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

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Motivation

- Electricity represents 20% of global energy usage and 2 out of 3 kWh still from non-renewable sources.
- Solar photovoltaic (PV) supported in many countries, but diffusion still low.
- Commitment to renewable electricity provision by 2050 (i.e. Switzerland plans to cover $> 40\%$ by 2050 with solar PV)
- Increased academic attention:
  - Adoption (Socio-economic factors, profitability, government policies, peer-effects) Details
  - Solar PV rebound effect (i.e. increased consumption, due to lower costs / higher income) $\rightarrow$ 1:1 capacity replacement not sufficient.
  - Solar PV co-adoption of other elecricity intensive goods (i.e. electric vehicles) (Lyu, 2023)

Research Questions

- Is there a rebound effect in electricity consumption after solar PV adoption in Switzerland?
- Which factors explain the extent of the solar PV rebound effect?
- What are the estimates' implication(s) when accounting for co-adoption of other electricity intensive technologies?

Data sources (2008-2019)

1. Energy company (BKW) ▸ BKW - Area
   - Electricity consumption (kWh) and expenditure, solar PV installations
   - Electricity product (grey, green or blue)
   - Electricity feed-in
2. Solar Campus
   - Estimated PV production
3. Tax office of Bern
   - Income, wealth, household size, age, homeownership
4. Federal and cantonal offices (Statistics, Energy, Road, Meteo)
   - Buildings' and dwellings' characteristics
   - PV Potential
   - Car ownership data
   - Heating / Cooling degree days (Temperature)

Data management

I only use a sub sample of data due to various reasons:

1. PVs after 2014
2. Single family homes
3. PVs smaller than 20KWp
4. Eliminate outliers in consumption and self-consumption (Top / bottom 1%)

$\rightarrow$ Final sample: 58,104 households observed for 507,137 HH-year combinations. 1,433 solar PV installations observed for 4,023 HH-year combinations.

▸ Solar PV distributions ▸ Locations ▸ Relative Adoption shares ▸ Solar PV descriptives
▸ Summary statistics

Solar PV production simulation

Exact production of solar PV (ep_t) is unobserved:

$$ec_t = eg_t + es_t \tag{1}$$

$$es_t = \begin{cases} ep_t - ef_t, & \text{for PV households} \\ 0, & \text{for non-PV households} \end{cases} \tag{2}$$

$\rightarrow$ Estimation ($\hat{ep}_t$ through API accessed simulation.)

▸ Inputs ▸ Overview ▸ Evaluation

Empirical strategy

Relationship of interest:

$$ec_{it} = \delta PV_{it} + \alpha p_t + \beta X_{it} + \omega_i + \omega_t + \omega_c + \epsilon_{it}, \qquad (3)$$

PV_{it} is treatment either defined as indicator or observed production (i.e. $e\hat{p}_t$)

Empirical strategy - Identification

Perfect experiment would require solar PVs to be assigned to households randomly - likely violated.

1. Correlated unobservables (e.g. environmental awareness)
2. Selection into treatment (e.g. higher consumption is likelier to install)
3. Treatment effect heterogeneity (Goodman-Bacon, 2021; De Chaisemartin & d'Haultfoeuille, 2020)
4. Pre-Trends / Parallel trends

→ Conditional on observables (extensive set of control variables), households are assumed to would have evolved parallel. Available supporting statistical tests and robustness checks are conducted.

Empirical strategy - Heterogeneity

Add interaction terms to relationship of interest:

$$ec_{it} = \delta_1 PV_{it} + \delta_2 PV_{it} \cdot T_{it}^{k} + \alpha p_t + \beta X_{it} + \omega_i + \omega_t + \omega_c + \epsilon_{it}, \quad (4)$$

with T_{it}^{k} being a dummy variable illustrating if household i installed a specific technology k.

Empirical strategy - Decomposition

Individual treatment effect based on ML counterfactual prediction:

$$\hat{b}_{it} = \frac{Y_{it}(PV_{it} = 1) - \hat{Y}_{it}(PV_{it} = 0)}{\hat{Y}_{it}(PV_{it} = 0)} \tag{5}$$

Decomposition using semi-parametric linear regression:

$$\hat{b}_{it} = \theta + \varphi E_{it}^{k} + \sum_{g=1}^{G} \gamma_g Z_{it}^{g} + \eta_{it} \quad \text{, for all} \quad PV_{it} = 1 \tag{6}$$

Extent Solar PV rebound I

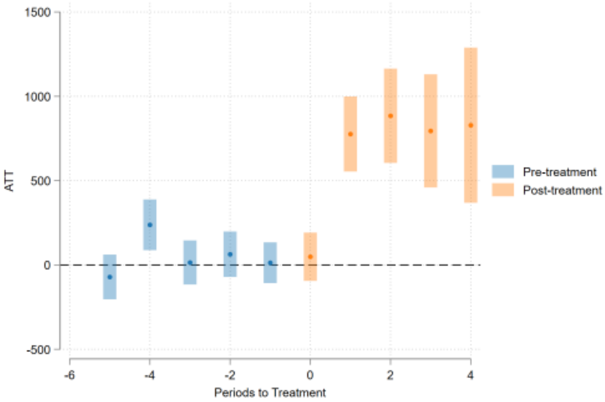
	(1)	(2)	(3)	(4)	(5)
PV HH	852.47 * ** (117.38)	824.22 * ** (107.98)	802.32 * ** (109.52)	763.63 * ** (109.29)	658.98 * ** (109.97)
Electricity price (log)		−6113.76 * ** (217.46)	−6223.30 * ** (219.72)	−6195.54 * ** (219.11)	
Electricity price					−223.22 * ** (8.91)
Feed-in electricity price					14.23*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

Note: This table presents selected coefficients of the estimates described in 3. Standard errors are clustered on an individual level and provided in parentheses. $\underline{\sigma_{fe}}$ and $\underline{\underline{\sigma_{fe}}}$ illustrate standard deviations under which the overall ATT or the ATT in all groups could be of opposite signs than the true effect according to De Chaisemartin & d'Haultfoeuille (2020).

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

▸ Two-way FE weights ▸ Production treatment

Extent Solar PV rebound II



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

▸ Alternative specifications

Extent Solar PV rebound - Robustness

- Functional form assumptions ▸ Results
- Data assembly ▸ Results
- Dynamic DiD estimator ▸ Results
- Various alternative estimators ▸ Results

Solar Rebound Results - Heterogeneity I

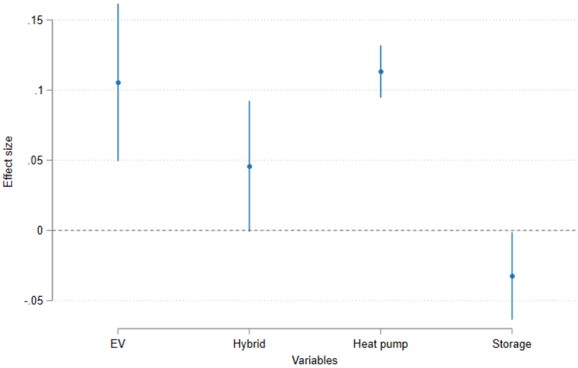
	Electrified Household				PV heterogeneity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PV HH	733.01 * **	747.28 * **	750.10 * **	718.37 * **	776.64 * **	601.34 * **	577.44 * **
	(111.69)	(109.75)	(111.24)	(129.69)	(112.16)	(135.52)	(113.34)
EV / Hybrid	−967.59						
	(898.47)						
EV		1338.95 * *					
		(462.61)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

Note: This table presents selected coefficients of the estimates described in 4. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated as described in **??**. Each model includes a different interaction term representing either co-adoption of household electrification or heterogeneity within the adopted solar PV system. EVs are pure battery electric vehicles whereas hybrids can be either plug-in hybrid vehicles or hybrid vehicles without external charging possibility. Yield measures the observed production per kWp installed for the solar PV panel whereas high capacity indicates solar PV installations exceeding median capacity of 8.6 kWp.

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

▸ Production treatment ▸ Split samples

Anatomy Solar PV rebound I

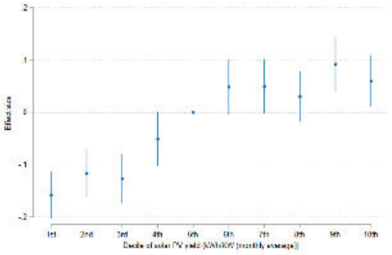


Note: This plot shows selected coefficients from a linear regression model of the predicted household-year solar PV rebound effect on adopter specific variables. The individual rebound effects are estimated using ML-based prediction of unobserved counterfactual consumption. 95% confidence intervals are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

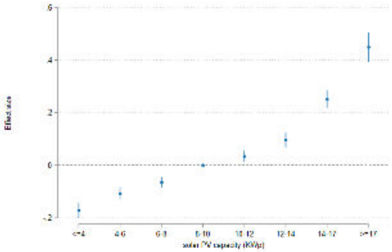
ML-Algorithms | ML-Estimated effects | ML-Model Selection | ML-Predictions
ML-Assumptions | ML-Resid test 1 | ML-Resid test 2 | ML-Resid test 3

Anatomy Solar PV rebound II

Panel (B): solar PV yield (kWh / kWp)



Panel (C): solar PV capacity (kWp)



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

Conclusion

- Estimate the Swiss solar rebound to around 7.9-11.1%
- No effect in year of adoption
- Anatomy of solar PV rebound effect shows:
  - Part of the effect driven by co-adoption / electrification
  - Effect driven by sub-sample with relative big installations / strong reaction to high yields
- Future electricity capacity forecasts should account for rebound effect, but potentially to a smaller extent than expected.
- Rebound effect does not necessarily increase solar PV subsidy abatement costs

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Literature Review

- Adoption
  - Socio-economic factors (e.g. Balta-Ozkan et al., 2015; Schelly, 2014)
  - Profitability (e.g. Kwan, 2012; Dharshing, 2017)
  - Government policies (e.g. De Groote & Verboven, 2019; Feger et al., 2022)
  - Peer-effects: Neighboring households are more likely to adopt new technology
- Rebound effect: Increased consumption, due to readily available (cheaper) electricity (i.e. lower average costs)
  - Estimated at around 16-20% (e.g. Qiu et al., 2019)
  - Evidence found in USA, Australia, UK, Belgium, Germany, Netherlands

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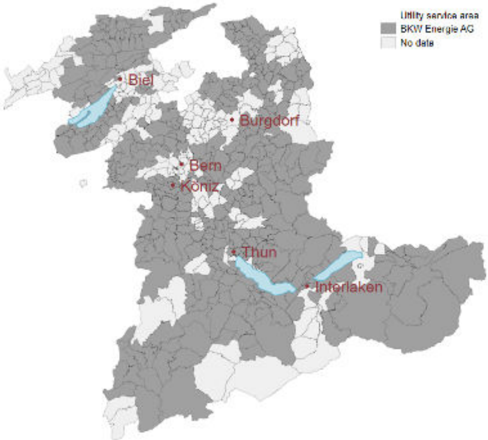
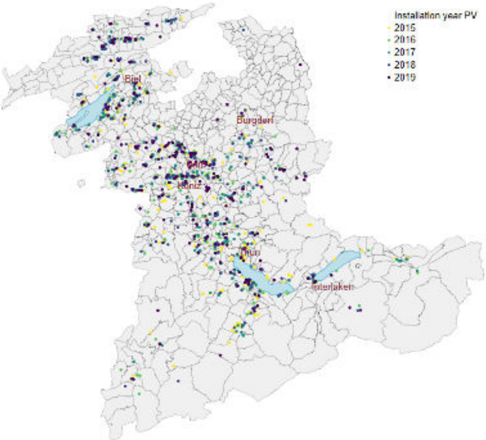
BKW Service area



Notes: This map illustrates the service area of our main data provider BKW. The darker shaded areas are serviced by BKW representing around 50% of the cantons total population and 70% of the cantons communities. Map was created by authors using Data from ELCOM and the Swiss Federal Institute of Statistics.

return

PV map



Notes: This map illustrates the spots where solar PVs are located within the service area and study region. The darker shaded areas are serviced by BKW representing around 50% of the cantons total population and 70% of the cantons communities. Map was created by authors using Data from ELCOM and the Swiss Federal Institute of Statistics and BKW.

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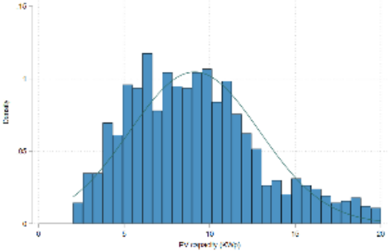
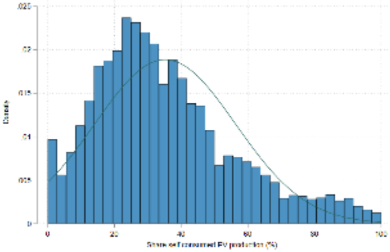
Distribution of solar PV

Panel (A): PV capacity



Panel (B): Self consumption share



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

return

PV data - Summary statistics

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

Note: Based on observed household-year combinations with solar PV instal-lations between 2015 to 2019. All Data provided by BKW Energie AG and Pronovo AG. PV production estimated based on simulation framework.

return

Summary Statistics

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

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

return

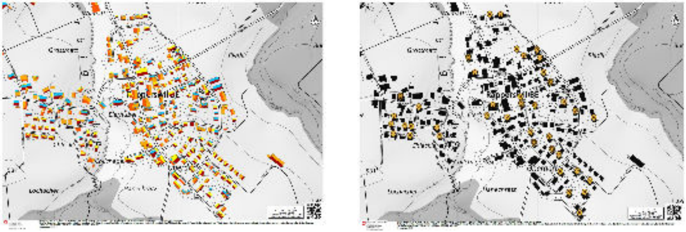
Solar PV Rooftop - Inputs Simulation

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

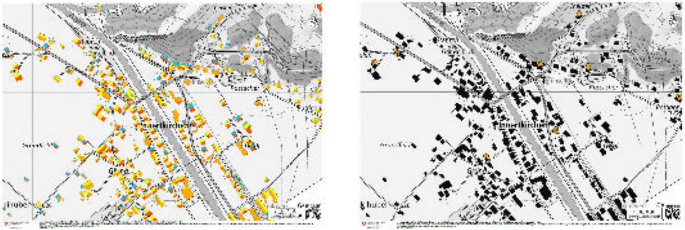
return

Solar Rootfop - Illustration

Panel (a): Highest average solar rooftop potential

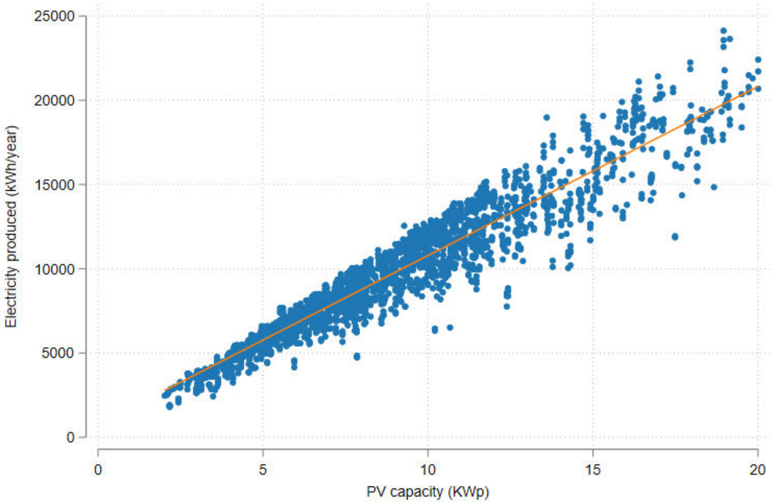


Panel (b): Lowest average solar rooftop potential



Notes: This figure shows partial maps of the zip code areas with (a) the highest average solar rooftop potential and (b) the lowest average solar rooftop potential in our study region. The left side of the figure shows solar rooftop potential. The right side of the figure shows actual solar panel installations at the time this study was conducted. (a): Rapperswil, BE; (b): Innertkirchen, BE.

Solar Rootfop - Output



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

Solar PV - Relative shares

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

Note: Notes: Based on observed households and solar PV adoptions between 2015 to 2019. High wealth and high income based on median cut-off for the respective value. Homeownership status as defined in the data. Urbanitiy, EV ownership and electricity based heating system based on data. For heating system both heatpumps and electric space heating are considered as electricity based.

return

Two-way FE weights - test

- If both summary measures are sufficiently big there is little statistical chance that:
  1. ATT and true treatment effect are of opposite sign
  2. All group ATTs and true treatment effect are of opposite sign
- What constitutes a sufficiently big test statistic:
  1. If treatment effects are uniformly distributed in population and we assume an upper bound B:
  2. Test statistic 1: $B\sqrt{3} \cdot x$ implausible high amount of treatment effect heterogeneity for ATT having different sign than estimated ATT.
  3. Test statistic 2: $B2\sqrt{3} \cdot x$ implausible high amount of treatment effect heterogeneity for ATT having different sign than estimated ATT.

$\rightarrow$ Implied upper bound thus is ATT of approximately 16% in specification 3, which has the lowest test scores.

Extent Solar PV rebound III

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

Note: This table presents selected coefficients of the estimates described in 3. Treatment is now defined as actually observed solar PV production in kWh in the post-adoption years. Hence, estimated treatment effects can be directly interpreted as average treatment effect on the treated. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated.

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

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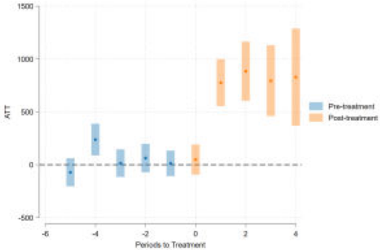
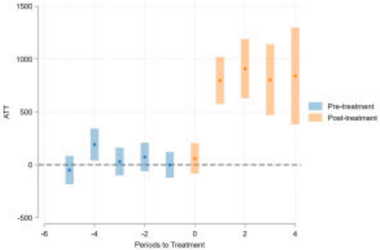
Extent Solar PV rebound IV

return

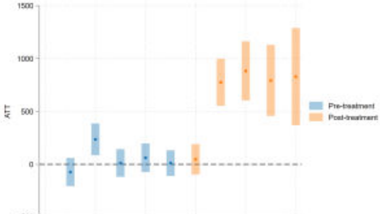
Panel (A): All controls, never treated



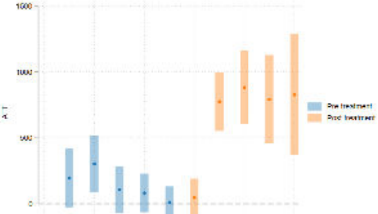
Panel (B): No energy controls, never treated



Panel (C): All controls, not yet



Panel (D): long gaps



Robustness checks - functional form

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

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

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

return

Robustness checks - Data

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

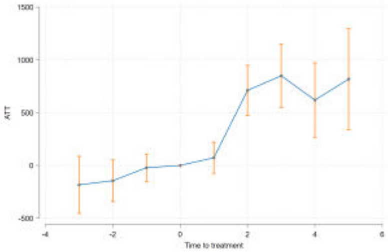
Note: This table presents selected coefficients of the estimates described in 3. Odd rows have treatment definition as indicator variable if household i owned a solar PV in year t. Even rows have treatment defined as actually observed solar PV production in kWh in the post-adoption years. Standard errors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

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

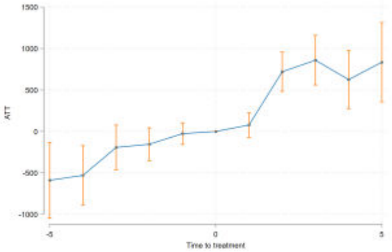
return

Robustness checks - DiD

Panel (A): 3 year pre-trend test



Panel (B): 5 year pre-trend test



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

return

Robustness checks - Alternative estimators

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

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

return

Solar Rebound Results - Heterogeneity II

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

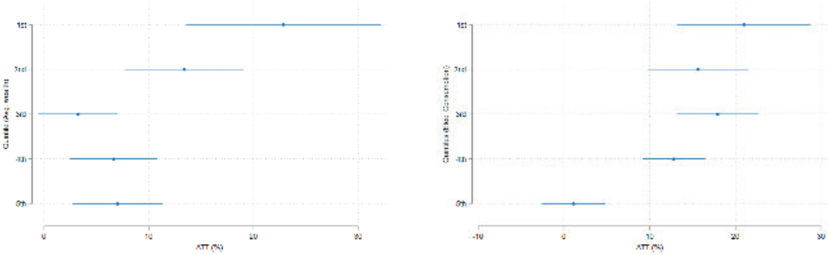
Note: This table presents selected coefficients of the estimates described in 4. Standard errors are clustered on an individual level and provided in parentheses. Control variables in estimation included if indicated as described in **??**. Each model includes a different interaction term representing either co-adoption of household electrification or heterogeneity within the adopted solar PV system. EVs are pure battery electric vehicles whereas hybrids can be either plug-in hybrid vehicles or hybrid vehicles without external charging possibility. Yield measures the observed production per kWp installed for the solar PV panel whereas high capacity indicates solar PV installations exceeding median capacity of 8.6 kWp.

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

return

Solar Rebound Results - Heterogeneity III

Panel (A): Split on wealth | Panel (B): Split on Elec. consumption



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

return

ML - Description

- List of Predictors: indicator of electricity mix (Blue, Green, Grey), income, wealth, home ownership status, age, household size (1, 2, 3, 4, 5+), living area, nb. of rooms, heating system/resource (oil, nat. gas, wood, district, heat pump, electric), house building period indicator (10 categories, mostly for decades), urbanity of location (urban, semi-urban, rural), mountain region indicator, vehicle fuel type (gasoline, diesel, electric, hybrid), electricity price, rooftop size, rooftop PV suitability, neighborhood solar PV density, heating degree days, cooling degree days and year indicator variables.
- Use all available non-treated observations (i.e. never and not-yet treated). Randomly split into 15% test sample and 85% training sample.
- Estimate ensemble of models using pystacked (Ahrens et al., 2022) and SuperLearner (Polley et al., 2019). XGBoost outperforms all other available alogrithms (Lasso, Ridge, Elasticnet, Random Forests, Gradient boosted trees, Neural Net regressor and linear Support Vector Machine)

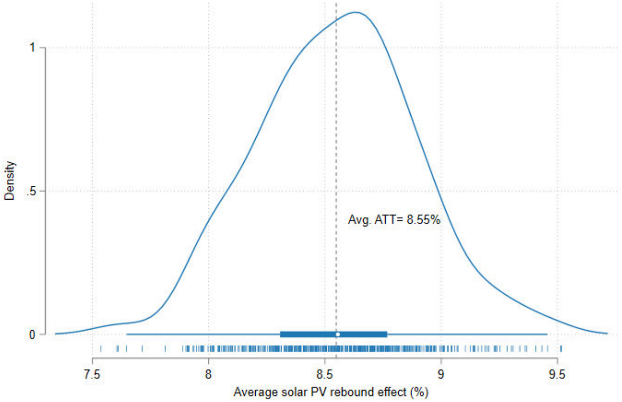
ML - model selection

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

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

return

ML-estimates



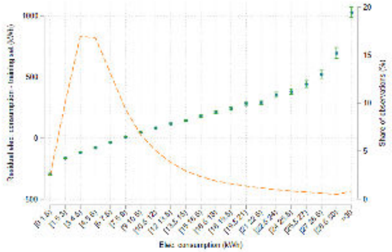
Note: This plot shows the distribution of the estimated average solar PV rebound effects using the ML based approach by predicting unobserved counterfactual. Estimation based on 500 stratified bootstrap samples. Average ATT is 8.55% which closely aligns with the estimated median.

◂ return

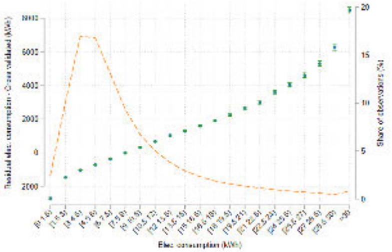
Machine learning - Prediction

Figure: Residuals for different Elec. consumption bins

Panel (A): In-Sample residuals

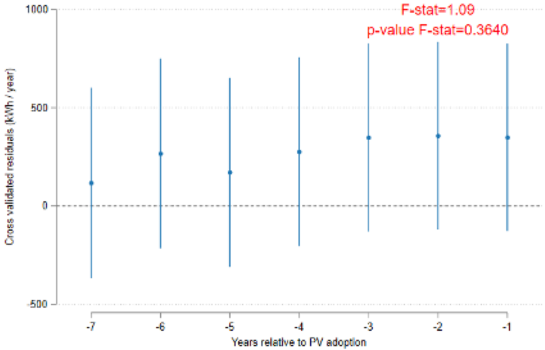


Panel (B): Cross-validated residuals



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

Machine learning - Stability / Pre-Trend

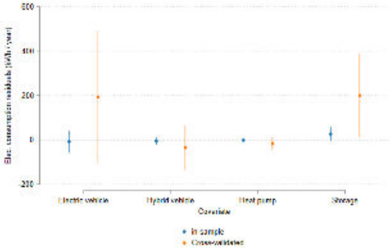


Note: This figure illustrates the estimated coefficients and their 95% confidence interval of a regression of the cross-validated residuals on indicator variables measuring relative time to solar PV adoption. Only not-yet treated observations are included. Regression included pre-treatment periods up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

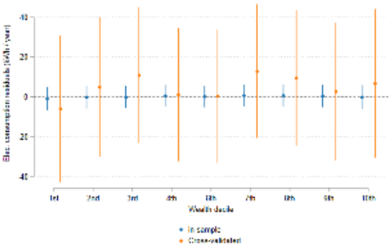
return

Machine learning - Residual correlation I

Panel (A): Energy related variables



Panel (B): Wealth deciles

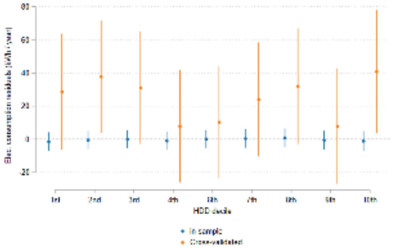


Note: The plot shows a selection of estimated regression coefficients from a linear regression of both in-sample and cross-validated residuals on explanatory variables. Whiskers illustrate 95% confidence interval based on stratified bootstrapped sampling.

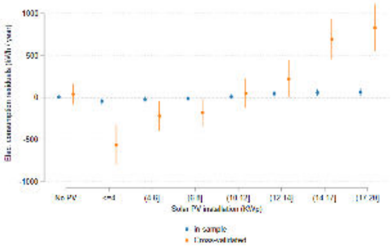
return

Machine learning - Residual correlation II

Panel (C): Weather



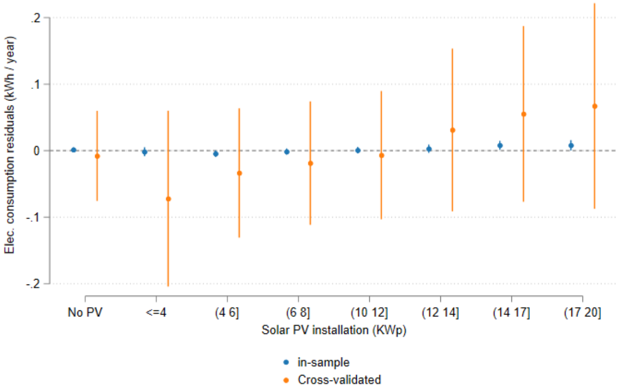
Panel (D): solar PV capacity



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

return

Machine learning - Residual correlation III



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

return