Welfare and Redistribution in Residential Electricity Markets with Solar Power*

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Abstract

Solar energy production has experienced an exponential growth worldwide over the last decade, mostly driven by government subsidies and declining solar panels' production costs. This is environmentally desirable, but an increasing number of households with solar power raises two challenges for regulators: network financing and vertical equity. First, these households still require network energy, leaving the fixed grid maintenance costs unchanged. However, producing their own energy, they contribute less to grid costs, mostly financed with consumptionbased tariffs. Second, these households are usually richer, shifting the burden of grid costs onto low income ones. In this paper we address these challenges proposing alternative tariff schemes that incentivize solar photovoltaic (PV) adoptions, while guaranteeing the sustainability and equitable distribution of network costs. We use a unique matched dataset on energy consumption, income, wealth, PV installations, and building characteristics for around 180,000 households in the Canton of Bern (Switzerland) in 2008-2013 to estimate models of energy demand and PV installation. Using counterfactual policy experiments we propose an optimal tariff design where the regulator achieves vertical equity, subject to a minimum green-energy target and a network financing constraint. We find that it is optimal for the regulator to stimulate PV adoption subsidising solar panels' fixed costs, financing this subsidy with an increase in both fixed grid fees and variable grid charges.

JEL-classification: D12; D31; L51; L94; L98; Q42

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

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1 Introduction

The reduction of greenhouse gasses 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 their own energy, these households contribute less to 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 180,000 households in the Canton of Bern (Switzerland) in 2008-2013 to estimate 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 that allows us to find the optimal combination of variable energy prices, fixed energy fees, and subsidies to PV installation costs to achieve a 1%, 3% or 5% solar energy target, guaranteeing network financing and an equitable distribution of grid costs across the income distribution.

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

 $^{^{1}}$ As of December 2016, 192 countries have signed the UNFCCC Paris Agreement, a negotiated effort 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.

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

tial 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 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 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.

This issue also applies to the subsidies for solar panel installations, and to the way these are financed. Most European Union members, the United Sates, and Switzerland have introduced feedin tariff programs for small scale renewable generation. These programs compensate producers for generating their own energy at a fixed electricity rate, which usually exceeds wholesale energy cost and is often financed by a surcharge paid on the electricity bill. Under a system of net metering where end users are allowed to consume the energy they produce, the owners of PV installations save not only on the per kWh charges that are used to recover fixed network transmission and distribution costs, but also on the surcharge that finances the feed-in tariff. This differential cost burden for households of different income levels raises questions about the vertical equity of the system, which may be discriminatory towards low income households, less able and less incentivized to finance PV installations.

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

⁴One CHF is around one USD.

⁵On 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.

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 change by the Swiss government from a feed-in system to installation subsidies, we decided to just focus on the latter.

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 neighbouring 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 simulate a benchmark scenario where all home owners in our data install a solar panel, calculating 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 140% to recover the missing revenue, and this increase would be borne mostly by low income households. In the second counterfactual 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 would make grid financing more progressive. In the last 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 1%, 3%, and 5% solar energy production targets, while recovering network costs and preserving vertical equity. To meet each of those targets, we find that it is optimal for the regulator to subsidize respectively 30%, 44%, and 51% of solar panels' fixed installation costs, financing this subsidy with a 6.6%, 20.6%, and 28.3% increase in fixed grid fees, and a 1%, 12.2%, and 34.7% rise in variable grid charges. 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.

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 with 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.

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 installation.⁶ 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 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.

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

⁶This debate and our approach are also valid for the diffusion of any energy efficient technology. In fact, under a system of volumetric charges households have an incentive to adopt any technology that allows them to consume less, which reduces energy demand and erodes utilities' revenues to finance the grid. For the same reasons explained for PVs, richer households are more likely to invest in these technologies, shifting the grid financing burden onto poorer households.

⁷This 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).

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

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, a number of other European countries (Italy and the UK 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 energy consumption cross-sectional survey data for 1,300 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. The richness of our data allows us to precisely estimate heterogeneous price elasticities across the income distribution. Ignoring this dimension of heterogeneity in price elasticities may underestimate the variance of the impact of energy price changes across consumers, distorting the welfare impacts of policy simulations.

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

⁹Papers 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).

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, as well as the different electricity bills. 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. Last, with data on PV production and households' energy consumption we can simulate several solar energy targets that a policymaker can achieve.

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 will only be 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 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 Canton of Bern (Switzerland) that combines yearly household level energy consumption, income, wealth, PV installations, and buildings' characteristics. With an area of around 6,000 km² 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, on 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.

¹⁰Related to our work, Dubin, 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.

Households in the Canton of Bern receive the electricity bill once a year. This is divided into a fixed fee, charged 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. Residential customers of two of the three operators (BKW and EWB) can only choose between a uniform tariff and a day-night tariff, with higher rates during the day. All households in the jurisdiction of Energie Thun, the third main operator in the Canton, are subject to a two part tariff. Table 1 reports the detailed price components for BKW for the years 2008-2013.¹¹

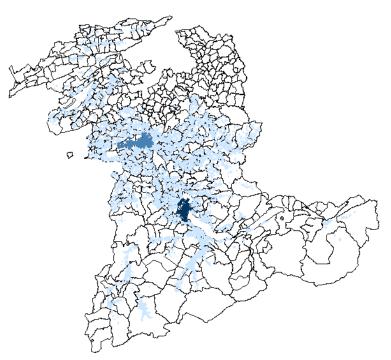
Table 1: ENERGY PRICES,	Network '	TARIFFS AND	TAXES -	BKW
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Variables	2008	2009	2010	2011	2012	2013
Double Tariff						
Energy Price HT (Rp/kWh)	11.57	11.57	11.57	12.16	12.2	11.88
Energie Price LT (Rp/kWh)	7.21	7.21	7.21	7.21	7.24	7.78
Grid Price HT (Rp/kWh)	10.48	11.29	11.29	11.13	9.18	9.18
Grid Price LT (Rp/kWh)	3.77	4.2	4.2	5.54	4.59	4.59
Grid Basic Fee (CHF)	180.67	180.66	180.64	141.97	123.08	123.12
Uniform Tariff						
Energie Price (Rp/kWh)	11.03	11.03	11.3	11.78	11.83	11.77
Grid Price (Rp/kWh)	10.49	11.3	11.3	10.6	8.91	8.91
Grid Basic Fee (CHF)	142.03	142.03	142.03	122.66	103.68	103.68
Both Tariffs						
Swissgrid (Rp/kWh)	0	0	0	0	.43	.33
KEV (Rp/kWh)	.16	.48	.48	.48	.49	.49
Municipal Tax (Rp/kWh)	1.59	1.59	1.59	1.59	1.6	1.6

Note: The table shows average prices in the sample. HT stands for "High Tariff" and LT stands for "Low Tariff". 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.

¹¹The corresponding numbers for EWB and ET are presented in Appendix 2.

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 the 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 2 presents descriptive statistics of households' energy consumption 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 4,942 kWh. Rows 5-12 in Table 2 display summary statistics for the different expenditure components of the electricity bill. The average annual household expenditure is CHF 1,059, most of which goes to energy price expenditures (46%) and network charges (45%).

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.¹² Table 3 provides summary statistics for different measures of income and household tax payments.

 $^{^{12}}$ The process of matching energy consumption and income data led us to the final sample of around 180,000 households. We describe in detail in Appendix 1 the assumptions we made during the data merging process.

Variables	N Obs	Mean	Std Dev	5th Perc	Median	95th Perc
Energy Consumption (kWh)	789,098	4,942	5,289.5	877	3,261	15,054
Consumption HT	495,915	2,820.7	2,432.9	591	2,161	7,417
Consumption LT	496,000	$3,\!588.2$	4,352.6	318	2,436	11,664.8
Consumption UT	$306,\!654$	2,352	1,721.5	702	1,931	5,308.4
Energy Expenditure (CHF)	789,098	1,058.9	872.9	293.6	791.9	2,821.4
Energy Price Expenditure	789,098	484	461.6	98.1	343.7	1,394.7
Price Expenditure HT	495,916	328.7	269.3	71	257.6	838.7
Price Expenditure LT	496,001	266	318.8	26.7	181.7	856.3
Price Expenditure UT	$306,\!656$	265.9	194.5	79	217.9	603.2
Grid Expenditure	789,098	481.6	345.5	146.7	382.3	1,184.8
Tax Expenditure	789,098	70.3	72.2	2.5	51.5	201.7
KEV Expenditure	789,098	21.6	24.4	2.9	13.9	67.1

Table 2: Energy Consumption and Expenditure

Note: The descriptive statistic is pooled over all companies and years. 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 shares (HT), low tariff shares (LT) and uniform tariff shares (UT). High and low tariffs are part of the double tariff scheme.

Variables	N Obs	Mean	Std Dev	5th Perc	Median	95th Perc
Total Income	789,098	99,061	125,027	26,416	82,428	209,727
Taxable Income	789,098	76,100	114,195	19,339	$63,\!556$	161,909
Total Wealth	789,098	542,563	2531557	0	259,016	1,696,888
Cantonal Tax	789,098	7,507	13,989	213	5,559	19,228
Municipal Tax	789,098	3,869	6,769	113	2,915	9,801
Federal Tax	789,098	1,788	9,206	0	499	6,530

Table 3:	INCOME,	WEALTH AN	d Tax	Payments
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Note: The table shows descriptive statistics for the sample pooled over all years. All variables are measured in Swiss francs (CHF). Negative income observations have been excluded from the sample. 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).

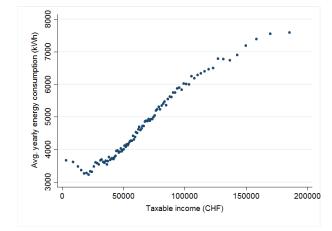
Table 4 reports the average energy consumption, energy expenditure, and the share of taxable income spent on energy by income decile. The table also displays the proportion of owner occupied housing, the average household size in each decile, the fraction of households with retirees, as well as the share of households who own a PV installation in each income decile. The last four rows report building or apartment characteristics relevant for energy consumption: the number of rooms, the apartment surface, and whether electricity is used for heating or hot water. 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 3,443 kWh per year, whereas those in the highest one have an yearly consumption of 7,817 kWh.

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Table 4: Energy and Household Characteristics by Income Decile

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.¹³ Supporting evidence of our argument that richer households are more likely to install a solar panel is given by the home ownership and one-apartment building dummy variables. Among households in the first income decile, only 23% are home owners and 15% live in a single house, whereas among households in the top income decile 76% are home owners and 51% live in a single house. Moreover, these two proportions are monotonically increasing across the income distribution. 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 (3,261 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 on 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.

 $^{^{13}}$ Figures with the distributions of taxable income and annual electricity consumptions are in Appendix 1.

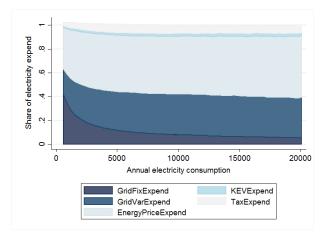


Figure 3: EXPENDITURE SHARE OF TARIFF ELEMENTS BY CONSUMPTION

Note: GridFixExpend corresponds to the yearly fee households are billed to be connected to the grid irrespective of energy consumption. GridVarExpend 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

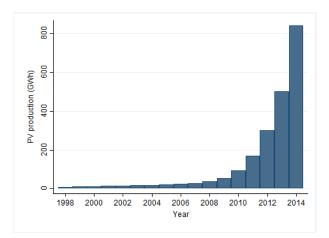
Between 2005 and 2013 PV production in Switzerland increased by 40 times, from 21 GWh to 500 GWh.¹⁴ A key driver of this growth was the introduction in 2008 of the feed-in tariff remuneration system. The incentive scheme was designed to last for 25 years, with tariffs varying depending on the type of 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,¹⁵ 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.¹⁶ Figure 4 presents the evolution of PV electricity generation in Switzerland between 1990 and 2014.

 $^{^{14}}$ In 2014 the energy produced by PV installations in the EU amounted to 6,953 in 1,000 tons of oil equivalent and in the United States to 6,201 MW.

 $^{^{15}}$ In 2014 tariffs ranged between 0.172 CHF/kWh for ground-mounted installations larger than 1,000 kW to 0.304 CHF/kWh for building integrated PV installations between 10 and 30 kW of size.

¹⁶The 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).

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.

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 various moments of the distribution of data on PV installations. In total 1,080 households in our dataset own PV installations. 986 of them are BKW customers, 19 EWB, and the rest Energie Thun.

Table 5:]	ΡV	Energy	PRODUCTION	AND	REMUNERATION
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Variables	N Obs	Mean	Std Dev	Min	Median	Max
PV Production (kWh)	2,785	6,304	$6,\!537$	0	4,800	94,100
PV Income (CHF)	2,785	2,481	2,308	0	2,064	27,327
PV Owner	2,568	.593	.491	0	1	1

Note: The descriptive statistic is 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 Income 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 his energy to the BFE. Matching to the KEV list was not possible (due to all installations having the same post code).

Figure 8 depicts the distribution of the PV installations in the BKW dataset by income decile. We notice an almost monotone increase in the frequency of PV installed over the income distribution. The density almost quadruples between the second and 10th income deciles, where the frequency of PVs installed for households earning more than CHF 130,000 is 24%.

Finally, we assembled a novel dataset on potential energy production of solar panels, estimated

installation costs, and on households' consumption profiles with the support of Eturnity AG, a Swiss startup company that provides an advisory platform for solar energy systems. 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.¹⁷

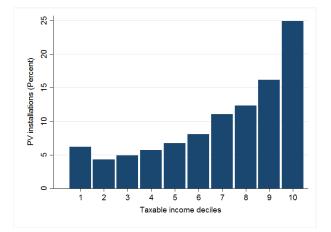


Figure 5: DISTRIBUTION OF PV INSTALLATIONS BY INCOME

Note: The graph shows the distribution of PV installation by income. The height of the bars corresponds to the percentage of PV installation in the sample for each taxable income decile.

Eturnity simulated for us potential household consumption profiles depending on a combination of heating system and hot water system, which can be both either electric, with heat pump, or with oil/gas/wood/coal, and decile of yearly energy consumption in kWh. These consumption profiles include average household-type specific day and night consumption, which we will use when estimating households' energy demand to weight households' day vs night marginal prices, as well as monthly consumption peaks, that we will use to simulate a capacity fixed fee in the counterfactuals.¹⁸ Eturnity then simulated the potential production of a rooftop solar panel for each building in our data, based on an approximate size of the PV given the building surface, as well as on the zip code of the building, which Eturnity 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. Capacity is defined as the maximum energy consumption of a household in a fifteen minutes interval based on buildings characteristics and appliances. It varies widely across households ranging from 1.6 kW up to 81.7 kW. Average yearly energy production of solar panels amounts to 17,090 kWh, which corresponds to

¹⁷See Appendix 4 for a template of the kind of price and production quotes that Eturnity can provide to a household. For more information visit www.eturnity.ch.

¹⁸A monthly consumption peak is defined as the 15-minutes interval within that month with the highest recorded kilowatt use.

more than three times the energy consumption of an average household. It is directly proportional to the peak power of the solar panel. This variation is essentially driven by rooftop area that leads to the installation of solar panels of different sizes. Of this energy production only 18.2 percent can be directly consumed by a household, while the rest is necessarily fed into the grid. On average, households can produce roughly 50% of the energy they consume themselves. Last, Table 7 displays the feed-in tariff (KEV) remunerations and the estimated installation costs across time and across size in kWp of solar panel. The time series variation shows the trade-off that households faced, between declining feed-in tariffs and declining installation costs.

Variables	N Obs	Mean	Std Dev	5^{th} Perc	Median	95 th Perc
Capacity (kW)	735,148	11.9	19.9	1.6	5	81.7
PV Prododuction (kWh)	$730,\!149$	17,090.4	$13,\!821.2$	5,408.4	14,789.5	$35,\!879$
% for Own Consumption	$735,\!143$	18.2	22.5	.2	9.5	79.8
% Autonomy	$735,\!143$	45.4	15	16	46.3	62.5

Table 6: SIMULATED CAPACITY AND ENERGY PRODUCTION

Note: The variables show simulated capacity and potential energy production across households. Values are simulated based on roof size, appliances and geographic location.

	2009	2010	2011	2012	2013
Feed-In Remuneration (CHF/kWh)					
$kWp \le 10$	0.75	0.62	0.48	0.4	0.33
$10 < kWp \le 30$	0.65	0.53	0.47	0.37	0.27
$30 < kWp \le 100$	0.62	0.51	0.42	0.35	0.25
kWp > 100	0.60	0.49	0.38	0.32	0.23
Installation Cost (CHF/kWp)					
$kWp \le 2$	9,117	$7,\!805$	$5,\!259$	$3,\!103$	2,831
$2 < kWp \le 5$	8,448	$6,\!837$	5,188	$3,\!189$	2,664
$5 < kWp \le 10$	8,274	6,013	5,096	$3,\!118$	2,665
$10 < kWp \le 15$	8,748	6,048	4,942	2,938	2,627
$15 < kWp \le 20$	6,861	6,043	4,874	3,016	2,555
$20 < kWp \le 30$	6,836	$5,\!899$	$4,\!687$	2,660	2,423
$30 < kWp \le 50$	6,949	$5,\!679$	4,616	2,590	2,403
$50 < kWp \le 75$	-	5,420	4,182	2,723	2,331
$75 < kWp \le 100$	6,040	$4,\!668$	4,158	2,505	2,200
kWp > 100	5,830	$4,\!622$	3,936	2,423	1,836

Table 7: FEED-IN REMUNERATION AND AVERAGE INSTALLATION COST

Note: The upper part of the table shows remuneration fees for on-roof solar panels in Switzerland, source Swiss Federal Office of Energy (SFOE). The lower part depicts average installation costs collected by an annual survey published by the company PhotovoltaikZentrum für Solarmarketing (http://www.photovoltaikzentrum.de/).

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:

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

$$V(S_1) = \max_{\substack{c(S_t), q(S_t), \mathcal{PV}(S_t) \\ \text{s.t.}}} \sum_{t=1}^{\infty} \rho^{t-1} E \left[u(c_t, q_t, \mathcal{PV}_t, S_t; \Lambda) - C(\mathcal{PV}_t, S_t; \theta) + \varepsilon(\mathcal{PV}_t) \Big| S_1 \right]$$
(2)

where $u(.;\theta)$ is a household's utility from energy consumption c_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 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. Last, we normalize 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,¹⁹ with the budget constraint defined in equation 2, that gives us the following energy demand function:

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

$$\ln(c_{it}) = \alpha + \beta \ln(P_{ut}) + \gamma \ln(I_{it} - f_{ut} + \tau_t Y_{it}) + X'_{it}\omega + \nu_{it}.$$
(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:

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

where \hat{c}_{it}^1 and \hat{c}_{it}^0 are predicted energy consumptions for households, respectively with and without a solar panel, based on equation 3. To simplify 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.²⁰ 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 $v_{it}^{1R} = \tau_t Y_{it}$, 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 $v_{it}^{1C} = -\frac{1}{\beta+1} P_{ut} \hat{c}_{it}^1$. This substantially reduces the state space, as it implies that

¹⁹In Appendix 5 we show the functional form of the utility function, deriving energy demand and indirect utilities.

²⁰In the estimation we actually eliminate the term $I_{it} - f_{ut}$ from each indirect utility, as this is invariant to the adoption decision.

instead of forming expectations over the evolution of P_{ut} , I_{it} , f_{ut} , τ_t , 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 $C(\mathcal{PV}_{it}, S_{it}; \theta) = \theta F_{it}$.

Based on this, in the second stage we estimate the transition probabilities of all the state variables in the simplified model \tilde{S}_t with an autoregressive process of order one for each, using the estimated parameters of these processes $\hat{\delta} = \{\hat{\delta}_{v1R}, \hat{\delta}_{v1C}, \hat{\delta}_{v0}, \hat{\delta}_F\}$ as inputs for the dynamic model in the next step.

In a standard regenerative optimal stopping problem, as in Rust (1987), 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:

$$PDV_{it} = \sum_{s=1}^{25} \rho^s (1-\zeta)^s \tau_t Y_{it} + \sum_{s=26}^{\infty} \rho^s (1-\zeta)^s \widehat{\delta}_{v1C}^s P_{ut} Y_{it} + \sum_{s=1}^{\infty} \rho^s \widehat{\delta}_{v1C}^s \Big[-\frac{1}{\widehat{\beta}+1} P_{ut} \widehat{c}_{it}^1 \Big], \quad (6)$$

where $\hat{\delta}_{v1C}$ is the parameter of the AR(1) for v_{it}^{1C} , ρ is the discount factor, and ζ is the panel's degrade factor.²¹ The part of the v_{it}^1 indirect utility that captures the revenue from selling energy to the grid ($v_{it}^{1R} = \tau_t Y_{it}$) 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. Households form expectations about the evolution of PDV_{it} following $\hat{\delta}_{v1R}$ for the revenue during the feed-in period (first term on the right hand side of equation 6), and following $\hat{\delta}_{v1C}$ for the other terms.

To summarize, our state variables are $\tilde{S} = \{v^{1R}, v^{1C}, v^0, F\}$, and all evolve according to a first order autoregressive process. Following Rust (1987), we assume conditional independence, such that the Markov transition probability of the state variables can be expressed as:

$$p(\widetilde{S}',\varepsilon'|\widetilde{S},\varepsilon;\delta,\lambda) = p_1(\widetilde{S}'|\widetilde{S};\delta)p_2(\varepsilon'|\widetilde{S}';\lambda)$$
(7)

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

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

²¹We set the degrade factor to 3% for the first year and 0.7% for the following years, up to 25 years. We take this 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.

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:

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

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

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

We recover the parameters of the utility function θ, μ that maximize the following log-likelihood function:

$$L(\theta) = \sum_{i} \sum_{t} \log \left[\Pr(\mathcal{PV}_{it} | \widetilde{S}_{it}; \theta) \right].$$
(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 of interest, is understanding what is 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, all the three providers offer a uniform tariff, under which marginal and average prices are equivalent. The only potential non-linearity in marginal prices comes from the option that BKW and EWB propose of a dual tariff, with lower charges during the night. We focus on the marginal price for each customer, corresponding to the sum of all variable tariff components (energy, grid, taxes). For the double tariff, we assume that the marginal price is a weighted average of the high and low tariff, with weights given by the household-specific day vs night consumption profiles simulated by Eturnity.

However, failing to model households' choice of uniform vs double tariff, and conditional on double tariff their choice of consumption during the day vs night, is likely to introduce two sources of bias in our estimation of price elasticities. First a selection bias, as households experiencing a positive shock to their energy demand are more likely to switch to a double tariff scheme and adjust their consumption to the lowest tariff, which reduces their marginal price. Second an endogeneity bias, as conditional on being in a double tariff, a customer hit by a positive shock to energy demand may shift consumption from day to night, reducing her marginal price. Both of these would induce a negative correlation between demand shocks and the energy price, generating a downward bias in our price coefficient. We do however observe in our data that the choice of uniform vs double is highly correlated with the type of heating or water systems that households have. For example, nearly 100% of households that don't have an electric heating system opt for a uniform tariff. We therefore assume that controlling for household and building characteristics in our model limits the extent of the selection and endogeneity bias described above.²²

There is another dimension of potential endogeneity that we focus on. In our setting each utility adjusts prices once a year, which implies that with only 3 utilities and 6 years of data we have little variation in prices that we can exploit for identification, and cannot include utility-year fixed effects.²³ So if households in the area served by BKW face tougher weather conditions during one year compared to those served by EWB, then the former will demand more energy, which might require BKW to import more energy or produce more with its marginal (more expensive) power plants, driving BKW's prices up. This will induce a positive correlation between demand shocks and energy price at the utility-year level, generating an upward bias in our price coefficient.

We address this identification concern with a geographical boundary regression discontinuity design (RDD), similarly to Black (1999) and Ito (2014), and with 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-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.²⁴ We are able to exploit time-series and especially cross-sectional variation at the spatial discontinuity of the three different electricity service regions within the same Canton. Issues such as omitted variable bias or potential sorting at the border which may be problematic with a RDD (Lee and Lemieux (2010)) are unlikely to affect our design for two reasons. First, households in the Canton of Bern are not allowed to choose their energy provider, and it is very unlikely that they will sort based on their energy bill. Our estimation strategy will account for boundary-year fixed effects to correct for between service area unobserved heterogeneity. Second, in the MBDD we inverse-weigh our observations such that households that are close neighbors receive a larger weight, following Gibbons, Machin, and Silva (2013).

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. Using geographical information in terms of latitude and longitude we determine for each household its spatial location. 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's located up to 1 km from it on either side of the border.²⁵ Based on this design the new specification becomes:

$$\ln(c_{it}) = \alpha + \beta \ln(P_{ut-1}) + \gamma \ln(I_{it} - f_{ut-1} + \tau_t Y_{it}) + X'_{it}\omega + \xi_{bt} + \nu_{it},$$
(12)

²²We leave for future research modelling households' choices to improve the energy efficiency of their home other than PV installation, or to adopt an electric heating system.

²³This limited time series variation also prevents us from using household fixed effects, which absorb all the crosssectional variation and make it hard for us to identify price coefficients out of only 6 time-series data points.

²⁴The maps in Appendix 3 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.

 $^{^{25}}$ We experimented with alternative distances (250 meters, 500 meters, 1.5 km) finding similar results.

where ξ_{bt} are boundary-year fixed effects, absorbing all time varying unobservable determinants of energy consumption specific to the border point area. These fixed effects will capture location-year specific unobservables, like weather conditions in the previous example, which are likely to equally affect households' consumption at the border, but not equally affect prices. Differently from equation 4, here we assume that households respond to lagged prices and fees. 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 marginally 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, as they receive their electricity bills for the previous year at the beginning of the new year.

When we extend the geographical 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 stage we regress energy consumption for household i assigned to border point b and utility u at time t on all covariates but energy price:

$$\ln(c_{ibut}) = \alpha + \gamma \ln(I_{it} - f_{ut-1} + \tau_t Y_{it}) + X'_{it}\omega + \pi_t + \nu_{ibut}$$

$$\tag{13}$$

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:

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

where *i* corresponds to a households of EWB/ET and *i'* corresponds to the matched counterfactual observation of the BKW. Thus, in a first step we regress energy consumption on the full set of controls for the subsample of all observations within 1 km of the predefined border but exclude the price as independent variable. Then, we create a counterfactual for each ET/EWB observation which is a distance-weighted average of the 50 nearest BKW observations²⁶. In a second step we regress the difference of the unexplained variation in energy consumption ($\hat{\nu}_{ibut} - \hat{\nu}_{i'bu't}$) 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 neighbors.²⁷ 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. Differently from equation (12), in specification (??) we eliminate common area specific trends by spatial differencing, and account for the distance between households on opposite sides of the border.

Table 8 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

²⁶The observations need to have the same assigned border point.

 $^{^{27}\}mathrm{In}$ this specification we compute standard errors clustered at the boundary-year level.

the service area of BKW and ET. These characteristics don't differ significantly from the same observables in the full sample.

Variables	Full Sample	< 1km Bo	rder Bern	< 1km Bo	rder Thun
	-	BKW	EWB	BKW	\mathbf{ET}
Energy Consumption (kWh)	4,058	3,229	2,996	4,437	4,239
	(3,666)	(2,817)	(2,950)	(3,497)	(4,521)
Home Ownership	.41	.32	.25	.55	.59
-	(.49)	(.47)	(.43)	(.5)	(.49)
Household Size	× /		× ,		
1	.43	.47	.53	.38	.4
	(.5)	(.5)	(.5)	(.49)	(.49)
2	.35	.33	.3	.38	.38
	(.48)	(.47)	(.46)	(.48)	(.48)
3	.08	.08	.07	.09	.08
	(.28)	(.27)	(.26)	(.29)	(.27)
4	.1	.09	.08	.11	.11
	(.3)	(.29)	(.27)	(.31)	(.31)
5	.03	.03	.02	.04	.04
	(.18)	(.17)	(.15)	(.19)	(.2)
Heating System					
Electric	.04	.02	.03	.04	.04
	(.19)	(.13)	(.16)	(.2)	(.2)
Heat Pump	.05	.04	.01	.1	.05
	(.22)	(.2)	(.1)	(.31)	(.21)
Oil/Gas/Coal	.91	.94	.96	.86	.91
	(.29)	(.24)	(.19)	(.35)	(.28)
Water System					
Electric	.39	.27	.32	.42	.24
	(.49)	(.44)	(.47)	(.49)	(.43)
Heat Pump	.03	.03	.02	.04	.03
	(.16)	(.18)	(.13)	(.2)	(.18)
Oil/Gas/Coal	.58	.7	.67	.54	.73
	(.49)	(.46)	(.47)	(.5)	(.44)
Number of Rooms	3.74	3.58	3.4	3.9	3.95
	(1.14)	(1.15)	(1.1)	(1.08)	(1.13)
Apartment Surface (sqmt)	98	93	88	105	103
	(40)	(38)	(34)	(40)	(41)
Income (CHF)	$72,\!897$	$80,\!156$	$75,\!680$	71,029	$75,\!453$
	(114, 438)	(88, 183)	(82, 313)	(61, 417)	(65,702)
Wealth (CHF)	$474,\!057$	$512,\!093$	436,272	$487,\!087$	$578,\!010$
	(2,144,077)	(2,708,309)	(1, 864, 227)	(1,004,514)	(1,066,666)
N Obs	669,345	58,778	55,281	12,832	$11,\!189$

Table 8: HOUSEHOLD CHARACTERISTICS AT CITY BORDERS

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 to closer than 1km to the border.

5 Results

5.1 Energy Demand Model

We report the results of the most basic OLS regression in column (1) of Table 9. In columns (2) to (3) we include respectively year and household fixed effects. In all specifications we control for apartment/building characteristics, such as the number of rooms, the apartment's surface, and the building's construction period. We also include 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. Last, we control for household's income and wealth, its size, and home ownership. We can see from Table 9 that household fixed effects explain a large part of the variation in energy consumption, as the R^2 increases from 0.49 to 0.97 once we include them. This highlights that most of the variation in our data is cross-sectional, but as we have little time series variation in prices we decide to focus on the geographic RDD specification in column (4) as our preferred one. As expected, we find that richer households consume more energy, as a 1% increase in income increases electricity consumption by around 1%. We also find that larger and wealthier households, 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.

The price elasticity of demand is negative and significant, declining in absolute terms from around -0.8 to -0.2 only when we control for household fixed effects. In our RDD specification the elasticity decreases to nearly -0.9, confirming our prior of an upward bias described in Section 4.1. In Figure 6 we plot the price elasticity across the income distribution, estimated using our RDD specification, which shows that households in lower income deciles are more price elastic. Elasticities vary from around -1.2 for households in the first income decile to around -0.6 for households in the tenth income decile.

In columns (4), (5), (6) we report the results of the RDD and MBDD estimation strategies respectively. In these columns we focus only on the subsample of households residing within 1 km on each side of the border.²⁸ This leads to a smaller sample size, around 20% of the total sample. Column (4) reports the results for equation (12) including border-year fixed effects. In column (5) we display the results for the first stage of the matched boundary discontinuity design, as of equation (13). Column (6) reports the results of the second stage of the MBDD, as of equation 14. The elasticity reported for the MBDD estimation strategy is -0.31. With this approach however our sample shrinks considerably, as the number of observations decreases to 38,771, corresponding to around 7% of the total sample. Given the small sample size of the MBDD estimates, we consider these results as robustness checks and will instead use the results of column (4) in Table 9 as our preferred ones for the counterfactual analysis.

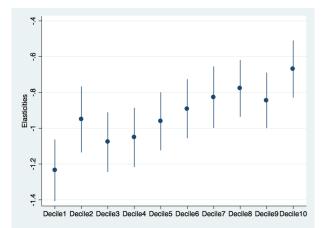
 $^{^{28}}$ We experimented with other distances, like 250 meters, 500 meters, and 1.5 km, with similar results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Price	78***	81***	26***	89***		31***
	(0.01)	(0.01)	(0.01)	(0.03)		(0.12)
Income	01***	01***	.01***	.01**	00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	
Wealth	.00***	.00***	00	.00**	.00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Home Owner	.24***	.23***	.02***	.13***	.17***	
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	
Number of Rooms	.21***	.21***	.33***	.14***	.16***	
	(0.00)	(0.00)	(0.12)	(0.01)	(0.01)	
Number of Rooms Sq	01***	01***	03**	00*	00**	
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	
Apartment Surface	.00***	.00***	.00	.00***	0.00***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Constant	6.57***	6.50***	7.23***	5.97^{***}	7.57***	
	(0.04)	(0.04)	(0.32)	(0.08)	(0.07)	
Household Size FE	Yes	Yes	Yes	Yes	Yes	No
Heating System FE	Yes	Yes	Yes	Yes	Yes	No
Water System FE	Yes	Yes	Yes	Yes	Yes	No
Construction Period FE	Yes	Yes	Yes	Yes	Yes	No
Year FE	No	Yes	Yes	No	Yes	No
Household FE	No	No	Yes	No	No	No
Border-Year FE	No	No	No	Yes	No	No
N Obs	500,660	500,660	500,660	102,226	102,295	38,771
R^2	0.487	0.488	0.965	0.505	0.470	0.015

 Table 9: Energy Price Elasticities

Note: Significance levels: *** 0.01, ** 0.05, * 0.1. Standard errors in parentheses. Log of total yearly energy consumption is used as dependent variable. Price and Income variables are in logs, wealth is in levels. Column (4) shows the results for the RDD model. Columns (5) and (6) show respectively the first and second stage of the MBDD.

Figure 6: 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 (4) of Table 9.

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,²⁹ 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 70 intervals of length, respectively of 200, 1,500,³⁰ and 1,000 CHF. 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 10. 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 0.74 shows that installation costs are declining over time, whereas a value of δ_{v1R} of 0.81 implies that the revenue component of the indirect utility from adopting is reducing over time, driven by the decrease in feed-in tariffs.

Parameter	s
δ_{v0}	.99***
	(0.00)
δ_{v1R}	0.81^{***}
	(0.00)
δ_{v1C}	0.99^{***}
	(0.00)
δ_F	0.74^{***}
	(0.00)
θ	.99***
	(0.03)
N Obs	64,808

Note: Significance levels: *** 0.01, ** 0.05, * 0.1. Standard errors in parentheses.

²⁹PV systems are more likely to be adopted in non-urban areas, which are the ones served by BKW.

³⁰We actually discretized the present discounted value variable PDV, which is the sum of current and future indirect utilities from adopting v^{1R} , v^{1C} .

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,³¹ 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 argument for progressive households' contribution to network costs is also supported by what actually constitutes a grid maintenance cost for energy providers. 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, which always needs to balance demand and supply. A way to address this is to substitute 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 from the grid during a fixed time span (usually 15 minutes).³² For these reasons, in our simulations we also allow the regulator to choose between a uniform and capacity fixed fee.

The last instrument is a subsidy to solar panel installation costs, set as a share of total PV adoption costs.³³ 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 change 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

³¹According to our estimates changes in fixed fees do not significantly alter energy consumption and have no impact on PV adoption.

³²The energy providers in the Canton of Bern already apply a capacity fixed fee to business users, but not to household users.

³³Since 2015 Switzerland provides a subsidy of 30% of installation cost for smaller solar panels.

Switzerland and of other countries, we assume that the revenue to finance the subsidy is recovered from households' electricity bills.

We conduct three counterfactual exercises using data from the last year in our sample (2013) for the main provider (BKW). In the first experiment we simulate a benchmark scenario where all home owners in our data install a solar panel, calculating 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 counterfactual we address the regressive nature of fixed fees simulating a complete decoupling of grid revenues from energy consumption. Thus, we analyse redistribution when the regulator only relies on a combination of uniform and capacity fixed fees to recover grid costs. In the last 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 renewable 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.³⁴

For the first and last counterfactual exercise we separate the marginal price into its energy component P_E 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,³⁵ which implies that the households' consumption from the grid that we'll use in our simulations can be expressed as:

$$\widehat{c}_{i}(\mathcal{P}\mathcal{V}_{i}, P_{G}, f) = \begin{cases}
P^{\widehat{\beta}_{i}}(I_{i} - f + \tau Y_{i})^{\widehat{\gamma}}e^{\widehat{\alpha} + X_{i}'\widehat{\omega} + \widehat{\xi}_{b}} - OC_{i}Y_{i} & \text{if } \mathcal{P}\mathcal{V}_{it} = 1\\
P^{\widehat{\beta}_{i}}(I_{i} - f)^{\widehat{\gamma}}e^{\widehat{\alpha} + X_{i}'\widehat{\omega} + \widehat{\xi}_{b}} & \text{if } \mathcal{P}\mathcal{V}_{it} = 0,
\end{cases}$$
(15)

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

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

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:

$$GC_0 = \sum_{i=1}^{N} GE_{i0}(P_{G0}, f_0) = Nf_0 + \sum_{i=1}^{N} \overline{c}_i P_{G0}$$
(17)

³⁴We define welfare as consumer surplus, as the utility is a non-profit oriented institution. We calculate welfare change as $\Delta W = \int_{P_0}^{P_1} c_i(P) dP + f_0 - f_1$, where P_0 and P_1 correspond to the variable price before and after the change in tariffs, $c_i(.)$ is the energy demand function of household *i*, and f_0 and f_1 are the fixed fees before and after the change in tariffs.

 $^{^{35}}$ Eturnity provided us with simulated data on own consumption, according to which on average a household can use for own consumption 18% of the energy it produces.

where N is the total number of households, \bar{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 Exogenous Increase in PV Adoption

We first consider the effects on volumetric charges only of a benchmark increase in penetration of distributed energy. In particular, we simulate a scenario where all home owners of single houses in our data have a solar panel. We focus on these households as it's likely that for them adopting a PV is easier 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:³⁶

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

In Table 11 we present the energy expenditure and consumer surplus changes per household under two different scenarios. In the first scenario we assume that households consume the share of energy they produce as predicted by Eturnity (18% on average), as reported in Table 6. In the second case we assume the limit case in which households consume 100% of the energy produced, simulating the case where households with a PV also install a battery. The first two rows show the change in the variable grid price in CHF and percentage terms. Allowing for current potential own consumption, as reported in column (1), variable grid tariffs rise by over 50%, from approximately 0.095 CHF to 0.145 CHF. With 100% own consumption, as reported in column (2), they increase by almost 140% to 0.225 CHF.

Looking at the distributional effect of this price change, we find that under both scenarios households above the sixth income decile benefit from lower grid expenditures, as reported under the ΔGE_i columns. We also find that this increase is for households that don't adopt a PV, whereas those that install a solar panel experience a substantial reduction in their grid expenditure. This confirms the regressive effect of volumetric charges under an increased number of PV adoptions. The corresponding consumer surplus changes are presented under the ΔCS_i columns, and outline a similar picture.

³⁶We use a numerical minimization as $c_i(P_G)$ is a nonlinear function of P_G .

Variables	Eturni	ty OC	100%	o OC	
CHF Price (P_G) Increase	.0457		.1	3	
$\%$ Price (P_G) Increase	5	3	13	37	
% Change by PV Installation	ΔGE_i	ΔCS_i	ΔGE_i	ΔCS_i	
No PV Installed	26.1	-29.3	68	-77.5	
PV Installed	-18.8	15.1	-49.1	38.1	
% Change by Income Decile					
1^{st} decile	5.5	-7.6	13.3	-19.2	
2^{nd} decile	4.1	-6.1	9.4	-15.2	
3^{rd} decile	3.7	-5.6	8.2	-13.9	
4^{th} decile	3.3	-5.3	7.9	-13.6	
5^{th} decile	2.2	-3.8	4.6	-9.6	
6^{th} decile	0.7	-2.6	1.4	-7.1	
7^{th} decile	-3.6	-1.6	-1.8	-3.8	
8^{th} decile	-1.4	-0.5	-4.0	-1.5	
9^{th} decile	-3	1.2	-7.1	1.9	
10^{th} decile	-6.8	5	-14.1	8.8	

Table 11: GRID EXPENDITURE AND CONSUMER SURPLUS % CHANGE

Note: The table illustrates the effect of all home owners of single houses having a solar panel and consuming their own energy on variable grid tariffs while keeping the fixed tariff constant.

6.2 Capacity Fixed Fee

An alternative solution to the missing grid revenue coming from households' decentralised energy production is a capacity fixed fee, which allows an energy provider to decouple grid revenue from energy consumption while preserving vertical equity. The downside of this instrument is that it eliminates the incentive to adopt a solar panel that volumetric charges instead provide. For the remainder of the paper, we allow the fixed fee to be household specific as follows:

$$f_i = \sigma_0 + \sigma_1 k W_i \tag{19}$$

where kW_i is the capacity of a household 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.³⁷ 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:

³⁷One efficiency argument to rely on capacity fixed fees is that buildings with greater capacity usually necessitate higher local grid investments. From a distributive perspective, they host households with a larger number of appliances (and a higher energy consumption).

$$f_{i} = \underbrace{\frac{(1 - share_{cf})GC_{0}}{N}}_{\text{uniform fee}} + \underbrace{\frac{share_{cf} * kW_{i} * GC_{0}}{\sum_{i} kW_{i}}}_{\text{capacity fee}}$$
(20)

Table 12 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 fees. We also report the percentage change in grid expenditure and consumer surplus, under the ΔGE_i and ΔCS_i columns, across the income distribution. In 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, as can be seen in the last three columns. We show instead in the columns under "Capacity Fee" that a capacity fixed fee ($share_{cf} = 1$) leads to lower expenditures for households up to the 7th income decile. Last, we consider a combination of uniform and capacity fees ($0 < share_{cf} < 1$), as reported in the columns under "Uniform & Capacity Fee". Here we calculate the optimal share of uniform vs capacity minimising the sum of each household's squared expenditure changes between the current and the counterfactual scenario. We find that it is optimal for the regulator to finance $share_{cf} = 30\%$ 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 5th income decile, and a reduction for richer ones.³⁸

Income Deciles	Current	Capacity Fee			Unifor	m & Cap	acity Fee
	Share	Share	ΔGE_i	ΔCS_i	Share	ΔGE_i	ΔCS_i
1^{st} decile	8.2	7	-14.6	38	9.2	12.2	-32.2
2^{nd} decile	8.4	7.2	-14.3	37.1	9.2	9.5	-29.4
3^{rd} decile	8.6	7.6	-11.6	35.2	9.3	8.1	-27.1
4^{th} decile	9	8.2	-8.9	32.2	9.5	5.6	-22.9
5^{th} decile	9.4	8.9	-5.3	29.4	9.7	3.2	-18.2
6^{th} decile	10	9.8	-2	25.9	9.9	-1	-12.7
7^{th} decile	10.5	10.4	-1	23.9	10.1	-3.8	-8.8
8^{th} decile	11	11.3	2.7	20.7	10.4	-5.5	-4.7
9^{th} decile	11.5	12.4	7.8	15.5	10.7	-7	-1.8
10^{th} decile	13.3	17.2	9.3	-2.5	12	-9.8	3.4

Table 12: GR	ID EXPENDITURE	AND CONSUMER	SURPLUS %	Change

Note: 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 gain roughly 70% of total grid costs through a uniform fixed fee.

 $^{^{38}}$ In Appendix 6 we extend this result for the case where the regulator is also able to finance part of the total grid costs through volumetric charges. In the table we report the respective expenditure and welfare changes for two-part tariffs which include both a variable and a fixed tariff component.

6.3 Optimal Tariff Design

In the last 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, fixed fees, and subsidies. In this counterfactual we use the estimated parameters of both energy demand and PV adoption model, but modify some state variables in the latter. In fact, 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. However, grid financing is not threatened if households with a PV don't directly consume the energy they produce.³⁹

During the last few years in various countries there has been a switch from feed-in based to subsidy based solar incentives. In Switzerland, since 2015 solar panels with capacity below 10 kW, which represent 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 allow households to directly consume the energy they produce, and the excess energy households produce is remunerated by the energy provider based on 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, as households save on variable grid costs by consuming their own energy.

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

$$\min_{P_G, f_i, s} \sum_{i} \frac{\left[GE_i(P_G, f_i) - GE_{i0}\right]^2}{I_i} = \sum_{i} \frac{\left[\hat{c}_i(\mathcal{PV}_i, P_G, f_i)P_G + f_i - GE_{i0}\right]^2}{I_i}$$
s.t. $GC_0 + \sum_{i} sF_i \Pr(\mathcal{PV}_i = 1|P_G, f_i, s) = \sum_{i} \left[f_i + \hat{c}_i(\mathcal{PV}_i, P_G, f_i)P_G\right]$ (network financing)

s.t. $\frac{\sum_{i} Y_i \Pr(\mathcal{PV}_i = 1|P_G, f_i, s)}{\sum_{i} \hat{c}_i(\mathcal{PV}_i, P_G, f_i)} \ge SET$ (solar energy target)

(21)

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, and *SET* is the Solar Energy Target, expressed as a the lower bound of the ratio of energy produced from solar panels over total energy consumed by households.⁴⁰

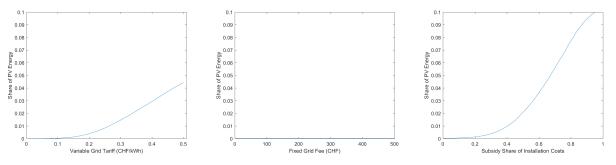
In Figure 7 we present three graphs, showing how the share of energy consumed coming from solar panels changes as we vary each of the three instruments. In these graphs we vary one instrument at a time, holding the other two fixed to the current values. From these figures we can conclude that the probability of adopting a solar panel is increasing in the variable price and in the subsidy to installation costs, whereas it's not affected by changes in the fixed fee. As the graphs show, subsidising the fixed installation costs is the most effective way to stimulate solar panels' adoption. The results are robust to various levels of the green energy target and to alternative specifications of the regulator's objective function.

³⁹Assuming PV installations do not mandate extensive additional grid investments.

⁴⁰See Appendix 7 for a detailed description of how we solve the regulator's optimization problem.

In Table 13 we present the optimal tariff design for the three solar energy targets, one for each column. In the top part of the table we show the percentage increase in variable price and fixed fee, as well as the share of installation cost that the subsidy should cover, in order to achieve each of the targets. In the bottom part of the table we show the percentage increase in households' grid expenditure needed to achieve each target, with a breakdown by income decile. As the results show, our constrained optimisation approach guarantees that the increase in grid expenditure to finance the transition to more solar energy is equally spread across the income distribution, preserving vertical equity.





Note: These figures show how the share of energy consumed coming from solar panels changes as we vary variable price (left), fixed fee (middle), and subsidy as share of installation cost (right). The scale of the vertical axis is from 0% to 10%.

Table 13: % CHANGE IN VARIABLE PRICE, FIXED FEE, SUBSIDY, GRID EXPENDITURE

	Sola	r Energ	gy Target
Variables	1%	3%	5%
% Price (P_G) Increase	1	12.2	34.7
% Fixed Fee (f) Increase	6.6	20.6	28.3
Subsidy (s) as % of Installation Cost	30	44	51
% Change GE_i by Income Decile			
1^{st} decile	2.6	13.8	29.9
2^{nd} decile	2.5	13.8	29.9
3^{rd} decile	2.5	13.7	29.9
4^{th} decile	2.4	13.6	29.9
5^{th} decile	2.4	13.5	30
6^{th} decile	2.3	13.3	29.9
7^{th} decile	2.2	13.2	30
8^{th} decile	2.2	13.1	29.9
9^{th} decile	2.1	12.9	29.8
10^{th} decile	1.9	12.5	29.4

Note: The table illustrates the change in variable price, fixed fee, subsidy required to achieve a 1%, 3%, 5% 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 three targets.

7 Conclusion

In this paper we propose an optimal tariff design for residential electricity markets facing an increasing penetration of PV installations and substantial 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 green-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. We propose a financing scheme decoupled from consumption, showing its welfare effects across households' income distribution.

To calculate these welfare changes we estimate models of energy demand and PV installation using a detailed dataset with 180,000 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 renewable energy target, while preserving network financing and vertical equity. We conduct three counterfactual simulations. First, we show that a benchmark increase in PV adoptions would generate a substantial missing revenue, which would require an increase in volumetric charges with regressive consequences. Second, we show that decoupling grid financing from energy consumption with a capacity fixed fee would make the tariff structure more progressive, at the cost of reducing households' incentives to install a solar panel. Last, we find the optimal combination of variable prices, fixed fees, and subsidies to installation costs that would allow a policymaker to achieve a 1%, 3% or 5% solar energy target, guaranteeing network financing and an equitable distribution of grid costs across the income distribution.

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 datasets contain both households and businesses. We collapse the data by customer as some households may have more than one meter. 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 allows 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 300,000 grid connections from 2008 to 2013. We first use the imperfect sector identifier of BKW⁴¹ and drop customers denominated as firms, which reduces our sample to about 250,000 grid connections. Collapsing by customer we end up with a sample of about 210,000 households by year. Of these customers we manage to match around 110,000 households with tax information (in 2013). The mismatches are mainly due to data imprecision, different ways to write names and addresses, and the fact that the BKW sample may still include a number of businesses. 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 down to around 85,000 in 2008, as some households relocated during this time period.

For the city of Bern we use a list of about 110,000 grid connections per year from 2008 to 2015. This data is collapsed to a sample of 85,000 business partners, including both households and firms. Matching the energy data with the tax data leads to about 40,000 matched households per year. Beside losses due to data imprecision, all firms drop out in the merging $process^{42}$. As we have historical information on names and addresses in the energy data of the EWB the successful matches only decline slightly to about 36,000 in the earlier years. As to the city of Thun, we start with a list of about 28,000 grid connections per year between 2009 and 2014^{43} . This is equivalent to about 24,000 Energie Thun customers including both households and firms. During the merging process this number is reduced to approximately 15,000 households with both energy and tax data. Again, as we have historical personal information on the energy customers this number is fairly steady during the relevant period. In the aggregated sample of around 175,000 households per year we undertake further adjustments. First, we exclude all grid connections with annual energy consumption below 500 kWh. This number is chosen arbitrarily to exclude abnormal energy meters and false data. For comparison, a single person household usually with only one grid connection has a minimum energy usage of over 2,550 kWh per year⁴⁴. Second, we drop all households reporting negative income.

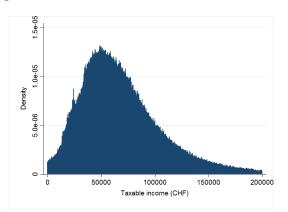
 $^{^{41}\}mathrm{Imperfect}$ as some small businesses are wrongly labelled as households.

⁴²Although there may still be some self-employed people in the data.

 $^{^{43}}$ Unfortunately the data prior to 2009 is not available due to a system change.

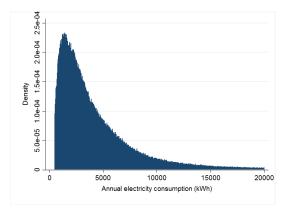
 $^{^{44}}See \ http://www.ewb.ch$

Figure 8: 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 9: 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.

Appendix A2: Energy Prices, Tariffs and Taxes

	2008	2009	2010	2011	2012	2013
Double tariff						
EnergyPriceHT(Rp/kWh)	11.93	11.93	11.92	12.05	11.6	11.21
EnergiePriceLT(Rp/kWh)	7.58	7.58	7.57	7.46	7.19	6.91
GridPriceHT(Rp/kWh)	7.23	8.57	8.05	7.06	6.4	7.11
GridPriceLT(Rp/kWh)	1.69	2.11	1.94	1.88	1.81	3.12
GridBasicFeeDT(CHF)	166.19	142.16	130.64	129.86	121.6	68.1
Uniform tariff						
EnergiePriceUT(Rp/kWh)	10.81	10.81	10.85	10.82	10.48	10.09
GridPriceUT(Rp/kWh)	6.65	7.98	7.83	6.85	5.89	6.57
GridBasicFeeUT(CHF)	127.89	104.13	91.96	91.05	85.78	46.79
Both tariffs						
Swissgrid(Rp/kWh)	0	0	0	.07	.43	.4
KEV(Rp/kWh)	.07	.45	.49	.49	.49	.51
MunicipalTax(Rp/kWh)	.04	.27	.29	.29	.63	2.53

Table 14: ENERGY PRICES, NETWORK TARIFFS AND TAXES - ENERGIE BERN

Note: The table shows average prices in the sample. However, the underlying tariff structure of Energie Bern is more complex. Customers can choose between several energy products with different prices. These products distinguish themselves from each other by their main energy source (e.g. water, solar). In addition, customers are billed yearly but at different times during the year such that each customer has a unique mixture of prices from two consecutive year. For instance, a customer billed in March will pay energy his consumption from Januar to March according to the respective year's prices and the other 9 month according to last years prices. All prices include the value-added tax.

Table 15:	Energy	PRICES,	Network	TARIFFS AND) TAXES -	Energie	Thun

	2009	2010	2011	2012	2013
Double tariff					
EnergyPriceHT(Rp/kWh)	12.15	12.13	12.55	12.54	12.54
EnergiePriceLT(Rp/kWh)	9.45	9.43	9.85	9.84	9.84
GridPriceHT(Rp/kWh)	8.62	8.63	9.16	9.06	8.53
GridPriceLT(Rp/kWh)	2.16	2.16	2.48	2.48	2.27
GridBasicFeeDT(CHF)	90.55	90.66	90.92	90.81	84.22
Swissgrid(Rp/kWh)	.43	.43	.83	.5	.34
KEV(Rp/kWh)	.49	.49	.49	.49	.49
MunicipalTax(Rp/kWh)	4.64	4.62	4.66	3.35	3.24

Note: The table shows average prices in the sample. The underlying tariff structure of Energie Thun is more complex. Customers can choose different energy sources (e.g. water, solar) with different prices. In contrast to the other companies, Energie Thun does not offer a uniform tariff. There is also no price information for the year 2008 as the data for this year is not available due to system changes in the company.

Appendix A3: Maps - Bern, Thun and surroundings

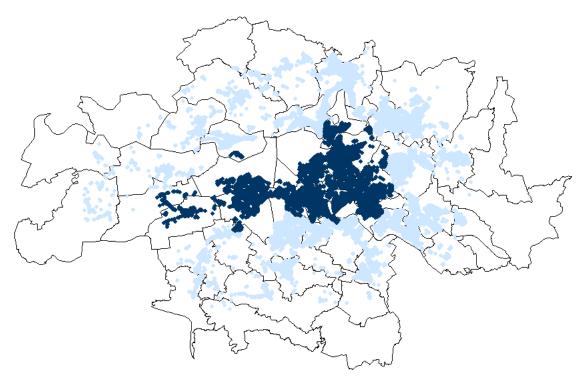
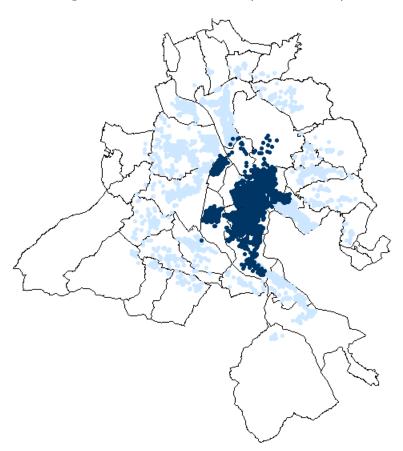


Figure 10: MAP CITY BERN (HOUSEHOLDS)

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 Energy Bern, while the light blue area shows the BKW customers.

Figure 11: 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 A4: Example of Eturnity Offer



PROFITA-

34'579 CHF

22'579 CHF

FUNDAMENTALS

PRODUCTION COSTS

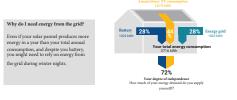
15,7 Rappen

1 kWh solar energy from your roof cost

BILITY

3

<section-header><section-header><section-header><section-header><complex-block>



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



(c) Breakdown of PV installation costs and energy savings

«SOLARENERGIE LOHNT

23'578 CHF

4'600 CHE

2'254 CHF

28'178 CHF 30'432 CHF

-8'472 CHF 21'960 CHF

-3'294 CHF

19'357 CHF

nal interest rate

with battery

1,03%

INVESTMEN COSTS

Solar panel

Battery sys

VAT 8%

Total exkl. VAT

Total inkl.VAT Subsidy

Your Investmen

Final costs

Expected tax deductio

INTEREST YIELD

rn of your cap

2,44%

SICH FÜR SIE»

REVENUE

(d) Quantification of CO_2 saving

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:

$$\max_{\substack{c,q\\s.t.}} u(c,q,I,X)$$
s.t. $q + Pc \le I$
(22)

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:

$$u(c,q,I,X) = q + \frac{\eta - 1}{\eta} c^{\frac{\eta}{\eta - 1}} I^{\frac{\gamma}{1 - \eta}} e^{\frac{X'\omega}{1 - \eta}}.$$
(23)

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

$$c^* = P^{\beta} I^{\gamma} e^{X'\omega}$$

$$q^* = I - P^{\beta+1} I^{\gamma} e^{X'\omega},$$
(24)

where we define $\beta = \eta - 1$. Based on this, the indirect utility function will be:

$$v(P, I, X) = I - \frac{1}{\beta + 1} P^{\beta + 1} I^{\gamma} e^{X'\omega} = I - \frac{1}{\beta + 1} P c^*.$$
(25)

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:

$$v(P, I, X, f, \tau, Y) = \begin{cases} I - f + \tau Y - \frac{1}{\beta+1} P^{\beta+1} (I - f + \tau Y)^{\gamma} e^{X'\omega} & \text{if } \mathcal{PV}_{it} = 1\\ I - f - \frac{1}{\beta+1} P^{\beta+1} (I - f)^{\gamma} e^{X'\omega} & \text{if } \mathcal{PV}_{it} = 0. \end{cases}$$
(26)

Appendix A6: Two-Part Tariffs

In the main body of the text we considered two extreme cases: adjusting the variable grid tariff to make up for lost grid revenue of PV owners, and completely switching to lump-sum fees to finance the grid. However, energy providers are likely to choose a new combination of variable and fixed tariff components. In order to compute these optimal two-part tariffs we need to make an assumption about the distributional goals of the regulator. Following Wolak (2016), we assume that the regulator takes the current households' grid expenditure GE_{i0} as the desired benchmark from an income distribution perspective, and hence specify the following regulator's constrained optimization problem:

$$\min_{P_G, f_i} \sum_i \frac{[GE_i(P_G, f_i) - GE_{i0}]^2}{I_i} = \sum_i \frac{\left[\hat{c}_i(\mathcal{PV}_i, P_G, f_i)P_G + f_i - GE_{i0}\right]^2}{I_i}$$
s.t. $GC_0 = \sum_i \left[f_i + \hat{c}_i(\mathcal{PV}_i, P_G, f_i)P_G\right]$ (network financing) (27)

where $GE_i(P_G, f_i)$ is the grid expenditure of household *i* under the alternative tariff scheme. This optimization process implies that the regulator sets a combination of variable and fixed tariffs to minimize the distributional distortion under own consumption, while still satisfying the grid financing constraint.

Table 16 summarizes the optimal two-part tariffs under different assumptions. The first row corresponds to the status quo where households face a marginal price of approximately 0.10 CHF and pay a yearly uniform fixed fee of 117 CHF. In row (2) we include the effect of own consumption. This results in a slight increase in variable grid tariffs and an almost double fixed fee. In rows (3) and (4) we allow instead for a capacity-based fixed fee. Without own consumption (row (3)), it is optimal from a redistributive point of view to only charge a variable tariff. With own consumption instead levying a capacity-based fixed fee becomes optimal, although marginal prices also increase significantly. To give a more direct interpretation of the capacity fee, the total amount of the fixed fee ranges from 27 CHF to 1,360 CHF, while a household with median capacity pays 85 CHF annually. Finally, in the last row we look at a case where energy providers can charge both a uniform fixed fee and a capacity fixed fee. In this scenario it is optimal to keep variable grid prices constant while combining both types of fixed fees. This suggests that the different redistributional impacts of both fixed fee designs might cancel each other out.

Table 16: OPTIMAL TWO-PART TARIFF WITH OWN CONSUMPTION (BASE YEAR 2013)

Scenario	Own Consumption	P_G (CHF)	f (CHF)	f_i (CHF per kW)	$\sum_{(\text{kWh})} \widetilde{c}_i$
Current	No	0.098	117	-	376 Mio
Uniform Fee	Yes	0.1025	216	-	374 Mio
Capacity Fee	No	0.1264	-	0	366 Mio
Capacity Fee	Yes	0.155	-	17	369 Mio
Capacity & Uniform Fee	Yes	0.0974	95	18.4	376 Mio.

Note: Optimal tariffs are calculated to minimize the sum of square deviation in grid expenditures (difference between baseline and counterfactual scenario).

Appendix A7: Regulator's Optimization

We solve the regulator's optimization problem sequentially. Following the evidence shown in Figure 7, 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 respect the network financing constraint. Third, for each combination of variable tariff, subsidy and fixed fees (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 interval of variable tariffs the one between 0 and 0.5 CHF/kWh, discretized by 0.01 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% with 1% intervals. Specifically, we increase the subsidy until the share of solar energy reaches the desired threshold. This gives us 51 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. We justify this assumption with the evidence presented in Figure 7.
- 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 20. We discretize this share using 10% intervals, ranging from 0% to 100%. Hence, for each combination of variable tariff and subsidy there are 10 different combinations of capacity and uniform fixed fees. Ultimately, this step results in 510 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 510 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.

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