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Abstract

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JEL Classification: D12, D31, L94, L98, Q42, Q52

Keywords: N/A

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Welfare and Redistribution in Residential Electricity Markets with Solar Power*

Fabian Feger†, Nicola Pavanini‡, Doina Radulescu§

December 2017

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An increasing number of households installing solar panels raises two challenges for regulators: network financing and vertical equity. We propose an optimal tariff design for policymakers to incentivise solar panel adoptions, while guaranteeing the sustainability and equitable distribution of network costs. We estimate structural models of energy demand and solar panel adoption, using a unique matched dataset on energy consumption, income, wealth, solar panel installations, and building characteristics for 135,000 households in the Canton of Bern (Switzerland) in 2008-2013. Our counterfactuals recommend the optimal solar panel installation cost subsidies and optimal tariffs to achieve various solar energy targets.

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Keywords: energy; photovoltaics; income distribution; welfare; RDD; structural estimation

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1 Introduction

The reduction of greenhouse gases emissions is a global challenge that has become increasingly important in recent years.[1] To meet this goal, policymakers, companies, and individuals worldwide have contributed to the development of renewable energy systems, with a global investment in these new technologies of $285.9 billion in 2015. In particular, governments have introduced several incentive programs to ease the transition towards more green energy. Solar photovoltaic (PV) is one of the leading technologies among renewables, experiencing a remarkable growth in the last years. Electricity generated by solar power worldwide went from around 4 GWh in 2005 to over 200,000 GWh in 2015, and in 2014 for the first time PV systems achieved meeting 1% of the world electricity demand.[2] Two main forces have been stimulating this exponential growth. First, until now 93.6% of the global PV market depends on governmental support schemes, for the most part being feed-in tariffs. Second, PV modules' production costs have dropped significantly, from around 7 USD/W in the early 2000 to around 0.5 USD/W in 2015.[3]

While this trend is desirable from an environmental perspective, the rapid expansion of distributed generation comes at a cost for utilities worldwide (MIT, 2011, The Economist, 2017). There are two main challenges that a growing number of PV adoptions poses to regulators. First, households with PV installations still require network energy, leaving the fixed grid maintenance costs unchanged. However, as they produce and consume their own energy, these households contribute less to covering grid costs, as these are mostly paid with consumption-based tariffs. This is likely to make the sustainability of network financing problematic. Second, households who can afford installing a solar panel are usually richer, which can generate a regressive redistributive effect of green energy incentives. While the first point also applies to companies installing solar panels, the second is mostly relevant for residential users.

In this paper we address these challenges proposing an optimal tariff design that a regulator can implement to achieve various solar energy targets, while guaranteeing the sustainability and equitable distribution of network costs. We use a unique matched dataset on energy consumption, income, wealth, solar panel installations, and building characteristics for around 135,000 households in the Canton of Bern (Switzerland) in 2008-2013 to estimate structural models of energy demand and PV installation. We identify energy demand elasticities using a regression discontinuity design that exploits price variation at spatial discontinuities between electricity providers, and model PV adoption as a dynamic single agent optimal stopping problem. Using a counterfactual exercise, we specify the regulator's constrained optimization problem (Wolak, 2016) that allows us to find the optimal combination of variable energy prices, fixed energy fees, and subsidies to PV installation costs to achieve various solar energy targets, guaranteeing network financing and an equitable distribution of grid costs across the income distribution. Our approach can be easily generalised to any household's technology adoption decision that affects network costs and vertical equity of the system.

Under the current technology, almost all buildings that install solar panels are still connected to the electric-

[1] In December 2016 192 countries have signed the UNFCCC Paris Agreement to limit the world temperature increase, "making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development".

[2] In the Swiss Canton of Bern, for which we have access to detailed data, there was an average yearly growth rate in PV installations of 60% in the period 2008-2013.

[3] Sources: International Energy Agency, "Trends 2015 in Photovoltaic Applications"; International Renewable Energy Agency.

ity grid, but intermittently produce their own energy. This implies that energy distribution and transmission lines are still indispensable for the supply of energy. In most countries a substantial part of transmission and distribution network costs is recovered through volumetric kilowatt hour-based (i.e. consumption-based) rates, to promote households' energy conservation. However, increased penetration of PV installations implies lower energy demand from the grid, and together with volumetric charges this leads to lower revenues for electricity and network providers. To give an example from our data, consider a household with average yearly energy consumption of around 5,000 kWh, and assume that it installs a solar panel producing on average 6,000 kWh annually, of which around 20% can be used for own consumption. Under this scenario, with a volumetric grid charge of 0.1 CHF/kWh, the household's yearly contribution to finance the grid would drop by 24%, from 500 CHF to 380 CHF.[4] As network costs are largely fixed, it is likely to become increasingly difficult for utilities to recover these costs under volumetric charges and increased PV adoptions. Furthermore, the solar PV technology creates large variations in the net energy demand, placing additional stress on distribution feeders not designed for simultaneously accommodating outflows and inflows of energy, potentially increasing network operation costs (Joskow, 2012).

This increasing trend in solar PV adoptions may therefore even induce a "death spiral" of rising volumetric rates, distorting consumer incentives and inducing them to switch to alternative energy sources in an inefficient way (Borenstein, 2014).[5] A large share of households' energy bill comes from consumption-based tariffs, generating stronger incentives for households with greater electricity consumption to install solar panels. These are usually richer households, who are more likely to adopt a PV for two main reasons. First, they have the resources to pay the fixed installation cost. Second, they are more likely to own the house they live in and own a single family house, two conditions that largely facilitate the adoption decision. As a consequence, the burden of financing the energy infrastructure is progressively shifted onto non PV owners, who are usually lower income households. In our data for the Canton of Bern, the average income of households with a PV installation is 45% higher than the average income of households without a solar panel. This highlights the second issue that a growing number of PV adoptions causes, the vertical equity of the current tariff design.

Most EU members, the United States, and Switzerland initially introduced feed-in remuneration schemes to foster small scale renewable energy generation. These programs rewarded energy production at a favourable rate above wholesale energy cost, providing an incentive for PV owners to feed all of their energy production into the grid. However, later on various countries switched from feed-in tariffs to installation costs subsidies with own consumption, mostly for three reasons. First, as the number of PV adoption rose, feed-in schemes became extremely expensive for regulators, leading, as happened in Switzerland, to a long waiting list for households that applied for feed-in remuneration. Second, as the cost of PV systems declines over time, subsidies to installation costs will become cheaper to finance for regulators. Last, incentivising households to consume the energy they produce reduces uncontrolled variance in grid traffic, which is beneficial to grid

[4] One CHF is around one USD.

[5] On the other hand, a large increase in energy produced by renewable sources may lead to a reduction in energy prices, as renewables produce at zero marginal costs. This would in turn reduce the incentive to adopt solar panels, leading to the so called "cannibalization effect" of renewables (The Economist, 2017). In our paper we don't model this possibility, as we assume that the energy suppliers in the Canton of Bern are too small to affect the wholesale electricity price they face.

stability. The downside of instruments that stimulate own consumption, differently from feed-in tariffs, is their impact on grid financing and vertical equity, challenges we address in this paper.

We propose an optimal tariff design that a regulator can implement to achieve a solar energy production target, while recovering network costs and preserving vertical equity. We allow the policymaker to rely on three different instruments, all commonly used in various electricity markets worldwide: volumetric charges and fixed fees in households' energy bills, as well as subsidies to solar power installation costs. Volumetric charges are used to generate revenues to finance energy and grid costs, and represent an incentive for both energy conservation and solar panel adoption. Fixed fees instead generate no incentive for households' energy conservation or solar power installation, but guarantee a steady revenue to recover fixed network costs that doesn't depend on households' energy consumption or production. The last instrument is a subsidy to solar panel installation costs. This is one of the two main incentives historically used by policymakers to foster solar panels' adoptions, the other being feed-in tariffs. The main difference between the two instruments is that the first subsidises up front installation costs, whereas the second subsidises future revenues from energy production. De Groote, Verboven (2016) are able to show that Belgian households undervalued future solar panel revenues, concluding that in their setting, where a feed-in tariff was in place, an upfront investment subsidy would have promoted PV adoptions at a lower budgetary cost. Based on their findings, and on the recent switch by the Swiss government from a feed-in system to installation subsidies, we decided to just focus on the latter for our counterfactuals. However, volumetric charges have similar characteristics to feed-in tariffs, as they also provide an additional stream of revenue from energy production through grid cost savings. Thus, an increase in volumetric charges can be considered equivalent to an increase in a feed-in tariff.

We define a framework to model how households respond to fixed and variable energy charges, as well as subsidy to PV adoption, in their optimal electricity consumption and solar panel installation decisions. We let households be forward looking and solve a dynamic problem, in the spirit of Hendel, Nevo (2006). We estimate the model in three stages. First, we assume that households solve a static utility maximization problem to choose their optimal energy consumption, conditional on their solar panel adoption decision. We estimate the parameters of their energy demand function using a geographical boundary regression discontinuity design, similarly to Black (1999) and Ito (2014), to address the endogeneity of energy prices and fees. This approach allows us to identify price elasticities exploiting tariffs variation between neighboring households, located on opposite sides of border points between different electricity suppliers. Second, we estimate transition probabilities for the state variables, to determine how households form expectations over the evolution of the their indirect utilities from consumption, as well as PV installation costs and revenues. Third, we estimate households' PV adoption decisions as an optimal stopping problem, following Rust (1987), where households choose when to install a solar panel, trading off declining subsidies in the form of decreasing feed-in tariffs, and installation costs that reduce over time due to lower panels' production costs.

We use the results from these models to conduct three counterfactual exercises. In the first experiment we quantify the "death spiral", simulating a benchmark scenario where all home owners of single or double apartment buildings in our data install a solar panel, and calculate the increase in variable grid tariff required

to guarantee network financing. In the worst scenario, we find that volumetric charges would need to rise by up to 123% to recover the missing revenue, and this increase would be borne mostly by low income households. In the second experiment we solve the policymaker's optimization problem, following Wolak (2016), to find the optimal tariff design in terms of variable prices, fixed fees, and subsidies, in order to achieve 2%, 3%, 5% or 9% solar energy production targets,[6] while recovering network costs and preserving vertical equity. To meet each of those targets, we find that it is optimal for the regulator to subsidise respectively 18%, 23%, 28%, and 34% of solar panels' fixed installation costs, financing this subsidy with a 6%, 13%, 29%, and 75% rise in variable grid charges, and increasing fixed grid fees by 118%, 119%, 117%, and 61%. We show that these tariff schemes are optimal, as they guarantee under each scenario that households across the income distribution experience the same percentage increase in electricity bills. In the third experiment, we address the regressive nature of fixed fees, simulating a complete decoupling of grid revenues from energy consumption. We show that a capacity fixed fee (also known as demand charges) would make grid financing more progressive compared to a uniform fixed fee.

We have access to a unique panel dataset at the household-year level for the Canton of Bern over the 2008-2013 period. We constructed this data matching information from four different sources. First, the three main energy providers in the Canton provided us data on households' energy consumption and expenditure, electricity prices with detailed breakdown for each component of the bill charged to users, and households' PV adoptions. Second, the Tax Office of the Canton of Bern gave us yearly information on each household's income, wealth, tax payments, and demographics, including location. To the best of our knowledge, this is the first paper that is able to match households' energy consumption with exact income and wealth data. Third, the Swiss Federal Statistical Office gave us access to cross-sectional information on each households' building characteristics, including number of rooms, house/apartment surface, heating and water systems, and building construction period, all key determinants of households' energy consumption. Last, the Swiss start-up company Eturnity AG, which provides an advisory online platform for solar energy systems, simulated for us a novel dataset on potential energy production of solar panels on each building in our data, including also estimated installation costs, and households' consumption profiles. Eturnity has developed a software that uses building location and characteristics to forecast the potential production of a rooftop solar panel and its installation cost, using local weather and potential sun exposure, roof surface, and estimates of solar panel installation costs from local households and suppliers. Moreover, based on an aggregate household consumption measure and on the feed-in tariff in place, it can recover a detailed household consumption profile to determine the total savings that a solar panel would guarantee over a 25-years horizon, corresponding to the usual life cycle of these systems.

Our paper is related to various strands in the literature. First, it contributes to the debate on network financing and vertical equity posed by the growth in solar power installations. Borenstein (2008) shows that the costs of adopting the PV technology exceed its market benefits, contradicting the argument that solar panels have reduced the costs of energy transmission and distribution, since power is generated at the end-user's location. Bushnell (2015) highlights how volumetric charges imply that the more efficient energy consumption becomes, the less households contribute to the infrastructure costs of national energy utility

[6]These targets are expressed as percentage of energy consumed coming from solar panels.

distributors. Consequently, increasing distribution rates may provide even larger incentives to reduce energy consumption, shifting costs to third parties (MIT, 2011). Picciariello, Ramirez, Guillén, Marin, and Söder (2014) show that cross subsidization from customers without self generation to those with self generation is likely to arise in case volumetric tariffs and net metering is adopted.[7] As suggested by Joskow (2012), a potential solution to these issues is an alternative financing scheme that provides for the separation of the cost recovery from energy consumption, known as "revenue decoupling". This could take the form of a fixed charge faced by all customers, or of a demand charge based on individual consumers' peak load on the distribution system, as we investigate in one of our counterfactuals.

Connected to this literature, we rely on various contributions in public finance to motivate the vertical equity concern of a policymaker in the design of energy tariffs. While Atkinson, Stiglitz (1976) argue that redistribution should only be achieved via income tax, Stiglitz (1982), Naito (1999), and Cremer, Ghavari (2002) support the use of a second instrument to achieve income redistribution, and a number of papers promotes the redistributive role of public utility pricing.[8] This literature on public utility pricing commonly assumes that the regulator is constrained in the design of income taxation, one of the reasons being the political cost of changing income taxes. This provides an argument for vertical equity that is particularly relevant in Switzerland, where direct democracy implies that changes in income tax can only be achieved via national referenda. Based on this principle, Switzerland and other European countries (UK and Italy for example) have separate budgets for energy versus other types of government spending, avoiding cross-subsidization between different areas.

Second, our work is part of a large literature estimating price elasticities of residential electricity demand.[9] Reiss and White (2005) use cross-sectional survey data on energy consumption of 1,300 U.S. households, evaluating the effect of different tariff structures on energy demand. Ito (2014) has access to a household-level panel on energy consumption from two major Californian energy providers. He exploits price variations at spatial discontinuities between these operators to identify price elasticities, finding that despite the non-linear price schedules offered, consumers only respond to average instead of marginal prices. A common feature of these papers, as others in the literature, is that they can only imperfectly match households' energy consumption with income census data, using aggregate zip code information. Our data has two fundamental advantages compared to the existing literature. First, it covers almost the whole population of the Canton of Bern, the second largest Canton in Switzerland, as opposed to previous papers only having access to a representative sample of households. Second, we have a perfect match of households' yearly energy consumption to their yearly income and wealth, as well as to detailed building characteristics and potential PV costs and production. We are not aware of any other paper exploiting this detailed household-level information on income and wealth.

[7] This problem has also been acknowledged in further studies, such as Pérez-Arriaga, Ruester, Schwenen, Battle, and Glachant (2013), and Eid, Guillén, Marin, and Hakvoort (2014).

[8] See for instance Feldstein (1972a), Feldstein (1972b), Munk (1977), Saez (2002), Hellwig (2007). We explore this question further in a follow-up paper.

[9] Papers using aggregate data, typically at the U.S. state level, are: Herriges and King (1994), Maddock, Castano and Vella (1992), Kamershen and Porter (2004), Alberini, Gans, and Velez-Lopez (2011), Alberini and Filippini (2011) or Bernstein and Griffin (2006). Papers focusing on European energy markets include Filippini, Blazquez, and Boogen (2012) (using Spanish data), Mohler and Müller (2012), and Boogen, Datta, and Filippini (2014) (both focusing on Switzerland).

Last, our work contributes to a recent literature on reduced form and structural models of households' solar panel adoption, the latter mostly based on Rust (1987). Using data on residential PV installations in California, Borenstein (2015) finds that income distribution of PV adopters is skewed towards wealthier households, showing that the increasing-block pricing (IBP) scheme generates greater incentives for households with higher energy consumption to adopt a PV system. Burr (2014) estimates a household level dynamic PV installation model for California, showing that upfront capacity-based subsidies result in lower welfare costs and more solar adoptions than production-based subsidies (feed-in tariffs). Reddix (2014) estimates a similar model, allowing for product differentiation in PV systems, to show that in California in the absence of government subsidies over 54% of all PV installations would have not occurred, with the largest share of lost adoptions originating from larger capacity installations. Last, De Groote and Verboven (2016) estimate a dynamic model of PV adoptions using market share data for small local markets in Belgium, recovering households' discount factor, and showing that an upfront investment subsidy is more effective than feed-in tariffs at promoting PV adoptions.

None of these papers has detailed data on households' energy consumption, expenditure, and income. This allows us to specify a richer model, where households decide both their optimal electricity consumption and PV adoption, subject to their budget constraint.[10] In particular, when choosing whether to install or not, households trade-off the indirect utility from optimal consumption with and without a solar panel, the impact on their electricity bills, and revenue and cost from their solar panel. Moreover, from a regulator's perspective, we can simulate alternative tariff designs making sure that the network and subsidies' costs are recovered through the electricity bills while also achieving a set solar energy target. Last, our perfect income match on household level allows us to correctly identify the redistributive effects of tariff schemes.

Our paper is structured as follows. Section 2 introduces the institutional features of the Swiss energy market and describes the data. In Section 3 we present the model, and in Section 4 we describe the estimation strategy and the identification. Section 5 shows the results, Section 6 presents the counterfactuals, and Section 7 concludes.

2 Data and Swiss Electricity Market

Switzerland is a federal state, divided into 26 Cantons and roughly 3,000 municipalities of varying size and population. The supply of energy is decentralized and is organized by each Canton. Within each Canton one or more utilities have a local monopoly when it comes to households' energy provision. Large scale consumers with an annual energy consumption exceeding 100 MWh can choose their provider since 2009, but households are only able to do so from 2018. This means that even within the borders of a Canton residential customers can be assigned different energy providers, depending on their location. Utility providers can have the legal form of purely private companies, but in most cases they are still at least partially public monopolies. In the Canton of Bern for example, 52% of the main utility (BKW Energie AG) is owned

[10] Related to our work, Dubin and McFadden (1984) propose a static model to jointly estimate households' electricity consumption and appliance holdings. We differ from their approach as we have a dynamic model of PV adoption, but estimate our two models sequentially rather than jointly for tractability.

by the Canton of Bern. This implies that these utilities are not profit oriented and cannot set their prices independently, but have to follow the requirements of the regulatory agency ELCom.

We constructed a unique dataset for the Swiss Canton of Bern that combines yearly household level energy consumption, income, wealth, PV installations, and buildings' characteristics. With an area of around 6,000 km^2 and just over 1 million inhabitants the Canton of Bern is the second largest Swiss Canton in terms of population. The three main energy providers in the Canton are BKW Energie AG (BKW), Energie Wasser Bern (EWB), and Energie Thun (ET). The major provider is by far BKW, supplying more than 7,500 GWh of energy to around 200,000 households in 400 municipalities in the Canton. EWB supplies energy to around 70,000 households and is mainly responsible for the city of Bern, whereas ET serves only 20,000 households in the city of Thun. These three main energy providers made available to us their data on household energy consumption, household PV installations, and infrastructure network costs and tariffs. The map in Figure 1 shows the geographical distribution of households and the coverage of the respective energy providers in the Canton of Bern. The dark blue area represents the city of Thun, the blue area the city of Bern, and the larger light blue area the rural part of the Canton, where households are supplied by BKW. This map highlights the clear spatial discontinuities between providers that we will exploit to identify price elasticities.

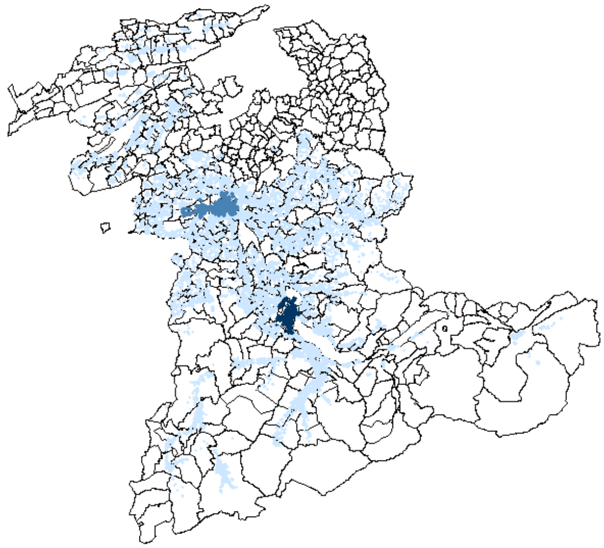
Households in the Canton of Bern receive the electricity bill once a year. The costs are divided into a fixed fee to recover network costs, and a variable price, which consists of four major components. First, a variable energy price defined by the individual supplier, reflecting the costs of internal production and of procurement of electricity on the market. Second, a variable price for grid usage, covering the energy distribution network costs and again varying between providers. Third, a uniform surcharge levied by the federal state used to promote renewable energy. Fourth, taxes levied by the communal, cantonal, and federal authorities. As opposed to Californian utilities which usually resort to IBP schemes, Swiss utilities apply a constant price per kWh irrespective of the amount of electricity consumed.

However, part of the households in our data face a double tariff scheme, with different prices between night and day,[11] and with higher daytime price steering consumption to off-peak hours. While ET only offers a double tariff to its customers, BKW and EWB assign either double or uniform tariffs to each of their clients.[12] Both providers base this tariff assignment on building characteristics, such as electrical boilers/heating and whether a double tariff meter is installed, and expected consumption patterns. Furthermore, EWB and ET offer differentiated energy products, as customers receive electricity from renewable sources by default but can opt out to a cheaper option that provides energy from conventional power sources. We omit this dimension from the paper, as most customers (around 80%) stay with the baseline renewable product. For the estimation and simulation we use the prices of this baseline product for all customers. Table 1 reports the detailed price components for each company.

[11] For BKW customers day time lasts from 7am to 9pm. For EWB and ET customers from 6am to 10pm.

[12] Customers with a double tariff meter have the option to switch to a uniform tariff, but for almost all households in our data this would result in a higher electricity bill. Switching from a uniform to a double tariff scheme would instead require the household to install a double tariff meter, costing approximately 200 CHF. Due to these reasons, we observe almost no switch in our data.

Figure 1: MAP CANTON BERN (HOUSEHOLDS)



Note: The figure depicts the Canton of Bern and the coverage of the three main energy providers. The dark blue area represents the customers of Energie Thun and hence the city Thun. The blue area consists of the customers of Energie Wasser Bern and is equivalent to the city of Bern. The light blue area corresponds to the customers of BKW and therefore most of the Canton besides the two mentioned cities. Note that only households matched to the income information are shown in the figure.

Table 1: ENERGY PRICES, NETWORK TARIFFS AND TAXES

	BKW		**EWB**		**ET**	
	Mean	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Fixed Fee HT/LT (CHF/year)	153	27	121	22	111	19
Price HT (Rp./kWh)	24.4	.8	19.7	1	25.6	.6
Energy Price	11.8	.3	11.6	.4	12.4	.2
Grid Price	10.4	1	7.3	.8	10.9	1.7
Municipality Tax	1.8	.2	.4	.2	1.8	1.5
KEV Tariff	.4	.1	.4	.2	.5	0
Price LT (Rp./kWh)	14	.8	10.3	.4	14.9	1.4
Energy Price	7.3	.2	7.4	.3	9.7	.2
Grid Price	4.5	.5	2	.4	2.9	.4
Municipality Tax	1.8	.2	.4	.2	1.8	1.5
KEV Tariff	.4	.1	.4	.2	.5	0
Fixed Fee UT (CHF/year)	125	17	90	23		
Price UT (Rp./kWh)	23.8	.6	18.2	1		
Energy Price	11.4	.4	10.5	.4		
Grid Price	10.2	1	6.8	.9		
Municipality Tax	1.8	.2	.5	.2		
KEV Tariff	.4	.1	.4	.2		

Note: The table shows average prices and standard deviation in the sample. HT stands for "High Tariff" (day), LT stands for "Low Tariff" (night), and UT stands for "Uniform Tariff". KEV Tariff is the surcharge used to promote renewable energy. Rp means Rappen, that is one-hundredth of a Swiss franc (CHF). Some municipalities refrain from levying a municipal tax. All prices include the value-added tax.

Table 2 presents descriptive statistics of households' energy consumption and annual expenditures, with a breakdown for the different components of the electricity bill. As displayed in the first row of Table 2, the annual household energy consumption is on average 4,919 kWh. Rows 5-12 in Table 2 display summary statistics for the different expenditure components of the electricity bill. Detailed household income and wealth yearly data are provided by the Tax Office of the Canton of Bern, and cross-sectional information on building characteristics is obtained from the Swiss Federal Statistical Office.[13] Table 3 provides summary statistics for different measures of income and household tax payments.

Table 2: ENERGY CONSUMPTION AND EXPENDITURE

	N Obs	**Mean**	**Std Dev**	**5th Perc**	**Median**	**95th Perc**
Energy Consumption (kWh)	657,750	4,919	5,189	854	3,293	14,902
Consumption HT	419,202	2,804	2,329	597	2,182	7,264
Consumption LT	419,202	3,571	4,325	308	2,436	11,670
Consumption UT	238,548	2,360	1,671	667	1,962	5,321
Energy Expenditure (CHF)	657,750	1,066	917	284	793	2,900
Energy Price Expenditure (CHF)	657,750	477	461	93	338	1,394
Price Expenditure HT	419,202	333	276	71	260	861
Price Expenditure LT	419,202	266	320	26	181	863
Price Expenditure UT	238,548	263	188	73	218	597
Grid Expenditure (CHF)	657,750	497	358	170	396	1,212
Tax Expenditure (CHF)	657,750	71	88	0	44	238
KEV Expenditure (CHF)	657,750	21	24	2	14	67

Note: The descriptive statistic is pooled over all companies and years. HT stands for "High Tariff" (day), LT stands for "Low Tariff" (night), and UT stands for "Uniform Tariff". KEV Expenditure is the surcharge used to promote renewable energy. The sample includes households with up to three grid connections (with potentially double and uniform tariff expenses on their bill). Consumption and expenditure are further differentiated by high tariff, low tariff, and uniform tariff components. High and low tariffs are part of the double tariff scheme.

Table 3: INCOME, WEALTH AND TAX PAYMENTS

	N Obs	**Mean**	**Std Dev**	**5th Perc**	**Median**	**95th Perc**
Total Income (CHF)	657,750	95,225	128,644	15,944	80,179	206,576
Taxable Income (CHF)	657,750	72,940	117,831	7,736	61,860	159,247
Total Wealth (CHF)	657,750	529,660	2,053,701	0	248,283	1,646,737
Cantonal Tax (CHF)	657,750	7,352	14,566	0	5,463	18,894
Municipal Tax (CHF)	657,750	3,792	6,965	0	2,868	9,639
Federal Tax (CHF)	657,750	1,752	9,510	0	482	6,300

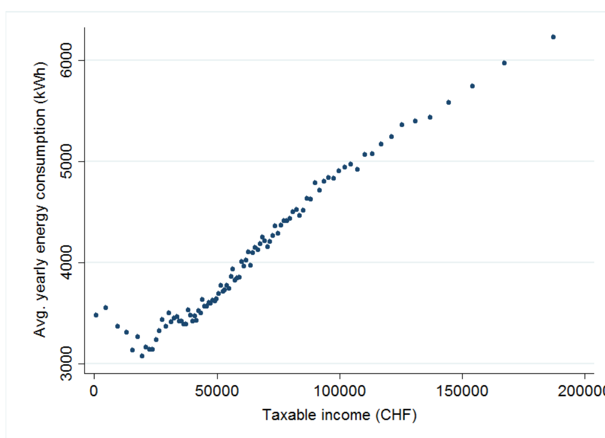
Note: The table shows descriptive statistics for the sample pooled over all years. All variables are measured in Swiss francs (CHF). Taxable income is defined as total income (in the form of labor income or income from self-employment) plus rental value of owner occupied housing less mortgage interest payments and commuting and living expenses. Given the federal structure of Switzerland, households are subject to three different income taxes levied by the three different levels of government (Cantonal, Municipal, and Federal).

[13]The process of matching energy consumption and income data led us to the final sample of around 135,000 households. We describe in detail in Appendix A1 the data merging process.

Table 4 reports the average energy consumption, energy expenditure, and the share of taxable income spent on energy by income decile. The table also displays the proportion of owner occupied housing, the proportion of married couples, the average age of the household head, the average household size, as well as the share of households who own a PV installation. The last nine rows report building or apartment characteristics relevant for energy consumption: whether electricity is used for heating or hot water, the number of rooms, the apartment surface, and the number of apartments in the building. The unconditional means in Table 4 suggest that the annual average electricity consumption as well as energy expenditures rise monotonically with income. Households in the lowest income decile consume on average 3,196 kWh per year, whereas those in the highest one have a yearly consumption of 7,888 kWh.

A more disaggregate version of this trend is presented in Figure 2, which shows the average energy consumption for each percentile of the income distribution.[14] Supporting evidence of our argument that richer households are more likely to install a solar panel is given by home ownership and apartment characteristics. Among households in the first income decile, only 15% are home owners, whereas among households in the top income decile 78% are home owners. Moreover, the number of apartments in the building is monotonically decreasing across the income distribution, showing that richer households are more likely to live in a single house. Figure 3 presents the share of each component of the electricity bill across the distribution of electricity consumption. For low levels of annual energy consumption, corresponding to low income deciles, the fixed grid charge represents the largest share of the bill. For the median level of energy consumption instead (3,293 kWh) the share of the fixed grid charge is below 20%, whereas the variable grid charge is around 30%, and the variable energy price represents over 40% of the bill. The contributions of taxes and of renewable energy financing are very limited.

Figure 2: ANNUAL ELECTRICITY CONSUMPTION BY INCOME



Note: Each dot corresponds to the average energy consumption for a percentile of the distribution of taxable income. The higher energy consumption for the lowest percentiles could be a consequence of the definition of taxable income, as it is possible to reach an extraordinary low income through tax deductions. A similar picture emerges if we use household wealth instead of taxable income.

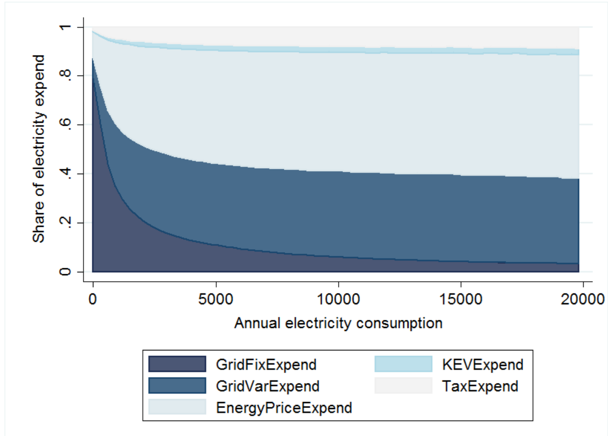
[14] Appendix A1 includes similar figures displaying the distributions of taxable income and annual electricity consumptions.

Table 4: ENERGY AND HOUSEHOLD CHARACTERISTICS BY INCOME DECILE

	1^{st}	**2^{nd}**	**3^{rd}**	**4^{th}**	**5^{th}**	**6^{th}**	**7^{th}**	**8^{th}**	**9^{th}**	**10^{th}**
Variables	**<24k**	**24k-36k**	**36k-45k**	**45k-53k**	**53k-62k**	**62k-71k**	**71k-82k**	**82k-97k**	**97k-124k**	**>124k**
Energy Consumption (kWh)	3,196	3,445	3,762	4,121	4,382	4,882	5,249	5,817	6,451	7,888
Energy Expenditure (CHF)	735	787	845	914	968	1,062	1,134	1,237	1,354	1,626
Energy Price Expenditure (CHF)	318	337	366	400	427	474	509	561	620	760
Grid Expenditure (CHF)	362	386	410	436	459	497	525	565	612	718
Income Share Energy (%)	5	3	2	2	2	2	2	2	1	1
Home Ownership (%)	15	29	33	36	41	47	53	59	68	78
Married (%)	14	21	30	39	50	62	69	74	79	83
Age HH Head	53.4	58.9	56	54.4	54.7	55.4	55.2	54.8	54.8	55.4
Householdsize (%)										
1	80	72	63	54	43	32	24	19	15	10
2	15	22	28	30	35	43	46	48	49	46
3	3	3	5	6	8	9	11	12	13	14
4	1	2	4	7	10	12	14	16	18	21
> 5	1	1	1	2	4	4	5	5	6	8
PV Installation (%)	.2	.2	.3	.3	.4	.5	.6	.7	.8	1.3
Heating System (%)										
Electric	4	5	5	6	5	6	6	7	8	9
Heat Pump	2	3	4	4	5	6	8	10	12	13
Oil/Gas/Coal	94	92	91	90	89	88	86	83	81	79
Heating System (%)										
Electric	38	40	41	41	43	43	45	46	48	49
Heat Pump	1	2	2	2	3	3	4	4	5	6
Oil/Gas/Coal	60	58	57	56	55	54	52	50	46	45
Number of Rooms	3.1	3.4	3.4	3.5	3.6	3.8	3.9	4.1	4.3	4.8
Apartment Surface (sqmt)	78.5	84.1	86.6	89.9	93.7	98.5	103.9	110.9	120.7	139.7
Apartments in Building	2.7	2.5	2.5	2.5	2.4	2.3	2.2	2.2	2	1.8
N Obs	65,778	65,773	65,776	65,776	65,775	65,772	65,776	65,774	65,778	65,772

Note: The table displays the mean of each variable based on the pooled sample. Deciles are measured in thousands of CHF, therefore "24k" means CHF 24,000.

Figure 3: EXPENDITURE SHARE OF TARIFF ELEMENTS BY CONSUMPTION



Note: "GridFixExpend" corresponds to the yearly fee households are billed to be connected to the grid irrespective of energy consumption. "Grid-VarExpen" is the volumetric charge to finance the energy grid. "EnergyPriceExpend" is the volumetric charge for energy. "KEVExpend" and "TaxExpend" are taxes. The graph shows the average share of these different components for each level of energy consumption in the sample.

2.1 Solar Power in Switzerland

Between 2005 and 2013 total capacity of solar panels in Switzerland increased by 30 times, from 28 MW to 756 MW (Swissolar, 2017).[15] A key driver of this growth was the introduction in 2008 of the feed-in tariff remuneration system known as "KEV".[16] The incentive scheme was designed to last for 25 years from the PV adoption date, with tariffs varying depending on the type of PV installed (ground-mounted, rooftop or building integrated), and its size, ranging between 10 kW and 10,000 kW. Since 2008 the compensation has been progressively reduced, both because the pre-determined budget couldn't match the large number of incentive requests, and because of the sharp decline in PV installation costs.[17] Figure 4 presents the evolution of PV electricity generation in Switzerland between 1990 and 2014.

Of the 141 GWh of energy produced by PV installations subject to feed-in remuneration in Switzerland in 2013, those in the area supplied by BKW produced 46 GWh, so around one third. In Table 5 we show descriptive statistics for our data on PV installations. In total 1,181 households in our dataset own PV systems by the end of the sample period. 1,036 of them are BKW customers, 34 EWB, and the rest Energie Thun. As shown in Figure 5, the percentage of households with a PV increases almost monotonically across the income distribution for BKW clients. The density almost quadruples between the second and 10th

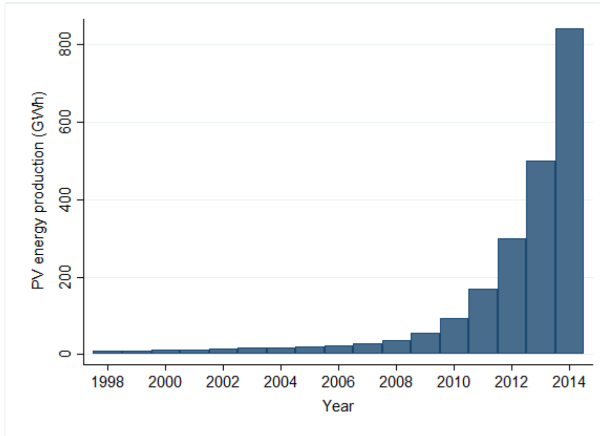
[15] In 2014 total capacity of solar panels in the EU amounted to 88,700 MW and in the United States to 6,500 MW (Solar Power Europe, 2016).

[16] An abbreviation for the German expression *Kostendeckende Einspeisevergütung*, which means feed-in remuneration at cost.

[17] The overall amount of feed-in remuneration paid by the government amounted to around CHF 23 million in 2011, CHF 45 million in 2012, and CHF 66 million in 2013. Of these amounts, CHF 8 million, CHF 14 million, and CHF 17 million were allocated to households in the respective years. These tariffs were financed by an energy consumption surcharge. Between 2009 and 2013 the surcharge amounted to around 0.0045 CHF/kWh and it has been steadily increased since then. Nowadays it amounts to 0.011 CHF/kWh. In 2013 almost 6,000 installations received feed-in tariffs, and their overall production amounted to 141 GWh (Swiss Federal Office of Energy, 2015).

income deciles, where the frequency of PVs installed for households earning more than CHF 124,000 is 26%.

Figure 4: PV ELECTRICITY GENERATION IN SWITZERLAND (IN GWH)



Note: The figure shows the evolution of total photovoltaic electricity production in Switzerland. In 1998 the production amounted to 8.4 GWh. Source: Swiss Overall Energy Statistic 2014, Swiss Federal Office of Switzerland.

Table 5: PV ENERGY PRODUCTION AND REMUNERATION

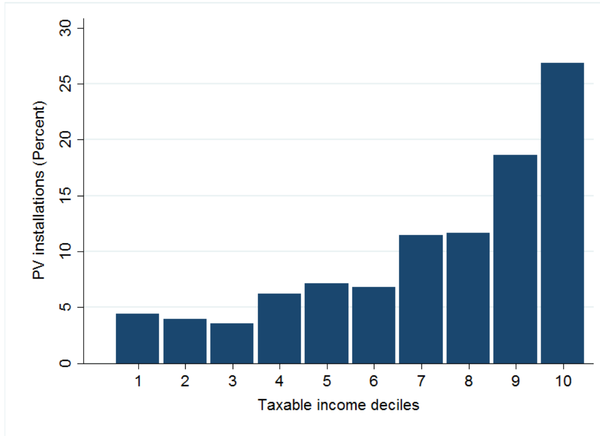
Variables	N Obs	Mean	Std Dev	5th Perc	Median	95th Perc
PV Production Capacity (kW)	2,628	8.1	16.6	1.9	5.6	20.5
PV Energy Production (kWh)	3,020	7,176	14,677	1,470	5,000	16,750
PV Remuneration (CHF)	3,020	2,088	3,133	171	1,546	5,741

Note: The descriptive statistics are pooled over all companies and years. The dataset of the BKW does not contain data on actual production of PV installations. The authors make use of an estimated production of the BKW for each installation. PV Remuneration is constructed as the estimated production times the remuneration fees of the respective year. The KEV subsidized installations of the BKW were additionally matched with an official KEV list of the Bundesamt für Energie (BFE). For all successful matches the data corresponds to actual production and income. In contrast, the data of Energie Thun and Energie Wasser Bern did contain actual production and income. However, there is no data for installations subsidized by the KEV as the PV owner directly sells her energy to the BFE. Matching to the KEV list was not possible (due to all installations having the same post code).

Finally, we assembled a novel dataset with the support of Eturnity AG, a Swiss startup company providing an advisory platform for solar energy systems, which developed a software to forecast the potential production of rooftop solar panels, using data on roof surface and local weather as proxies for potential sun exposure. The company used their software to simulate the PV production capacity (in kWp) and energy production (in kWh) of a solar panel on the rooftop of every building in our sample. Eturnity also provided us with estimates of PV installation costs across time and PV production capacity, based on survey evidence among local households and suppliers. Moreover, using information on households' electricity consumption and the feed-in tariff in place, Eturnity recovered a detailed household consumption profile to determine the total savings that a solar panel would guarantee over a 25-years horizon.[18]

[18]See Appendix A3 for a template of the price and production quotes that Eturnity provides to a household, and Appendix A4

Figure 5: DISTRIBUTION OF PV INSTALLATIONS BY INCOME



Note: The graph shows the percentage of PV installation by taxable income deciles.

Eturnity simulated for us potential household consumption profiles based on households' heating and hot water systems, which can be both powered by electricity, heat pump, or oil/gas/wood/coal, and depending on households' decile of yearly energy consumption in kWh. These consumption profiles include monthly consumption peaks, that we will use to simulate a capacity fixed fee (i.e. demand charge) in the counterfactuals.[19] Last, when Eturnity simulated the potential production of a rooftop solar panel for each building in our data, it used information on an approximate potential size of the PV (as a share of the building surface), as well as on the zip code of the building, which it can match to detailed local weather information. This last piece of data will be useful when estimating households' PV adoption decision.

Table 6 summarizes a selection of variables supplied by Eturnity. The average simulated PV production capacity is 5.7 kWp, whereas the corresponding average PV energy production is 9,430 kWh, almost double the annual energy consumption of an average household, as reported in Table 2. However, due to the mismatch between time of production and consumption, only 15.7% of the energy produced could potentially be consumed by a household, while the rest would be fed into the grid. This implies that, on average, around 42.5% of the energy consumed by a household can be supplied by its own solar panel. Last, Figure 6 displays the feed-in tariff (KEV) remunerations and the estimated installation costs across time and size of solar panel in kWp. The time series variation shows the trade-off that households faced between declining feed-in tariffs and declining installation costs, which motivates our use of a dynamic framework to model households' PV adoption decision.

for a description of the formulae, methods and assumptions that were applied by Eturnity for the simulations provided to us. For more information visit www.eturnity.ch.

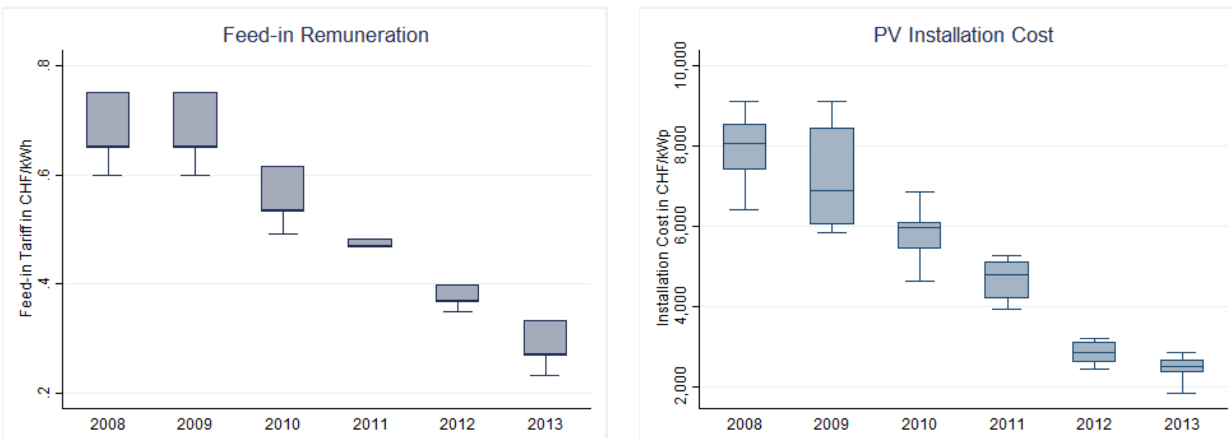
[19] A monthly consumption peak is defined as the 15-minutes interval within that month with the highest recorded kilowatt use.

Table 6: SIMULATED CAPACITY AND ENERGY PRODUCTION

	N Obs	Mean	Std Dev	5th Perc	Median	95th Perc
PV Production Capacity (kWp)	202,420	5.7	8.5	1.4	3.1	25.4
PV Energy Production (kWh)	202,420	9,431	5,027	4,759	8,280	17,721
% for Own Consumption	202,420	15.7	11.2	4.9	11.9	41.7
% Autonomy	202,420	42.5	14.1	15	39.4	60.1

Note: The variables show simulated capacity and potential energy production over time for households homeowners of single or double apartment buildings. This is the subset of households that in our PV adoption model will be allowed to choose whether to install a solar panel or not. Values are simulated based on roof size, appliances and geographic location. kWp means kilo-watt peak, which is the capacity of a solar panel under standard test conditions.

Figure 6: FEED-IN REMUNERATION AND AVERAGE INSTALLATION COST



Note: The left panel shows remuneration fees for on-roof solar panels in Switzerland, source Swiss Federal Office of Energy (SFOE). The right panel depicts average installation costs in Switzerland collected by an annual survey published by the company PhotovoltaikZentrum für Solarmarketing (http://www.photovoltaikzentrum.de/). kWp means kilo-watt peak, which is the capacity of a solar panel under standard test conditions.

3 The Model

We define a framework to model how households respond to fixed and variable energy charges, as well as subsidy to PV adoption, in their optimal electricity consumption and solar panel installation decisions. We let households be forward looking and solve a dynamic problem, in the spirit of Hendel, Nevo (2006). Estimating the structural parameters of this model will allow us to simulate a counterfactual scenario, in which the policymaker finds the optimal tariff design to achieve a renewable energy target, while preserving vertical equity and network financing. We model the supply side as a regulator's constrained optimization problem, adapting Wolak's (2016) approach for water utilities. We will now describe the household's problem, and introduce the regulator's problem in Section 6.

In our model a household $i = 1, ..., N$ decides every period $t = 1, ..., \infty$ the amount of energy in kWh to consume c_{it}, its consumption of the outside good q_{it}, and whether to install a solar panel $\mathcal{PV}_{it} = \{0, 1\}$,

such that:

$$\mathcal{PV}_{it} = \begin{cases} 1, & \text{install the solar panel,} \\ 0, & \text{don't install the solar panel.} \end{cases} \tag{1}$$

We assume that installing a PV is an absorbing state, so if a household adopts one at time t, it cannot substitute it or install another one in the future. This makes the framework a non-regenerative optimal stopping problem. Omitting subscript i for simplicity, we represent a household's problem as follows:

$$\begin{aligned} V(S_1) \quad &= \max_{c(S_t),q(S_t),\mathcal{PV}(S_t)} \sum_{t=1}^{\infty} \rho^{t-1} E \quad \Big[u\big(c_t, q_t, \mathcal{PV}_t, S_t; \Lambda\big) - C\big(\mathcal{PV}_t, S_t; \theta\big) + \varepsilon(\mathcal{PV}_t)\Big|S_1\Big] \\ &\text{s.t.} \qquad\qquad c_t > 0, \quad q_t \geq 0, \quad P_t c_t + q_t + f_t \leq I_t + \tau_t Y_t \end{aligned} \tag{2}$$

where $u(.;\Lambda)$ is a household's utility from consumption of energy c_t and of the outside good q_t, $C(.;\theta)$ represents a household's cost to install a solar panel, $\rho > 0$ is the discount factor, Λ, θ are the structural parameters we want to estimate, and $\varepsilon(\mathcal{PV}_t)$ are independently and identically distributed type 1 extreme value shocks to the solar panel adoption choice, a state variable unobserved to the econometrician. We assume that the state variables observed by the econometrician S_t evolve following an exogenous first-order Markov process. Among these state variables, which we will specify in detail in the next section, are the variable price P_t and the fixed fee f_t for energy consumption, and a household's income I_t. Note that the variable price is the sum of the three components described in Section 2, that is energy price, grid price, and taxes. Other state variables that we include are household and building characteristics X_t that are likely to determine energy consumption, such as household size and wealth, home ownership, electric and water heating, house surface and number of rooms. Moreover, we include as state variables determining solar panel adoption the PV installation cost F_t, the solar panel production Y_t in kW, and the feed in tariff τ_t, at which the electricity produced by the solar system can be sold back to the grid. We should note at this point that feed in revenues are actually net of tax, as this kind of income is also subject to income taxation. Hence $\tau_t Y_t = (1 - t^p)(\tau_t Y_t)^g$, where t^p is the household's marginal income tax rate, and $(\tau_t Y_t)^g$ are gross feed-in revenues. Last, we normalise the price of the outside good to 1.

4 Estimation

We estimate our model by maximum likelihood with the nested fixed point algorithm developed by Rust (1987), which nests the numerical solution of the dynamic model at each step of the search over the structural parameters. We face two main challenges in this estimation strategy. First, the large dimensionality of the state space is very likely to make the problem computationally intractable. Second, letting households solve the dynamic model with respect to both consumption and solar panel adoption further complicates the estimation. To overcome these issues, we simplify the estimation of the structural model in three steps, following the example of Hendel, Nevo (2006).

In the first stage, we assume that households solve a static utility maximization problem to choose their optimal energy consumption, conditional on their solar panel adoption decision. We specify a quasilinear utility function,[20] with the budget constraint defined in equation (2), that gives us the following energy demand function:

$$c_{it}(\mathcal{PV}_{it}, S_{it}; \Lambda) = \begin{cases} P_{ut}^{\beta}(I_{it} - f_{ut} + \tau_{it}Y_{it})^{\gamma} e^{\alpha + X_{it}'\omega + \nu_{it}} & \text{if } \mathcal{PV}_{it} = 1 \\ P_{ut}^{\beta}(I_{it} - f_{ut})^{\gamma} e^{\alpha + X_{it}'\omega + \nu_{it}} & \text{if } \mathcal{PV}_{it} = 0 \end{cases} \tag{3}$$

where P_{ut} and f_{ut} are respectively the electricity variable price and fixed fee charged by energy utility $u \in \{BKW, EWB, ET\}$ at time t, ν_{it} are shocks to energy demand, and $\Lambda = \{\alpha, \beta, \gamma, \omega\}$ are the parameters of the demand function that we want to recover. We estimate these parameters with the following regression model, similar to Reiss, White (2005) and Wolak (2016), postponing to the next section the discussion on the details of the model and of the identification strategy:

$$\ln(c_{it}) = \alpha + \beta \ln(P_{ut}) + \gamma \ln(I_{it} - f_{ut} + \tau_{it}Y_{it}) + X_{it}'\omega + \nu_{it}. \tag{4}$$

We use the estimates of this model to compute the indirect utility from energy consumption $v_{it}(\mathcal{PV}_{it}, S_{it}; \widehat{\Lambda})$ that households would get with and without a solar panel, that is:

$$v_{it}(\mathcal{PV}_{it}, S_{it}; \widehat{\Lambda}) = \begin{cases} I_{it} - f_{ut} + \tau_{it}Y_{it} - \frac{1}{\widehat{\beta}+1} P_{ut}\widehat{c}_{it}^{1} & \text{if } \mathcal{PV}_{it} = 1 \\ I_{it} - f_{ut} - \frac{1}{\widehat{\beta}+1} P_{ut}\widehat{c}_{it}^{0} & \text{if } \mathcal{PV}_{it} = 0, \end{cases} \tag{5}$$

where $\widehat{c}_{it}^{1}$ and $\widehat{c}_{it}^{0}$ are predicted energy consumptions for households, respectively with and without a solar panel, based on equation (3). To simplify the households' dynamic decision to install a solar panel, we assume that the indirect utilities from consumption with and without a PV, defined respectively as v_{it}^{1} and v_{it}^{0}, are two of the state variables that households keep track of when choosing whether to adopt or not.[21] In particular, we divide the indirect utility from adopting into two components, which households keep track of separately. First, households form expectations over the revenues they derive from installing a PV $v_{it}^{1R} = \tau_{it}Y_{it}$, to capture the idea that households are aware of the decline in feed-in tariffs over time. Second, households form expectations over the evolution of electricity costs $v_{it}^{1C} = -\frac{1}{\widehat{\beta}+1} P_{ut}\widehat{c}_{it}^{1}$. This substantially reduces the state space, as it implies that instead of forming expectations over the evolution of $P_{ut}, I_{it}, f_{ut}, \tau_{it}, Y_{it}, X_{it}$, households just consider v_t, such that $F(v_t|S_{t-1})$ can be summarized by $F(v_t|v_{t-1})$. This assumption, also used in terms of inclusive values by Gowrisankaran and Rysman (2012), Melnikov (2011), and Schiraldi (2011), rests on the idea that consumers are boundedly rational and only use a subset of the information available to them to form expectations. We assume that the PV installation cost function is linear in the fixed installation cost F_{it}, such that $C\big(\mathcal{PV}_{it}, S_{it}; \theta\big) = \theta F_{it}$. These costs are also declining over time. Since fixed installation costs are fully tax deductible from the income tax, we assume throughout the paper $F_{it} = (1 - t_i^p)F_{it}^g$, where t_i^p is the household's marginal income tax, and F_{it}^g is the gross

[20] In Appendix A56 we show the functional form of the utility function, deriving energy demand and indirect utilities.

[21] In the estimation we actually eliminate the term $I_{it} - f_{ut}$ from each indirect utility, as this is invariant to the adoption decision.

fixed installation cost. Hence, F_{it} already captures the effect of the income tax deduction. This tax credit further exacerbates the redistributive issues involved in the adoption of solar panels, as richer households have larger incomes, hence higher marginal taxes and possibly larger homes, such that the amount of tax deduction they can benefit from is larger than for low income households.

In the second stage we estimate the transition probabilities of all the state variables in the simplified model $\widetilde{S}_t = \{v_t^{1R}, v_t^{1C}, v_t^0, F_t\}$ with an autoregressive process of order one for each, using the estimated parameters of these processes $\widehat{\delta} = \{\widehat{\delta}_{v1R}, \widehat{\delta}_{v1C}, \widehat{\delta}_{v0}, \widehat{\delta}_F\}$ as inputs for the dynamic model in the next step. Following Rust (1987), we assume conditional independence, such that the Markov transition probability of the state variables can be expressed as:

$$p(\widetilde{S}', \varepsilon' | \widetilde{S}, \varepsilon; \delta, \lambda) = p_1(\widetilde{S}' | \widetilde{S}; \delta) p_2(\varepsilon' | \widetilde{S}'; \lambda) \tag{6}$$

In a standard regenerative optimal stopping problem the present discounted value (PDV) of future utilities is determined using estimates of the transition probabilities of the state variables and value function iteration. We differ from this setting because installing a solar panel is an absorbing state, which implies that the PDV of future utilities from not adopting a PV is still obtained by value function iteration, but the PDV from adopting is not, and we need to compute it. Therefore, using the estimates of the transition probabilities, we construct the PDV of household i from adopting at time t as follows:

$$PDV_{it} = \overbrace{\sum_{s=1}^{25} \rho^s (1-\zeta)^s \tau_{it} Y_{it}}^{\text{Feed-in period}} + \overbrace{\sum_{s=26}^{\infty} \rho^s (1-\zeta)^s \widehat{\delta}_{v1C}^s P_{ut} Y_{it}}^{\text{Post feed-in period}} + \sum_{s=1}^{\infty} \rho^s \widehat{\delta}_{v1C}^s \big[-\frac{1}{\widehat{\beta}+1} P_{ut} \widehat{c}_{it}^1 \big], \tag{7}$$

where $\widehat{\delta}_{v1C}$ is the parameter of the AR(1) for v_{it}^{1C}, ρ is the discount factor, and ζ is the panel's degrade factor.[22] The part of the v_{it}^1 indirect utility that captures the revenue from selling energy to the grid ($v_{it}^{1R} = \tau_{it} Y_{it}$) is divided in two periods. During the first 25 years the household enjoys the KEV feed-in tariff, and after that the household sells the electricity it produces to the grid at the same price at which it buys it.[23] Households form expectations about the evolution of PDV_{it} following $\widehat{\delta}_{v1R}$ for the revenue during the feed-in period (first term on the right hand side of equation (7)), and following $\widehat{\delta}_{v1C}$ for the other terms.

In the third stage we define the Bellman equation of the simplified problem as:

$$V(\widetilde{S}_t) = \max_{\mathcal{PV}_t} \left\{ v_t(\mathcal{PV}_t) + \varepsilon(\mathcal{PV}_t) + \mathcal{PV}_t \Big(PDV_t - \theta F_t \Big) + (1 - \mathcal{PV}_t) \rho E \Big[V(\widetilde{S}_{t+1} | \widetilde{S}_t) \Big] \right\}, \tag{8}$$

[22] We set the degrade factor to 3% for the first year and 0.7% for the following years. We take these values from the guidelines of a popular European panel manufacturer at: http://www.kiotosolar.com/de/assets/media/downloads/produktdatenblaetter/strom/power60/KIOTO_SOLAR_DB_POWER60_DE_250416.pdf.

[23] For the calibrated values of the degrade factor ζ and of the discount factor ρ, the second period ends up carrying very little weight in the present discounted value formula.

where θ represents the disutility from the installation cost F. Under conditional independence we can write the following alternative specific expected value functions, describing a non-regenerative optimal stopping problem:

$$\mathrm{EV}(\widetilde{S}, \mathcal{PV}) = \begin{cases} v(1) + PDV - \theta F + \varepsilon(1) & \text{if } \mathcal{PV} = 1 \\ v(0) + \varepsilon(0) + \rho \int_{\widetilde{S}'} \mathrm{EV}(\widetilde{S}') p_1(\widetilde{S}' | \widetilde{S}; \widehat{\delta}) & \text{if } \mathcal{PV} = 0. \end{cases} \tag{9}$$

Given the extreme value distribution of ε, the probability of installing a solar panel will be:

$$\Pr(\mathcal{PV} = 1 | \widetilde{S}; \theta) = \frac{\exp\left[v(1) + PDV - \theta F\right]}{\exp\left[v(1) + PDV - \theta F\right] + \exp[v(0) + \rho \mathrm{EV}(\widetilde{S}', 0)]}. \tag{10}$$

We recover the parameters of the utility function θ that maximise the following log-likelihood function:

$$L(\theta) = \sum_i \sum_t \log\left[\Pr(\mathcal{PV}_{it} | \widetilde{S}_{it}; \theta)\right]. \tag{11}$$

4.1 Identification

In the first stage we estimate the energy demand model described in equation (4). One of the challenges we face to correctly identify price and income elasticities, our key parameters, is understanding the price that households actually respond to. Ito's (2014) work addresses precisely this question, using a sample of U.S. household-level monthly energy consumption data. He finds that despite a regime of non-linear tariffs, households actually respond to average prices instead of marginal ones, which questions the efficacy of Increasing Block Pricing schemes at encouraging energy efficiency. He also finds that households respond to lagged rather than contemporaneous prices, as they receive electricity bills at the end of monthly billing periods. We follow Ito's (2014) approach to understand what is the price that households actually respond to.

Households in the Canton of Bern face simpler tariff schemes compared to U.S. ones, which makes the choice of marginal vs average price less of a concern in our context. In fact, two providers (BKW and EWB) offer uniform tariffs under which marginal and average prices are the same. However, all providers also offer a double tariff, with different marginal prices between day and night time. For customers under a double tariff scheme we construct marginal prices as a weighted average based on their day and night consumption shares, as described in detail in Appendix A6. Differently from U.S. households, Swiss households receive their final energy bill once a year,[24] which includes their total energy consumption and all variable and fixed tariff components (energy, grid, taxes). We focus on the sum of all variable tariff components as

[24] BKW and ET customers all receive their bill at the end of each year. EWB customers receive their bill yearly but at a customer specific time, based on when their meter is read by EWB.

the relevant marginal price, and based on billing time and previous literature we use lagged prices in the estimation.[25]

Since our data consists of 3 utilities and 6 years, with utilities adjusting prices only once a year, we also rely on price differences within companies across tariff schemes for identification. Overall, we exploit four sources of price variation for identification: time-series, between utilities, between double and uniform tariff customers of the same provider, and price variation from differences in shares of day and night energy consumption within double tariff customers. For each source of price variation we face a potential bias in price elasticities.

First, we are likely to face a positive correlation over time between prices and demand shocks, which might bias upwards our price elasticities. For instance, severe weather conditions could increase households' energy consumption and lead utilities to import more energy or increase production through their marginal (more expensive) power plants, driving up prices. We address this concern with year fixed effects.

Second, there might be systematic differences across households served by different providers, which simultaneously affect energy demand and prices. In fact, EWB and ET households are all located in cities, whereas BKW households are mostly in rural areas. Providers serving systematically larger households, or areas with systematically colder weather, will experience higher energy consumption and therefore higher prices, causing an upward bias in price elasticities. The limited times series variation prevents us from including utility-year fixed effects to address this.[26] We instead use our rich set of household and building characteristics to control for any differences across households. Moreover, we further address this concern estimating both a geographical boundary regression discontinuity design (RDD), similarly to Black (1999) and Ito (2014), and a matching boundary discontinuity design (MBDD), in the spirit of Fack and Grenet (2010). These methods allow us to control for observable household and building characteristics X_{it}, as well as for unobservable location and year specific characteristics, exploiting the exogenous variation in energy prices for similar households close to the border that divides each energy supplier's area of control.[27] Potential sorting at the border, which may be problematic with a RDD (Lee and Lemieux, 2010), is unlikely to affect our design, as households are not allowed to choose their energy provider and energy prices are a negligible factor in location choice.

Third, we might face two sources of bias by comparing uniform and double tariff customers. On the one hand, BKW and EWB assign their customers to uniform or double tariffs based on households' energy consumption and appliances (i.e. if they have an electric heat pump), which means that double tariff households tend to have a higher energy consumption and lower prices.[28] On the other hand, all ET customers are billed

[25]Following Ito (2014), we test whether households respond to current or lagged prices including both in our regression model, and find that conditional on lagged prices current prices are very weakly statistically significant with very small economic magnitude, about 5% the size of the elasticities of lagged prices. Hence, we infer from this that households mostly respond to lagged prices and fees.

[26]It also prevents us from using household fixed effects, which absorb all the cross-sectional variation and make it hard for us to identify price coefficients out of only 6 time-series data points.

[27]The maps in Appendix A2 represent respectively the city of Bern and the city of Thun and their surroundings, and highlight the border areas of the two cities which are illustrative for our geographical RDD design.

[28]Double tariff prices are always lower than corresponding uniform tariff prices.

under the double tariff scheme, implying that ET households have on average a lower energy consumption than double tariffs customers of one of the other companies. Not controlling for these differences would induce a downward bias in price elasticities, therefore we include in our model a dummy variable for double tariff customers of BKW and EWB, and a separate dummy variable for all ET customers. We do not expect selection bias to be an issue in comparing double and uniform tariff households, as double tariff households face lower prices so have no incentive to switch to a uniform tariff, and uniform tariff households need to invest in a costly new meter to be able to access the double tariff. The data contains only a handful of households that change tariff schemes (after relocating) and we drop them from the sample when estimating elasticities.

Last, we face a potential downward bias when comparing double tariff households with different day vs night time consumption shares, as a customer hit by a positive shock to energy demand may shift consumption from day to night, reducing her marginal price. Additionally, households with higher energy consumption might have more flexibility to shift consumption to night time. To address this potential endogeneity we predict household consumption shares based on household characteristics, rather than using actual shares (see Appendix A6 for details and results). Moreover, the use of lagged prices helps to reduce the potential endogeneity of consumption shares.

We observe the annual energy consumption of household i in year t falling within the service area of utility $u \in \{BKW, EWB, ET\}$. Each household is uniquely assigned to the service area of one of the three energy providers. We determine each household's exact location using the latitude and longitude of its address. Additionally, we define several border points b at the boundary of two service areas. Each household is assigned to the nearest border point if it is located up to 1 km from it on either side of the border.[29] Based on this design the new specification becomes:

$$\ln(c_{it}) = \alpha + \beta \ln(P_{ut-1}) + \gamma \ln(I_{it} - f_{ut-1} + \tau_{it} Y_{it}) + X_{it}' \omega + \xi_b + \mu_t + \nu_{it}, \tag{12}$$

where ξ_b are boundary fixed effects, absorbing all the time-invariant unobservable determinants of energy consumption specific to the border point area, which are likely to equally affect households' consumption at the border, but not equally affect prices. When we extend the geographic regression discontinuity design by matching households on opposites sides of the borders (MBDD), we assume that households that are sufficiently close share the same time-varying vicinity effect in energy consumption. We follow a two step estimation, where in the first step we regress energy consumption for household i assigned to border point b and utility u at time t on all covariates but energy price:

$$\ln(c_{ibut}) = \alpha + \gamma \ln(I_{it} - f_{ut-1} + \tau_{it} Y_{it}) + X_{it}' \omega + \nu_{ibut}. \tag{13}$$

We then predict the residuals and use them in the second stage, taking as dependent variable the difference in residuals between household i and its matched counterpart i', which is in the same border point b but served by utility u'. This gives us the following regression model:

[29]We experimented with alternative distances (250 meters, 500 meters, 1.5 km) finding similar results.

$$\widehat{\nu}_{ibut} - \widehat{\nu}_{i'bu't} = \beta(\ln P_{uit-1} - \ln P_{u'it-1}) + (\epsilon_{ibut} - \epsilon_{i'bu't}), \tag{14}$$

where i corresponds to households of the BKW and i' corresponds to the matched counterfactual observation of EWB/ET. We create the counterfactual for each BKW observation as the distance-weighted average of the 50 nearest EWB/ET observations with the same tariff scheme.[30] We regress the difference of the unexplained variation in energy consumption ($\widehat{\nu}_{ibut} - \widehat{\nu}_{i'bu't}$) on the price difference using OLS. Each pair receives a weight $\sum_{j=1}^{J} \frac{1}{d_{ij}}$, where d_{ij} is the distance between household i and household i', such that greater weight applies to households that are closer neighbours.[31] Assuming that all other unobservable factors vary continuously at the boundary, the coefficient β can be interpreted as the unbiased price elasticity of energy demand. If other determinants were also to vary discontinuously at the border, we would not be able to isolate the energy price effects. For this reason we eliminate boundaries that coincide with significant geographical barriers, such as rivers. Differently from equation (12), in specification (13) we eliminate common area specific trends by spatial differencing, and account for the distance between households on opposite sides of the border.

Table 7 presents a comparison of means of households' characteristics across the border for the two bordering areas in our data, that are the city of Bern and the city of Thun. We can show that households at 1km from the border between the service are of BKW and EWB are very similar across all dimensions, and the same is true for households at 1km from the border between the service area of BKW and ET. These characteristics don't differ significantly from the same observables in the full sample.

In the second stage of the estimation we recover the parameters δ of the transition probabilities of the state variables. Each of these parameters rely on different sources of identifying variation. The AR(1) parameter for the revenue side of the indirect utility from installing (δ_{v1R}) is identified by both time series and cross-sectional changes in feed-in tariffs τ_{it}, as well as by cross-sectional heterogeneity in PV potential production Y_{it}. The AR(1) parameters for the cost side of the indirect utility from installing (δ_{v1C}) and for the indirect utility from not installing (δ_{v0}) are identified by time series and across utility variation in variable prices and fees, as well as cross-sectional heterogeneity in household characteristics. Last, identification of the AR(1) parameter for fixed installation costs (δ_F) relies on both time series and cross-sectional variation in fixed installation costs, as PV systems of different sizes faced different costs.

In the last stage, the dynamic PV adoption decision, the parameter of interest is the disutility of fixed installation cost θ. The identification of this parameter relies on cross-sectional variation in fixed installation costs, conditional on the indirect utilities and the present discounted value of installation computed in the previous stages.

[30]The observations need also to have the same assigned border point.

[31]In this specification we compute standard errors clustered at the boundary-year level.

Table 7: HOUSEHOLD CHARACTERISTICS AT CITY BORDERS

Variables	**Full Sample**	$< 1km$ **Border Bern**		$< 1km$ **Border Thun**	
		BKW	**EWB**	**BKW**	**ET**
Energy Consumption (kWh)	4,919	3,960	3,208	5,341	4,538
	(5,189)	(4,610)	(3,261)	(4,947)	(4,783)
Income CHF	72,940	83,028	72,652	71,639	73,959
	(117,831)	(113,865)	(91,682)	(65,050)	(61,308)
Wealth (CHF)	335,409	430,961	354,237	325,934	344,452
	(1865925)	(2887249)	(1925876)	(978,893)	(925,799)
Home Ownership (%)	46	34	26	60	61
	(50)	(48)	(44)	(49)	(49)
Married (%)	52	47	38	57	57
	(50)	(50)	(48)	(49)	(50)
Householdsize					
1 (%)	41	45	53	37	40
	(49)	(50)	(50)	(48)	(49)
2 (%)	36	34	30	39	39
	(48)	(47)	(46)	(49)	(49)
3 (%)	8	8	7	10	8
	(28)	(28)	(26)	(29)	(27)
4 (%)	10	10	7	11	10
	(31)	(30)	(26)	(31)	(30)
> 5 (%)	4	3	2	4	4
	(19)	(17)	(14)	(20)	(19)
PV Installation (%)	.5	.2	.1	.9	1.9
	(7.6)	(4.8)	(3.3)	(9.5)	(18.2)
Heating System					
Electric (%)	6	4	2	6	4
	(24)	(19)	(15)	(24)	(19)
Heat Pump (%)	7	4	1	11	4
	(25)	(21)	(10)	(32)	(20)
Oil/Gas/Coal (%)	87	92	97	83	92
	(33)	(28)	(18)	(38)	(27)
Heating System					
Electric (%)	43	35	38	45	25
	(50)	(48)	(48)	(50)	(43)
Heat Pump (%)	3	3	2	4	3
	(17)	(18)	(12)	(19)	(17)
Oil/Gas/Coal (%)	53	62	61	51	72
	(50)	(49)	(49)	(50)	(45)
Number of Rooms	3.8	3.6	3.3	4	3.9
	(1.2)	(1.2)	(1.1)	(1.1)	(1.1)
Appartment Surface (sqmt)	100.6	95.2	87.2	107.5	103
	(42.3)	(41.8)	(34.8)	(41.5)	(42)
Appartm. in Building	2	3	3	2	2
	(.9)	(.8)	(.7)	(.9)	(.9)
N Obs	657,750	57,932	44,995	12,938	11,087

Note: The table shows means with standard deviations in parentheses. Column (1) shows household characteristics for the full sample. Columns (2) and (3) only include households from BKW and EWB sharing a common border in the city of Bern. Column (4) and (5) show descriptives for households of BKW and Energie Thun located at the common border in the city of Thun. We define border households as those being at most 1km away from the border.

5 Results

5.1 Energy Demand Model

We report the results of the baseline OLS regression in column (1) of Table 8. In column (2) we add double tariff dummies to control for unobserved heterogeneity between uniform and double tariff customers. Column (3) includes fixed effects for deciles of day vs night consumption shares of double tariff customers, as a robustness check against differences in consumption patterns. Column (4) reports the regression with double tariff dummies for the subsample within 1km of the city borders of Bern and Thun. Column (5) adds border fixed effects to the border sample regression. Last, column (6) and (7) present the first and second step of the MBDD regression respectively. In all specifications we control for apartment/building characteristics, such as the number of rooms and the apartment's surface, including also fixed effects for the number of apartments in the building and the building's construction period. We further add fixed effects for whether a household's dwelling uses electricity, a heat pump, or other sources (oil/gas/wood) for its heating system or for hot water heating. Additionally, we control for income and wealth of the household, the age of the household head, its size, and home ownership. Last, we add dummy variables for households with negative income and negative wealth, as we observe atypical consumption pattern from these groups.[32]

Table 8 shows that the price elasticity of demand is negative and significant, ranging between -0.06 and -0.18 across all specifications other than the baseline in column (1). In fact, just adding double tariff dummies to the baseline regression reduces the coefficient from -0.91 to -0.10, which is in line with the downwards bias we expected. The elasticity based on the RDD specifications in columns (4) and (5) slightly decreases compared to column (2), confirming the expected upward bias from cross company comparison. The elasticity of the MBDD in column (7) slightly increases to -0.08 compared to the RDD specification. In the MBDD approach our sample shrinks considerably, as the number of observations decreases to 21,690, corresponding to around 7% of the total sample. For this reason we consider the MBDD strategy as a robustness check and use the RDD results in column (5) as our preferred specification for the counterfactuals. As expected, we find that high income households consume more energy. The small magnitude of the income elasticity is not surprising, as we control for various household and building characteristics correlated with income. We also find that larger households, home owners, and households using electricity for heating or hot water, consume more energy. More recent buildings consume less, as these are likely to have more efficient isolation. In Figure 7 we plot the price elasticity across the income distribution, estimated using our RDD specification, showing that households in lower income deciles are more price elastic.

Our preferred estimates in column (5) display lower price elasticities in absolute terms compared to other papers in the literature. For example, Reiss, White (2005) estimate the distribution of electricity price elasticities for a sample of households in California, finding it to be centred at -0.39. There are two main differences between our setting and theirs, as well as with others' work. First, they derive this result for a sample of 1,307 households over two years, whereas our dataset covers around 135,000 households over

[32]The sample includes 8,600 households with non-positive income in at least one period, and 18,400 households with non-positive wealth.

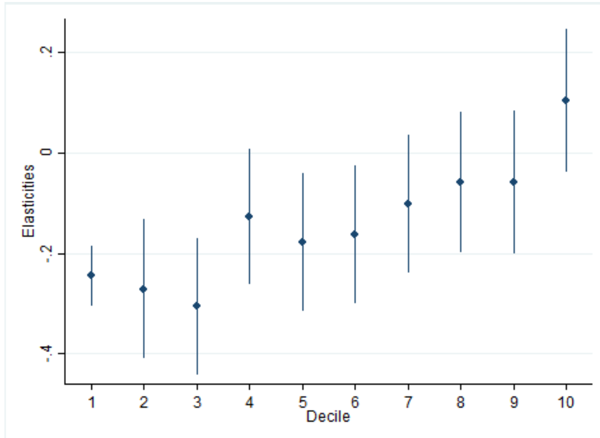
6 years, which is a far larger sample than most of the papers estimating energy demand in the literature. Second, households in Switzerland face a simpler pricing structure, mostly determined by a uniform or double tariff and a fixed fee, whereas U.S. households are offered a more complicated Increasing Block Pricing schedule. Our results might also imply that the complexity of the tariff structure can affect the responsiveness of households to tariff increases.

Table 8: ENERGY PRICE ELASTICITIES

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Price	-0.91	-0.10	-0.06	-0.18	-0.16		-0.08
	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)		(0.01)
Double Tariff BKW/EWB		0.43		0.41	0.41		
		(0.00)		(0.01)	(0.01)		
Double Tariff ET		0.14		0.25	0.24		
		(0.01)		(0.01)	(0.02)		
Income	0.00	0.01	0.01	0.01	0.01	0.01	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Wealth	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Home Owner	0.17	0.14	0.14	0.10	0.10	0.13	
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	
Number of Rooms	0.14	0.09	0.09	0.12	0.11	0.11	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	
Number of Rooms Sq	-0.01	-0.00	-0.00	-0.01	-0.01	-0.01	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Apartment Surface	0.11	0.11	0.12	0.14	0.15	0.16	
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	
Constant	6.97	8.19	7.94	8.01	8.06	8.67	
	(0.04)	(0.05)	(0.05)	(0.09)	(0.09)	(0.08)	
Share FE	No	No	Yes	No	No	No	No
Household Size FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Household Age FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Heating System FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Water System FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Apartment No. FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Construction Period FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Non-Positive Income/Wealth FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	No	No
Border FE	No	No	No	No	Yes	No	No
N Obs	460,081	460,081	460,081	92,090	92,090	92,090	21,690
R^2	0.551	0.581	0.587	0.583	0.586	0.527	0.070

Note: Standard errors in parentheses. Standard errors are clustered at the household level in specifications (1)-(5) to account for serial correlation. Log of total yearly energy consumption is used as dependent variable. Price, Income and Wealth variables are in logs. Aparment Surface is in hundreds of squared meters. Column (5) shows the results for the RDD model. Columns (6) and (7) show respectively the first and second stage of the MBDD.

Figure 7: PRICE ELASTICITIES BY INCOME DECILES



Note: The graph shows the estimates of price elasticities with standard errors for each income decile with the specification in column (5) of Table 8.

5.2 PV Adoption Model

To estimate the PV adoption model we restrict the sample to the main energy provider (BKW), which serves 94% of the solar panels installed,[33] and to single family houses or buildings with at most two apartments, for which it is more likely that a single household is making the installation decision. We calibrate the discount factor to $\rho = 0.8788$, which is the value estimated by De Groote, Verboven (2016) for PV adoption decision of Belgian households. Unfortunately we don't have the same rich time series variation in feed-in tariff that they have to identify the discount factor in our setting, but we believe that time preferences of Swiss households for PV installation are likely to be similar to Belgian ones.

Following Rust (1987), we discretize the state space to make the computation tractable. The four state variables, indirect utilities without (v^0) and with (v^{1R}, v^{1C}) solar panel, and installation costs (F) are all discretized to around 60 intervals of length, respectively of 40, 300, 2500 and 2,500 CHF.[34] We then estimate the parameters of the AR(1) processes for the state variables ($\delta_{v0}, \delta_{v1R}, \delta_{v1C}, \delta_F$). Next, the estimation procedure consists of an inner loop, where the value function for a given parameter θ is found using the nested fixed point algorithm, and an outer loop, where we search over parameter values using maximum likelihood. We use bootstrap to derive the standard errors.

Estimation results of the parameters of the AR(1) processes and of the coefficient for fixed installation costs θ are reported in Table 9. A positive θ implies that households are less likely to install the higher are fixed installation costs. We find that δ_{v0} and δ_{v1C} are very close to 1, so there is not much variation over time in the indirect utility from not adopting and in the cost component of the indirect utility from adopting. The coefficients of the AR(1) processes for the other state variables identify the trade off that households face from adopting a PV versus waiting. A value of δ_F of 0.76 shows that installation costs are declining

[33]PV systems are more likely to be adopted in non-urban areas, which are the ones served by BKW.

[34]We actually discretized the present discounted value variable PDV, which is the sum of current and future indirect utilities from adopting $v^{1R} + v^{1C}$.

over time, whereas a value of δ_{v1R} of 0.82 implies that the revenue component of the indirect utility from adopting is reducing over time, driven by the decrease in feed-in tariffs.

Table 9: PV ADOPTION RESULTS

Parameters	
δ_{v0}	.99
	(0.00)
δ_{v1R}	.82
	(0.00)
δ_{v1C}	.99
	(0.00)
δ_F	.76
	(0.00)
θ	1.03
	(0.00)
N Obs	52,705

Note: Standard errors in parentheses.

6 Counterfactuals

We propose an optimal tariff design that a regulator can implement to achieve a solar energy production target, while recovering network costs and preserving vertical equity. We allow the policymaker to rely on three different instruments, all commonly used in various electricity markets worldwide: volumetric charges and fixed fees in households' energy bills, as well as subsidies to solar power installation costs. Volumetric charges are similar to an energy tax, as they generate revenues to finance energy and grid costs, but also discourage households' excessive energy consumption. These variable tariffs represent an incentive to adopt a solar panel, as households with a PV can save on their energy bill by consuming the electricity they produce. However, the combination of volumetric charges and a growing number of solar power installations can have a regressive effect on households' energy bills, for the following reason. High income households generally consume more, paying a higher share of the fixed network cost, in line with the principle of progressive taxation. Richer households are however also more likely to install a solar panel, as they commonly are home owners of single houses and have the resources to pay the installation costs. This implies that rich households with a PV could end up contributing less to the fixed network costs, while still using the grid to consume and sell energy, in turn making poorer households bear an increasing share of fixed network costs.

The second instrument, a fixed fee, is equivalent to a lump-sum tax to finance grid costs. Being fixed, these

fees generate no incentive for households' energy conservation or solar power installation,[35] but guarantee a steady revenue to recover fixed network costs that doesn't depend on households' energy consumption or production. The reason why fixed network costs are not decoupled from energy consumption, i.e. fully financed with a fixed fee, is the lack of incentives for energy conservation and the regressive effect this would have on households' electricity bills.

The last instrument is a subsidy to solar panel installation costs, set as a share of total PV adoption costs.[36] This is one of the two main incentives historically used by policymakers to foster solar panels' adoptions, the other being feed-in tariffs. The main difference between the two instruments is that the first subsidises up front installation costs, whereas the second subsidises future revenues from energy production. De Groote, Verboven (2016) are able to show that Belgian households undervalued future solar panel revenues, concluding that in their setting, where a feed-in tariff was in place, an upfront investment subsidy would have promoted PV adoptions at a lower budgetary cost. Based on their findings, and on the recent move by the Swiss government from a feed-in system to installation subsidies, we decided to just focus on the latter. In line with the case of Switzerland and of other countries, we assume that the revenue to finance the subsidy is recovered from households' electricity bills.

We conduct two main counterfactual exercises using data from the last year in our sample (2013) for the main provider (BKW). In the first experiment we quantify the "death spiral", simulating a benchmark scenario where all home owners of single and double apartment buildings in our data install a solar panel, and calculate the increase in variable grid tariff required to guarantee network financing, based on our energy demand model. This exercise aims at quantifying the extent of the decline in revenues to finance the grid from a large increase in PV installations, as well as the regressive effect that the increase in volumetric charges could have. In the second policy experiment we allow the policymaker to find the optimal tariff design, in terms of variable prices, fixed fees, and subsidies, in order to achieve various solar energy production targets, while recovering network costs and preserving vertical equity. For each scenario we calculate the change in households' welfare and contribution to grid costs between the current and the counterfactual tariff scheme.[37]

In Appendix A7 we present an additional counterfactuals with exogenous PV adoption. In that exercise we address the regressive nature of fixed fees simulating a complete decoupling of grid revenues from energy consumption, allowing the regulator to rely on a combination of uniform and capacity fixed fees to recover grid costs. In fact, what is typically more costly for the network is not the average energy consumption of a household over time, but the variance of it, as large spikes can generate costly imbalances for a network that always needs to balance demand and supply. A way to address this without regressive effects is to substitute or complement uniform fixed fees with capacity fixed fees, which still allow to decouple grid financing from energy consumption, but are set based on the maximum amount of energy a household is able to consume

[35] According to our estimates changes in fixed fees do not significantly alter energy consumption and have no impact on PV adoption.

[36] Since 2015 Switzerland provides a subsidy of 30% of installation cost for small solar panels. The tax credit for installation costs that households receive is implicitly also a subsidy. We don't however allow the regulator to adjust that too, focusing only on the explicit one.

[37] We define aggregate welfare as the sum all households' indirect utilities.

from the grid during a fixed time span (usually 15 minutes).[38]

For all counterfactuals, we separate the marginal price P into its energy component P_E, its tax component P_T, and its grid component P_G, and only allow the latter to vary. Moreover, we allow households with a PV to consume a share OC_i (Own Consumption) of the energy they produce Y_i with their solar panel,[39] which implies that the household's consumption from the grid that we'll use in our simulations can be expressed as:

$$\widehat{c}_i(\mathcal{PV}_i, P_G, f) = \begin{cases} P^{\widehat{\beta}_i}(I_i - f + \tau_i Y_i)^{\widehat{\gamma}} e^{\widehat{\alpha} + X_i'\widehat{\omega} + \widehat{\xi}_b} - OC_i Y_i & \text{if } \mathcal{PV}_{it} = 1 \\ P^{\widehat{\beta}_i}(I_i - f)^{\widehat{\gamma}} e^{\widehat{\alpha} + X_i'\widehat{\omega} + \widehat{\xi}_b} & \text{if } \mathcal{PV}_{it} = 0, \end{cases} \tag{15}$$

where we keep everything fixed, apart from PV adoption status, variable grid prices P_G, and fixed fees f. We use this to define each household's contribution to grid costs as the following grid expenditure GE_i:

$$GE_i(P_G, f) = f + \widehat{c}_i(\mathcal{PV}_i, P_G, f) P_G. \tag{16}$$

Energy providers in our setting are cost-plus regulated, implying they recover total grid cost without making any additional profits. Hence, using our data on households' grid expenditure under the current tariff scheme, we can recover the baseline total grid cost GC_0 that the regulator recovered from BKW in 2013, which we assume will need to be recovered under every scenario, as:

$$GC_0 = \sum_{i=1}^{N} GE_{i0}(P_{G0}, f_0) = N f_0 + \sum_{i=1}^{N} \overline{c}_i P_{G0} \tag{17}$$

where N is the total number of households, $\overline{c}_i$ is households' consumption from our data, and f_0 and P_{G0} are fees and prices in the current tariff scheme.

6.1 Simulating the Death Spiral

We first consider the effects on volumetric charges of a benchmark increase in penetration of distributed energy, simulating a scenario where all home owners of single or two apartment buildings in our data have a solar panel. We focus on these households as it is likely to be easier for them to adopt a PV compared to households renting or living in apartments. To isolate the effect that this increase would have on the variable grid price P_G, we assume that the regulator only relies on this instrument to recover the missing grid revenue, holding fixed fees constant for now. We calculate the counterfactual optimal variable grid price under this scenario solving the following regulator's cost minimization problem:[40]

[38] The energy providers in the Canton of Bern already apply a capacity fixed fee to business users, but not to household users.

[39] Eturnity provided us with simulated data on own consumption, according to which on average a household can use for own consumption 15.7% of the energy it produces.

[40] We use a numerical minimization as $c_i(P_G)$ is a nonlinear function of P_G.

$$\min_{P^G} \left| GC_0 - \sum_{i=1}^{N} GE_i(P_G, f) \right| \tag{18}$$

In Table 10 we present changes in energy grid expenditure and welfare under two different scenarios, where the changes are only related to grid financing and thus exclude gains from solar panel revenue. In the first scenario we assume that households consume the share of energy they produce as predicted by Eturnity (15.7% on average), as reported in Table 6. In the second case we consider the limit case in which households consume 100% of the energy produced,[41] trying to mimic a scenario where all households also installed a battery. The first two rows show the change in the variable grid price in percentage terms. Allowing for current potential own consumption, as reported in column (1), variable grid tariffs rise by around 13%. With 100% own consumption instead, as reported in column (2), they increase by 123%. In the middle and bottom parts of Table 10 we report the percentage change compared to the status quo in household-specific grid expenditure ΔGE_i and consumer surplus ΔCS_i, respectively for households that have or don't have a PV, and across the income distribution. We find that under both scenarios households with (without) a PV experience a decline (increase) in grid expenditure and an increase (decline) in consumer surplus. Last, Table 10 shows the regressive effect of this increase in prices, as low income households experience the highest increase in grid expenditure and the largest reduction in consumer surplus. This regressive effect is caused by the lower likelihood of poor households to adopt a solar panel.

[41] We do not allow own consumption to exceed total annual consumption of the household.

Table 10: GRID EXPENDITURE AND CONSUMER SURPLUS % CHANGE

	Eturnity OC		100% OC	
Instruments				
% Price (P_G) Change	13		123	
	ΔGE_i	ΔCS_i	ΔGE_i	ΔCS_i
% Change by PV Installation				
% PV Installed	-8.2	7.2	-78.1	68.1
No PV Installed	7.9	-8.6	73.2	-81.6
% Change GE_i by Income Decile				
1^{st} decile	3.9	-4.8	37.7	-46.4
2^{nd} decile	2.5	-3.3	29.1	-37.5
3^{rd} decile	2.6	-3.4	27.1	-35.6
4^{th} decile	2.9	-3.7	28.6	-37.3
5^{th} decile	2.8	-3.6	26.4	-35.2
6^{th} decile	2.5	-3.3	22.1	-31.1
7^{th} decile	2	-2.8	16.3	-25.4
8^{th} decile	1.6	-2.4	10.5	-19.8
9^{th} decile	.7	-1.6	1	-10.5
10^{th} decile	-1.9	1	-23.8	14

Note: The table illustrates the change in variable grid tariffs when all home owners of single and two apartment buildings have a solar panel and consume their own energy. Fixed tariffs are kept constant at the current level.

6.2 Optimal Tariff Design

In the second counterfactual we find the optimal tariff design that a regulator can implement to achieve a solar energy production target, while recovering network costs and preserving vertical equity. We let the regulator solve a constrained optimisation approach, in the spirit of Wolak (2016), to find the optimal combination of variable prices P_G, fixed fees f_i,[42] and subsidies s as a percentage of the installation cost. In this counterfactual we use the estimated parameters of both energy demand and PV adoption models, but modify some state variables in the latter.

We estimated the PV adoption model under a feed-in tariff system in which households were feeding all the energy produced back to the grid, and still buying from the utility all the energy they consumed. This means that households with a PV were still fully contributing to grid financing. However, during the last few years in various countries there has been a switch in PV adoption incentives, going from feed-in tariffs to installation cost subsidies. In Switzerland, since 2015 newly installed solar panels with a capacity below 10 kW, therefore comparable to most of the PVs in our data, do not receive feed-in remuneration anymore, but are instead entitled to a subsidy covering 30% of the investment costs. Moreover, energy providers must

[42]We allow the fixed fee to be household i specific using a capacity fixed fee, see Appendix A7 for a detailed description of this.

allow households to directly consume the energy they produce, and must remunerate excess solar energy production at least at the market price for energy. In our counterfactual scenario we therefore assume no feed-in remuneration, allowing households to consume their PV produced energy directly and to feed only excess energy back into the grid (at the market price of energy). Under this scenario higher variable grid tariffs incentivise PV adoption because households save on variable grid costs when consuming their own energy.

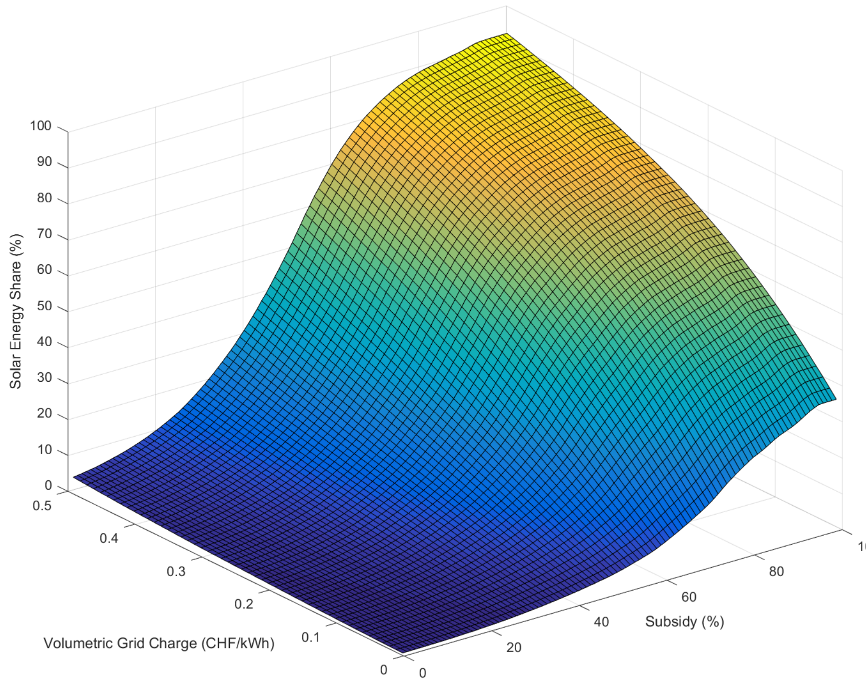
The regulator minimises an objective function taking households' current grid expenditure GE_{i0} as the desired benchmark from an income distribution perspective, accounting for a grid financing and a solar energy target constraint. This translates into the following regulator's optimization problem:

$$\begin{aligned}
\min_{P_G, f_i, s} \quad & \sum_i \frac{\left[GE_i(P_G,f_i)-GE_{i0}\right]^2}{I_i} = \sum_i \frac{\left[\widehat{c}_i(\mathcal{PV}_i,P_G,f_i)P_G+f_i-GE_{i0}\right]^2}{I_i} \\
& \text{s.t. } GC_0 + \sum_i sF_i \Pr(\mathcal{PV}_i = 1|P_G, f_i, s) = \sum_i \left[f_i + \widehat{c}_i(\mathcal{PV}_i, P_G, f_i)P_G\right] \qquad \text{(network financing)} \\
& \text{s.t. } \frac{\sum_i Y_i \Pr(\mathcal{PV}_i=1|P_G,f_i,s)}{\sum_i \widehat{c}_i(\mathcal{PV}_i,P_G,f_i)} \geq SET \qquad \text{(solar energy target)}
\end{aligned} \tag{19}$$

where $\Pr(\mathcal{PV}_i = 1|P_G, f_i, s)$ is a function of the variable grid tariff and the parameters estimated in the model of Section 5.2. In fact, tariffs set by the regulator impact the probability to adopt by changing the state variables of the households. While subsidies decrease installation cost by sF_i, volumetric charges increase the revenue from owning a PV through PDV_i. SET is the Solar Energy Target, expressed as a lower bound of the ratio of energy produced from solar panels over total energy consumed by households. See Appendix A8 for a detailed description of how we solve the regulator's optimization problem.

Figure 8 illustrates the share of solar energy as we vary volumetric charges and subsidies. Based on our simulation the fixed fee does not directly impact the probability to install a solar panel, therefore we treat it solely as a financing tool. As the figure shows, the probability of adopting a solar panel is increasing in both the subsidy and the volumetric charge. Moreover, the instruments seem to complement each other. The multiplicative effect of both instruments also holds for the cost of the instrument. Stimulating PV adoption through higher volumetric charges also increases the cost of a subsidy, and vice versa. Due to declining solar panel production costs, a further advantage of these subsidies is that they are likely to become less expensive for the government over time.

Figure 8: SHARE OF SOLAR ENERGY INDUCED BY VARIABLE PRICE AND SUBSIDY



Note: The figure shows how the share of energy consumed from solar panels changes as we vary variable price and subsidy to installation cost.

In the counterfactual, we let investment costs decline according to the AR(1) process and use the year 2013 as a benchmark for prices and household characteristics. Without an adjustment in tariffs compared to 2013 we predict a share of solar energy of 0.5%. In Table 11 we present the optimal tariff design for four solar energy targets. The highest target corresponds to the short term energy target set by the Swiss regulator.[43] In the top part of the table we show the percentage increase in variable grid price and fixed fee,[44] as well as the share of installation cost that the subsidy should cover, in order to achieve each of the targets. In the middle part of the table we show the percentage increase in households' grid expenditure needed to achieve each target, with a breakdown by income decile. The bottom part of the table reports average costs per kWh of solar electricity. The costs are calculated as total subsidy costs divided by the total amount of electricity produced. As the results show, the regulator should rely on subsidies to stimulate PV adoption, increasing both volumetric charges and fixed fees to cover subsidy costs. Furthermore, the cost of the transition to more

[43]According to the newly introduced Swiss energy law, until 2020 total annual electricity consumption is to be reduced by 3% compared to 2000, i.e. to 50,801 GWh based on 52,373 GWh in 2000 (Swiss Electricity Statistic, 2016). Simultaneously, the policymaker specifies an annual renewable electricity production target of 4,400 GWh until 2020, excluding hydro energy. A benchmark scenario of solar panels fully accounting for this increase, and households contributing according to their consumption share, results in a solar energy target of approximately 9%.

[44]We allow the fixed fee to be a function of household consumption capacity. However, for the chosen solar energy targets the regulator should always rely on a uniform fixed fee.

solar energy is equally spread across the income distribution. As the last row of the table shows, stimulating solar energy is rather costly and increases with a higher solar energy target. Each kWh of renewable energy costs the regulator between 0.36 and 0.68 CHF in subsidies. This is a multiple of the market price for electricity of 0.10 CHF.

Table 11: % CHANGE IN VARIABLE PRICE, FIXED FEE, SUBSIDY, GRID EXPENDITURE

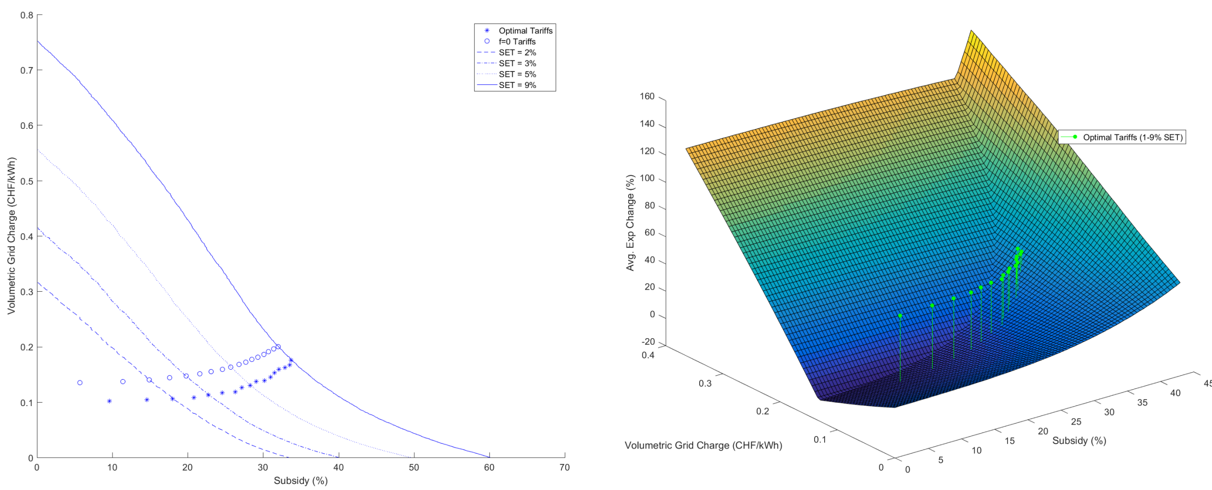
	Solar Energy Target			
	2%	**3%**	**5%**	**9%**
Instruments				
% Price (P_G) Change	5.5	12.5	29.4	75.2
% Fixed Fee (f_i) Change	117.5	119.4	117.1	61
Subsidy (s) as % of Installation Cost	18	22.7	28.3	33.7
% Change GE_i by Income Decile				
1^{st} decile	6.2	10.9	21	40
2^{nd} decile	6.2	10.8	20.9	39.4
3^{rd} decile	6.1	10.8	21.1	40.4
4^{th} decile	6.1	10.8	21.2	40.9
5^{th} decile	6	10.8	21.3	42.1
6^{th} decile	5.9	10.8	21.4	42.9
7^{th} decile	5.8	10.7	21.4	43.3
8^{th} decile	5.7	10.6	21.5	44.2
9^{th} decile	5.5	10.3	21.3	44.7
10^{th} decile	5.1	10	21.3	45.8
CHF per kWh Solar Energy	.36	.46	.57	.68

Note: The table illustrates the change in variable price, fixed fee, subsidy required to achieve 2%, 3%, 5%, 9% solar energy targets, preserving grid financing and vertical equity. It also shows the percentage change in households' grid expenditure across the income distribution for the four targets. The last row shows the average subsidy cost per kWh to stimulate production of renewable energy.

Figure 9 provides two graphical illustrations of optimal tariffs. In the left panel we compare tariff combinations that satisfy the same energy target, whereas the right panel shows average expenditure changes for each instrument combination. The lines in the left hand plot of Figure 9 are combinations of volumetric charges and subsidies that meet the corresponding solar energy targets (2%, 3%, 5% and 9%). All points above a line also satisfy the same target, however, with at least one of the two instruments being strictly higher. Besides optimal tariffs, denoted by asterisks, corresponding to the values in Table 11, we also present tariff combinations with a zero fixed fee, marked by circles. Combinations with a zero fixed fee represent a benchmark because they are the least costly in terms of aggregate households expenditure. In fact, the regulator should increase volumetric charges to fully cover grid costs and subsidies if the only scope is to minimize aggregate household expenditure. From the plot we can see that optimal tariffs are below the benchmark tariff combinations but tend to converge for higher targets. The right-hand panel of Figure 9 illustrates the average change in household grid expenditure for combinations of volumetric charges and subsidies. The

discontinuity in the plot surface, starting just above 0.1 volumetric grid charge when the subsidy is zero, relates to a zero fixed fee. At the discontinuity, increasing volumetric charges leads to excess revenue over grid and subsidy costs, while decreasing volumetric charges requires positive fixed fees to satisfy the network financing constraint. The plot also displays optimal tariffs for rising solar energy targets, equivalent to the left plot. The results show that the regulator optimally increases both volumetric charges and subsidies simultaneously to reach the energy target.

Figure 9: FRONTIER OF OPTIMAL TARIFFS



Note: Optimal tariffs represent tariff combinations that minimize the objective function of the regulator. f=0 tariff combinations mean that volumetric grid charges just cover total grid costs and PV subsidies. SET stands for solar energy target, which is the percentage of household consumption produced by household PVs. The lines in the left hand plot correspond to all tariff combinations with the specified SET. The dots and asteriks show tariff combinations for different SETs ranging from 1% to 9%, with an interval of 0.5%.

This counterfactual provides some general conclusions on the efficiency and equity properties of volumetric charges and subsidies. From an efficiency perspective, installation cost subsidies are costly, as they require additional financing, whereas volumetric charges both incentivize PV adoptions and contribute to grid costs. Thus, a regulator that wants to achieve a solar energy target, while recovering network costs and minimizing aggregate expenditure, should finance subsidies and grid costs only with volumetric charges, setting fixed fees to zero. However, if the regulator prioritizes welfare maximization and minimization of equity distortions instead of minimization of aggregate expenditure, then it should follow a different approach. In fact, from a welfare perspective, higher volumetric charges generate a welfare loss by reducing energy consumption. Moreover, they have also a regressive effect by shifting grid costs to households without PVs, which tend to be poorer. For these reasons, we find that a regulator concerned with vertical equity should incentivize PV adoptions offering subsidies financed with a combination of volumetric charges and fixed fees. In fact, the latter make sure that subsidies and grid costs are financed by both households that adopt and don't adopt solar panels.

7 Conclusion

In this paper we propose an optimal tariff design for residential electricity markets facing an increasing penetration of PV installations and mostly fixed network costs. We derive this optimal design specifying a regulator's optimization problem that aims at guaranteeing vertical equity, under the constraints of both network financing and achieving a minimum solar energy target, in order to encourage a sustainable and equitable diffusion of distributed renewable energy generation. We consider alternative tariff schemes, because the increasing penetration of PV installations combined with a system of net metering and kWh based rates may not guarantee the financing of the energy infrastructure network in the long run.

To calculate these optimal tariffs we estimate models of energy demand and PV installation using a detailed dataset with 135,000 Swiss households in the Canton of Bern for the years 2008-2013. We adopt a regression discontinuity design to identify price elasticities, and estimate a structural dynamic model of PV adoption. We use the estimates of these models in a regulator's constrained optimization approach, in order to find the optimal tariff design to achieve a solar energy target, while preserving network financing and vertical equity. We conduct two main counterfactual simulations. First, we show that a benchmark increase in PV adoptions would generate a substantial missing revenue to finance fixed network costs, which would require an increase in volumetric charges with regressive consequences. Second, we calculate the optimal combination of variable prices, fixed fees, and subsidies to installation costs that would allow a policymaker to achieve a 2%, 3% , 5% or 9% solar energy target, guaranteeing network financing and an equitable distribution of grid costs across the income distribution. As for the optimal policy, we show that the regulator should rely on both variable prices and subsidies to stimulate PV adoption, while financing part of the subsidy cost through a rise in fixed fees. Furthermore, the model estimates that stimulating PV adoption is costly for the economy, ranging from 0.4 to 0.7 CHF per kWh of solar energy. However, with declining solar panel costs, the costs incurred by the regulator from subsidising photovoltaic installations are bound to decrease.

Despite our results being constrained by the extent of the institutional setting and available data, they open the floor for various other relevant questions that we hope will be addressed in the near future. First, our framework could be extended to consider longer term solar energy targets, incorporating the decline in installation costs for solar systems. Second, to better characterize the direction towards which various residential electricity markets worldwide are evolving, our model could be adapted to the case of a competitive market for retail and distribution of electricity. Third, more detailed data on grid costs could allow us to incorporate into our model the potential rise in network expenditure due to increasing PV adoptions, caused by the larger uncontrolled variance in inflow-outflow of energy produced by solar panels. Last, through the lens of our model, a regulator interested in maximising production of solar energy could consider heterogeneous subsidies for PV installation depending on buildings' sun exposure, favoring installations by households with the highest potential "solar power productivity". We regard each of these topics as worth of future research.

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Appendix For Online Publication

Appendix A1: Data Cleaning Process

We obtained a list of grid connections (i.e. energy meters) with their respective energy usage, energy infusion, customer information and some other household specific variables from all three energy providers. These data sets contain both households and businesses. With the support of the Tax Office of the Canton of Bern we were able to match the energy customer information with the tax data and the building characteristics data. This ultimately allowed us to create the final data set, which combines energy, income, wealth data and building information for each household. The data provided by the tax administration also includes additional household level information, such as household size, number of children, marital status, and whether the house is occupied by the owner.

The original list provided by BKW contains data on about 340,000 meters from 2008 to 2013. Of these meters we manage to match around 158,000 with tax information. The mismatches are mainly due to data imprecision and the BKW sample including businesses in addition to households. We then use the imperfect sector identifier of BKW[45] and drop meters of customers denominated as firms. Further, we drop meters with non-households tariffs and meters with energy consumption readings below 100 kWh.[46] We end up with a sample of 142,000 meters which we collapse to 125,000 households. As we only have the current address for BKW customers but historical personal information in the tax data, the matches steadily decline in the earlier years, as some households relocated during this time period.

For the city of Bern we use a list of about 97,000 grid connections from 2008 to 2014. Matching the data with tax information we end up with a sample of 58,000 meters. Of these we drop meters that do not match the customer address, meters using non-household tariffs and meters with close to zero readings. While from the BKW and ET we received annual consumption and infusion for each meter, the EWB was only able to provide individual readings.[47] We exclude readings significantly longer or shorter than a year as most households are checked on a regular 365 days basis. Ultimately we end up with 44,200 readings which we collapse to 44,100 households. The sample contains several customers for a meters with a change in households because the EWB provided us with historical personal information on their customers.

As for the city of Thun, we start with a list of about 29,000 grid connections per year between 2009 and 2014.[48] After the matching procedure we end up with 20,000 meters which we further reduce to 19,000 with adjustments equivalent to the other companies. Ultimately, we end up with data on 20,400 households.

The combined sample for the three companies includes energy and tax data on 185,000 households. We

[45] Imperfect as some small businesses are wrongly labeled as households.

[46] For comparison, a single person household usually with only one grid connection has a minimum energy usage of over 2,550 kWh per year.

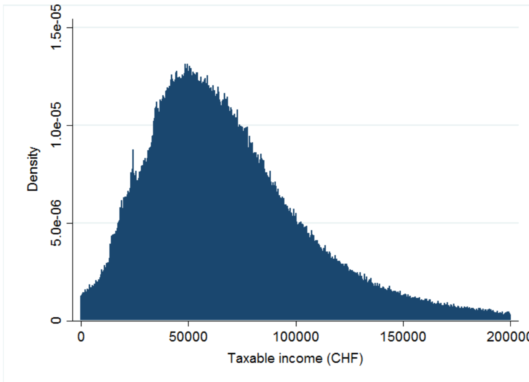
[47] The EWB reads different households meters at different times during the year and bills accordingly. BKW and EWB read all meters at the end of the year.

[48] Unfortunately the data prior to 2009 is not available due to a system change.

match the sample with information on buildings characteristics provided by the Swiss Federal Statistical Office. Doing so reduces the sample to 173,000 households due to data imprecision.

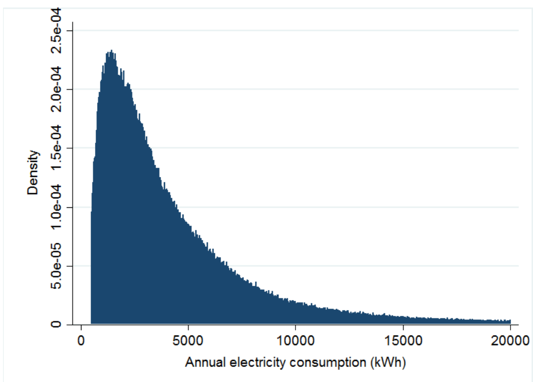
The final estimation and simulation sample includes several additional adjustments. First, we exclude all observations of households that relocate in the same year.[49] This adjustment should guarantee that we measure consumption for the full duration of 365 days. Second, we drop observations for households that change tariff schemes. Tariff changes are rare and are usually accompanied by simultaneous changes in appliances. Third, we drop households with multiple meters. Fourth, we drop observations with an annual energy consumption below 500 kWh and over 50'000 kWh to make sure we do not include private firms or farms. These adjustments ultimately reduce our sample to 135,000 households.

Figure 10: DISTRIBUTION OF TAXABLE INCOME



Note: The figure shows the distribution of taxable income in the sample. All observations with a taxable income below zero have been excluded from the sample. The maximum level of taxable income in this graph has only been chosen for illustrative purposes.

Figure 11: DISTRIBUTION OF ANNUAL ELECTRICITY CONSUMPTION

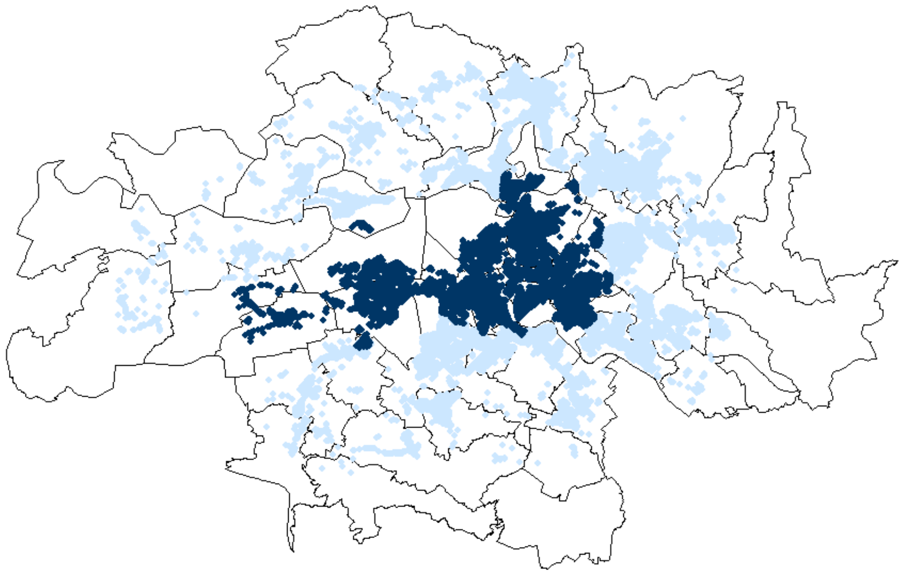


Note: The figure shows the distribution of annual electricity consumption in the sample. All observations with an annual consumption of less than 500 kWh have been omitted from the sample. Furthermore, the maximum annual consumption is set to 50,000 kWh in the sample. These limits have been chosen arbitrarily to ensure that only households (not firms) are included in the sample. In the graph the upper limit is set to 20,000 kWh for illustrative purposes.

[49] Households are identified as relocating if they change address in the tax data or if they enter or leave the sample.

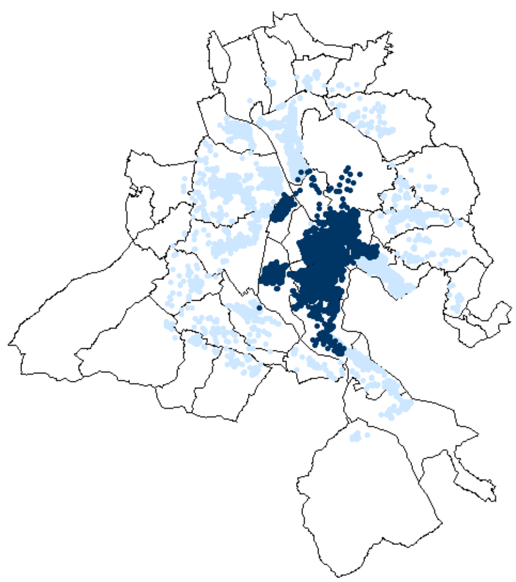
Appendix A2: Maps - Bern, Thun and Surroundings

Figure 12: Map City Bern (Households)



Note: The figure shows a map of the city of Bern and its surroundings. The dark blue area consists of all households in the sample supplied by EWB, while the light blue area shows the BKW customers.

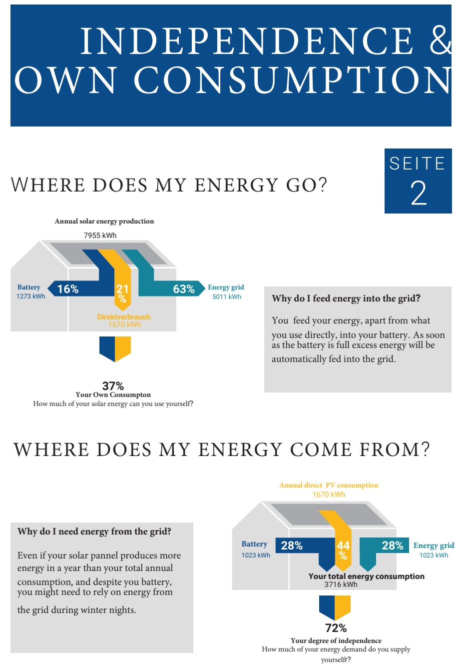
Figure 13: Map City Thun (Households)



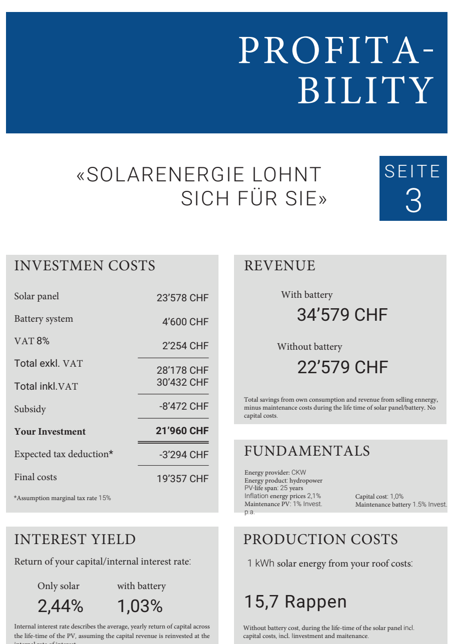
Note: The figure shows a map of the city of Thun and its surroundings. The dark blue area consists of all households in the sample supplied by Energy Thun, while the light blue area shows the BKW customers. The white area adjacent to the coverage of Energy Thun without any households shows the lake of Thun.

Appendix A3: Example of Eturnity Offer

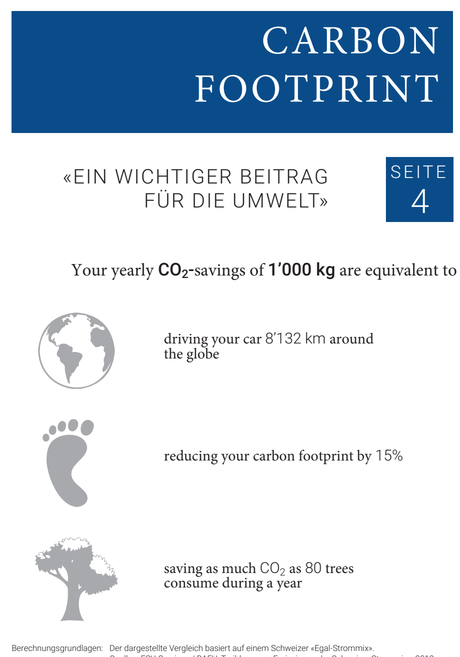
(a) PV installation investment preview



(b) Description of where the PV energy comes from and where it goes



(c) Breakdown of PV installation costs and energy savings



(d) Quantification of CO_2 saving

Appendix A4: Eturnity PV Simulation Method

1 Introduction

This document describes the formulae, methods and assumptions that were applied to the PV-system simulations that were ran in order to provide a solid basis for the interpretation of the results (PV Adoption Research PLZ.xlsx, PV Adoption Research Simulation.xlsx).

1.1 Consumption Profiles & Scaling

The simulations were run with a number of different load profiles that differ from each other by the heating and hot water system. The following table gives an overview for the yearly consumption of the load profiles that were used for the simulation:

Heating System	Hot Water System	Yearly Consumption (kWh)
electric	electric	18930.0
electric	heat pump	17649.3
heat pump	electric	11807.6
heat pump	heat pump	11188.8
oil/gas/wood/coal	electric	5136.0
oil/gas/wood/coal	heat pump	4041.0
oil/gas/wood/coal	oil/gas/wood/coal	3493.5

During the simulation, these profiles were scaled linearly to fit the yearly consumption of the consumption deciles that were provided as input data. This method will give unrealistic values for the consumption_peak_power_kw results for consumption deciles that differ from the physically reasonable values.

1.2 Heating System and Hot Water System

While running the simulations, it was noticed that the data input contained samples with the following rather rare combinations of heating and hot water system:

- Heating = Electric & HotWater = Oil/Gas/Wood/Coal
- Heating = Heat Pump & HotWater = Oil/Gas/Wood/Coal

Because these combinations are so rare, Eturnity does not have a validated load profile for such a combination. After having noticed that such combinations exist in the input data, we have tried to find out where they are coming from. We ended up with the best guess that probably "solar thermal systems" were classified under "Oil/Gas/Wood/Coal". With this assumption, we have then used load profiles that we consider reasonably accurate for the purpose of the research project to complete the simulations:

Original Combination (Heating system:Hot water system)	Used Combination for the Simulation (Heating system:hot water system)
electric:oil/gas/wood/coal	electric:heat pump
heat pump:oil/gas/wood/coal	heat pump:heat pump

1.3 Geo-Location

To determine the geo-location of each zip code we used an Open-Street-Map-Service. The search was based on the zip code and the city. The following addresses could not be found in Open-Street-Map and their latitude/longitude was identified manually:

- 3434 Obergoldbach
- 3435 Ramsei
- 3439 Ranflüh
- 3513 Bigenthal

1.4 Number of Solar Panels From Building Surface

The PV-simulation requires the number of panels, which had to be determined by the building surface that was given as input data.

Definitions:

building_surface ***A***	is defined by the floor plan of the building (see figure 1)
obstacle_factor ***of***	obstacle factor because of chimneys, etc. The obstacle factor was set to 0.9. This factor was determined by evaluating a larger number of roofs.
gable_roof_factor ***grf***	for simplicity, it was assumed that all roofs are gable roofs and that only one side of the gable roof can be covered with solar panels. This factor was set to 0.5.
roof_slope **rs**	30° (as per specification), roof slope of south-facing side of the gable-roof
panel_width ***pw***	1m (as per specification)
panel_length ***pl***	1.65m (as per specification)
number_of_panels **p**	number of panels used for the simulation

The following formula was used to approximate the number of panels:

$$p = \left\lfloor \frac{of \cdot A \cdot grf}{pw \cdot pl \cdot \cos(30°)} \right\rfloor$$

Figure 1: Example building surface

1.5 Determination of specific base yield for simulation

In order to keep the number of simulations as low as possible (around 900 instead of 350'000), all the simulations were ran for exactly one location. In order to determine which location was most representative for all of the locations specified we've used the median value of the collection of specific yields (kWh/kWp) for all the locations specified by the input data.

Median value: 1002 kWh/kWp
Location chosen for simulation: 3047 Bremgarten bei Bern

Appendix A5: Utility and Indirect Utility

We assume that household i in period t maximises its utility from consuming electricity c_{it} and the outside good q_{it}, subject to a budget constraint. We specify the following household's constrained optimization problem, omitting the subscripts for convenience:

$$\begin{aligned} \max_{c,q} \quad & u(c, q, I, X) \\ \text{s.t.} \quad & q + Pc \leq I \end{aligned} \tag{20}$$

where I and X are respectively household's income and other characteristics (wealth, size, etc..), P is the energy price. We normalize the price of the outside good to 1. We define the following functional form for households' utility:

$$u(c, q, I, X) = q + \frac{\beta}{\beta + 1} c^{\frac{\beta+1}{\beta}} I^{\frac{\gamma}{-\beta}} e^{\frac{X'\omega}{-\beta}}. \tag{21}$$

The first order conditions lead us to the following energy demand function (c^*) and optimal consumption of the outside good (q^*):

$$\begin{aligned} c^* &= P^{\beta} I^{\gamma} e^{X'\omega} \\ q^* &= I - P^{\beta+1} I^{\gamma} e^{X'\omega}. \end{aligned} \tag{22}$$

Accordingly, the indirect utility function can be expressed as:

$$v(P,I,X) = I - \frac{1}{\beta+1} P^{\beta+1} I^{\gamma} e^{X'\omega} = I - \frac{1}{\beta+1} P c^*. \tag{23}$$

In the structural model we distinguish between the two indirect utilities that a household derives depending on whether it has a solar panel on not. What differentiates the two indirect utilities is the income that a household has under each case. With no solar panel a household has an income of $I - f$, with f being the fixed fee, whereas with a solar panel a household has an income of $I - f + \tau Y$, with τ being the feed-in tariff, and Y being the solar panel production. Hence, the indirect utility we use for the structural model will be the following:

$$v(P,I,X,f,\tau,Y) = \begin{cases} I - f + \tau Y - \frac{1}{\beta+1} P^{\beta+1} \big(I - f + \tau Y\big)^{\gamma} e^{X'\omega} & \text{if } \mathcal{PV}_{it} = 1 \\ I - f - \frac{1}{\beta+1} P^{\beta+1} \big(I - f\big)^{\gamma} e^{X'\omega} & \text{if } \mathcal{PV}_{it} = 0. \end{cases} \tag{24}$$

Appendix A6: High/Low Tariff Share Prediction

We assume the marginal price of a double tariff household to be a weighted average of day and night consumption shares. Consequently, low daytime consumption shares correspond to low prices. This weighting allows for additional price variation in the elasticity estimation but also introduces a potential endogeneity bias, because the consumption pattern of a household might be closely related to its aggregate consumption. For instance, households with a high total energy consumption might have more flexibility to shift part of their consumption to night time. Similarly, the share of night time consumption is correlated with energy intensive appliances, such as electric boilers. To address this potential bias we use predicted consumption shares instead of actual consumption shares to construct prices for double tariff households. Specifically, we predict the consumption share of each double tariff household as a function of household and apartment characteristics, estimating the following OLS[50] regression:

$$htshare_{it} = \eta_0 + X^s_{it}\eta_1 + \epsilon^s_{it}. \tag{25}$$

[50] We assume a simple linear form of the share function. OLS performs well as the predicted values closely resembles the actual distribution of shares

where $htshare_{it}$ is the actual high (i.e. daytime) tariff share of household i, and X_{it}^{s} are household and apartment characteristics including income. We estimate the model separately for each provider for two reasons. First, BKW defines daytime consumption over shorter intervals than EWB and ET.[51]. Second, by allowing coefficients to vary across companies we add heterogeneity to prices, which is based on observable characteristics. Table 12 presents the results for the share prediction.

Table 12: ENERGY PRICE ELASTICITIES

Variables	**(BKW)**	**(EWB)**	**(ET)**
Income	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Wealth	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Home Owner	-0.00	0.04	-0.01
	(0.00)	(0.00)	(0.00)
Number of Rooms	0.01	0.01	0.01
	(0.00)	(0.01)	(0.01)
Number of Rooms Sq	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)
Apartment Surface	0.01	0.01	-0.02
	(0.00)	(0.01)	(0.01)
Constant	0.20	0.28	0.32
	(0.01)	(0.03)	(0.02)
Household Size FE	Yes	Yes	Yes
Household Age FE	Yes	Yes	Yes
Heating System FE	Yes	Yes	Yes
Water System FE	Yes	Yes	Yes
Apartment No. FE	Yes	Yes	Yes
Construction Period FE	Yes	Yes	Yes
Non-Positive Income/Wealth FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N Obs	263,688	49,604	54,295
R^2	0.178	0.245	0.375

Note: Standard errors in parentheses. Standard errors are clustered at the household level to account for serial correlation. Income and Wealth variables are in logs. Column (1) shows the results for BKW, Column (2) for EWB, and Column (3) for ET.

Appendix A7: Capacity Fixed Fee

We provide results for an additional counterfactual where the regulator decouples grid financing from energy consumption, only relying on fixed fees to cover grid costs. To reduce the regressive impact of the decoupling, we simulate fixed fees that are a function of a household's grid capacity. We solve the regulator's optimization problem for an exogenous increase in solar panels and without the solar energy target, that is choosing the optimal mix of volumetric charge and fee. When decoupling grid financing from energy

[51] Daytime consumption of BKW is from 7am to 9pm. Daytime consumption of EWB and ET is from 6am to 10pm.

consumption, we allow the fixed fee to be household specific, introducing a capacity fixed fee defined as follows:

$$f_i = \sigma_0 + \sigma_1 kW_i \tag{26}$$

where kW_i is the capacity of household i measured in kilowatt (kW), σ_0 is a uniform contribution and σ_1 a contribution per kilowatt. Capacity is defined as the maximum amount of energy a household is able to consume through the grid during a fixed time span (usually 15 minutes). Loosely speaking, capacity relates to the "size" or "strength" of the grid connection.[52] In order to isolate the distributional effects of f_i, in this counterfactual we don't simulate any adoption of solar panels, eliminate volumetric charges P_G, and assume that the regulator only decides on the share of total grid costs recovered with the capacity fee ($share_{cf}$). Thus, total grid costs GC_0 are spread among households as follows:

$$f_i = \underbrace{\frac{(1 - share_{cf})GC_0}{N}}_{\text{uniform fee}} + \underbrace{\frac{share_{cf} * kW_i * GC_0}{\sum_i kW_i}}_{\text{capacity fee}} \tag{27}$$

Table 13 reports shares of total grid costs for each income decile under the current scenario (variable price and fixed fee), as well as under two counterfactual scenarios: a capacity fixed fee and a combination of uniform and capacity fixed fee. We also report the percentage change in grid expenditure ΔGE_i and consumer surplus ΔCS_i across the income distribution. According to the current tariff scheme lower income deciles bear a smaller share of total grid costs. This implies that switching to a uniform fixed fee ($share_{cf} = 0$) would have adverse effects on poorer households. In the columns labelled "Capacity Fee" we show that a capacity fixed fee ($share_{cf} = 1$) also leads to higher expenditures for households up to the 5^{th} income decile. However, the additional burden for low income households under a capacity fixed fee is lower than with a uniform fixed fee. Last, we consider a combination of uniform and capacity fees ($0 < share_{cf} < 1$), as reported in the columns "Uniform & Capacity Fee". Here we calculate the optimal share of uniform vs capacity minimising the objective function of the regulator equivalent to Equation 19. We find that it is optimal for the regulator to finance $share_{cf} = 25\%$ of the grid cost with a capacity fee and the rest with a uniform fee, which leads to an increase in expenditure for households up to the 8^{th} income decile, and a reduction for richer ones. Overall, lower income deciles bear a larger share of total grid cost when decoupling grid financing from energy consumption. However, depending on the PV adoption trend they still might be better off compared to an increase in volumetric charges.

[52] One efficiency argument to rely on capacity fixed fees is that buildings with greater capacity usually require higher local grid investments. From a redistribution perspective, they host households with a larger number of appliances (and a higher energy consumption).

Table 13: GRID EXPENDITURE AND CONSUMER SURPLUS % CHANGE (BASE YEAR 2013)

	Current	Capacity Fee		Uniform & Capacity Fee	
Income Deciles	**Share**	**Share**	ΔGE_i	**Share**	ΔGE_i
1^{st} decile	8.4	9.1	6	9.8	29.4
2^{nd} decile	8.2	9.3	9.5	9.9	31.3
3^{rd} decile	8.7	9.3	4.1	9.9	25.7
4^{th} decile	9	9.6	2.5	9.9	22.6
5^{th} decile	9.6	9.7	-.4	9.9	16.8
6^{th} decile	10	10	-2.1	10	12.1
7^{th} decile	10.4	10.2	-4	10	8
8^{th} decile	11.1	10.5	-6.2	10.1	2.1
9^{th} decile	11.7	10.5	-10.1	10.1	-3.1
10^{th} decile	13	11.9	-8.4	10.4	-11.7

Note: All values in the table are in percent. The table illustrates the redistributive effect of switching to grid financing through fixed fees. The "Capacity Fee" columns show the effect of a capacity based fixed fee, while the "Uniform & Capacity Fee" columns include two different kinds of fixed fees, a uniform and capacity based fixed fee. Under the scenario with two fixed fees it is optimal to cover roughly 75% of total grid costs through a uniform fixed fee.

Appendix A8: Regulator's Optimization

The functional form of the PV adoption probability poses a challenge for the regulator's optimization. For each change in tariffs we need to recalculate the household's position in the state space, which substantially increases computational time. To circumvent this challenge, we solve the regulator's optimization problem sequentially. Based on preliminary simulations, we assume that the fixed fee does not impact the solar energy target constraint. This assumption allows us to simplify the problem and solve it in three steps. First, we let the regulator define a bounded set of combinations of variable tariffs and subsidies (P_G, s) to achieve the solar energy target. Second, for each of these combinations the regulator finds the unique fixed fee f necessary to satisfy the network financing constraint. Third, for each combination of variable tariff, subsidy and fixed fee (P_G, s, f) we calculate the regulator's objective function. We define as optimal instruments the combination of P_G, s, f that minimizes equity distortions relative to the status quo. Here are the details of each step:

1. *Solar Energy Target*: Knowing that the current variable tariff is around 0.1 CHF/kWh, we consider as feasible range of variable tariffs the one between 0 and 1 CHF/kWh, discretized by 0.001 intervals. For each value of the variable tariff we calculate the lowest subsidy needed to reach the solar energy target, where the subsidy ranges between 0% and 100% of installation costs, with 0.001% intervals. Specifically, we increase the subsidy until the share of solar energy reaches the desired threshold. This gives us 1001 combinations of variable tariff and subsidy (P_G, s). For high variable tariffs the generated revenue might exceed total grid costs. In that case we use the excess revenue to further increase the subsidy percentage, as is implied by the inequality of the solar energy target and the

equality of the network financing constraint. In this first step we hold the fixed fee constant, although it is a choice variable of the regulator and enters the solar energy target through the PV adoption probability and energy consumption.

2. *Network Financing*: In this step we impose the network financing constraint. For each P_G, s combination we calculate the total sum of fixed fees required by the energy provider to break even. The allocation of total fixed fees to individual households depends on the design of the fixed fee. We allow the regulator to choose the share of the fixed fee that is capacity-based vs uniform-based, as shown in equation (27). We discretize this share using 20% intervals, ranging from 0% to 100%. Hence, for each combination of variable tariff and subsidy there are 5 different combinations of capacity and uniform fixed fees. Ultimately, this step results in 5005 different feasible combinations of instruments, each including a variable tariff, a subsidy percentage, and a sum of capacity and uniform fixed fees.

3. *Equity Distortion*: Last, we calculate the regulator's objective function for all combinations of instruments defined in the second step, resulting in 5005 values for the objective function. We select the instruments with the lowest value of the objective function as the regulator's optimal tariffs, as those are the ones that minimize equity distortions relative to the status quo.