green). The last column presents the evolution of the average electricity consumption.

Table 2.A.4. Treatment - summary statistics

	N	**Mean**	**Sd**	**Min.**	**Median**	**Max.**
Panel A: Densities						
PV density	2,205,014	.514	.393	.012	.45	1.949
EV density	2,205,023	.114	.162	0	.07	3.34
Green mix density	2,205,023	.804	1.085	.009	.337	10.663
Apartment density	2,204,968	48.379	24.33	8.278	40.135	105.674
Building density	2,205,023	17.578	5.572	4.714	17.193	29.635
Panel B: Instruments						
PV potential density	2,204,968	1,309.79	17.313	1,205.93	1,316.12	1,346.38
PV costs (CHF/W)	2,205,023	1.294	1.205	.395	.619	4.499

Note: This table presents summary statistics of our defined treatment, a selection of control variables and the instruments.

Table 2.A.5. Variation of instrumental variables

	Mean	**Sd**	**Min**	**Max**	**Observations**
Panel A: PV density					
Overall	0.514	0.393	0.012	1.949	2,205,014
Between		0.352	0.013	1.715	262,708
Within		0.241	-0.533	1.782	8.39
Panel B: PVpot density					
Overall	1,309.78	17.31	1,205.93	1,346.38	2,204,968
Between		17.46	1,207.87	1,341.32	262,700
Within		2.80	1,226.96	1,378.85	8.39
Panel C: PV costs					
Overall	1.294	1.205	0.395	4.50	2,205,023
Between		0.617	0.395	4.50	262,708
Within		1.141	-0.949	4.775	8.39

Note: This table presents summary statistics and the source of variation for our treatment and both of our instrumental variables. N represents the total number of observations for overall, the total number of individuals for between and the average number of time periods for within.

Table 2.A.6. First stage results

	Electricity		Durables	
	(1) Green mix	(2) Elec. consumption	(3) EV	(4) Solar PV
PV potential	0.0034 ∗ ∗∗	0.0028 ∗ ∗∗	0.0027 ∗ ∗∗	0.0029 ∗ ∗∗
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PV potential x PV costs	−0.0007 ∗ ∗∗	−0.0009 ∗ ∗∗	−0.0009 ∗ ∗∗	−0.0009 ∗ ∗∗
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	928, 821	1, 834, 745	1, 825, 197	1, 765, 332
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*

Note: This table presents the linear estimations of Equation 2.4 as the first stage regression of the instrumental variable estimation. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table.

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 2.A.7. Solar PV potential and socioeconomics

	Raw	**Centered (ZIP x year)**	**First year (2008)**	**Last year (2019)**
Household income	.008	-.002	.009	.0089
Household size	.0049	.0027	.0109	.0115
Homeowner	-.026	-.0195	-.0193	-.0274
Age	-.0252	-.013	-.0279	-.0087
Single family home	-.0115	-.0099	-.0066	-.0083
Living space (m2)	.0285	.0032	.0346	.046
Number of vehicles	-.0059	-.0028	-.0016	-.0017
Electricity price	-.0267	-.0141	-.0282	-.0001
Building density	.0401	.0407	.0354	.0381
Apartment density	.0352	.0174	.0287	.0312
Building older 1945	.072	.0672	.0728	.0325
Building age 1945-1980	-.0411	-.0278	-.0574	-.0133
Building age 1980-2000	.0154	.0131	.012	.0408
Building younger 2000	-.0659	-.0834	-.0442	-.0724
Oil heating system	.0386	.0478	.0286	.0417
Nat. Gas heating system	-.0198	-.0177	-.0254	-.0458
Electric heating system	.0103	.0094	.0115	.017
Heat pump	-.0148	-.0317	0	-.0203
N	2,095,868	1,968,432	161,153	128,358

Note: This table presents correlation between rooftop PV potential and selected socioeconomic characteristics of household living in the building. Column (1) presents raw correlations, column (2) presents correlations of standardized measures at the zip x year. Standardization was calculated by subtracting the within zip code-year average and dividing by the standard deviation. Column (3) presents raw correlation in the first year of observation and column (4) in the last. All correlations are relatively small.

Table 2.A.8. GREY MIX RESULTS

Dependent variable:	Grey mix	
	(1) OLS	(2) IV
PV density	$-0.0628***$	-0.1254
	(0.0187)	(0.0776)
EV HH	0.0404+	0.0403+
	(0.0209)	(0.0209)
PV HH	$0.0322***$	$0.0353***$
	(0.0086)	(0.0094)
N	928, 821	928, 821
ZIP x year FE	*No*	*No*
Individual fe	*Yes*	*Yes*
Control variables	*Yes*	*Yes*
First stage F-stat	N/A	494.1
p-value Kleibergen-Paap	N/A	$8.03e-132$
p-value Hansen's J'	N/A	0.00828

Note: This table presents selected coefficients of a linear fixed effects and an instrumental variable approach on the household's adoption of gray mix electricity product. Standard errors clustered on individual level presented in parentheses. Odd columns represent OLS estimations while even columns are IV regressions.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$.

2.A.3. Robustness

Table 2.A.9. PLACEBO TEST

Dependent variable:	Income	
	(1)	(2)
	OLS	IV
PV density	0.0087	0.0795
	(0.0455)	(0.1996)
PV HH	0.0247*	0.0206
	(0.0105)	(0.0152)
EV HH	−0.0827	−0.0828
	(0.0595)	(0.0595)
N	1, 834, 745	1, 834, 745
ZIP x year fe	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*
Control variables	*Yes*	*Yes*
First stage F-stat	*N/A*	1647.7
p-value Kleibergen-Paap	*N/A*	0
p-value Hansen's J	*N/A*	0.908

Note: This table presents selected coefficients of a linear fixed effects and an instrumental variable approach on selected placebo outcome (Log of income). Standard errors clustered on individual level presented in parentheses. Odd columns represent OLS estimations while even columns are IV regressions.

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 2.A.10. Robustness - Rings electricity

Dependent variable:	Elec. consumption			Green mix		
	(1)	(2)	(3)	(4)	(5)	(6)
PVs within [0,100m]	−0.0506+			−0.0096		
	(0.0292)			(0.0180)		
PVs within [0,250m]		−0.0134			−0.0016	
		(0.0086)			(0.0034)	
PVs within [0,500m]			−0.0054			−0.0009
			(0.0036)			(0.0020)
PV HH	−0.0559∗	−0.0832 ∗ ∗∗	−0.0922 ∗ ∗∗	0.0117	0.0071	0.0065
	(0.0253)	(0.0121)	(0.0095)	(0.0113)	(0.0054)	(0.0051)
EV HH	0.1538 ∗ ∗∗	0.1508 ∗ ∗∗	0.1495 ∗ ∗∗	0.0160	0.0157	0.0155
	(0.0401)	(0.0400)	(0.0408)	(0.0184)	(0.0184)	(0.0184)
N	1, 834, 745	1, 834, 745	1, 834, 745	928, 821	928, 821	928, 821
Community x year fe	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	13.99	16.39	27.81	87.02	292.2	254.2
p-value Kleibergen-Paap)	0	0	0	0	0	0
p-value Hansen's J	0.351	0.320	0.254	0.863	0.774	0.752

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. All estimates include individual level control variables and the count of PVs within a certain ring from the household is instrumented with the distance weighted average rooftop solar PV potential and the interaction with global PV costs.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.11. Robustness - Rings durables

Dependent variable:	EV			Solar PV		
	(1)	(2)	(3)	(4)	(5)	(6)
PVs within [0,100m]	0.0029∗			0.0079 ∗ ∗		
	(0.0013)			(0.0028)		
PVs within [0,250m]		0.0008+			0.0020∗	
		(0.0004)			(0.0009)	
PVs within [0,500m]			0.0003+			0.0009∗
			(0.0002)			(0.0004)
PV HH	0.0045 ∗ ∗	0.0061 ∗ ∗∗	0.0066 ∗ ∗∗			
	(0.0014)	(0.0010)	(0.0010)			
EV HH				0.0785 ∗ ∗∗	0.0793 ∗ ∗∗	0.0796 ∗ ∗∗
				(0.0164)	(0.0165)	(0.0165)
N	1, 825, 197	1, 825, 197	1, 825, 197	1, 765, 332	1, 765, 332	1, 765, 332
Community x year fe	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	13.76	16.92	30.44	17.36	18.24	27.68
p-value Kleibergen-Paap)	0	0	0	0	0	0
p-value Hansen's J	0.159	0.138	0.0850	0.969	0.989	0.817

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. All estimates include individual level control variables and the count of PVs within a certain ring from the Household is instrumented with the distance weighted average rooftop solar PV potential and the interaction with global PV costs.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.12. Robustness - Cut-off density 10 km

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.3573*	−0.0312	0.0210*	0.0540 ***
	(0.1680)	(0.1257)	(0.0106)	(0.0154)
PV HH	−0.0737 ***	0.0075	0.0055 ***	
	(0.0130)	(0.0079)	(0.0012)	
EV HH	0.1500 ***	0.0152		0.0795 ***
	(0.0363)	(0.0184)		(0.0170)
N	1, 834, 104	928, 630	1, 825, 197	1, 764, 740
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	699.8	182.8	679.0	636.5
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	0.278	0.803	0.0714	0.974

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. All estimates include individual level control variables and the density of PV installations within 10Km from the Household is instrumented with the distance weighted average Rooftop potential and the interaction with global PV costs.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$.

Table 2.A.13. Robustness - No energy controls

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.1702*	−0.0330	0.0108*	0.0224 ***
	(0.0742)	(0.0475)	(0.0043)	(0.0065)
N	1, 834, 745	929, 205	1, 827, 385	1, 766, 732
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	1657.3	494.4	1641.5	1531.1
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	0.667	0.933	0.321	0.172

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. These models do not include household energy controls.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001$.

Table 2.A.14. Robustness - Contemporaneous energy controls

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.1764*	−0.0321	0.0106*	0.0223 * **
	(0.0743)	(0.0476)	(0.0044)	(0.0062)
EV HH	0.1548 * **	0.0021		0.0862 * **
	(0.0307)	(0.0105)		(0.0141)
PV HH	−0.0434 * **	0.0175 * *	0.0065 * **	
	(0.0093)	(0.0061)	(0.0010)	
N	1, 834, 745	928, 815	1, 825, 655	1, 765, 671
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	1648.0	491.7	1590.7	1527.0
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	0.623	0.922	0.296	0.217

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. These models do not lag household energy controls.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.15. Robustness - No EV & Green mix densities

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.2167 * *	−0.0091	0.0105*	0.0202 * *
	(0.0726)	(0.0461)	(0.0044)	(0.0064)
PV HH	−0.0808 * **	0.0065	0.0061 * **	
	(0.0097)	(0.0055)	(0.0010)	
EV HH	0.1501 * **	0.0153		0.0794 * **
	(0.0363)	(0.0184)		(0.0170)
N	1, 834, 745	928, 821	1, 825, 197	1, 765, 332
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	1653.9	492.6	1561.9	1541.2
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	0.417	0.793	0.296	0.130

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. These models do not include the EV and green mix densities, as they are potentially bad controls.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.16. Robustness - Initial PV Potential

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.1824 ∗ ∗	−0.0327	0.0101∗	0.0200 ∗ ∗
	(0.0708)	(0.0450)	(0.0043)	(0.0062)
PV HH	−0.0835 ∗ ∗∗	0.0079	0.0061 ∗ ∗∗	
	(0.0096)	(0.0055)	(0.0010)	
EV HH	0.1502 ∗ ∗∗	0.0154		0.0795 ∗ ∗∗
	(0.0363)	(0.0184)		(0.0170)
N	1, 834, 745	928, 821	1, 825, 197	1, 765, 332
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	1918.4	559.3	1802.2	1790.8
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	0.459	0.937	0.334	0.0932

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. PV density is instrumented using the historic distance weighted average PV potential (as of 2008) of a neighborhood as well as the interaction between this potential and the global PV costs to address potential concerns of strategic construction.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.17. Robustness - No Movers

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.2395 ∗ ∗	−0.0292	0.0149∗	0.0283 ∗ ∗
	(0.0895)	(0.2192)	(0.0071)	(0.0100)
PV HH	−0.1010 ∗ ∗∗	0.0102	0.0053 ∗ ∗∗	
	(0.0106)	(0.0128)	(0.0012)	
EV HH	0.1419 ∗ ∗∗	0.0222		0.1087 ∗ ∗∗
	(0.0423)	(0.0265)		(0.0244)
N	1, 310, 908	675, 499	1, 303, 969	1, 258, 399
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	2200.9	780.5	2085.5	2081.9
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	0.134	0.107	0.0622	0.376

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. PV density is instrumented using distance weighted average PV potential of a neighborhood as well as the interaction between this potential and the global PV costs. Households that moved within our time frame of observation are dropped from the sample.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.18. Robustness - No Movers & Initial Potential

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.1902∗	−0.1291	0.0189 ∗ ∗	0.0312 ∗ ∗
	(0.0910)	(0.2614)	(0.0073)	(0.0105)
PV HH	−0.1040 ∗ ∗∗	0.0154	0.0051 ∗ ∗∗	
	(0.0106)	(0.0148)	(0.0012)	
EV HH	0.1420 ∗ ∗∗	0.0223		0.1087 ∗ ∗∗
	(0.0422)	(0.0266)		(0.0243)
N	1, 310, 908	675, 499	1, 303, 969	1, 258, 399
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	4267.5	1557.4	4050.2	4065.7
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	*N/A*	*N/A*	*N/A*	*N/A*

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. PV density is instrumented using historical distance weighted average PV potential (as of 2008) of a neighborhood as well as the interaction between this potential and the global PV costs to address potential concerns of strategic construction. Households that moved within our time frame of observation are dropped from the sample.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.19. Robustness - Logit & PPML

Dependent variable:	Green mix		EV		Solar PV		Elec. Consumption	
	(1) OLS	(2) Logit	(3) OLS	(4) Logit	(5) OLS	(6) Logit	(7) OLS	(8) PPML
PV density	−0.0479∗	−0.0395∗	0.0049+	0.0037+	0.0125 ∗ ∗	0.006∗	−0.1756∗	−0.1620∗
	(0.0237)	(0.0171)	(0.0030)	(0.0019)	(0.0044)	(0.0027)	(0.0743)	(0.0789)
N	945, 977	945, 977	1, 836, 573	1, 836, 573	1, 776, 634	1, 776, 634	1, 834, 745	1, 835, 629
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: This table presents selected coefficients of an instrumented linear fixed effects model estimation of Equation 2.2, and compares the effects to average partial effects of logit models using a control function approach for the binary dependent variables in columns (1) - (6). In column (7)-(8) estimates of an instrumented log-linear model are compared to a Poisson pseudo maximum likelihood (PPML) model. Standard errors clustered on individual level presented in parentheses. The dependent variable is indicated in the top row of the table. PV density is instrumented using distance weighted average PV potential of a neighborhood as well as the interaction between this potential and the global PV costs. Linear model IV estimation is conducted using 2SLS, while non-linear IV estimation is conducted using a control function approach.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.20. Robustness - Community fixed effects

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.4975∗	−0.0529	0.0110	0.0386 ∗ ∗
	(0.1946)	(0.0627)	(0.0095)	(0.0146)
PV HH	−0.0655 ∗ ∗∗	0.0087	0.0061 ∗ ∗∗	
	(0.0143)	(0.0059)	(0.0011)	
EV HH	0.1586 ∗ ∗∗	0.0066		0.0793 ∗ ∗∗
	(0.0372)	(0.0198)		(0.0170)
N	1, 836, 485	930, 066	1, 826, 933	1, 767, 054
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	626.9	660.2	701.8	549.6
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	0.102	0.341	0.929	0.00380

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2 with PV density being instrumented by surrounding average PV potential and the interaction of PV potential and global PV costs. Standard errors are clustered on individual level and fixed effects on community times year fixed effects instead of zip code times year fixed effects.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 2.A.21. Robustness - ZIP code clustered SE

Dependent variable:	Elec. consumption	Green mix	EV	Solar PV
	(1)	(2)	(3)	(4)
PV density	−0.1756+	−0.0091	0.0104 ∗ ∗	0.0219 ∗ ∗
	(0.0950)	(0.0442)	(0.0039)	(0.0077)
PV HH	−0.0838 ∗ ∗∗	0.0065	0.0061 ∗ ∗∗	
	(0.0107)	(0.0068)	(0.0010)	
EV HH	0.1502 ∗ ∗∗	0.0153		0.0795 ∗ ∗∗
	(0.0403)	(0.0205)		(0.0165)
N	1, 834, 745	928, 821	1, 825, 197	1, 765, 332
ZIP x year fe	*Yes*	*Yes*	*Yes*	*Yes*
Individual fe	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
First stage F-stat	43.77	69.69	42.82	42.37
p-value Kleibergen-Paap)	0	0	0	0
p-value Hansen's J	0.551	0.835	0.307	0.209

Note: This table presents selected coefficients of a linear fixed effects model estimation of Equation 2.2 with PV density being instrumented by surrounding average PV potential and the interaction of PV potential and global PV costs. Standard errors are clustered on zip level.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

2.A.4. Cost-Benefit Analysis

We estimate the average expected abatement costs that would arise if our randomly placed additional solar PVs were subsidised by the subsidy system applied at the time. Switzerland supports the uptake of solar PV in various ways depending on the size of installation. For private households installing solar PVs with a production capacity below 30 kWp is supported by upfront price subsidies that are capped at 30% of installation costs. We assume average values for capacity, installation costs, and subsidies as documented in Table 2.A.22. The average capacity is generated from our data, while the average installation costs and subsidies are based on information from Pronovo AG, which handles the register and payment of solar PV subsidization schemes. To assess

Table 2.A.22. ASSUMPTIONS COST-BENEFIT ANALYSIS

Parameter	Value	Source
Installed solar PV capacity (kW)	8 KWp	Data (median)
Solar PV production (kWh / kWp) p.a.	900 kWh	Pronovo
Installation costs (CHF / kWp)	CHF 2,700	Pronovo
Subsidy (max. 30% of costs)	CHF 6,000	Pronovo
Solar PV electricity emission factor (kg CO_2eq / kWh)	0.07	Vuarnoz and Jusselme, 2018; Wernet et al., 2016 and `www.horocarbon.ch`
Swiss electricity emission factor (kg CO_2eq / kWh)	0.203	Vuarnoz and Jusselme, 2018 and `www.horocarbon.ch`
Combustion engine LCA emission (kg CO_2 eq / km)	0.27	Cox et al., 2020
EV / (P)HEV LCA emission (kg CO_2 eq / km)	0.21	Cox et al., 2020
Mileage consumption per vehicle (km) p.a.	12,000	Bigler and Radulescu, 2022
Solar PV rebound effect (kWh) p.a.	20%	Qiu et al., 2019
Discount rate	2.75%	Worldbank (real interest rate)
Solar PV lifetime	30 years	Pronovo

Note: This table presents the assumed values and sources employed in the assessment of the environmental effects of our identified peer effects and the calculation of solar PV subsidy induced GHG abatement costs.

the direct benefits of the solar PV subsidy we suppose that the 100 additional solar PV installations all have a capacity of 8 kWp, each kWp on average produces 900 kWh per year, and the installations were subsidized by CHF 6,000 each. In total, the generated electricity from these installations accounts for 720 MWh of additional solar PV electricity. We assume that this electricity replaces the average Swiss grid electricity and that the difference in embedded GHG emissions is 133 g CO_2 eq emissions per kWh. Thus, the total direct emission reduction induced accounts for around 95.76 tons of CO_2 eq.

For the indirect effects we use the average of our simulated peer effects as well as an assumed electricity rebound effect of 20%. Thus, solar PV adopters will increase their electricity consumption by 1,860 kWh[46] and we again assume this rebound to be at the average emission intensity of the Swiss grid. Furthermore, there are pro-environmental peer effects that increase the benefits induced by the additional solar PV adoption. Neighboring households increase their electricity conservation efforts and reduce consumption in total by 310 MWh, which we again assess at the average Swiss grid emission intensity. Furthermore, 6 additional PVs are installed that we assume to have the same modifications as the above mentioned PVs and we again account for the replacement of grid electricity, the anticipated rebound effect of the additional adopters and the invoked additional subsidies. Furthermore, 4 additional alternative fuel vehicles (EVs or hybrids) are adopted. We

[46] This corresponds to 20% of the average solar PV adopter's pre-adoption consumption of 9,300 kWh.

assume that they are driven 12,000 kilometers per year and replaced an internal combustion engine vehicle, which again leads to reductions in GHG emissions. We furthermore account for the additional public outlays caused by the 6 new PV adopters, but do not account for additional secondary effects of these installations.

We present the predicted GHG reductions by accounting for both direct and embedded GHG emissions in CO_2 equivalents. Table 2.A.23 presents the results. The total public outlays of CHF 600,000 lead to annual direct GHG reductions of 95.76 t CO_2 eq. Not accounting for additional costs and benefits caused by our estimated peer effects underestimates the emission reductions by approximately 33%. We distinguish between direct and indirect benefits when calculating abatement costs, and between discounting future GHG emission reductions by 2.75% or not discounting future expected reductions. The abatement cost are reduced by about 20% if we consider all the benefits, rather than just the direct benefits, which greatly improves the cost-benefit assessment of the solar PV subsidy currently in use. If future GHG reductions are not discounted and both direct and indirect benefits are considered, abatement costs are about CHF 166.55 per ton of CO_2 eq. This value is relatively close to current estimates of average social costs of carbon at around USD 185 (Rennert et al., 2022). However, the abatement costs are higher than current carbon pricing in Switzerland where fossil heating fuels are taxed at CHF 120 per ton of CO_2 (BAFU, 2021) and the average EU ETS emission price in 2022 at EUR 80 (UBA, 2023).

Table 2.A.23. COST BENEFIT ANALYSIS

Panel A: Benefits	Value	Δ GHG per unit	Δ GHG
Direct benefits			
PV Electricity production (MWh p.a.)	720	-0.133 (kg CO_2 eq)	-95.76 (t CO_2 eq)
Indirect Benefits			
Electricity consumption (MWh p.a.)	310	-0.203 (kg CO_2 eq)	-62.93 (t CO_2 eq)
Additional PV production	43.2	-0.133 (kg CO_2 eq)	-5.75 (t CO_2 eq)
Additional EV /(P)HEV driving (KM p.a.)	48,000	-0.06	-2.88 (t CO_2 eq)
Rebound effect			
Direct rebound (MWh p.a.)	186	0.203 (kg CO_2 eq)	37.76 (t CO_2 eq)
Additional adopters rebound (MWh p.a.)	11.16	0.203 (kg CO_2 eq)	2.27 (t CO_2 eq)
Panel B:Aggregate values			
Initial subsidy costs	CHF 600,000		
Additional subsidy costs	CHF 36,000		
Direct GHG reduction	95.76 t CO_2 eq		
Indirect GHG reduction	31.53 t CO_2 eq		
Panel C: Abatement costs	Direct benefits	All benefits	Difference
Discounted benefits (CHF / t CO_2 eq)	309.43	246.74	62.68
Non-discounted benefits (CHF / t CO_2 eq)	208.86	166.55	42.31

Note: This table presents the simplified cost-benefit analysis for the subsidy structure in place assuming the 100 additional PV installations that we randomly place were supported by 30% upfront subsidies at installation costs. All assumed values are described in the text or in Table 2.A.22.

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Chapter 3

Extent and Anatomy of the Solar Photovoltaic Rebound: Evidence from Swiss Households

Patrick Bigler

Abstract

I examine rebound effects in electricity consumption induced by solar photovoltaic (PV) adoption using detailed panel data of 60,000 Swiss single family home residents (2008-2019). I find that solar PV adoption increases a household's electricity consumption by an average of around 8% post-adoption. The decomposition of the rebound effect, using machine learning based counterfactual prediction, illustrates that household fuel switching accounts for part of this effect. This manifests through household electrification, such as electric vehicle adoption. Further results suggest that rebound effects are mainly driven by a sub-sample of solar PV households that adopt relatively large installations and adjust their consumption profile drastically.

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3.1. Introduction

Electricity accounts for roughly 20% of total global energy usage and still, nowadays, almost 2 out of 3 kWh are produced from non-renewable energy sources (IEA, 2021). Although Switzerland has a higher share of electricity in total energy usage at 25%, its carbon intensity is much lower, as the majority of electricity is produced from renewable sources (BFE, 2021a). With increasing electrification of the road transport and residential heating sector, Switzerland's total electricity demand in 2050 is projected to increase by up to 50% (VSE, 2022). At the same time, both nuclear power and fossil-based electricity are being phased-out throughout Europe. Distributed energy, including residential solar photovoltaic (PV), is regarded as an important contributor to the fulfilment of future (renewable) electricity capacity requirements. For example, Switzerland expects to cover more than 40% of its electricity production in 2050 through solar PV production (BFE, 2020).

Growing solar PV diffusion is not only part of policy debate, but has also received increased academic attention. While most of this academic debate has focused on understanding patterns in adoption (e.g. Balta-Ozkan et al. (2015)), solar PV support policy evaluation (e.g. De Groote and Verboven (2019)), as well as consequences of increased solar PV diffusion (e.g. Feger et al. (2022) and Gonzales et al. (2023)), a growing part of the literature on renewable electricity generation is related to rebound effects (e.g. Qiu et al. (2019)). This refers to offsets in energy consumption reductions caused by behavioral changes in response to efficiency improvements, and is often associated with increased consumption resulting from reduced costs (Gillingham et al., 2016). Such effects have important implications for the prediction of future energy system requirements, government policy program evaluation, as well as the environmental impact of increased renewable capacity. Specifically, in the context of solar PV, any increase in decentralized electricity generation will reduce the need for conventional electricity production by the same proportion. However, if agents' post-adoption consumption increases, additional solar PV electricity production will not displace conventional sources on a one-to-one basis (Pretnar and Abajian, 2023). On the other hand, recent evidence suggests that households with solar PVs are more likely to purchase an EV (Lyu, 2023) and adjust their charging behavior based on availability of self-produced solar PV electricity (Liang, Qiu, and Xing, 2022). If such co-adoption patterns persist and transfer to other technologies, such as heat pumps, estimated rebound effects might overestimate the additional electricity production required, since within-household fuel-switching is not accounted for in energy requirement forecasts (Beppler et al., 2023).

In this paper, I estimate the solar PV rebound effect using annual electricity consumption data and extensive household level information from the Swiss canton of Bern covering five years of post-adoption observations. I focus on a subsample living in single family housing and account for socioeconomic variables, and energy-related information, such as heating systems, as well as ownership of electric and hybrid vehicles. Examining households that co-adopt solar PV and electricity-intensive goods allows for differentiation of solar PV rebound effects. For example, if a household installs a solar PV and purchases an EV, conventional solar rebound estimates would aggregate the additional electricity required to fuel the vehicle into the solar PV rebound. From an environmental perspective, however, this fuel-switching is likely positive (i.e. average grid emissions are lower than average transport emissions (Holland et al., 2016)). However, most current studies associate solar PV rebound effects as lowering environmental benefits of increased solar PV diffusion.

To address potential endogeneity concerns related to selection into treatment as well as correlated unobservables when identifying rebound effects, I employ different estimation strategies. Extensive household-level information allows me to control for factors that might explain both a household's decision to adopt solar PV as well as their annual electricity consumption. In my preferred two-way fixed effect specification, I use within-household variation in solar PV adoption, while accounting for socioeconomics (e.g. household income and wealth), location and building-specific variables (e.g. weather, building size and rooftop PV potential), as well as local idiosyncratic shocks that vary over time (i.e. zip code-year fixed effects). I account for concerns about treatment effect heterogeneity in two-way fixed effects models with staggered adoption by employing difference-in-differences (DiD) techniques robust to heterogeneous treatment effects. This allows me to further illustrate that electricity consumption conditional on observables was similar for both adopting and non-adopting households, and that group treatment effects are similar in years following adoption, but not in the year of adoption. Afterwards, I train a supervised machine learning (ML) model, based on regularized gradient boosting (XGBoost (Chen and Guestrin, 2016)), to predict unobserved counterfactual electricity consumption for all post-adoption periods. I then infer individual solar PV rebound effects for each household-year combination. Using linear regression and stratified bootstrap sampling, I decompose the estimated solar PV rebound effects based on observed information.

I find an average solar PV rebound effect of around 8%. This effect is almost identical between two-way fixed effects specifications, DiD estimates robust to heterogeneous treatment effects, as well as aggregated deviations from predicted unobserved counterfactual electricity consumption using ML. I find that rebound effects are quite persistent over time, except for the initial period of adoption, during which households do not yet adjust their electricity consumption. There is little heterogeneity between early and late adopters in my sample, but if I use the estimated solar PV production as treatment, the inferred rebound effect is slightly higher at 11%. Part of the rebound effect could thus be driven by household-year combinations with high solar PV yields, due to either bigger capacity or relatively high solar irradiation.

Leveraging the extensive energy related, socioeconomic and location specific variables allows me to further decompose the solar PV rebound effect. In a first step, I estimate both heterogeneity due to increased home and transport electrification, as well as solar PV installation specific heterogeneity using interaction terms in two-way fixed effect models. I find some suggestive evidence that parts of the rebound effect might be explained by transport electrification, but the statistical power of these models is not sufficient to make strong claims of heterogeneity. In a second step, I decompose the ML predicted household-year specific rebound effects via semi-parametric linear regressions. I find that households which co-adopt electricity-intensive technologies such as EVs, hybrids and heat pumps have relatively higher solar PV rebound effects compared to households that do not. For example, a solar PV household with an EV has a 11 percentage points stronger consumption increase, which is more than double the baseline estimated average rebound effect of 8.5%. This result suggests that part of the rebound effect is within household fuel-switching. Moreover, I document larger rebound effects for adopters with bigger solar PV capacity and higher relative solar PV yields (kWh / kWp), which suggests that there is heterogeneity based on the installed capacity, as well as based on observed production.

The decomposition of the solar PV rebound effects has important implications for policy makers. Rebound effects are often an argument against the implementation or extension of solar PV subsidies (e.g. Boccard and Gautier (2021)). The main reasoning is that the environmental impact of increased solar PV diffusion is smaller, if standard grid electricity is not replaced on a one-to-one basis. However, as illustrated, the increased electricity consumption post-adoption, for example, might replace gasoline with renewable electricity. Hence, the environmental impact of increased solar PV diffusion might be more positive, particularly in countries with a relative environmentally friendly average electricity mix such as Switzerland (Vuarnoz and Jusselme, 2018). On one hand, if policy makers only account for renewable technologies to replace conventional non-renewable electricity capacities, and do not account for rebound effects, they might underestimate future capacity requirements. On the other hand, forecasts of electrified transport and residential heating sectors that account for individual rebound effects, overestimate requirements, as the prognosticated additional demand and the within household fuel-switching comprised in the rebound effect are twice accounted for. It is thus vital to understand both behavioral components that drive solar PV adoption, but also the electricity consumption reaction through the lens of a complete household energy portfolio mix.

Related Literature and Contribution

This paper contributes to a growing literature on energy rebound effects and solar PV rebound effects more specifically. Rebound effects have been found to exist over a large range of topics such as building energy efficiency improvements (Liang, Qiu, James, et al., 2018), adoption of energy-efficient household appliances (Davis et al., 2014), or passenger transportation (Frondel and Vance, 2013; Gillingham, 2014). A rapidly growing number of empirical studies has estimated the impact of residential solar PV adoption on domestic electricity consumption. Solar PV rebound effects have been found in Australia (Deng and Newton, 2017; La Nauze, 2019), the United States (Beppler et al., 2023; Qiu et al., 2019; Schwarz et al., 2023; Spiller et al., 2017), as well as in European countries, such as the United Kingdom (McKenna et al., 2018), Belgium (Boccard and Gautier, 2021), Germany (Frondel, Kaestner, et al., 2023) or the Netherlands (Aydın et al., 2023). For example, Qiu et al. (2019) use hourly electricity meter and solar panel generation data in Phoenix, Arizona to quantify that an increase by 1kWh in solar electricity generation leads to an increase in total electricity consumption of solar homes by 0.18kWh. Similarly, Deng and Newton (2017) employ quarterly observations from 4,819 Australian solar and non-solar customers to estimate that the solar PV rebound effect ranges between 16.9% and 20.9%, depending on the feed-in-tariff rate. More closely related to my study is Beppler et al. (2023), who use comparable electricity billing data from a utility company in the United States' Northeast, but abstract from socioeconomic information. They estimate a 28.5% solar PV rebound effect using a matched data set on observed grid electricity consumption and feed-in. To the best of my knowledge, my study is the first that estimates the solar PV rebound effect using the universe of all PV and non-PV consumers provided by an electricity utility and matched to extensive socioeconomic and location specific information. While my electricity data is relatively aggregated at the household-year level, compared to the recently employed smart-meter data, my estimates are almost identical to the one in the Netherlands (7.9%) (Aydın et al., 2023). These researchers document the importance of accounting for short-term household optimization behavior in reaction to relatively sunny periods. They observe significant consumption shifting between days of high solar PV production and days of low solar PV production. I automatically account for this fact, due to the usage of yearly data. My paper is the first solar PV rebound estimate for Switzerland, where other energy efficiency rebound effects, for instance for industrial processes, have been documented (Zimmermann et al., 2021).

This paper's main contribution is the analysis of the solar PV rebound effect's anatomy. I account for co-adoption of electricity intensive goods such as EVs or heat pumps, as well as socioeconomic factors, and solar PV system heterogeneity. While the argument persists that solar PV electricity might not replace grid electricity on a one-to-one basis, the replaced fuel in the total energy consumption is likely more carbon intensive than the average grid kWh. Environmental implication thus differ drastically. This paper also contributes to a small but growing literature of technology co-adoption between solar PV and other electricity intensive goods (e.g. (Lyu, 2023)), and the impact of household electrification on electricity grids and residential electricity consumption (Burlig, Bushnell, et al., 2021; Liang, Qiu, and Xing, 2022). Moreover, I illustrate another application of ML based counterfactual prediction. This technique has been employed in different context in the environmental and energy economics literature, for instance, to understand performance of energy efficiency investments (Burlig, Knittel, et al., 2020; Christensen et al., 2023), infer treatment effects for electricity consumers facing different cost structures (Prest et al., 2023) or ex-post policy evaluation of carbon pricing in the electricity generation sector (Abrell et al., 2022).

The remainder of the paper proceeds as follows. Section 3.2 presents the study setting, the data employed and some descriptive statistics. Section 3.3 describes the empirical approach and discusses potential threats to identification and Section 3.4 presents the results. Finally, Section 3.5 concludes.

3.2. Background, Data, and Summary Statistics

3.2.1. The Swiss Electricity Market

This study focuses on the canton of Bern, the second most populous canton in Switzerland, a federal state with strong local governments and a highly decentralized political system. Similarly, the electricity market is also decentralized. Utilities are local monopolists in providing electricity to households and often own and operate the regional grid as well. Thus, households are assigned electricity providers based on community borders. Prices are fixed for a year, independent of electricity consumption, and vary only based on product choice (i.e. amount of renewable energy in specific electricity mix) and tariff choice.[1] Meter readings are usually taken once a year and households are billed based on those readings.

There are public support systems for solar PV adoption. Up until 2015 feed-in-tariffs were granted to early adopters and nowadays private solar PV installations are granted upfront price subsidies.

[1] Households can opt-in for double-tariff pricing, which differentiates between day and night electricity consumption and incentivizes shifts from peak consumption during the day to off-peak consumption at night with a lower price per kWh.

The local utility is required to purchase excess solar PV production from households at average annual market prices. Solar PV adopters can operate as 'prosumers', meaning they first consume their self-produced electricity and only excess consumption / production is balanced out through the grid. Furthermore, installations exceeding 30 kWp and installations receiving public support have to be registered with federal authorities.[2]

3.2.2. Data

I employ panel data of approximately 58,000 unique households spanning from 2008 to 2019.[3] The data is gathered from various sources.[4] First, I obtain yearly electricity billing data from BKW, the largest cantonal electricity provider. Information includes annual electricity consumption, solar PV ownership, their peak power capability (kWp), as well as electricity product choice, electricity price, solar PV remuneration, and solar PV electricity fed into the grid. Second, the Bern Tax Administration provides me with annual income and wealth data, as well as various demographic information (e.g. age, home ownership, household size). Third, from the Swiss Federal Statistical Office I obtain building data (e.g. living space, nb. of rooms, heating system, construction year, geolocation), as well as various community level measures (e.g. urbanity classifier, mountain classifier, zip code). Fourth, I was provided individual car ownership data from the Cantonal Road Traffic Office (SVSA Bern). Fifth, I obtain information on each dwellings solar PV potential and rooftop size from an online calculator provided by the Swiss Federal Office of Energy.[5] Last, Meteoswiss provides me with grid information (km^2) on annual cooling degree (CDD) and heating degree days (HDD).

My outcome of interest is total electricity consumption in year t for household i. Electricity consumption is based on billing data. Bills are sent to customers on an annual basis, and usually electricity meters are read once per year towards, at, or around the end of the calendar year. Households with multiple electricity meters are summed together such that I have one data point for each household-year combination. The reading period is normalized for all households to 365 days[6] and observations with reading periods smaller than 180 days were dropped. In addition, I need to derive some information that is crucial for the solar PV rebound estimation. I formally

[2]Installations that neither received public support and are not connected to the grid might be missing from my sample. There are, however, strong financial incentives to have your solar PV registered. First, households are able to receive upfront solar PV subsidies covering on average 10-15% of the costs. Second, agents can receive solar PV remuneration that on average were at 40-50% of the observed electricity price in the time frame of this study.

[3]Due to the nature of the data not all households are observed in each period (e.g. moving, deaths).

[4]The different datasets are matched based on first, exact matching, and second, weighted string matching algorithms. In total around 66% of billing data is matched to the tax data. Non-matched customers are companies, since we only observe individual income taxation information. There is a small number of non-matched customers from holiday homes and secondary homes, which are thus tax-exempt in the community of secondary residence. All non-matched observation are subsequently dropped.

[5]`sonnendach.ch`

[6]Less than 5% of total observations are adjusted.

define total electricity consumption (ec_t) as:

$$ec_t = eg_t + es_t \tag{3.1}$$

$$es_t = \begin{cases} ep_t - ef_t, & \text{for solar PV households} \\ 0, & \text{for non-solar PV households} \end{cases} \tag{3.2}$$

The utility provides information on the amount of electricity each household takes from the grid in a given year (eg_t). Furthermore, I observe how much solar PV customers sell back to the grid (ef_t). The calculation of total electricity consumption differs between households with and without solar PV, as the latter have the option to self-consume (es_t). For non-solar PV customers the electricity taken from the grid is equal to their total electricity consumption (i.e. $es_t = 0$). However, solar PV households' total electricity consumption has to be adjusted with the net consumption of produced electricity (ep_t). The electricity provider does not have data on solar PV production, but only observes ef_t. Thus, I have to estimate ep_t which then, together with ef_t, implies es_t. To this end, a Swiss company that specializes in solar PV system design, provides me with simulated solar PV production based on the geolocation, year of installation and capacity of each solar PV system. The simulation employs historical weather data while accounting for the rooftop's solar PV suitability in terms of inclination, shading and orientation.[7]

While I observe each household living in the service area of BKW,[8] I focus on a specific subset for various reasons: First, I only use solar PV adopters that installed between 2015 and 2019, due to the fact that feed-in to the electricity utility is only observed starting in 2015, because of data warehouse changes.[9] An additional benefit of this strategy is that all solar PV households represented in the sample were eligible for the same subsidy policy, as the change from feed-in tariffs to upfront subsidies also occurred in 2015. Second, I, for several reasons, only employ single family homes (incl. detached and semi-detached) and drop household data from apartment complexes or mixed use buildings. On one hand, solar PV installation in multi-family houses is scarce (less than 15% of total installations). On the other hand, it is hard to determine whether self-consumption is occurring by the registered owner or whether all occupants can self-consume.[10] Third, I drop all observations of solar PV households that have installed capacity exceeding 20 kWp.[11] This procedure eliminates observations such as, for instance, farms which might use solar PV production as an additional means of business, and thus are not perfectly comparable to

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[7] The company also provides the simulation framework for the Swiss Federal Office of Energy's cost and benefit calculator for solar PV installations `https://www.energieschweiz.ch/tools/solarrechner/`. A more detailed explanation of the simulation procedure and its results can be found in subsection 3.A.3.

[8] A visual representation of the service area is provided in Figure 3.A.1.

[9] Earlier adopters would thus have mismeasured total electricity consumption in the years prior to 2015, as their self-consumed electricity cannot be estimated. All observations of households that have adopted solar PV before 2015 are thus discarded, which represents approximately 48% of observed solar PV installations between 2008-2019.

[10] There are special legal entities which allow multi-family home owners to produce solar PV electricity and directly sell it to their renters. Furthermore, groups of persons can own and operate solar PV installations together. If such observations were kept in the sample they might bias the estimates, as self-consumption is hard to estimate as ownership shares in common solar PV installations are unknown.

[11] This excludes again around 15% of all solar PV installations in Bern.

residential electricity consumers. Furthermore, I consider it important to account for outliers in the electricity consumption data, which might be present due to the fact that the annual readings are taken manually in the buildings, and later entered into the data system. I drop the top and bottom 1% of total electricity consumption observations within the selected subsample to not have results driven by outliers. In addition, I try to account for potential simulation errors in the solar PV production data. Such errors may arise, for example, from the fact that some of the solar PV systems are not installed on the rooftop with the best available solar irradiation or on an additional building such as a garage or a shed. Another reason could be that the month of registration and the actual start of operation are not perfectly registered. Therefore, I exclude all observations with negative self-consumption (i.e., where $ef_t > ep_t$) as well as the top and bottom 1% of self-consumption shares. Final data consists of 58,104 households observed between 2008-2019 and a total of 1,433 solar PV installations observed for 4,023 household-year combinations.[12]

3.2.3. Descriptive Statistics

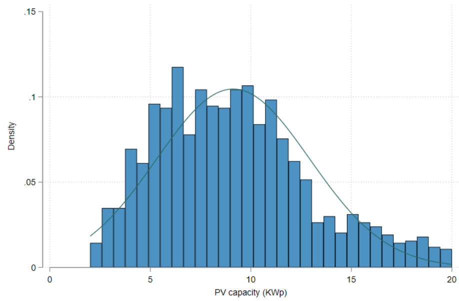
In Figure 3.1, I present both the distribution of solar PV capacity, as well as the distribution of self consumption share in the observed solar PV households. The average capacity of sampled solar PVs at 8.95 kWp is comparable to the Swiss-wide average capacity based on sub sampling criteria (8.71 kWp between 2013-2018) (BFE, 2021b). There is some excess mass in the distribution at around 4-6 kWp and at the upper tail of the distribution towards 20 kWp, compared to the fitted normal distribution. On average, the sampled households consume 35% of produced electricity themselves. The distribution is right skewed with the median being lower than the mean. Nevertheless, there appears to be some household-year observations where most of the produced electricity is self-consumed. In Figure 3.A.2, I present and compare the distribution of two subsamples that might help explain this heterogeneity. On one hand, households that, in addition to their solar PV installation, also installed storage capacity might have more flexibility to increase their self-consumption. On the other hand, households with higher solar PV capacity would require more drastic adjustments to consume excess production, especially on sunny days when solar PV production is high. I differentiate the sample into above and below median solar PV capacity and into households with and without storage. As expected, households with lower solar PV capacity and households with installed storage capacity have a higher share of self consumed electricity. Households with high self-consumption shares seem concentrated within the sample of storage adopters.

However, as illustrated in Table 3.1, only 4% of the household-year combinations with a solar PV installation also have storage capacity. Further summary statistics indicate that installed capacity ranges from 2 kWp to 20 kWp, and is quite centered with mean and median at 8.95 and 8.58 kWp respectively. Solar PV installations occurred at similar rates between 2015 and 2019. Figure 3.A.3 depicts the location and year of installation for each sampled solar PV household. Solar PV remuneration, on average, was around CHF 0.09 per kWh and varies depending on year and whether or not households also sell a renewable electricity certificate. With this additional compensation

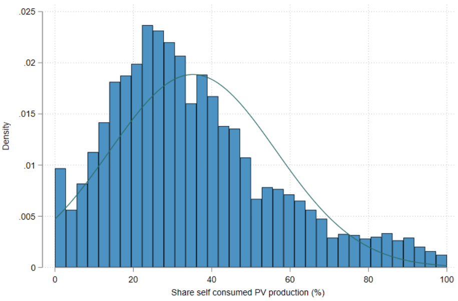
[12]This corresponds to around 12% of all solar PV installations in the canton of Bern.

Figure 3.1. Solar PV sample

Panel (A): PV capacity



Panel (B): Self consumption share



Note: The plot shows the distribution of solar PV capacity in Panel (A) based on the solar PV installations represented in the data. Panel (B) presents the share of self consumed solar PV electricity in percent. The self consumption share is calculated separately for each year. The green line represents a fitted normal distribution.

remuneration can reach up to CHF 0.16. The average solar PV production accounted to around 8,176 kWh per year of which, on average, 5,623 kWh were fed back into the grid.[13]

Table 3.1. Summary Statistics - solar PV installations

	N	Mean	Sd	Min.	Median	Max.
PV capacity (KWp)	4,090	8.96	3.73	2.01	8.58	20
PV production (kWh/year)	4,090	8,172.24	4,542.8	75	7,966.6	24,142.7
PV feed in (kWh/year)	4,090	5,616.48	3,638.02	0	5,389	19,837
Self consumption share (%)	4,090	35.2	21.16	0	31.18	100
Feed-in price (CHF/kWh)	4,090	9.05	3.2	0	8.9	16
Storage installed	4,090	.04	.19	0	0	1
Installation year 2015	309	1	0	1	1	1
Installation year 2016	207	1	0	1	1	1
Installation year 2017	233	1	0	1	1	1
Installation year 2018	247	1	0	1	1	1
Installation year 2019	267	1	0	1	1	1

Note: Based on observed household-year combinations with solar PV installations between 2015 to 2019. All Data provided by BKW Energie AG and Pronovo AG. PV production simulation framework presented in subsection 3.A.3.

[13]The distribution and linear fit between installed capacity and simulated production is also presented in Figure 3.A.9.

Panel A in Table 3.2 presents the summary statistics of all energy related variables. On average, sample households consume 8,490 kWh electricity per year. The distribution is right skewed, as the median consumption of 6,538 kWh is substantially smaller and the maximum observed annual consumption is almost 46,500 kWh. On the other hand, there is little variation in electricity prices, which is not surprising, as the sample only consists of customers from one electricity provider observed in 12 years of relatively constant prices. The variation comes from tariff plan choices, as households could opt into peak pricing plans and into more ("Green") or less ("Grey") environmentally friendly electricity mixes. However, less than 7% of household-year observations have opted out of the standard hydroelectricity mix ("Blue").[14] In terms of energy intensive durable goods, on average, 14% of household-year combinations use a heat pump as primary heating system, while the majority (52.6%) uses an oil based heating system.[15] Adoption in terms of electricity based vehicles is less prominent, as both hybrid electric vehicles (HEV) and pure battery electric vehicles (EV) are observed in less than 1% of household-year combinations.[16]

In terms of socioeconomic variables presented in Panel B, the sample is clearly right skewed both within the sample, but also compared to Swiss averages. This is due to the fact that households living in single family homes are relatively older, wealthier and receive higher incomes. Average income of CHF 123,000 and average wealth of almost CHF 1,000,000, lie 50% and 30% above Swiss-wide averages respectively. Rate of homeownership is also substantially higher at 80% compared to 39% nationwide. Nevertheless, the extensive socioeconomic information available, is important to understand drivers of both electricity consumption, as well as solar PV adoption decisions. I complement the data with building and location specific information presented in Panel C. Although I focus my analysis on single family homes, it is important to account for differences between the housing units. There is substantial variation in terms of number of rooms, living area, as well as the construction period, which might explain differing energy consumption. Moreover, I observe a rooftops' solar PV potential and its size. This allows me to account for variation in solar PV installation profitability. Around one quarter of houses were constructed before 1945 while only 13% are new buildings. The distribution of observations between urban, suburban and rural communities is quite equal with roughly one third of household-year combinations observed in each category.[17] There is substantial variation in weather conditions as well. Some households do not experience a single cooling degree day (CDD) in a given year and some households have more

[14]Customers only had a choice starting in 2016. Before then all households received the same electricity mix pre-dominantly based on hydro power. Double tariff structures were available throughout the observation period and I calculate electricity prices as the weighted average between on- and off-peak consumption based on actually observed consumption.

[15]The remaining households use natural gas (3.9%), electricity (11.9%), district heating (1.33%) and Wood (16.2%) as main heating resource.

[16]This is not that surprising as both vehicle types are relatively new technologies and thus not observed that frequently in the early years of the observation period. In 2019 the share of households owning an EV and HEV are 0.4% and 1.3% respectively.

[17]This means that the rural population is oversampled, which is not further surprising. Most cities in the canton have their own electricity provider, but also a small number of single family homes.

Table 3.2. SUMMARY STATISTICS

	N	Mean	Sd	Min.	Median	Max.
Panel A: Energy information						
Electricity consumption (kWh/year)	507,137	8,490.38	6,538.38	479.674	6,435	46,279.5
Electricity price (CHF/kWh)	507,130	21.568	3.289	0	21.489	32.22
Green mix adopted	507,137	.011	.106	0	0	1
Grey mix adopted	507,137	.054	.227	0	0	1
Hybrid vehicle	507,137	.006	.075	0	0	1
Electric vehicle	507,137	.001	.028	0	0	1
Heat pump	507,137	.141	.348	0	0	1
Oil heating	507,137	.526	.499	0	1	1
Panel B: Socio-Economics						
Household income (TCHF)	507,137	122.541	171.932	0	102.748	59,097.2
Household wealth (TCHF)	507,137	964.363	4,872.66	0	561.61	1278524
Household size	507,137	2.391	1.185	1	2	5
Homeownership	507,137	.801	.399	0	1	1
Age	507,137	57.66	14.668	16	57	105
Panel C: Housing / Location						
Living space (m2)	507,137	138.105	52.454	10	131	995
Nb. rooms	507,137	4.985	1.22	1	5	26
Construction year pre 1945	507,137	.242	.428	0	0	1
Construction year after 2000	507,137	.135	.341	0	0	1
Rooftop PV potential (kWh/m2)	502,535	1,314.67	136.35	47	1,327	1,611
Rooftop size (m2)	502,535	101.72	81.308	.125	82.636	6,168.53
Urban community	507,137	.327	.469	0	0	1
Rural community	507,137	.324	.468	0	0	1
Cooling degree days	507,137	113.503	54.542	0	108.145	296.431
Heating degree days	507,137	3,512.5	371.201	2,550.84	3,507.45	6,069.89

Note: Based on observed households from 2008 to 2019. Consumption measured in kWh. Potential measured in kWh per year based on the best suited roof area. PV and storage capacity measured in KW. All Data sources as described in Section 3.2.

than 6,000 heating degree days (HDD).[18]

I also compare whether households, that opted into installing a solar PV installation, differ in terms of observed characteristics. Table 3.A.1 presents the relative adoption rate of solar PV per

[18] I follow the definition of Meteoswiss which aligns with the official EU definition: $HDD_t = \sum_{d=1}^{D} \mathbb{1}_d^{W_d<12°C}(20°C - W_d)$, $CDD_t = \sum_{d=1}^{D} \mathbb{1}_d^{W_d>18.3°C}(W_d - 18.3°C)$. In words this means, heating degree days are the sum of temperature deviations from an average daily temperature (W_d) of 20 degree Celsius if the daily average temperature is below 12 degree Celsius. Reversed for cooling degree days it is the sum of daily deviations from 18.3 degree Celsius for days where the average daily temperature exceeded 18.3 degrees.

year and in selected subsamples. On average 1.88% of household-year combinations have a solar PV installed. While diffusion rates in 2015 are relatively low, they are substantially higher in 2019 at 3.22%. All selected subsamples indicate an above average rate of adoption. High income and wealth households have average solar PV adoption rates of 2.55% and 2.70%, respectively. Most strikingly is the high diffusion rate in households that also own an EV. In 2019, one out of three EV owners also had solar PV installed, which further illustrates potential synergies between the installation of private electricity production and an electricity intensive durable good. A similar, but less extreme pattern can also be observed for households that have heat pumps.

3.3. Empirical Strategy

To uncover effects of solar PV adoption on electricity consumption, it is vital to understand factors influencing both solar PV adoption, as well as household electricity consumption. The theoretical foundation for rebound effects is a mix of two well-known economic principles. On one hand, private solar PV production, conditional on adoption, lowers a household's electricity price, as the marginal costs of consumption are equivalent to the opportunity costs of selling this particular kWh to the grid. Since solar PV remuneration is generally smaller than grid electricity prices, the marginal costs of consumption are lower. Hence, baseline economic theory suggests that households consume more electricity.[19] On the other hand, the rebound effect could also be motivated as an income effect. If households adopt solar PV and sell excess electricity to the grid, they generate more income, which expands their budget set. Increased budget likely corresponds with higher consumption. If the additional consumption bundle includes electricity products, the rebound effect resembles an income effect.[20] In Figure 3.2, I present raw evidence for a rebound effect by illustrating the distribution of electricity consumption differentiating into the first and last year of observation, as well as into solar PV adopters, and non-solar PV households. The average and distribution of electricity consumption in non-adopting households remains almost unchanged over time, whereas solar PV adopters seem to be consuming more in the period post-adoption than pre-adoption.

It is likely that a household's decision to adopt a solar panel and its electricity consumption level are related. I try to overcome this potential source of treatment assignment bias by adopting several different strategies, and exploiting the extensive information available. Following Qiu et al. (2019), I examine household i's electricity consumption at point in time t (ec_{it}) as the following linear model:

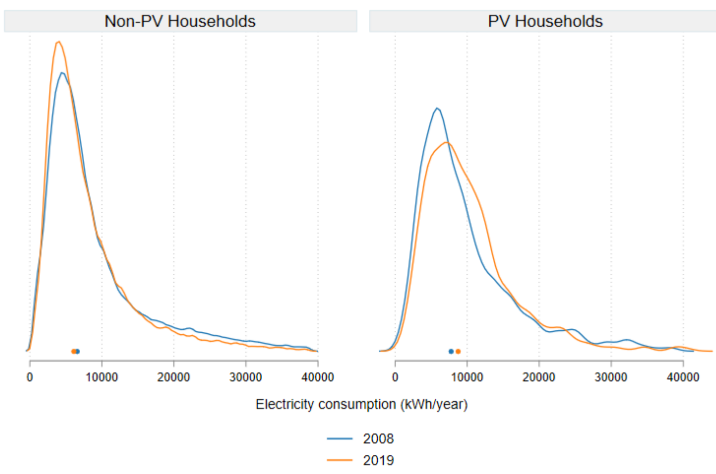
$$ec_{it} = \delta PV_{it} + \alpha p_t + \beta X_{it} + \omega_i + \omega_t + \omega_c + \varepsilon_{it}, \tag{3.3}$$

[19] The same argument can be made based on average costs. If households consume parts of their self-produced electricity at lower marginal costs, their average price of consumption decreases, which could lead to higher consumption. According to Ito (2014) electricity consumers tend to adjust consumption based on average and not marginal costs.

[20] I refer the reader to either Qiu et al. (2019) or Aydın et al. (2023) and a more general energy efficiency rebound effect overview in Chan and Gillingham (2015) for a more detailed overview of theoretical motivations for the rebound effect.

Treatment variable, PV_{it}, is defined in two different ways. First, PV_{it} is a dummy variable indicating whether household i at point in time t has a solar PV adopted. Second, I employ ep_{it}, which is solar electricity production of household i in year t, as treatment. Both definitions can help recover the average treatment effect on the treated (ATT) given some assumptions. When treatment is defined as dummy variable, the ATT can be recovered by dividing $\hat{\delta}$ with the pre-treatment mean of solar PV households. When treatment is defined as the annual solar electricity production, $\hat{\delta}$ directly recovers the ATT, as it measures the average increase in annual electricity consumption for each additionally produced solar PV kWh. α measures average price sensitivity. X_{it} is a matrix of control variables consisting of socioeconomics (e.g. income, wealth, age), building specific information (e.g. construction period, nb. of rooms, size), location specific (e.g. HDD and CDD) as well as energy specific (e.g. heating system, EV ownership) information and β is the corresponding vector of coefficients. ω_i, ω_t and ω_c are household, year and zip code fixed effects that control for unobserved factors influencing electricity consumption at the respective level. For example, ω_t controls for non-parametric trends in the evolution of electricity consumption overall. This could, for instance, be increased overall energy efficiency. I also interact zip code and year fixed effects. This controls for location specific shocks to electricity consumption, for instance, driven by local policies to enhance climate awareness, or local investment programs into energy efficiency. With the household fixed effect, I allow for a household-specific baseline level of electricity consumption and thus control for unobserved, individual preferences (e.g. environmental awareness). Hence,

Figure 3.2. RAW EVIDENCE FOR SOLAR PV REBOUND



Note: This figure presents raw evidence for a solar PV rebound effect. While average and distribution of electricity consumption for non-solar PV adopters remains fairly similar between 2008 and 2019, solar PV adopters consume substantially more electricity in 2019 compared to 2008.

identifying variation comes from within households while accounting for common idiosyncratic shocks at the zip code (and) year level, and conditioning on time-varying control variables, such as income, and weather. Standard errors are clustered at the household level.

Identification - Rebound effects are difficult to identify, as a credible source of exogenous variation in treatment assignment is hard to observe, unless households were randomly assigned solar PV installations (Qiu et al., 2019). There are, in total, four potential threats to identification. First, electricity consumption might be correlated with unobserved variables that also affect a household's decision to install a solar PV. Such variables could, for instance, be environmental friendliness or relative energy efficiency within the data domain (i.e. size, building period and heating system within the same zip code). Related to this problem is the second concern. Households that select into treatment (i.e. install a solar PV) might be significantly different from households that do not. If such differences are unobserved and correlated with both the decision to adopt solar PV, as well as electricity consumption, the estimated rebound effect might be biased. I address both these concerns by allowing each household to have a different baseline environmental awareness (i.e. household fixed effect). Furthermore, I allow for idiosyncratic shocks to environmental awareness on a low aggregation spatial level in each year (i.e. zip-year fixed effect). Moreover, I include an extensive set of control variables such as socioeconomic data and building and location information, which allows me to identify the effect of solar PV installation on electricity consumption conditional on observables. In other words, there should be no time-varying deviance between individuals, correlated with both the decision to adopt a solar PV, and their electricity consumption, which are not captured through the control variables (i.e. shocks to personal income might cause increases in electricity consumption, but also lead to the installation of solar PV). My extensive set of control variables, for instance, allows me to approximate changes in a households' environmental awareness by controlling for the adoption of a green electricity mix.[21]

The third and fourth concern are related to recent developments in the econometrics literature, which illustrate potential concerns of employing two-way fixed effects strategies to identify ATTs in a setting with staggered adoption (Borusyak et al., 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). Since households install solar PV at different points in time, the ATT is only identified if treatment effects are homogeneous and parallel trends, conditional on controls, are assumed. Homogeneous treatment effects in this setting mean that a household adopting a solar PV in 2015 in the first post-treatment period (i.e. 2015) reacts similar to a household adopting in 2019. Furthermore, the effect should not disappear but persist. Goodman-Bacon (2021) illustrates that the estimated ATT in the two-way fixed effects setting is a weighted average of individual-year specific treatment effects. De Chaisemartin and d'Haultfoeuille (2020) provide a statistical test to control for the potential threat of sign reversal between the inferred ATT and the 'true effect'.[22] I will report these test statistics and information about negative weights for my

[21] Further potential confounding variables that might be of concern in different settings such as the adoption of other electricity intensive goods (e.g. air conditioning) are of less concern in my empirical setting as the diffusion is relatively low. For instance, per capita sales of AC in Switzerland was by more than factor 10 lower in 2020 compared to the US (Statista, 2023a,b). I also control for potential peer effects by including the solar PV density as control variable (e.g. Bollinger and Gillingham (2012).

[22] Such a sign reversal would be possible if some treatment effects of different sign to the estimated ATT received negative weights in the convex combination that calculates the overall ATT.

two-way fixed effect estimates in Section 3.4. Assuming parallel trends means that, conditional on observables, the researcher expects that households, which opted into installing a solar PV, would have evolved on the same electricity consumption trajectory as the households that have not (yet) installed a solar PV. In other words, the decision to install a solar PV should not be driven by an (unobserved) anticipated change in electricity consumption. Roth et al. (2023) and De Chaisemartin and d'Haultfoeuille (2022b) provide an overview, and best practice recommendations for this setting. They illustrate how to test whether parallel trends and homogeneous treatment effects are violated. I conduct robustness checks for the two-way fixed effect estimates using the techniques proposed by Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2022a). This helps to assess both pre-trends (i.e. an indicative test for parallel trends) and treatment effect heterogeneity. Furthermore, I report breakdown values of the parallel trends assumption (Rambachan and Roth, 2023).

Heterogeneity - I identify heterogeneity in reaction to solar PV adoption based on observable characteristics. I am mainly interested in whether the rebound effect differs for households that adopt other electricity intensive technologies, such as electric vehicles, and electricity based heating systems. To identify such heterogeneity, I add interaction terms to my baseline estimation model:

$$ec_{it} = \delta_1 PV_{it} + \delta_2 PV_{it} \cdot T_{it}^k + \alpha p_t + \beta X_{it} + \omega_i + \omega_t + \omega_c + \varepsilon_{it}, \tag{3.4}$$

with T_{it}^k being a dummy variable that measures whether household i at point in time t owns the specific technology k (e.g. EV, heat pump, storage) . As previously, technology indicator variables are also included in the matrix of control variables, X_{it}. These interaction terms allow me to illustrate if the rebound effect is a behavioral consumption expansion or an optimized household energy portfolio.

In a second step, I use ML based estimation methods[23] to uncover individual level treatment effects and analyze their anatomy. More formally, I follow the estimation framework proposed by Souza (2019), which has been recently employed to decompose the performance wedge of building energy efficiency investments (Christensen et al., 2023). I define the treatment effect of household i reacting to having a solar PV installation (PV_{it}) at point in time t as:

$$b_{it} = \frac{Y_{it}(PV_{it} = 1) - Y_{it}(PV_{it} = 0)}{Y_{it}(PV_{it} = 0)} \tag{3.5}$$

At a given point in time t households either have a solar PV installed (state (1)) or not (state (0)). I use ML based methods to predict the unobserved counterfactual electricity consumption for all solar PV households (i.e. $\hat{Y}_{it}(PV_{it} = 0)$) . As training data, I employ electricity consumption information from both never adopting households, as well as not-yet adopted observations from solar PV households. This allows me to infer estimates for the individual, relative treatment effect in the following way:

$$\hat{b}_{it} = \frac{Y_{it}(PV_{it} = 1) - \hat{Y}_{it}(PV_{it} = 0)}{\hat{Y}_{it}(PV_{it} = 0)} \tag{3.6}$$

[23]Details of the ML approach and model evaluation are presented in subsection 3.A.4

These effects can be decomposed to understand which factors are explaining changes in electricity consumption post-adoption.[24] After obtaining individual-year treatment effects, I run the following linear regression to assess the anatomy of solar PV rebound effects:

$$\hat{b}_{it} = \theta + \varphi E_{it}^{k} + \sum_{g=1}^{G} \gamma_g Z_{it}^{g} + \eta_{it} \quad \text{, for all} \quad PV_{it} = 1 \tag{3.7}$$

where θ is a constant, E_{it}^{k} are indicator variables for co-adoption of electricity based technologies (i.e. electric and hybrid vehicles, heat pumps and storage) and φ is the corresponding vector of coefficients. Z_{it}^{g} are additional explanatory variables mainly used in deciles or pre-determined bins. This flexible specification allows for non-linear and semi-parametric relationships between individual treatment effects and the different variables with γ_g as corresponding coefficient vector of bin g. Variables included are: heating and cooling degree days, electricity prices, solar PV remuneration, income, wealth, household size, age, urbanity indicator, living space, solar PV yield (kWh/kWp normalized by months of operation), solar PV capacity (kWp).[25] Standard errors are estimated via bootstrap to account for the additional layer of uncertainty in the counterfactual prediction.

3.4. Results

In this section, I present the estimated significant rebound effect of solar PV adoption in Switzerland. First, I discuss the extent of the solar PV rebound effect, and second, I delve into potential mechanisms and heterogeneity to discuss the anatomy of the rebound effect.

3.4.1. The extent of the rebound effect

In Table 3.3, I present the results of the two-way fixed effect estimates. In column (1), I employ the treatment indicator, individual, year and zip code fixed effect, but abstract from further control variables. Column (2) adds the control variables and in column (3) I add zip-year fixed effects, thus allowing for different idiosyncratic shocks in every year at low geographical aggregation. So far, I exclude energy related control variables, such as vehicle fuel type, or heating resource, as they could be caused by solar PV adoption. Nevertheless, these variables are also important determinants of a household's annual electricity consumption, and I add them to the estimation in column (4). In column (5) I, in addition, control for the feed-in prices households receive.

[24] They can also be aggregated and used as an additional estimate for the extent of the rebound effect.
[25] In further robustness checks I will also include year and year of installation fixed effects.

Table 3.3. Two-way Fixed Effect Estimation

	(1)	(2)	(3)	(4)	(5)
PV HH	852.47***	824.22***	802.32***	763.63***	658.98***
	(117.38)	(107.98)	(109.52)	(109.29)	(109.97)
Electricity price (log)		−6113.76***	−6223.30***	−6195.54***	
		(217.46)	(219.72)	(219.11)	
Electricity price					−223.22***
					(8.91)
Feed-in electricity price					14.23*
					(7.08)
Heat pump				880.41	874.92
				(615.13)	(613.00)
Electric vehicle				1556.40***	1565.11***
				(418.08)	(419.27)
ATT	8.67%	8.59%	8.36%	7.96%	6.86%
N	503, 522	498, 061	497, 746	497, 746	498, 306
Year FE	*Yes*	*Yes*	*No*	*No*	*No*
ZIP x year FE	*No*	*No*	*Yes*	*Yes*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Energy control variables	*No*	*No*	*No*	*Yes*	*Yes*
PV HH pre-treatment mean	9, 809.93	9, 595.40	9, 595.40	9, 595.40	9, 609.27
Sum of neg. weights	0.0004	0.0011	0.0013	0.0014	0.0798
$\underline{\sigma_{fe}}$	2, 233.48	2, 127.29	2, 044.43	1, 940.04	724.72
$\underline{\underline{\sigma_{fe}}}$	350, 656.19	81, 609.31	72, 665.16	64, 940.78	2, 627.75

Note: This table presents selected coefficients of the estimates described in Equation 3.3. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated as described in Section 3.3. PV HH denotes treatment and measures whether or not household i in year t had a solar PV installed. I differentiate into non-energy and energy control variables and only include energy control variables as potentially bad controls in column (4) and (5). $\underline{\sigma_{fe}}$ and $\underline{\underline{\sigma_{fe}}}$ illustrate standard deviations under which the overall ATT or the ATT in all groups could be of opposite signs than the true effect according to De Chaisemartin and d'Haultfoeuille (2020). Sum of negative weights with regards to the weighted average calculation of the ATT.

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

The implied rebound effect (ATT) in these specifications varies between 8.67% and 6.86%. Accounting for control variables, zip-year fixed effects, as well as for the observed energy related information seem to not change estimates drastically. For instance, adding the energy related control variables decreases the implied rebound effect slightly at 7.96%, compared to 8.36%. However, none of these effects are statistically significantly different from each other. Accounting for the remuneration households receive for the electricity they sell back to the grid, changes the result. This allows to identify the price effect conditional on the income effect. The income effect appears relatively small in magnitude, as the reduction in the estimated rebound effect between column (4) and (5) is approximately one percentage point. This suggests that the solar PV rebound effect is mainly a price reaction and not an income effect. This seems intuitive as additional income generated through solar PV remuneration is relatively small compared to average household income.[26]

[26] For example, a household producing and selling 20,000 kWh and having their solar PV installation certified on average received an annual remuneration of CHF 2,047 between 2015-2019 whereas average income accounts to CHF 122,541.

Control variables have the expected sign and significance and are mostly omitted. Electricity related control variables are, as expected, positively associated with electricity consumption.

In a setting with staggered adoption and two-way fixed effect models, it is important to check for negative weights in the calculation of the ATT (Goodman-Bacon, 2021). If treatment effects are significantly different between groups and over time, the recovered ATT is biased in the presence of negative weights. Such bias could be so severe that the estimated ATT exhibits a sign different from the 'true' effect. I recover each weight assigned to individual treatment effects. This allows me to report the minimum standard deviation required, such that the overall ATT could be of opposite sign than the estimate as $\underline{\sigma_{fe}}$, and the minimum standard deviation required such that each individual group treatment effect could be of opposite sign than the estimate as $\underline{\underline{\sigma_{fe}}}$ (De Chaisemartin and d'Haultfoeuille, 2020). If both these statistics are sufficiently big, it is unlikely that the estimate and the true average effect, or all individual group and time treatment effects, are of opposite sign.[27] I furthermore report the sum of negative weights in each specification, as well as control for potential correlation between covariates and the weights. Specification (5), in which I also control for the feed-in price paid to solar PV adopters, has a relative high share of negative weights that sum to almost 8%. Both standard deviations are also the smallest in this specification.[28] This result is not surprising, as all non-zero values in solar PV remuneration are perfectly correlated with the treatment. Hence, this additional control variable more closely resembles an additional treatment (or an outcome). Thus I no longer include the feed-in electricity price as covariate in the remaining estimations. In my opinion, this is justifiable as the effect is relatively small, and the main source of variation should be accounted for in the fixed effects.[29] In the remaining models, the sum of negative weights are relatively small and in addition both statistics ($\underline{\sigma_{fe}}$,$\underline{\underline{\sigma_{fe}}}$) seem sufficiently big. However, in my preferred specification (4), the weights are significantly correlated with EV, heat pump as well as household wealth. This is problematic if treatment timing is correlated with these variables. It appears as if certain group-specific heterogeneity patterns might not be sufficiently addressed in a two-way fixed effect estimation. Given these correlations, I next employ heterogeneity robust DiD estimators. I will further delve into underlying mechanisms that might explain the correlation between weights and covariates in the treatment decomposition exercise.

[27] Both statistics in any specification seem sufficiently big. For example, assuming that the group and time specific effects are drawn from a uniform distribution, the estimated $\underline{\sigma_{fe}}$ can be multiplied with $\sqrt{3}$. If the estimated coefficient is smaller than this product and the product is also larger than a credible upper bound of the effect it is statistically unlikely that the ATT and the estimated effect are of different sign. Similarly, the second measure can be compared to the estimated effect by multiplying the standard deviation $\underline{\underline{\sigma_{fe}}}$ with $2\sqrt{3}$. Again if both the estimated effect as well as a credible upper bound are smaller than this product it is unlikely that the estimated effect and all group and time specific effects are of different sign.

[28] Assuming a uniform distribution for the group specific ATTs we would need to assume an upper bound of approximately 15% for the rebound effect to reject the possibility that the ATT and the true effect are of reversed sign.

[29] Solar PV remuneration has 2 sources of variation: First, it varies by year for the entire service area. Second, it varies between households that have solar PV electricity certificates and sell them to this particular utility. Most households have solar PV certification immediately with installation and the price for the certificates is also only adjusted once per year.

There are various different reasons why treatment effect heterogeneity over time and between individuals could occur. First, over time, individual households could learn about relevant parameters, such as how much production their solar PV installation delivers, and how much remuneration they receive for each kWh sold. Furthermore, households might continue to electrify their home to further benefit from self-produced electricity. Second, households that adopt in 2019 might differ from earlier adopters in 2015. Over these four years, prices, technological capabilities and public sentiment of both solar PV, and storage capacities have evolved. In Figure 3.3, I present an event study graph using estimators that are robust to heterogeneous treatment effects following Callaway and Sant'Anna (2021). Furthermore, this technique allows me to test for pre-trends, through the estimation of pre-adoption parameters. Pre-trends seem flat except for a slightly positive and significant coefficient four years prior to adoption.[30] It seems that the rebound effect only appears in the second post-adoption year, which could be due to the following reasons: first, households might take some time to adjust electricity consumption behavior, or to learn how much their solar PV produces. Most likely, the absence of treatment effect originates in most households not having the solar PV installed for the entire year, which implies overall smaller electricity production.[31] In the following years, the effect is statistically significantly different from zero and similar in extent between the periods. The estimated ATT is 568.72 kWh or 5.93%, if the first post-treatment period is considered. If I neglect the first post-treatment period, the ATT is 816.25 kWh or 8.51%. The p-value testing the joint significance of the pre-treatment coefficients is 0.13 and thus not significant at conventional levels.[32] I further present similar estimates in Figure 3.A.4. Models differ depending on whether or not energy related control variables are included and not yet treated units are part of the control sample. Furthermore, Panel (D) presents the same estimate, but the pre-treatment comparison group is based on long instead of short gaps.

One potential explanation for the negligible effect of solar PV adoption in the year of installation is the fact that installations are evenly spread out through the year. The two months with most installations are March and September with slightly more solar PV's being connected to the grid in the second half of the year (54.68% vs. 45.32%). This discrepancy is accounted for in the estimation of the two-way fixed effects specification with the actually observed production as treatment.[33] This allows me to account for the potentially smaller production in the year of adoption, as well as for capacity decisions and productivity differences between households. These results depict the relative instead of the aggregated effect. Table 3.A.2 illustrates the results. The columns correspond to the same specifications as in Table 3.3 with column (4) being my preferred specification, where I control for both the extensive set of socioeconomic variables, as well as for the energy related information. The estimated coefficient can be directly interpreted as ATT, as it measures the reaction in electricity consumption to a change in solar PV electricity production (Qiu et al., 2019). On average a households' electricity consumption increases by 11.1 kWh for each additional 100

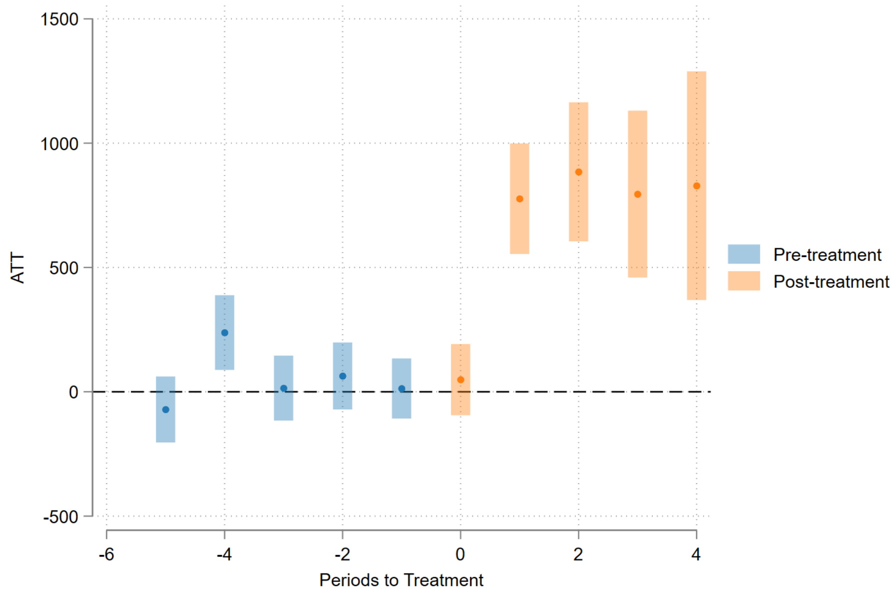
[30] I omit relative pre-adoption years from -12 to -6 in the graph but they are part of the estimation model.

[31] In the construction of the data I account for monthly production in the first year of observation.

[32] In total 40 group-year specific pre-trend coefficients are estimated. Only 2 out of these 40 are statistically distinguishable from zero at the 5% level.

[33] I employ two-way fixed effects estimates here, as the DiD estimators robust to heterogeneous treatment effects in a setting with staggered adoption, and continuous treatments are still work in progress (e.g. de Chaisemartin et al. (2022)).

Figure 3.3. EVENT STUDY ESTIMATES SOLAR PV REBOUND



Note: Event study estimates of solar rebound effect based on (Callaway and Sant'Anna, 2021). All controls included. Outcome is electricity consumption, treatment is PV installation dummy. Standard errors clustered on individual level. Control group includes never and not yet treated observations, group-specific treatment effects estimated using doubly robust inverse probability weighting. Treatment effect heterogeneity seems relatively low absent first period.

kWh of self-produced electricity. This effect corresponds to a rebound effect of 11.1% which is slightly higher than the aforementioned estimates.

My rebound effect estimates are comparable to most recent results in the literature. For example, Aydın et al. (2023) document a solar PV rebound in the Netherlands of 7.7%, which is almost identical to my preferred estimate of 7.96% when using the indicator variable as treatment. They furthermore provide evidence that researchers should account for a households' short-term intertemporal consumption adjustment by including lagged solar PV production in their specification. If they do not account for such adjustments, their estimated solar PV rebound effect of 17.7% is more closely aligned with prior estimates (e.g. 17.9% in Arizona (Qiu et al., 2019)). Such shifts between a small number of days are accounted for in my results, as I am employing annual consumption data. Other estimates using comparable electricity data, but less household information tend to have higher solar PV rebound estimates of 28% for the USA (Beppler et al., 2023), and 35% for Germany (Frondel, Kaestner, et al., 2023). Results based on smaller, self-selected samples for Australia (Deng and Newton, 2017) and Belgium (Boccard and Gautier, 2021) tend to be in a similar range of 20% to 35% respectively. In my opinion, my estimates are smaller due to the higher aggregation of electricity data and my extensive set of control variables. My socioeconomic and building level information allows for better comparison between treatment and control group, while accounting for other potential drivers of changes in electricity consumption.

Robustness - I conduct various robustness checks to evaluate whether the identified effect is driven by model and estimation assumptions. In the following, I will use both treatment definitions - the indicator variable, as well as the actually estimated solar PV electricity production - to evaluate the robustness of the two-way fixed effects estimator. First, I check the functional form assumptions being made explicitly and implicitly in the above discussed results. To further account for potential outliers, I also employ the natural logarithm of electricity consumption as outcome. Table 3.A.3 depicts the results in column (1) and (2). In the log-linear specification the estimated rebound effect, using a dummy variable as treatment, is at around 12%. Results are thus more closely aligned with the estimate using the actually observed solar PV production as treatment. The implied higher rebound effect suggests that households with higher electricity consumption, and a solar PV installation, seem to adjust their behavior less. Electricity consumption is an outcome that is naturally bounded at zero and countable. Hence, one could also use a Poisson pseudo maximum likelihood estimator to better approximate a potential data generating process (Silva and Tenreyro, 2006). These results are depicted in column (3) and (4). In columns (5) and (6), I estimate the equivalent of my preferred specification, but use control variables electricity price, wealth, income, housing area in levels instead of the natural logarithm. Results in specifications (3) to (6) in Table 3.A.3 are fairly comparable to the main results with implied rebound effects between 9.5% to 11.15% and thus not further discussed.

In a second step, I also conduct robustness checks for the data processing steps described in Section 3.2. Results are depicted in Table 3.A.4. First, I only use homeowners, as they actually have the decision power over the installation. The implied solar PV rebound effect when using the indicator treatment is slightly lower at 7%, and similarly decreases to 10.2% when using the actual production as treatment. In a next step, I further exclude household-year combinations exceeding 20,000 kWh of annual electricity consumption. Column (3) and (4) present the results and the estimated effect increases to 11.8% and 13.8%, when using the indicator or the production as treatment, respectively. This confirms the aforementioned pattern. Including high consumption households decreases the estimated solar PV rebound effect. In column (5) and (6), I drop household observations with solar PV capacity exceeding 15 kWp. The implied rebound effect in this specification, is again slightly lower at 7% and 9.24%, respectively. These robustness checks suggest that the rebound effect seems to be (partially) driven by households that install relatively big solar PV installations, but do not necessarily belong to the households with the highest electricity consumption.

I also conduct robustness checks for the supportive DiD results. First, I use the estimator proposed by De Chaisemartin and d'Haultfoeuille (2022a). I depict the results in Figure 3.A.5, where I use all control variables available, and estimate 5 year dynamic treatment effects. I differentiate between estimating 3 year placebo estimates, as well as 5 years placebo estimates to account for potential pre-trends. Results look similar to the estimates presented in Figure 3.3. Estimated ATTs are comparable at 5.4% and 7.8% respectively depending on whether or not the year of adoption is accounted for. Similar to the Callaway and Sant'Anna (2021) estimator, there seems to be some evidence for pre-trends in period 4. Hence, I follow the suggestions of Rambachan and Roth (2023) and illustrate the implications of observed pre-trend violations. The results are depicted in Figure 3.A.6, where I present the estimated rebound effects' implied confidence interval at a specific value of parallel trend violation. The x-axis illustrates the multiple of the biggest observed parallel trends violations (i.e. the biggest absolute deviation from zero estimated in the pre-adoption coefficients), and the y-axis measures the treatment effect in kWh per year. I use the estimates presented in Figure 3.3 and differentiate whether the year of adoption is taken into account in the calculation of the ATT. The breakdown values are 0.6 and 0.8 respectively. This implies that if the violation of parallel trends was 0.6 times the estimated coefficient in pre-adoption period 4, the conclusion that observed solar PV adopters exhibit a positive solar PV rebound effect would no longer be valid on the 95% level of statistical significance. If we ignore the treatment effect in the year of adoption, this breakdown value increases to about 0.8. Thus, the estimated rebound effect seems sensitive to potential parallel trends violations.

To account for this potential mismatch between control and treatment group, I conduct two additional robustness checks. First, I estimate a synthetic difference-in-difference (SDiD) model and thus impose parallel trends on the pre-treatment data (Arkhangelsky et al., 2021). Second, I use propensity score matching on post-observation data to estimate the rebound effect. I employ both nearest neighbor, and three nearest neighbor matching in terms of propensity to adopt a solar PV. In this two-step procedure, I first estimate a logit model predicting each observations propensity to install a solar PV, and then use the matched sample to estimate the rebound effect.[34] This approach, in my opinion, requires the strongest assumptions, which are conditional independence (i.e. after controlling for X potential outcomes are independent of treatment status) and common support (i.e. conditional on X all households have a probability to adopt a solar PV between zero and one). I present and discuss the detailed propensity score matching results in subsection 3.A.5.

All estimated robustness checks and their implied ATT are presented in Table 3.4. Estimates following Callaway and Sant'Anna (2021) differ on whether the first post-adoption period is included in the ATT calculation. For the estimates following De Chaisemartin and d'Haultfoeuille (2022a), I only present the estimates excluding the first period. SDiD estimates automatically include the first post-adoption period (Arkhangelsky et al., 2021). Propensity score estimates are presented for both one nearest neighbor matching, as well as three nearest neighbor matching. The last column presents the ML based estimates that are further discussed in the next section. Most estimates are comparable to the two-way fixed effect estimates. The biggest deviation is for the three nearest neighbor propensity score matching result. However, this result no longer includes individual level fixed effects and thus does not account for unobserved household specific preferences.

[34] Due to data limitation I can no longer account for household specific fixed effects as well as for zip code fixed effects in these models. They would too often predict non-adoption perfectly. Hence, unobservable differences between individuals and communities are no longer accounted for but approximated by the extensive set of covariates (e.g. income, age, solar PV potential, CDD, HDD).

Table 3.4. ATT - ROBUSTNESS CHECKS

Estimator	ATT	95% confidence interval
DiD (Callaway and Sant'Anna, 2021) incl. Period 1	6.95%	(4.61%, 9.29%)
DiD (Callaway and Sant'Anna, 2021) excl. Period 1	8.52%	(5.53%, 11.5%)
DiD (De Chaisemartin and d'Haultfoeuille, 2020) excl. Period 1	7.88%	(4.72%, 11.04%)
SDiD (Arkhangelsky et al., 2021) incl. Period 1	6.93%	(4.8%, 9.04%)
Propensity Score - Matching (1NN)	7.4%	(5.17%, 9.64%)
Propensity Score-Matching (3NN)	5.7%	(3.92%, 7.53%)
Machine Learning-Counterfactual (Souza, 2019)	8.55%	(7.88%, 9.22%)

Note: This table presents implied ATT and their 95% confidence interval for all estimated robustness checks. Some estimators differ based on whether or not the first post-adoption period was included in calculating the ATT as well as the employed technique to infer the rebound effect.

3.4.2. The anatomy of the rebound effect

As elaborated above, there is a discrepancy in the estimated rebound effect based on treatment definition as indicator variable or as actual production. This section's goal is to further delve into potential mechanisms that might explain those differences, and provide an overview of heterogeneity in estimated treatment effects. Furthermore, I am taking a household energy portfolio perspective to illustrate, and test whether parts of the rebound effect could be within household fuel-switching. In addition, I also provide evidence that rebound effects might be driven by a specific subsample of adopters.

In a first step, I present results from two-way fixed effects models including interaction terms between the treatment variable and specific technology indicators, as described in Equation 3.4. I control for heterogeneity based on the co-adoption of different energy intensive goods, or specific subgroups within the sample of solar PV adopters. Results are depicted in Table 3.5 and solar PV installation is measured as indicator variable.[35] Columns (1)-(4) present the results when accounting for additional electrification. While all interaction terms are positive only the term between solar PV installation as well as having a battery or hybrid electric vehicle is statistically different from zero at conventional levels (10%). This indicates that part of the rebound effect is fuel-switching, as households that co-adopt an EV / Hybrid together with a solar PV have a higher rebound effect compared to households that 'only' purchase a solar PV. While the overall baseline solar PV rebound effect in column (1) is 'only' reduced by 30 kWh (or 0.3 percentage points), the implied rebound effect for solar PV and EV / hybrid co-adopters is substantially bigger at 15.1%. There is some suggestive evidence that the higher effect is driven by households that purchase battery EVs, as this interaction term is stronger in extent, although not statistically significant. In columns (5) to (7) I evaluate potential heterogeneity in the rebound effect based on differences in installed solar PVs. I allow for treatment effect heterogeneity based on storage installation, above median capacity (8.6 kWp), or above median solar PV yield (i.e. kWh per kWp). These interaction

[35] In Table 3.A.5 I present the results when estimating the interaction terms with the solar PV production as treatment variable. Results are similar but now only the interaction term between hybrid vehicle and observed solar PV production is significantly different from zero and the other interaction terms are no longer statistically significant at conventional levels. The interaction effect with high capacity and high yield solar PVs is shown for consistency but it is not surprising that they are not statistically significant as both are already accounted for in the relative treatment definition of observed solar PV production.

terms suggest that solar PV adopters with high yield installations exhibit almost twice as strong rebound effects compared to low yield consumers. This is in line with previous findings that households adjust their electricity consumption stronger in sunnier periods (Aydın et al., 2023; Spiller et al., 2017). There are no significant differences stemming from high capacity solar PV households, and such that also install storage. In general, most interaction terms have the expected sign, but are not statistically significantly different from zero. One potential explanation is that identification, in this setting, is coming from a small subsample. For instance, co-adoption of pure battery EVs with solar PVs are around 2% of all post-adoption treated observations.

Table 3.5. Rebound Effect Heterogeneity

	Electrified Household				PV heterogeneity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PV HH	733.01 * **	747.28 * **	750.10 * **	718.37 * **	776.64 * **	601.34 * **	577.44 * **
	(111.69)	(109.75)	(111.24)	(129.69)	(112.16)	(135.52)	(113.34)
EV / Hybrid	−967.59						
	(898.47)						
EV		1338.95 * *					
		(462.61)					
Hybrid			38.21				
			(121.30)				
Heat pump				872.69			
				(614.47)			
PV & EV/Hybrid HH	720.16+						
	(419.18)						
PV & EV HH		897.03					
		(773.67)					
PV & Hybrid HH			525.35				
			(427.07)				
PV & Heat pump				166.88			
				(232.37)			
PV & Storage					−260.21		
					(472.09)		
PV & High capacity						328.73	
						(215.45)	
PV & High Yield							537.88 * **
							(160.95)
N	497, 746	497, 746	497, 746	497, 746	497, 746	497, 746	497, 746
Year FE	*No*	*No*	*No*	*No*	*No*	*No*	*No*
ZIP x year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Energy control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
PV HH pre-treatment mean	9, 595.40	9, 595.40	9, 595.40	9, 595.40	9, 595.40	9, 595.40	9, 595.40

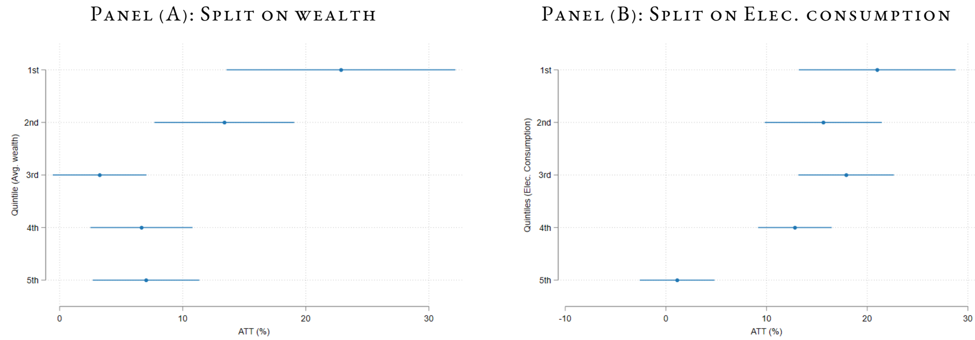
Note: This table presents selected coefficients of the estimates described in Equation 3.4. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated as described in Section 3.3. Each model includes a different interaction term representing either co-adoption of household electrification or heterogeneity within the adopted solar PV system. EVs are pure battery electric vehicles whereas hybrids can be either plug-in hybrid vehicles or hybrid vehicles without external charging possibility. Yield measures the observed production per kWp installed for the solar PV panel whereas high capacity indicates solar PV installations exceeding median capacity of 8.6 kWp.

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

In an additional heterogeneity analysis, I depict treatment effects of different subgroups based on average wealth and electricity consumption.[36] I split the sample into quintiles based on household averages and estimate my main two-way fixed effects specification for each subsample. Figure 3.4 illustrates the results. The rebound effect decreases with increasing wealth and increasing electricity consumption. Households that already consumed high amounts of electricity before adopting solar PV, adjust their consumption relatively less, as previously discussed. Similarly, less wealthy

[36] I also split on income, but do not present nor discuss the results as they are almost identical to wealth. This is not further surprising as correlation between wealth and income is high in my sample (>0.9).

Figure 3.4. Heterogeneity in solar PV rebound effect



Note: This plot illustrates estimated ATTs of selected subsamples based on the average observed value for wealth and electricity consumption. The sample is split into quintiles. Each estimated ATT corresponds to the coefficient of a two-way fixed effect regression, using a solar PV indicator variable as treatment, normalized by within-sample solar PV households' pre-treatment average consumption.

households adjust stronger post-adoption. These effects could have various reasons. One potential explanation is that households that are relatively less wealthy or consume relatively less electricity pre-adoption consider the investment into a solar PV installation as a bigger commitment due to budget constraints. An alternative explanation is that the actual adjustment in absolute terms is relatively similar, but the relative adjustment differs, because households in the higher consumption and wealth quintiles have relatively higher baseline consumption.[37]

Furthermore, I present and discuss the results from the ML based approach. I predict unobserved counterfactual electricity consumption for each solar PV adopter and post-treatment observation to estimate household-year treatment effects. This allows me to infer the anatomy of the solar PV rebound using linear regression. I provide further details of the ML algorithm, training data and model selection in subsection 3.A.4. I further illustrate and discuss the no-anticipation and stability of the counterfactual function assumptions necessary for this approach's validity (Souza, 2019). I use bootstrapped, stratified samples to account for the additional uncertainty caused by prediction. Both ATT confidence intervals, as well as regression standard errors are based on bootstrapped estimates. Overall, the ML estimate indicates an average solar PV rebound effect of

[37]This, however, can be checked. For the split sample estimates based on average consumption it is partially true, as the absolute effect for the lowest two quintiles is smaller in extent than for consumption quintiles 3 and 4. For the split samples based on average wealth it is not true. Here the lowest wealth quintile has both the highest average treatment effect in relative and absolute terms. Still the highest consumption quintiles do not expand their consumption as a reaction to installing a solar PV, which probably explains the discrepancy between some of the estimates (i.e. Indicator vs. production treatment, level vs. log outcome)

8.55%, with a 95% confidence interval spanning from 7.88% to 9.22%.[38] These estimates are fairly similar to the results from both the heterogeneity robust DiD estimates and the two-way fixed effects models.

In Figure 3.5, I depict selected coefficients[39] from a linear regression of the household-year treatment effect on the following explanatory variables: electricity price (natural logarithm), solar PV electricity remuneration, indicator variables for EV ownership, hybrid vehicle ownership, heating system (oil, natural gas, wood, heat pump, electricity, district), storage capacity installation, electricity product mix (green, grey, blue), household size (1, 2, 3, 4, 5+), urbanity (urban, rural, periphery), and categorical variables for bins of solar PV capacity installed and solar PV rooftop suitability, as well as decile membership for living area, cooling degree days, heating degree days, income, wealth, age, rooftop area and average monthly solar PV yield (kWh / kWp).[40] Panel (A) illustrates the conditional effect of household electrification on the individual solar PV rebound. I find that household-year observations with an EV have, on average, a solar PV rebound effect that is 0.11 higher compared to households without EV co-adoption. Considering that the baseline average rebound effect is 0.085 this more than doubles the estimated rebound effect for solar PV and EV co-adopting households. A similar pattern, although to a smaller extent, can be observed for households that co-adopt a hybrid vehicle. Thus, parts of the solar PV rebound seem to be within household fuel-switching.[41] There seems to be a slight negative association between rebound effects and the installation of storage capacity suggesting that households with storage systems have smaller solar PV rebound effects. Such households might less worry about consuming electricity when available, and are better equipped to smooth their consumption over short time-periods. This is in line with findings of Aydın et al. (2023), who illustrate that solar PV households shift consumption to particularly sunny days with high solar PV production expectations. Households thus might start their laundry machine prematurely on sunny days to benefit from relatively high solar PV production. Consequently, this implies higher electricity consumption over the year, as starting these processes prematurely will increase overall usage. Households that co-adopt a heat pump have a 0.113 percentage points higher rebound effect compared to electric resistance heating systems. It is important to note that solar PV rebound effects of households with heat pumps are not statistically significantly different from households with other heating resources such as oil, wood or natural gas. This, however, could be associated with the fact that heating systems

[38]The detailed distribution and overview of the estimated average solar rebound effect based on the ML unobserved counterfactual prediction is illustrated in Figure 3.A.7.

[39]I focus on electrification co-adoption, solar PV specific heterogeneity, as well as two interesting patterns based on socioeconomics and weather information. Most other coefficients show no patterns or no significant relationship with the estimated solar rebound effects and are thus not further discussed, but available upon request.

[40]I also estimated two separate models including either year or year of adoption indicator variables to account for potential heterogeneity over time. Results are consistent and not further discussed.

[41]This can be either from fossil fuel transportation to electricity based transportation, which would have the highest environmental benefits. If, on the other hand, these households would have purchased an EV without having a solar PV, the environmental implications of them charging it with their own locally produced solar PV differ. If driving behavior is independent of solar PV ownership, the environmental impact is neutral, as, instead of causing additional emissions embedded in the marginal grid kWh, the household uses the solar PV kWh that would have otherwise displaced this marginal grid kWh.

are mainly operated in winter. A period when solar production is relatively low, due to less solar irradiation caused by shorter days, relative higher sun distance, and increased disturbance from clouds and fog.[42] I investigate this pattern further by also including deciles of heating degree days in the regression. As illustrated in Panel (A) of Figure 3.A.8 rebound effects tend to be slightly higher for household-year combinations with relatively high heating degree days observations. This suggests that, although no direct difference between heat pump adopting households compared to non-electric heating resources can be found, parts of the higher rebound effects could be explained by colder temperatures. I also document a u-shaped association between wealth and the rebound effect. Households that constitute the lower and the higher end of the wealth distribution have relatively higher solar PV rebound effects compared to households in the middle of the wealth distribution as illustrated in Panel B of Figure 3.A.8.[43]

Panel (B) and Panel (C) of Figure 3.5 present the decomposition of the individual-year rebound effects based on solar PV specific information. First, I depict the observed average monthly solar PV yield.[44] I use indicator variables for deciles of solar PV yield in the linear regression. The average monthly solar PV yield exhibits a positive association with the estimated solar PV rebound effect. It appears as, even on yearly aggregated data, higher levels of solar PV production are associated with higher rebound effects. Surprisingly, this effect is mainly driven by low rebound effects at low levels of solar PV yield. There appears to be smaller adjustments to relatively high levels of production. While the average household increases their electricity consumption slightly post-adoption, households tend to re-adjust in periods of relatively little solar yield. However, this heterogeneity might also be (partially) driven by the lowest decile being pre-dominantly observations from the year of adoption, especially of households that adopted relatively late in the year, and thus were unable to adjust yet.[45]

Panel (C) illustrates an almost linear positive association between bins of solar PV capacity (kWp) and the estimated rebound effects. Households in the smallest category of solar PV panels have a 20 percentage points lower rebound effect compared to households with installations of 8-10 kWp. In comparison, agents with solar PV capacity exceeding 17 kWp have estimated rebound effects that are more than 40 percentage points higher than those of comparable households with installations between 8 kWp and 10 kWp. This suggests that part of the rebound effect ought to be driven by households opting into higher solar PV capacity than required to meet their electricity

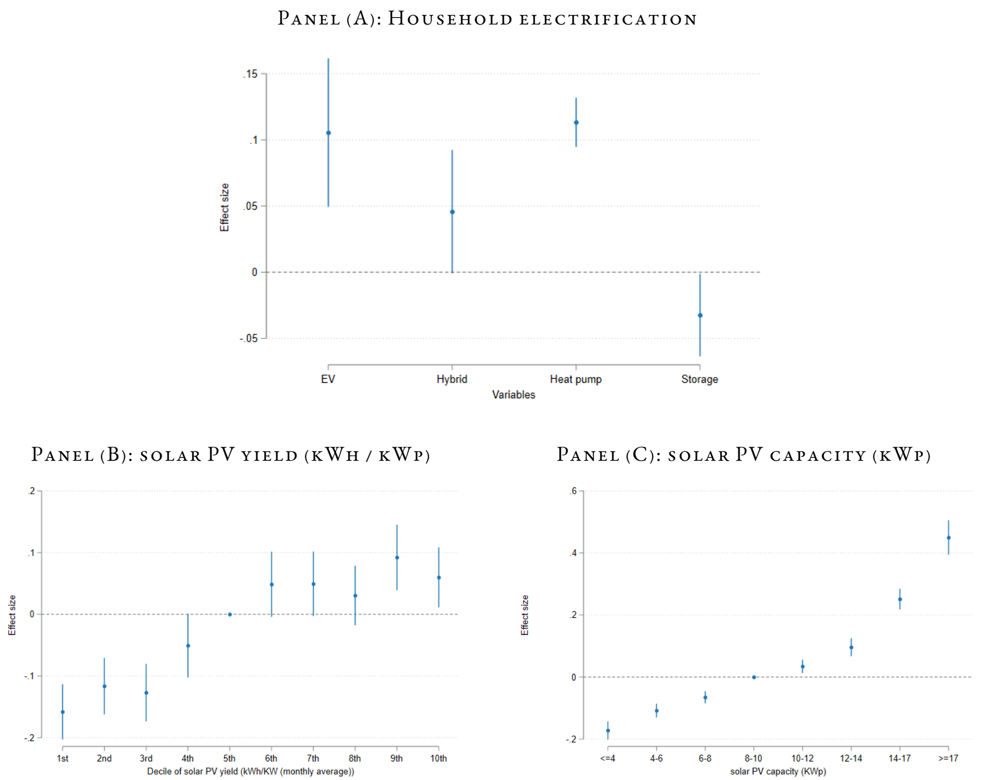
[42]While increased reflection thanks to snow cover can be beneficial it is important to note that in the periods of observation snow cover in the residential areas is relatively low and tends to be short-term. On average, less than 20% of solar PV production was produced in the five months between November and March.

[43]This contradicts the split sample estimates from the two-way fixed effects specifications in which lower wealth households had higher rebound effects. It is important to note here, that these results are based on different estimation samples, as these estimates only consider solar PV adopters, which tend to be wealthier than the average population.

[44]This is defined as the solar PV production (in kWh) per each installed kilowatt of peak power capacity (kWp). I further normalize this measure by months of operation to make initial periods comparable to the subsequent years.

[45]The decile of lowest solar PV yield consists of 95% of observations in the first year of observation and 4 out of 5 are household-year combinations that adopted in or after September. For the second decile this share is already strikingly smaller at around half of the observations.

Figure 3.5. Decomposition of solar PV rebound effects



Note: This plot shows selected coefficients from a linear regression model of the predicted household-year solar PV rebound effect on adopter specific variables. The individual rebound effects are estimated using ML-based prediction of unobserved counterfactual consumption. 95% confidence intervals are estimated using stratified bootstrap sampling with replacement to account for prediction uncertainty. Variables correspond to membership to a certain decile of the distribution, or as indicator variables for ownership of a certain technology. All decile coefficients should be interpreted as relative effect compared to the 5th decile. Electrification coefficients as relative to not-owning the product, whereas heat pump is relative to an electricity based heating system.

needs, which leads to stronger post-adoption consumption adjustments. Alternatively, households might invest into bigger capacity in anticipation of increased future electricity consumption. This, however, would mean that the solar PV installation is not the cause of the increased consumption, but the expected future rise in consumption is causing the decision to install (a particular capacity of) solar PV. This is a shortcoming of all existing solar PV rebound studies, which also qualifies my findings. Another explanation is that this association is driven by bigger prediction errors for households with higher electricity consumption, which also tend to self-select into higher solar

PV capacity.[46] I elaborate on this pattern in subsection 3.A.4 and show that the capacity bins are slightly correlated with the absolute prediction residuals. However, there is no statistically significant association between the solar PV capacity and the relative residual. Moreover, the effect size is less than a quarter of the post-adoption regression, which suggests that the pattern is not pre-dominantly caused by prediction errors.

3.5. Conclusion

I estimate the solar PV rebound effect for Switzerland using detailed household information of around 60,000 single-family home residents in the Swiss canton of Bern to infer a solar PV rebound effect between 7.9% and 11.1% depending on specification. I find some heterogeneity between adopting groups and over time, particularly in the year of adoption where no significant rebound effect is found. At the same time, I find that lower wealth, and lower average electricity consumers react stronger with rebound effects estimated at around 20%. My decomposition estimates illustrate that, at least part of, the solar PV rebound effect can be explained by co-adopters that electrify their heating system and/or their transportation mode. I also provide evidence of the solar PV rebound effect being mainly driven by a subsample of adopters, which opt into relatively high solar PV capacity, and react stronger to large solar PV yields.

This effect heterogeneity has important implications for forecasts of expected electricity production capacity requirements, as well as for policy evaluation. Parts of the rebound effects might be households anticipating higher consumption, and thus installing solar PV (or installing higher capacity of solar PV), while other households further electrified their home and transportation mode. Hence, solar PV rebound effects might be environmentally beneficial in a setting with relatively low grid emissions and relatively high transport and residential heating emissions. This within household fuel-switching is important to acknowledge when rebound effects are accounted for in solar PV subsidy evaluation, as well as in energy consumption forecasts. Nevertheless, parts of the rebound effect persist and it is thus not enough to replace current non-renewable energy capacity on a one-to-one basis to phase out conventional energy sources.

[46]The correlation between electricity consumption and installed solar PV capacity for solar PV households but only using pre-adoption periods is 0.23

3.A Appendix

3.A.1. Additional Tables

Table 3.A.1. Relative adoption frequencies of solar PV

	Overall	High income	High wealth	Homeowner	Urban	Elec. Vehicle	Heat pump
2015	.71	.88	1.07	.83	.8	6.25	1.49
2016	1.23	1.69	1.87	1.43	1.4	9.8	2.56
2017	1.82	2.38	2.64	2.08	2.01	20.9	3.6
2018	2.47	3.37	3.46	2.81	2.6	29.55	4.91
2019	3.22	4.49	4.48	3.64	3.43	32.03	6.04
Mean	1.88	2.55	2.7	2.15	2.03	24.04	3.73
N	217,393	108,697	108,696	176,985	69,533	366	33,188

Note: Based on observed households and solar PV adoptions between 2015 to 2019. High wealth and high income based on median cut-off for the respective value. Homeownership status as defined in the data. Urbanity, EV ownership and heat pump heating system based on data. All Data sources are described in Section 3.2.

Table 3.A.2. Two-way Fixed Effect Estimation - PV production

	(1)	(2)	(3)	(4)	(5)
PV production (kWh)	0.118 * **	0.117 * **	0.115 * **	0.111 * **	0.116 * **
	(0.014)	(0.013)	(0.013)	(0.013)	(0.015)
Electricity price (log)		−6103.967 * **	−6211.926 * **	−6184.320 * **	
		(217.366)	(219.654)	(219.050)	
Electricity price					−222.740 * **
					(8.902)
Feed-in electricity price					−5.035
					(8.129)
Heat pump				875.185	871.564
				(614.768)	(612.841)
Electric vehicle				1467.575 * **	1483.677 * **
				(418.218)	(419.510)
ATT	11.8%	11.7%	11.5%	11.1%	11.6%
N	503, 522	498, 061	497, 746	497, 746	498, 306
Year FE	*Yes*	*Yes*	*No*	*No*	*No*
ZIP x year FE	*No*	*No*	*Yes*	*Yes*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Energy control variables	*No*	*No*	*No*	*Yes*	*Yes*

Note: This table presents selected coefficients of the estimates described in Equation 3.3. Treatment is now defined as actually observed solar PV production in kWh in the post-adoption years. Hence, estimated treatment effects can be directly interpreted as average treatment effect on the treated. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated as described in Section 3.3.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 3.A.3. Robustness checks - functional form

	Log Consumption		Poisson		No log controls	
	(1)	(2)	(3)	(4)	(5)	(6)
PV HH	0.1263 * **		0.0907 * **		772.5270 * **	
	(0.0111)		(0.0113)		(110.0642)	
PV production (kWh)		0.0000 * **		0.0000 * **		0.1115 * **
		(0.0000)		(0.0000)		(0.0133)
Electricity price (log)	−0.5920 * **	−0.5909 * **	−0.5538 * **	−0.5524 * **		
	(0.0236)	(0.0236)	(0.0230)	(0.0230)		
Electricity price					−223.6249 * **	−223.1040 * **
					(8.9015)	(8.8958)
Heat pump	0.1037	0.1030	0.0899	0.0894	874.6923	869.4961
	(0.0739)	(0.0740)	(0.0729)	(0.0729)	(611.0341)	(610.6839)
Electric vehicle	0.1815 * **	0.1715 * **	0.1616 * **	0.1514 * **	1569.0214 * **	1479.7610 * **
	(0.0348)	(0.0351)	(0.0405)	(0.0409)	(419.1166)	(419.1870)
ATT	12.63%	N/A	9.49%	N/A	8.04%	11.15%
N	497, 746	497, 746	497, 746	497, 746	498, 306	498, 306
ZIP x year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Energy control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
PV HH pre-treatment mean	N/A	N/A	9, 595.40	9, 595.40	9, 609.27	9, 609.27
$\underline{\sigma_{fe}}$	0.318	N/A	N/A	N/A	1, 962.08	N/A
$\underline{\underline{\sigma_{fe}}}$	10.647	N/A	N/A	N/A	65, 734.10	N/A

Note: This table presents selected coefficients of the estimates described in Equation 3.3. Odd rows have treatment definition as indicator variable if household i owned a solar PV in year t. Even rows have treatment defined as actually observed solar PV production in kWh in the post-adoption years. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated as described in Section 3.3. Column (1) and (2) have natural logarithm of electricity consumption as outcome, column (3) and (4) estimate a Poisson model with electricity consumption as outcome. Column (5) and (6) are a level-level model where no control variable is used in natural logarithms. I do not report the sum of negative weights specifically but they never exceed 0.0015 where applicable.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

Table 3.A.4. Robustness checks - Data

	Homeowners		Large Elec. Consumption		Large solar PVs	
	(1)	(2)	(3)	(4)	(5)	(6)
PV HH	671.2089***		984.9611***		649.5216***	
	(111.1176)		(87.5678)		(109.7666)	
PV production (kWh)		0.1020***		0.1379***		0.0924***
		(0.0138)		(0.0108)		(0.0137)
Electricity price (log)	−7040.9869***	−7028.4072***	−3689.5583***	−3677.2822***	−6201.2216***	−6194.6158***
	(238.1416)	(238.0652)	(154.7671)	(154.6459)	(219.2396)	(219.2257)
Heat pump	2009.3516*	2004.8136*	1144.9619**	1139.7664**	870.9097	867.8747
	(979.4698)	(979.5558)	(410.0235)	(409.6350)	(617.3767)	(617.2027)
Electric vehicle	1397.9942***	1308.7889***	1262.1564***	1162.9233***	1495.3420***	1454.9073***
	(398.4756)	(397.2962)	(275.0327)	(272.8308)	(434.6917)	(435.7909)
ATT	7.01%	10.2%	11.79%	13.79%	6.96%	10.20%
N	400, 302	400, 302	465, 113	465, 113	496, 540	496, 540
ZIP x year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Energy control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
PV HH pre-treatment mean	9, 580.79	9, 580.79	8, 352.30	8, 352.30	9, 335.95	9, 335.95
$\underline{\sigma_{fe}}$	1, 626.65	N/A	2, 269.41	N/A	1, 669.46	N/A
$\underline{\underline{\sigma_{fe}}}$	75, 215.35	N/A	76, 762.02	N/A	56, 047.39	N/A

Note: This table presents selected coefficients of the estimates described in Equation 3.3. Odd rows have treatment definition as indicator variable if household i owned a solar PV in year t. Even rows have treatment defined as actually observed solar PV production in kWh in the post-adoption years. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated as described in Section 3.3. Column (1) and (2) only uses the sub-sample of homeowners, column (3) and (4) excludes households with very high observed electricity consumption (exceeding 20,000 kWh). Column (5) and (6) excludes bigger installed solar PV capacity between 15-20 kWp. I do not report the sum of negative weights specifically but they never exceed 0.0015 where applicable.

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 3.A.5. Rebound Effect Heterogeneity - Production

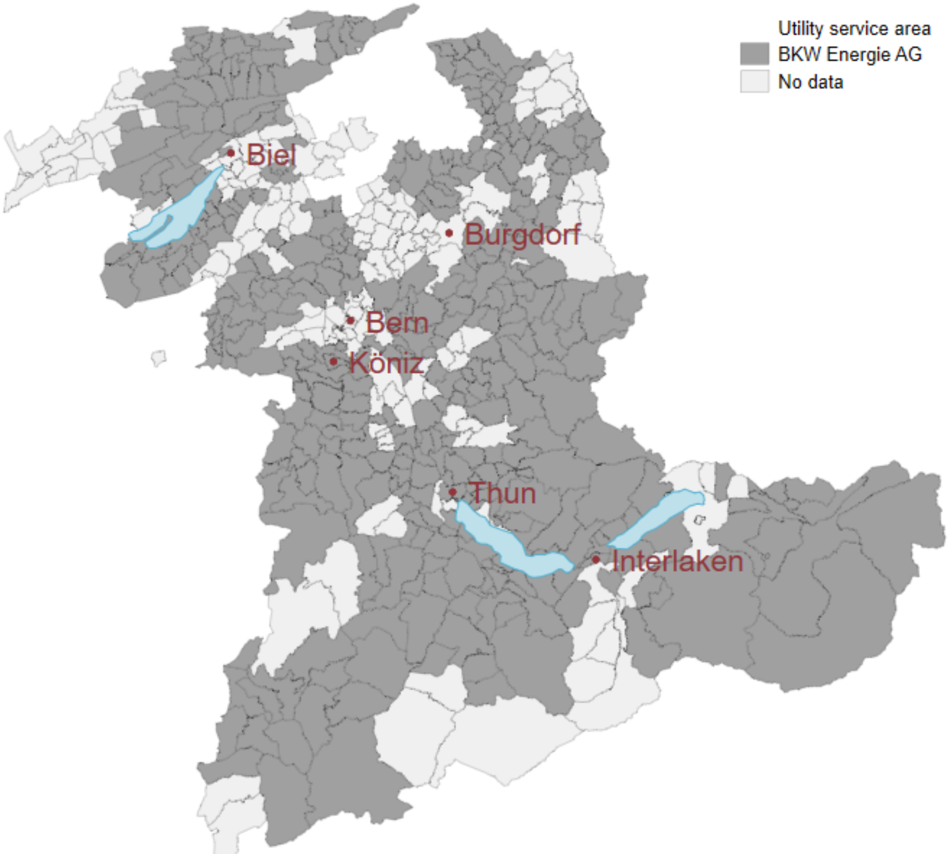
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PV production (kWh)	0.11***	0.11***	0.11***	0.11***	0.11***	0.12***	0.10***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
EV / Hybrid	−1123.29						
	(897.24)						
EV		1413.07**					
		(452.98)					
Hybrid			22.66				
			(120.87)				
Heat pump				872.05			
				(614.52)			
PV production * EV/Hybrid HH	0.06						
	(0.05)						
PV production * EV HH		0.02					
		(0.07)					
PV production * Hybrid HH			0.10*				
			(0.05)				
PV production * Heat pump				0.01			
				(0.03)			
PV production * Storage					−0.01		
					(0.07)		
PV production * High capacity						−0.01	
						(0.03)	
PV production * High Yield							0.02
							(0.02)
N	497, 746	497, 746	497, 746	497, 746	497, 746	497, 746	497, 746
ZIP x year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Energy control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: This table presents selected coefficients of the estimates described in Equation 3.4. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated as described in Section 3.3. Each model includes a different interaction term representing either co-adoption of household electrification or heterogeneity within the adopted solar PV system. EVs are pure battery electric vehicles whereas hybrids can be either plug-in hybrid vehicles or hybrid vehicles without external charging possibility. Yield measures the observed production per kWp installed for the solar PV panel whereas high capacity indicates solar PV installations exceeding median capacity of 8.6 kWp.

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

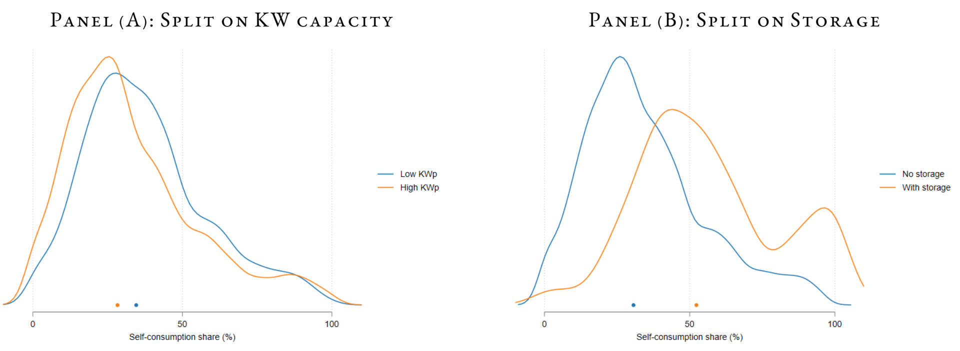
3.A.2. Additional Figures

Figure 3.A.1. Service area of data collaborator



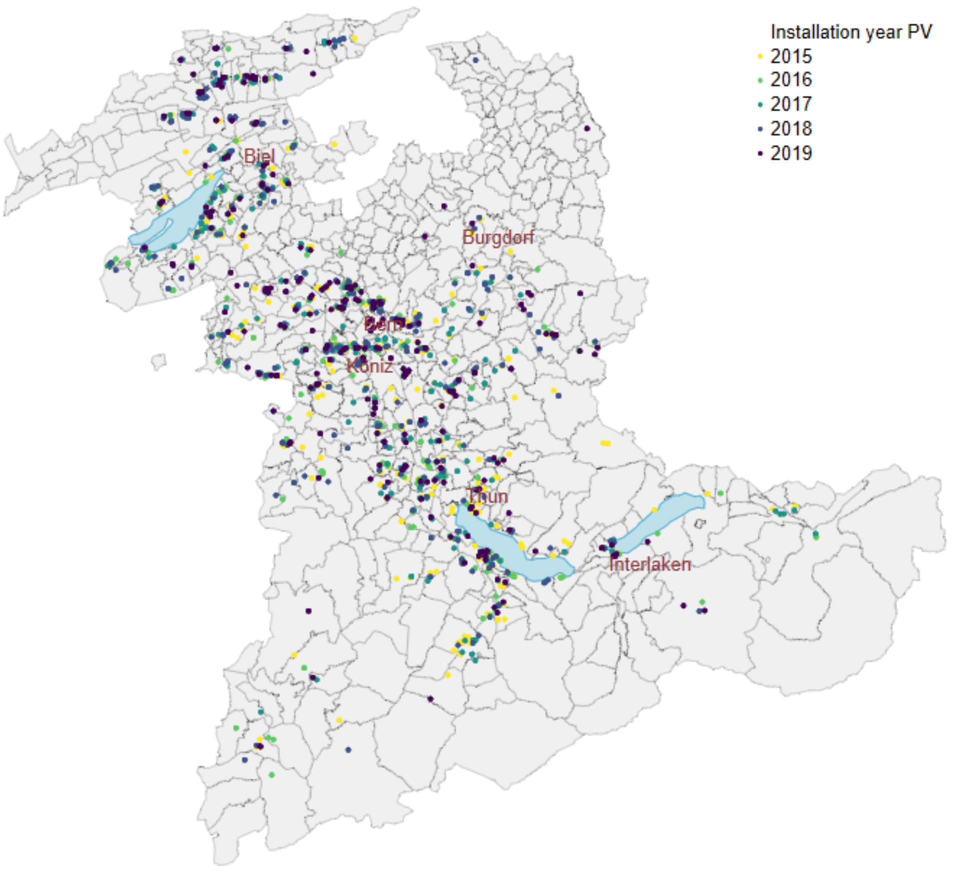
Note: This map illustrates the service area based on a ZIP code level from the data provider BKW. Source of information is ELCOM, the Swiss regulatory board for electricity markets.

Figure 3.A.2. HETEROGENEITY IN SELF CONSUMPTION SHARE



Note: The plot shows the distribution of the share of self consumption for PV households in the sample differentiated based on installed kWp and the availability of storage capacity. The dot below the distribution illustrates the average within the group.

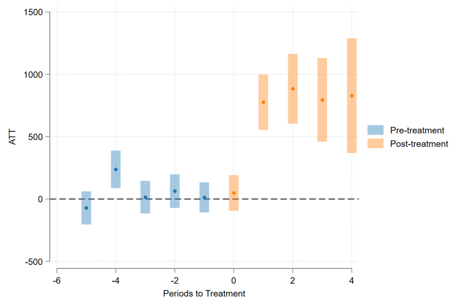
Figure 3.A.3. Solar PV estimation sample



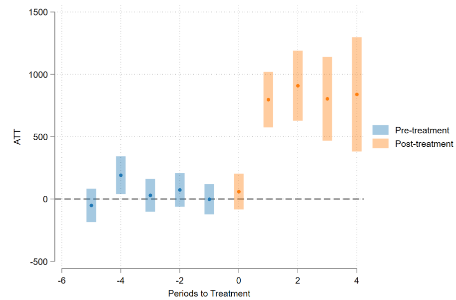
Note: This map illustrates the distribution of locations and years of installations of all solar PV installations that are part of the estimation sample. Different colors indicate different years of adoption while each point corresponds to the unique location of one solar PV installation.

Figure 3.A.4. EVENT STUDY ESTIMATES II

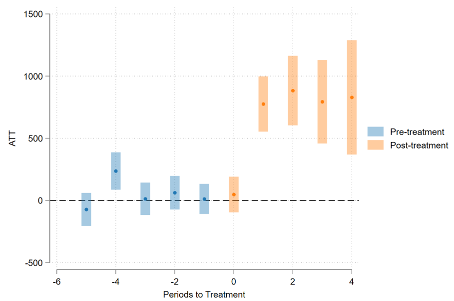
PANEL (A): ALL CONTROLS, NEVER TREATED



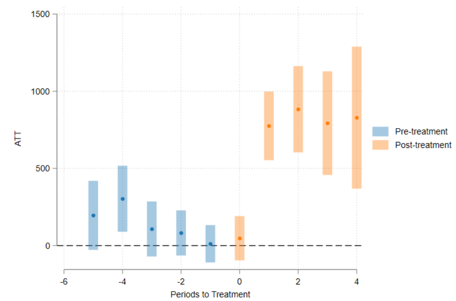
PANEL (B): NO ENERGY CONTROLS, NEVER TREATED



PANEL (C): ALL CONTROLS, NOT YET INCLUDED



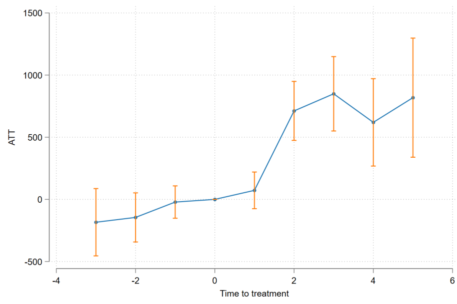
PANEL (D): LONG GAPS



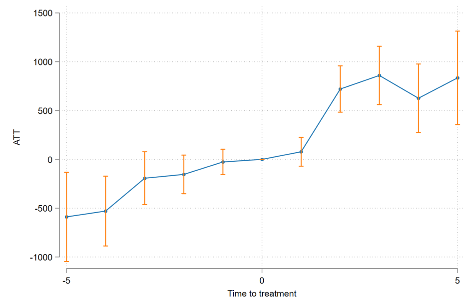
Note: This plot shows event study estimates of solar rebound effect based on (Callaway and Sant'Anna, 2021). Different models differ based on the inclusion of control variables and the composition of pre-treatment samples (control group). Panel (D) furthermore illustrates a model with long gaps and includes all controls and not yet treated observations. Outcome is electricity consumption, treatment is PV installation dummy. Standard errors clustered on individual level. Group-specific treatment effects estimated using doubly robust inverse probability weighting. Treatment effect heterogeneity seems relatively low absent first period.

Figure 3.A.5. Event study estimates III

Panel (A): 3 year pre-trend test



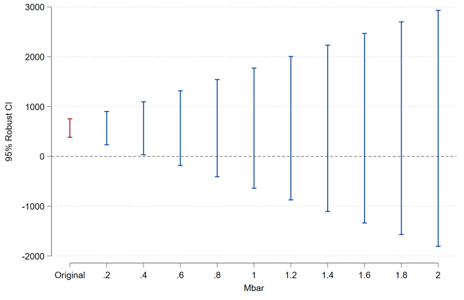
Panel (B): 5 year pre-trend test



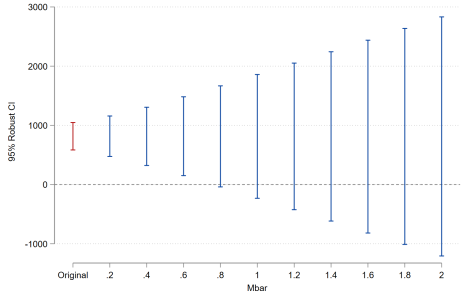
Note: This plot shows event study estimates of solar rebound effect based on (De Chaisemartin and d'Haultfoeuille, 2020). Both energy and non-energy specific control variables included. Outcome is electricity consumption, treatment is PV installation dummy. Standard errors clustered on individual level. Control group includes both never and not yet treated observations. Dynamic treatment effects estimated for 5 post-adoption and 3 pre-adoption periods or 5 (Placebo estimates).

Figure 3.A.6. Honest Parallel Trends

Panel (A): ATT based on all post-adoption periods

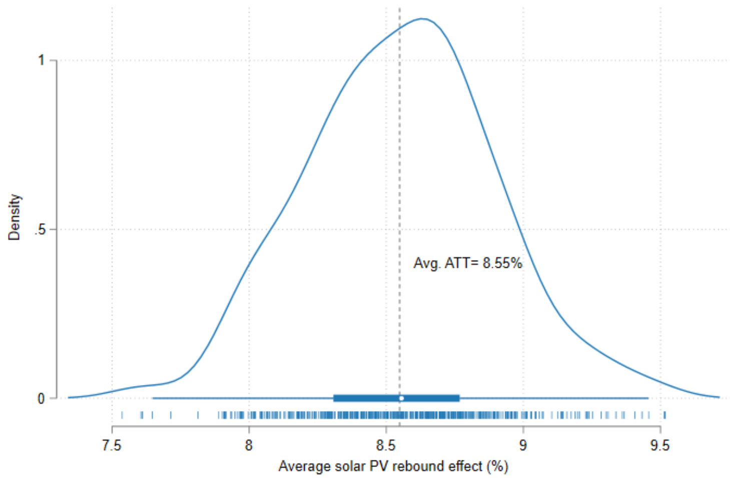


Panel (B): ATT ignoring year of adoption



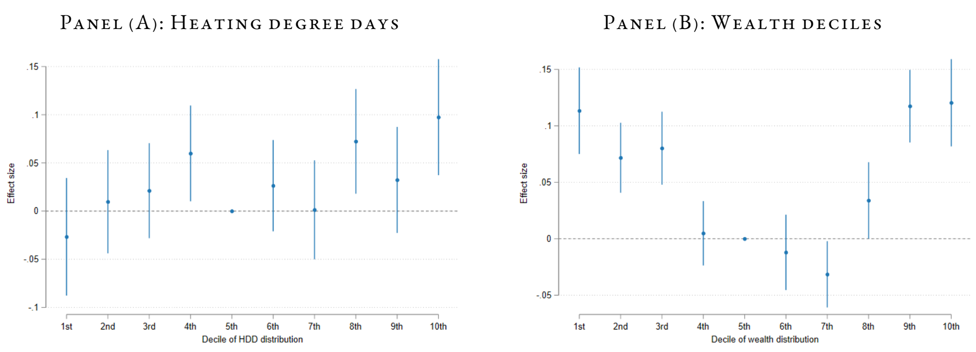
Note: This plot shows the breakdown values of the parallel trends assumption following the methodology outlined by Rambachan and Roth (2023). The x-axis measures the factor multiplying the biggest absolute observed pre-trend coefficient to illustrate how much violation in the pre-trend assumption is still credible with the conclusion about the significance of the estimated ATT.

Figure 3.A.7. Solar rebound effect - ML based estimates



Note: This plot shows the distribution of the estimated average solar PV rebound effects using the ML based approach by predicting unobserved counterfactual. Estimation based on 500 stratified bootstrap samples. Average ATT is 8.55% which closely aligns with the estimated median.

Figure 3.A.8. Decomposition of solar PV rebound effects



Note: This plot shows selected coefficients from a linear regression model of the predicted household-year solar PV rebound effect on solar PV adopter specific variables. The individual rebound effects are estimated using ML-based prediction of unobserved counterfactual. 95% confidence intervals are estimated using stratified bootstrap sampling with replacement to account for prediction uncertainty from the ML model. Both variables are defined as membership to a certain decile of the distribution. All coefficients should be interpreted as relative effect compared to the 5th decile.

3.A.3. Solar PV Electricity Production Simulation

The simulation of solar photovoltaic power production is based on the inputs displayed in Table 3.A.6. I provide the exact geolocation, the year of installation and the installed capacity in kWp. The simulation procedure then takes access data on meteorological information as well as rooftop geometry and has a model of degradation in prognosticating the actual observed month-year solar PV production. The annual average predicted solar PV yield (kWh / kWp) is 1,100 kWh, compared to a Swiss-wide non-simulated average of 1015 kWh/kWp. The most likely explanation for this discrepancy is that all simulated locations are within the canton of Bern, which shows slightly above-average solar yields (BFE, 2018). The simulated production data is accessed through a web-based API, which was specifically programmed for me. A Swiss engineering company, specializing in solar PV system design and solar PV advising, programmed both the interface, and simulation framework. Their expertise has also been employed by various public stakeholders, as they have, for instance, provided a Swiss-wide online calculator that enables households to simulate, and understand their private cost-benefit analysis of solar PV adoption[47]. Furthermore, the simulation framework takes the specific rooftops solar PV potential into account. So for each estimated solar PV production, not only rooftop orientation, but solar irradiation and geometry was also taken into account. Moreover, specific shading conditions from surrounding buildings, as well as natural sources, such as trees, and mountains are also accounted for. This data is based on the publicly available information on solar rooftop potential provided by (Federal Office of Energy (BFE) - Switzerland, 2023).

In the year of adoption only the production of the actual months of ownership are estimated. The dataset indicates the exact day the PV installation was connected to the grid and thus operational. Based on this date, I estimate the solar PV electricity production for each month. This ensures that there is no data mismatch between observed production and observed feed-in. For example, if a solar PV installed in November 2016 would be assumed to have been operational for all of 2016, the implied self-consumption would be significantly higher.

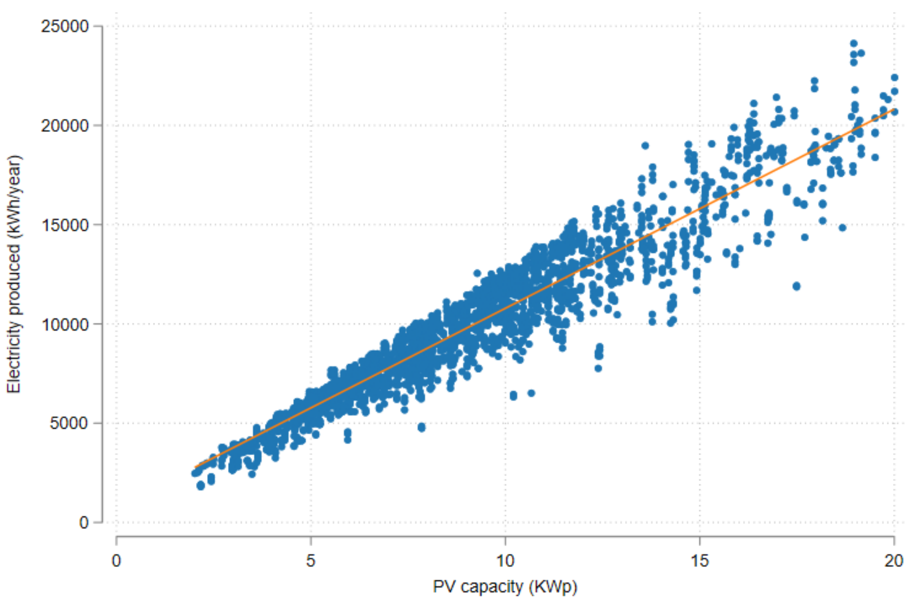
I present a few distributional statistics and descriptive graphs from the simulation outcome. Figure 3.A.9 presents the relationship between solar PV capacity (kWp) and the produced electricity. A perfect correlation (45° line) would indicate that one kWp produces 1,000 kWh per year. In my sample, the production gradient is slightly higher suggesting that locations or rooftops with above average solar PV production have installed. Furthermore, I also present both the linear relationship between self consumed electricity and produced electricity, as well as electricity sold to the grid and produced electricity in Panel A and Panel B of Figure 3.A.10. If there was no self consumption, Panel A would show a zero relationship, while Panel B would show a perfect correlation. Both relationships show a positive correlation meaning that most households consume part of the produced electricity themselves, and sell parts back to the grid. Higher production leads to both higher self consumption and higher electricity feed-in.

[47] `https://www.energieschweiz.ch/tools/solarrechner/`

Table 3.A.6. SOLAR PHOTOVOLTAIC POWER PRODUCTION SIMULATION INPUTS

Input	Description
Location	Geo-location of solar photovoltaic system
Meteorological data	Sun position, direct radiation, intensity and hemispherical distribution of diffuse radiation, snow cover, sky and ambient temperature, wind speed
Capacity	capacity of solar cells (in kWp)
Temperature	Correction due to the sky and ambient temperature
Radiation	Correction due to low-light
Geometry	Correction due to angle factor
Degradation	Correction due to age of the solar photovoltaic system

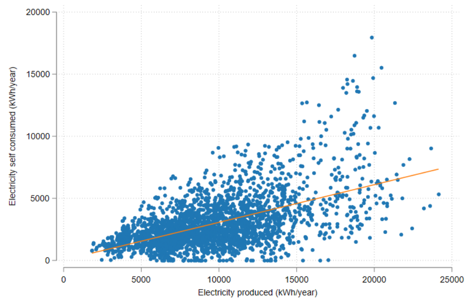
Figure 3.A.9. RELATIONSHIP BETWEEN CAPACITY AND SOLAR PV PRODUCTION



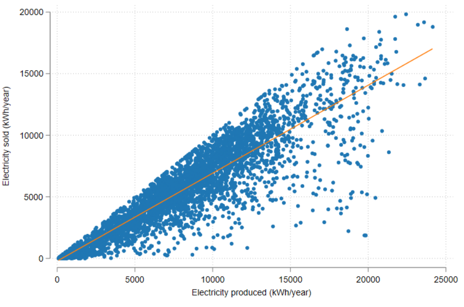
Note: This figure illustrates the simulation results for our sampled solar panels as a function of the installed capacity. The orange line depicts a simple linear regression.

Figure 3.A.10. Usage of own produced solar PV electricity

Panel (A): Production & self consumption



Panel (B): Production & feed-in



Note: The plot shows the correlation between the self consumption for solar PV households with the produced electricity, as well as the electricity sold back to the grid and produced electricity. The orange line represents a linear fit.

3.A.4. ML - Model selection and diagnostics

This section discusses in more detail how the machine learning (ML) models were trained, and what data was part of the estimation process. Furthermore, I describe which algorithms were used for model tuning.

Predictors - I employ the following features to predict observed electricity consumption of household i in year t: indicator of electricity mix (Blue, Green, Grey), income, wealth, home ownership status, age, household size (1, 2, 3, 4, 5+), living area, nb. of rooms, heating system/resource (oil, nat. gas, wood, district, heat pump, electric), house building period indicator (10 categories, mostly for decades), urbanity of location (urban, semi-urban, rural), mountain region indicator, vehicle fuel type (gasoline, diesel, electric, hybrid), electricity price, rooftop size, rooftop PV suitability, neighborhood solar PV density, heating degree days, cooling degree days and year indicator variables.

Data - I use all available observations, other than solar PV household's post-adoption observations. The sample data includes both never treated, and not-yet treated observations. I randomly create a holdout sample of 15% to test the predictive performance of the models, which are trained on the remaining 85%.

Model Algorithms - Rather than estimating each model separately, I estimate ensembles of predictor models, and directly compare the predictive performance on in-sample and out-of-sample prediction. I employ root mean squared prediction error (RMSPE) to evaluate performance. In a first step, I tested the following algorithms using the pystacked-package in Stata (Ahrens et al., 2022): Lasso, Ridge, Elasticnet, Random Forests, Gradient boosted trees, Neural Net regressor and linear Support Vector Machine. For some of the base learners I also provide polynomials of degree 2, meaning each variable squared, and all available interaction terms are also part of the possible set of features. Regularization terms in Lasso, Ridge and Elasticnet models are tuned via cross-validation. In this setting, random forests as well as gradient boosted trees perform best, and are the only ones receiving weights in the ensemble. I thus focus my attention on these two and furthermore employ the SuperLearner Package in R (Polley et al., 2019) to also train regularized gradient boosted trees (XGBoost), as they have exhibited best predictive performance in similar applications (Christensen et al., 2023; Souza, 2019). For these models, I include all base variables, as well as squared and cubic terms of continuous variables, but no interaction terms. Tree-based algorithms can approximate interaction terms directly and the interactions are thus not required as possible features.[48] In a next step, I employ 5-fold cross validation and different combinations of these three models. Overall XGBoost performs significantly better both in-sample and in the cross-validated samples. I focus on this ensemble as my preferred model.[49] Table 3.A.7 presents the eight XGBoost models that constitute the ensemble and each weight received separately. Overall, more complicated models with more iterations (nb. Trees) are preferred with the majority of the weight being given to a slow learning model (lower shrinkage) with deeper trees.

Predictions are quite accurate with average deviations of 0.02 kWh in the training sample and -8 kWh in the cross-validated sample. 90% of observations lie on the -500 to 500 kWh difference

[48] I test this by also running a random forest model with interaction terms and squared terms available and predictive performance is almost identical, but computation time increases significantly.

[49] XGBoost algorithms have root mean squared prediction errors of 432 in sample and 2,670 in the cross-validated sample, whereas random forest and gradient boosted algorithms (ensemble of 4 models each) have in-sample RMSPE of 2,579 and cross-validated RMSPE of 3,314 respectively.

Table 3.A.7. ML - Trained Model Outcomes

Model ID	Nb. Trees	Max. Tree Depth	Min. Obs. Node	Shrinkage	RMSPE (CV)	Ens. weight
1	500	20	25	0.05	2,911.70	0
2	1000	20	25	0.05	2,771.22	0.0906
3	500	30	25	0.05	2,778.26	0
4	1000	30	25	0.05	2,691.08	0.7524
5	500	20	25	0.5	3,180.34	0
6	1000	20	25	0.5	3,177.92	0.1148
7	500	30	25	0.5	3,257.17	0
8	1000	30	25	0.5	3,257.17	0.0422
Ensemble					2,676.04	1

Note: This table presents the ensemble of ML models that was trained. Models differ based on number of iterations, maximum depth allowed, the learning rate (shrinkage) and the minimum observations necessary per node. The cross-validated RMSPE is presented and used as evaluation tool. In the last column the weight of each separate model in the stacked ensemble is indicated. The last row summarizes the RMSPE of the cross-validated ensemble.

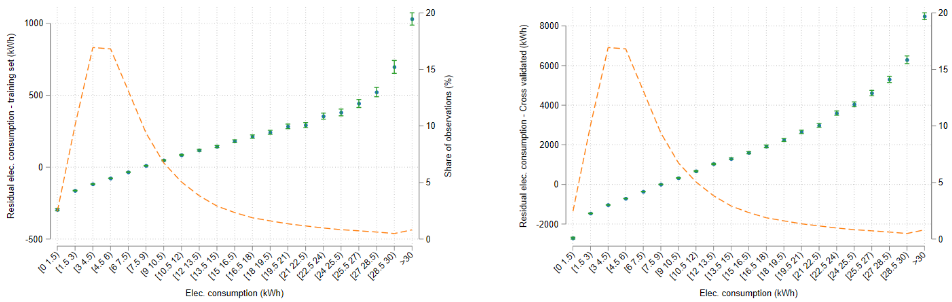
interval. I depict in Figure 3.A.11 the average residual, as well as the share of observations for different bins of electricity consumption. While Panel (A) presents the residuals of the training sample, Panel (B) illustrates the cross-validated residuals. In the area where the majority of observations lie, the prediction model performs relatively well with residuals close to zero. Overall the model over- (under-) estimates consumption for households that have below (above) average consumption, which is to be expected. While there are relatively big residuals for the cross-validated observations with very high consumption (exceeding 20,000 kWh), the residual would still be comparably low in relative terms. Moreover, there are very few observations within this area of the sample, as the last bin with a higher sampling share of 1%, is household-year combinations with consumption between 21,000 to 22,500 kWh.

I illustrate graphical support in favor of both necessary assumptions for the correct identification of the individual level treatment effect. The assumption are no anticipatory effects and stability of the counterfactual function (Souza, 2019). This is analogous to pre-trend tests in the DiD estimates. Figure 3.A.12 illustrates a regression of solar PV households pre-adoption residuals on relative time to adoption indicators. As illustrated, all estimated coefficients are not statistically significant at any conventional levels. Furthermore, I provide a test of joint-significance for all pre-trend coefficients, which, with a p-value of 0.364, can also not reject the null hypothesis of the coefficients jointly being different from zero at conventional levels. I present 7 pre-trend coefficients, which corresponds to the maximum available for households adopting in 2015. However, I estimate a linear regression model with pre-trend coefficients for up to 10 years prior to adoption, which I abstract from for reader friendliness. Results as well as statistical interpretation, however, remain unchanged and the F-test for joint-significance can also not be rejected at conventional levels when including all available pre-trend coefficients.

Moreover, I also illustrate correlation between residuals and the coefficients, which are discussed

Figure 3.A.11. Residuals for different Elec. consumption bins

Panel (A): In-Sample residuals　　　　Panel (B): Cross-validated residuals

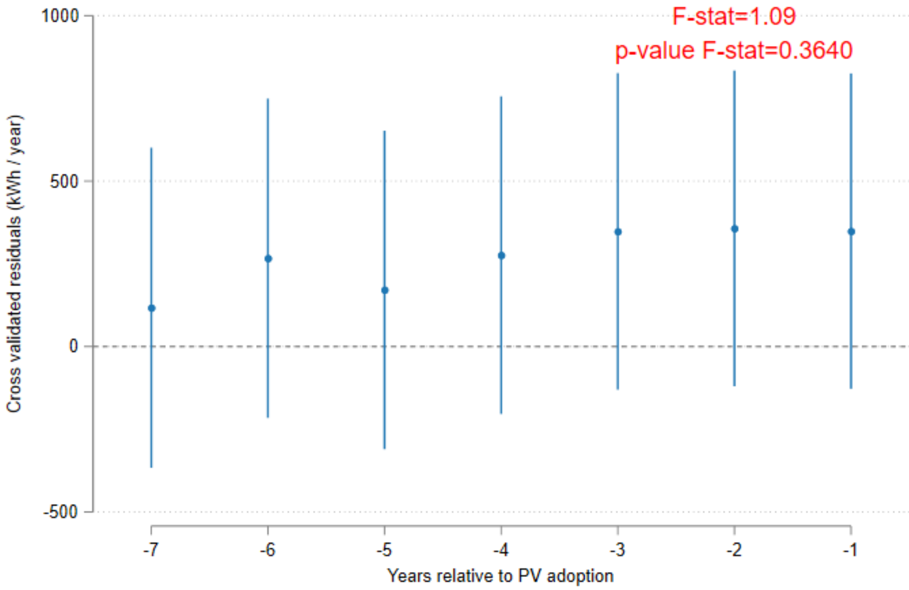


Note: The plot shows the average residual based on observed bins of electricity consumption. The orange line (measured on the additional y-axis on the right side) depicts the share of observation that constitute each bin. In-sample residuals are prediction deviations within the training sample, and cross-validated residuals are predicted residuals from cross-validation when a specific observation was not part of the training data.

as potential drivers of the estimated rebound effects. This is to illustrate that the actually observed estimates are behavioral changes and not due to prediction errors or biased estimates. Figure 3.A.13 presents a selection of estimated regression coefficients using both in-sample residuals, as well as cross-validated residuals as outcome of interest. The model includes the following covariates as explanatory variables: electricity price (natural logarithm), indicator variables for EV ownership, hybrid vehicle ownership, (future) storage ownership, heating system (oil, natural gas, wood, heat pump, electricity, district), household size (1, 2, 3, 4, 5+), electricity product adopted (green, grey, blue), urbanity (urban, periphery, rural), and categorical variables for bins of (future) solar PV capacity installed and solar PV rooftop suitability, as well as decile membership for living area, cooling degree days, heating degree days, income, wealth, age, rooftop area. I only illustrate variables that indicate some correlation with solar PV rebound effects.[50] One excluded variable from this estimation that is discussed in the main results is the solar PV yield. This is due to the fact that for the training sample no solar PV production information is available and thus I can not regress it on predicted residuals. Panel (A) depicts the estimated coefficients for EV, hybrid, heat pump and future storage ownership. Panel (B) for wealth deciles and Panel (C) for heating degree deciles. All coefficients seem to be unrelated with in-sample residuals, while a few are correlated with cross-validated residuals. However, there does not seem to be a clear pattern in correlation, as the significant deciles seem to be more or less random and not close to each other. While some hdd-deciles appear to be positively correlated with the cross-validated residuals, it is important to note the relative magnitude of the residuals, which are comparably low at an average effect size between 20-40 kWh. In Panel (D), however, there appears to be a clear pattern that cross-validated residuals are correlated with the (future) installed solar PV capacity categories. I bin the solar PV

[50] Full results are available upon request, but not further presented nor discussed here.

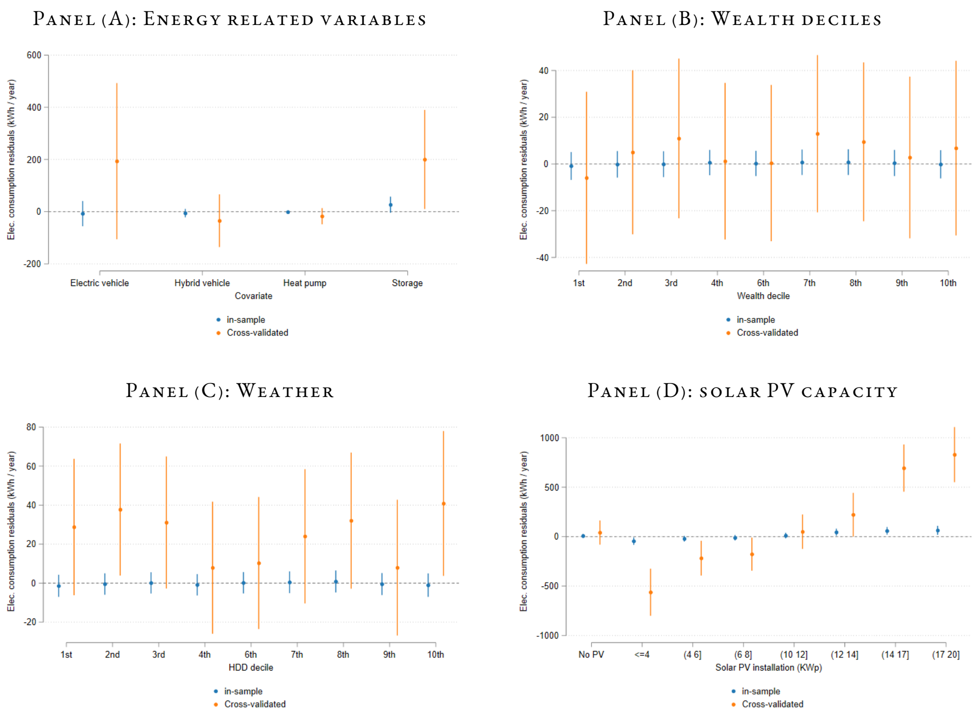
Figure 3.A.12. PRE-TREND TEST AND STABILITY OF COUNTERFACTUAL FUNCTION



Note: This figure illustrates the estimated coefficients and their 95% confidence interval of a regression of the cross-validated residuals on indicator variables measuring relative time to solar PV adoption. Only not-yet treated observations are included. Regression included pre-treatment periods up to 10 years prior to treatment but are abstracted here. F-test statistic and p-value for joint significance of all 7 pre-treatment coefficients as indicated cannot be rejected at conventional levels of statistical significance.

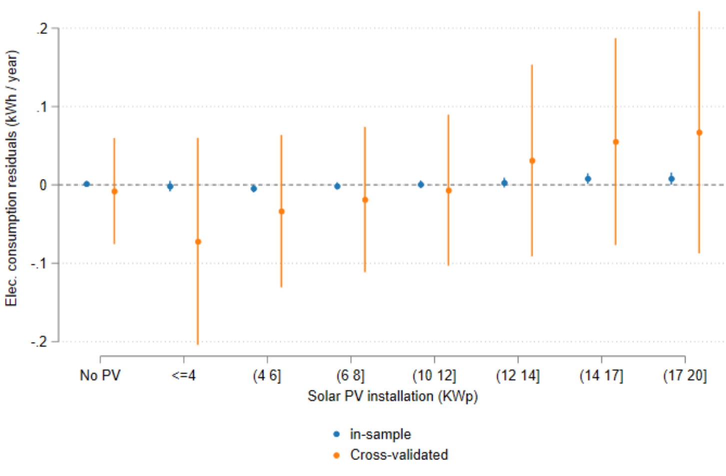
capacity based on 2 or 3 kWp intervals, and the higher the installed capacity the bigger the residual seems to be. At the same time, observations of never adopters seem to have average residuals close to zero. This pattern resembles the result in the decomposition of the individual treatment effect, and thus suggests that (part of) the heterogeneity might be sample bias. However, the association between residuals and solar PV capacity bins could also be caused by the fact that the prediction model makes absolute bigger mistakes (i.e. larger residuals in absolute terms) for households with higher observed electricity consumption. If these households select into bigger solar PV capacity installation, this correlation pattern would also be observed. To test these concerns, and support my result of higher solar PV capacity households having larger solar PV rebound effects, I estimate a regression model of the relative residual (i.e. percentage deviation from predicted value) on the same explanatory variables. This residual definition closer aligns to the dependent variable in the decomposition analysis. In Figure 3.A.14, I illustrate that the positive association between bigger solar PV capacity and the relative cross-validated residuals is no longer statistically significant at conventional levels. Nevertheless, the overall pattern of slightly increasing relative residuals with higher installed solar PV capacity persists.

Figure 3.A.13. Regression on prediction residuals I



Note: The plot shows a selection of estimated regression coefficients from a linear regression of both in-sample and cross-validated residuals on explanatory variables. Whiskers illustrate 95% confidence interval based on stratified bootstrapped sampling.

Figure 3.A.14. Regression on prediction residuals II



Note: The plot shows estimated regression coefficients from a linear regression of both in-sample and cross-validated relative residuals on the (future) solar PV capacity bins. Whiskers illustrate 95% confidence interval based on stratified bootstrapped sampling

3.A.5. Propensity score matching

This additional section describes the results from the propensity score estimates, which closely follows Qiu et al. (2019), although with different data aggregation and thus a slightly adapted empirical strategy.

In a first step, I model the conditional probability that a household installs a solar PV given observed characteristics using logistic regression models. I define the probability of household i to adopt a solar PV system at point in time t, as $y_j \in \{0, 1\}$, where j represents each combination of i and t observed in the data. The response variable y_j is related to household specific attributes with the following conditional probability:

$$\pi_j = p(y_j = 1|x_j) = \frac{exp(x_j^{'}\gamma)}{1 + exp(x_j^{'}\gamma)} \tag{3.8}$$

with $x_j^{'}$ being the vector of household i's characteristics at point in time t, representing all potential explanatory variables for adoption. Furthermore, $x_j^{'}$ includes time-specific constants (i.e. dummy variables indicating year t).[51]. γ is the vector of coefficients that can be estimated by maximizing the following log-likelihood function:

$$\ell = \sum_{j=1}^{J} \{y_j \log(\pi_j) + (1 - y_j) \log(1 - \pi_j)\} \tag{3.9}$$

Based on the estimated propensity scores, $\hat{y}_j$, I use k-nearest neighbor matching techniques. I match both the closest neighbor (i.e. $k = 1$), and the three closest neighbors (i.e. $k = 3$). Based on this matched sample, I estimate the following linear model:

$$ec_{it} = \delta PV_{it} + \alpha p_t + \beta X_{it} + \xi_{it}, \tag{3.10}$$

where the dependent variable ec_{it} measures electricity consumption of household i in year t, PV_{it} is either an indicator variable for solar PV ownership or solar PV electricity production, as defined in the main text. X_{it} are all the control variables, as elaborated in Section 3.2. The coefficient of interest δ measures either the absolute increase in consumption of household i, when owning a solar PV or how consumption of household i in year t changes with each additional kWh of solar PV production. In this sample I can no longer include individual specific fixed effects, as well as zip code-year fixed effects since there are no longer enough observations to estimate as many covariates. Some individuals might only be part of the control group in one period, as they might not be the k-nearest neighbor in all observation periods. Thus the included coefficients differ compared to the two-way fixed effect estimates.

The results are depicted in Table 3.A.8. The estimated ATT is 12.3% and 15.6% respectively if using

[51] I use time-specific constants instead of a trend or quadratic trend to non-parametrically capture technology break-through and a changing policy environment. However, technology adoption often exhibits exponential growth.

the actually observed production as treatment indicator. Using the indicator variable the estimated rebound effects is lower at 5.7% and 7.4% respectively. Both estimates compare relatively well to the two-way fixed effects estimates. The ATT when using the indicator variable is relatively similar to the heterogeneous DiD estimate(s). I support both necessary assumptions (i.e. sample balance and common support) with graphical evidence. On one hand, Figure 3.A.15 illustrates that, after matching, all covariates seem fairly balanced in the sample. Figure 3.A.16 presents the distribution of the estimated propensity scores based on treatment status. Again the matched sample seems fairly balanced, which illustrates that the common support assumption ought to be valid in this particular estimation exercise.

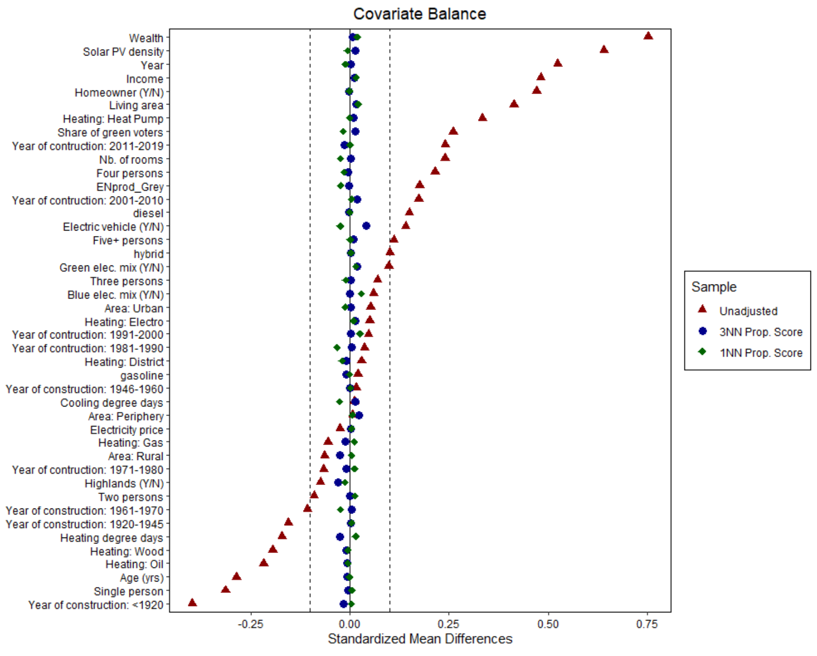
Table 3.A.8. REBOUND EFFECTS - PROPENSITY SCORE MATCHING

	(1)	(2)	(3)	(4)
PV HH			549.397 * **	710.859 * **
			(88.263)	(109.341)
PV production (kWh)	0.123 * **	0.156 * **		
	(0.009)	(0.011)		
Electricity price (log)	−13, 257.590 * **	−11, 896.460 * **	−13, 425.290 * **	−12, 405.970 * **
	(511.044)	(761.899)	(513.200)	(769.473)
Heat pump	4, 086.201 * **	3, 539.671 * **	4, 109.133 * **	3, 589.571 * **
	(111.434)	(155.276)	(111.923)	(156.957)
Electric vehicle	1, 349.617 * **	1, 530.895 * **	1, 452.927 * **	1, 626.568 * **
	(293.853)	(359.782)	(295.058)	(363.764)
ATT	12.3%	15.6%	5.7%	7.40%
N	16, 052	8, 026	16, 052	8, 026
Nb. nearest neighbors	3	1	3	1
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Energy control variables	*Yes*	*Yes*	*Yes*	*Yes*

Note: This table presents selected coefficients of the linear regression using Equation 3.10. Columns (1) and (2) have treatment definition as observed PV production, column (3) and (4) as indicator variable if household i owned a PV in year t. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included as described in Section 3.3. All estimates are based on a matched sample of 1 or 3 nearest neighbors based on propensity scores that were estimated using a logistic regression.

$+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.$

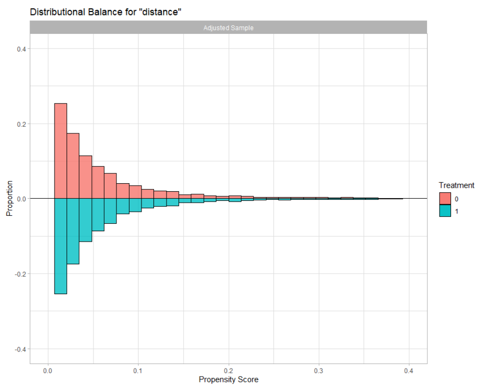
Figure 3.A.15. Covariate balance in matched sample



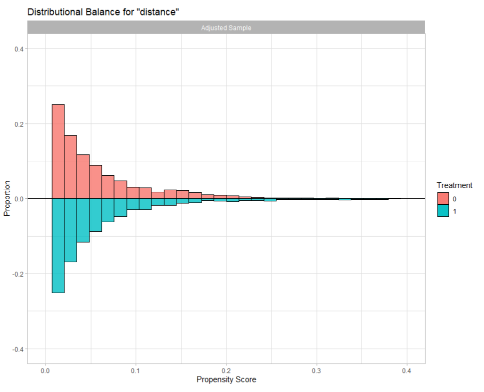
Note: This plot illustrates the balance of covariates between the matched and unmatched sample based on propensity score matching.

Figure 3.A.16. DISTRIBUTION OF PROPENSITY SCORES

PANEL (A): 1 NEAREST NEIGHBOR MATCHING



PANEL (B): 3 NEAREST NEIGHBOR MATCHING



Note: This plot shows the distribution of estimated propensity scores differentiated between treated and untreated households for both the 1 nearest neighbor matched sample as well as the 3 nearest neighbor matched sample. Distribution is fairly balanced.

3.B References

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