

LETTER • OPEN ACCESS

Can designs inspired by control theory keep deployment policies effective and cost-efficient as technology prices fall?

To cite this article: Alejandro Nuñez-Jimenez *et al* 2020 *Environ. Res. Lett.* **15** 044002

View the [article online](#) for updates and enhancements.

You may also like

- [Addressing integration challenges of high shares of residential solar photovoltaics with battery storage and smart policy designs](#)
Marius Schwarz, Jan Ossenbrink, Christof Knoeri et al.
- [An initial analysis of options for a UK feed-in tariff for photovoltaic energy, from an array owner's viewpoint](#)
Steve Plater
- [What are the social outcomes of climate policies? A systematic map and review of the ex-post literature](#)
William F Lamb, Miklós Antal, Katharina Bohnenberger et al.



LETTER

Can designs inspired by control theory keep deployment policies effective and cost-efficient as technology prices fall?

OPEN ACCESS

RECEIVED

27 October 2019

REVISED

15 January 2020

ACCEPTED FOR PUBLICATION

24 January 2020

PUBLISHED

13 March 2020

Original content from this work may be used under the terms of the [Creative Commons Attribution 4.0 licence](#).

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Alejandro Nuñez-Jimenez^{1,3} , Christof Knoeri¹ , Joern Hoppmann^{1,2}  and Volker H Hoffmann¹¹ Group for Sustainability and Technology, ETH Zurich, Weinbergstrasse 56/58, 8092 Zurich, Switzerland² Chair of Management, University of Oldenburg, Ammerländer Heerstraße, D-26129 Oldenburg, Germany³ Author to whom any correspondence should be addressed.E-mail: anunez-jimenez@ethz.ch**Keywords:** policy design, clean energy, deployment policy, agent-based model, feed-in tariff, adjustment mechanism, solar photovoltaicsSupplementary material for this article is available [online](#)

Abstract

Deployment policies based on economic incentives are among the most effective tools for speeding up the diffusion of clean energy technologies. Policy instruments such as feed-in tariffs have played a critical role in driving the growth of solar photovoltaics, and could accelerate the uptake of other technologies that are key to the decarbonization of energy systems. Historical experiences, however, show that failing to adjust economic incentives to falling technology prices can fundamentally undermine these policies' effectiveness and cost-efficiency. This paper addresses this challenge by assessing three novel policy designs. Based on control-theory principles, the proposed mechanisms modify incentives in response to changes in deployment, policy costs, or profitability for adopters. We assess the outcomes that each policy design would have achieved when applied to Germany's feed-in tariff for solar photovoltaics between 2000 and 2016. For this purpose, we developed an agent-based model that allows us to simulate the adoption decisions of individual households and medium-sized and large firms, as well as the evolution of technology prices. Our results show that responsive designs inspired by control theory might produce policies that follow their targets more closely, and at a lower cost. In addition, our analysis suggests that the studied designs could greatly reduce uncertainty over policy outcomes and windfall profits. This research also highlights the role of the temporal distribution of policy targets, and identifies policy design tradeoffs, drawing relevant implications for the design of future deployment policies.

1. Introduction

Deployment policies that aim to foster the uptake of clean energy through economic incentives, such as feed-in tariffs (FITs), investment subsidies, or tax credits, have proved effective tools for accelerating the growth of renewable energy technologies such as solar photovoltaics (PV) (Jenner *et al* 2013, Dijkgraaf *et al* 2014). Similar policies could speed up the diffusion of emerging technologies—such as energy storage or electric vehicles—upon which many decarbonization strategies depend (IRENA *et al* 2018, Rogelj *et al* 2018). However, historical experiences highlight the difficulty of adjusting incentives over time as technology prices fall, and raise questions about the cost-efficiency of such policies (Frondel *et al* 2010, Vaishnav *et al* 2017).

As economic incentives boost adoption, learning effects typically reduce technology costs, which contributes to the effectiveness of deployment policies (i.e. the policy's ability to accelerate the technology's diffusion) (Bollinger and Gillingham 2014). At the same time, as technology costs fall, if incentives are not adjusted, investors can often reap windfall profits that erode the policy's cost-efficiency (i.e. the ratio between deployment and policy cost) (Hoppmann *et al* 2014a). In countries such as Spain or the Czech Republic, slow incentive adjustments and rapid price reductions generated large windfall profits for PV adopters. These triggered surges in deployment that sent annual policy costs into the billions of euros, eventually leading to the dismantling of the policies (Gürtler *et al* 2019). These historical experiences, and others, demonstrate

the need to adjust incentives adequately as technology prices evolve in order to keep policies both effective and cost-efficient. Although this has long been recognized in both theory (Haas *et al* 2004) and practice (Sijm 2002), debate continues over how to achieve it (Wand and Leuthold 2011, Créti and Jouag 2012, Alizamir *et al* 2016, Li *et al* 2019).

Policymakers have tried out multiple mechanisms for adjusting the incentives of policies supporting renewable energies (Klein *et al* 2008, Mendonça *et al* 2009, Kreycik *et al* 2011). The latest attempts—responsive, automatic mechanisms—react to the attainment of specific policy targets (e.g. deployment milestones) by modifying incentives (e.g. reducing the FIT), and have been used, for example, in California, Germany, and Spain (German Parliament 2008, Spanish Parliament 2008, California PUC 2017). Although the available designs of such mechanisms are better than previous ones at keeping the policy cost-efficient, they can also endanger its effectiveness. For instance, while Germany and Spain avoided deployment surges after introducing responsive, automatic adjustments into their FITs, both countries missed their PV deployment targets (del Río and Mir-Artigues 2012, Bundesnetzagentur 2017a).

More recently, numerous countries have introduced competitive bidding mechanisms (e.g. auctions) to ascertain adequate levels of support for renewable energies. Although competitive mechanisms can promote the deployment of large installations of mature technologies successfully, such as wind energy, they are less well suited to promoting earlier-stage technologies for smaller-scale, distributed applications (e.g. residential energy storage, electric vehicles, or renewable heating) (Winkler *et al* 2018). For administratively-set incentives in policy instruments such as investment subsidies, tax credits, or FITs, the quest continues for a suitable mechanism to adjust incentives over time.

To our knowledge, only a handful of studies have quantitatively evaluated alternative policy designs to address this challenge. Leepa and Unfried (2013) showed with an econometric model that adjustments responsive to changes in technology prices could be more effective and efficient than non-responsive ones. Grau (2014) and Yaquob and Yamaguchi (2015) investigated the impact of different frequencies of responsive adjustments. Grau, using another econometric model, concluded that monthly adjustments are able to steer deployment towards policy goals, even with sudden changes in technology prices, while Yaquob and Yamaguchi, employing a system dynamics model, warned that adjustments made more frequently than monthly could slow down deployment. Pearce and Slade (2018) developed an agent-based model to reveal that a responsive adjustment based on deployment

milestones would be more cost-efficient and less uncertain than a linear reduction of incentives.

This study extends previous knowledge by (1) evaluating three novel policy designs based on control-theory principles that respond not only to the evolution of deployment or profitability but also to policy costs; (2) explicitly analyzing the designs' ability to curb windfall profits and reduce uncertainty over policy outcomes; and (3) assessing alternative ways of distributing policy targets. For this purpose, we simulate the policy designs for the case of Germany's FIT for PV during 2000–2016 using an agent-based model.

2. Method

In this paper, we develop an agent-based model (ABM) (see section 2.1 and details in the supplementary information (SI)) to study the adoption of PV by households and firms under different policy scenarios (see section 2.2). ABMs have been used extensively to study the influence of policy on the diffusion of PV (Haelg *et al* 2018, Schwarz *et al* 2019, Schiera *et al* 2019).

2.1. Agent-based model

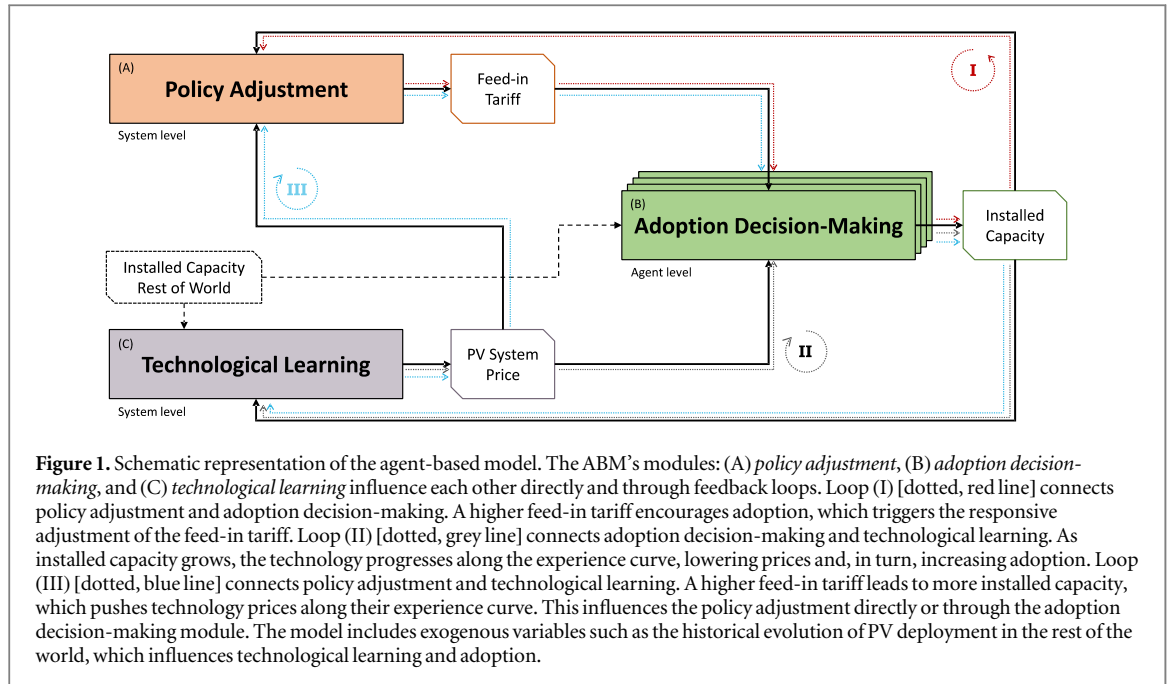
2.1.1. Model overview and outputs

Our ABM aims to represent the diffusion of PV in Germany in order to evaluate policy designs for adjusting the FIT between 2000 and 2016. The model creates an artificial population of heterogeneous households and firms that take decisions, which determine the evolution of solar deployment, based on their own attributes, variables in their environment, and their interactions with other agents.

The ABM has three modules: (A) *policy adjustment*, (B) *adoption decision-making*, and (C) *technological learning*, which it follows each time step (see figure 1). First, the FIT is adjusted according to the policy design being simulated. Second, agents decide whether to adopt PV or not. Third, PV prices progress along the technology's experience curve depending on the added capacity.

The ABM reports the installed capacity, policy costs, and windfall profits to adopters, which allow us to evaluate how successful each design is at keeping the policy (1) effective and (2) cost-efficient, and (3) to what extent it prevents windfall profits.

Deployment is measured by the PV capacity installed. Policy costs are the sum of $PC_{i,t}$ the incentives paid to each adopter i , calculated as the present cost of the annual FIT payments over the contract's duration (i.e. 20 years) since the installation month t (see equation (1)). This measure neglects other costs associated with the policy, such as administrative costs, since historically administrative costs account for a very small fraction of FIT payments in Germany (Netztransparenz.de 2019).



$$PC_{i,t} = \sum_{year=1}^{20} \frac{(FIT_t - EPW_{year}) \cdot GEN_{i, year} \cdot (1 - SC_i)}{(1 + DG_t)^{year}}. \quad (1)$$

Policy costs arise from the difference between the FIT_t and the yearly wholesale electricity market price EPW_{year} for the solar generation $GEN_{i, year}$ fed into the grid (i.e. not self-consumed SC_i). EPW_{year} prices are historical prices until 2016, after which we assume a 1.5% annual increase (see SI available online at stacks.iop.org/ERL/15/044002/mmedia) (Hoppmann *et al* 2014b). To discount future payments, we use the historical interest rates of German bonds DG_t for the month of installation (OECD 2017). Windfall profits $WP_{i,t}$ are the subsidies paid to each adopter above those required to induce them to invest (see section 2.1.4).

2.1.2. Model entities

There are two types of entities in the model: the observer and potential adopters. The observer is a system-level entity responsible for timekeeping, global variables, policy adjustment, and technological learning.

Potential adopters are individual, heterogeneous agents representing the population of electricity consumers in Germany. There are three categories of agents: residential; commercial and industrial; and utility-scale. According to their category, agents differ in PV system sizes, self-consumption ratios, electricity prices, discount rates, and FIT levels (see table 1).

Agents are distributed across urban and rural areas of Germany according to the density of residential buildings, where they receive the local annual irradiation (German Census 2014, NASA 2016). In addition to the category-dependent attributes, each agent has unique values for production factor, environmental

awareness, and individual discount rate (see tables S1–6 in SI).

2.1.3. Scale, temporal and spatial resolution

Due to computational power constraints, the population of agents was scaled down to 1:1000 (i.e. one agent in the model represents 1000 in reality), leading to 20 829 agents. Simulations ran from January 1992 to December 2016 on a monthly basis, using 10×10 km geographical patches.

2.1.4. Process scheduling

At each time step, the model proceeds through: (1) *policy adjustment*, (2) *adoption decision-making*, and (3) *technological learning*. The policies are in place between April, 2000 and December, 2016—as the historical FIT did in Germany (German Parliament 2000, BMWi 2016).

2.1.4.1. Policy adjustment

While the scheme is in place, the policy adjustment module monitors policy outcomes and, according to the design being simulated, corrects the FIT each month (see section 2.2).

2.1.4.2. Consumers' adoption decision-making

Agents decide whether to adopt or not, following a two-step process that non-adopters undergo every month.

Table 1. Main attributes of agents according to their category.

Type of agent	Number of agents in model ^a	System size ^b	Average solar self-consumption ^c	Electricity rate	Average discount rate ^d	Feed-in tariff level ^e
<i>Households</i>	16 891 ^f	0–10 kWp	30% ⁱ	Historical rates for households ^j	Historical lending rate ^k	100%
<i>Commercial and Industrial</i>	3853 ^g	10–40 kWp	20% ⁱ	Estimated historical rates ^j	Historical lending rate ^k	90%
<i>Utility-scale</i>	85 ^h	40–10 000 kWp	40% ⁱ	Historical rates for industry ^j	Historical lending rate ^k	70%

^a Average number of firms over several years are used to account for the variation in their populations during the years under study scaled down 1:1000.

^b The relative frequency of sizes within the range for each category, which reflects the categories considered in the German feed-in tariff in 2000, follows the empirical distribution observed in solar installations between 2009 and 2016 in Germany; see 11 in SI (Bundesnetzagentur 2017a).

^c Solar self-consumption rate is the fraction of electricity generated from the solar PV system that is consumed on-site by the adopter.

^d The historical lending rate for each adopter type is added to the individual discount rate of each agent.

^e Fraction of the feed-in tariff received by each adopter type based on the historical ratios between the feed-in tariffs for large and small installations in Germany (Bundesnetzagentur 2017a).

^f Based on the number of owner-occupied households in Germany (German Census 2014).

^g Average number of firms, except insurance activities of holdings, electricity, and finance firms, from 2008 to 2014 and average number of farms between 2000 and 2010 in Germany (Eurostat 2017a, 2017b).

^h Average number of electricity, financial, and insurance firms between 2008 and 2014 in Germany (Eurostat 2017a).

ⁱ The self-consumption rate of each agent is randomly assigned from a truncated normal distribution between 0 and 1, with the above mean, an assumed standard deviation of 0.05 (Fraunhofer ISE 2017).

^j Estimated monthly electricity rates based on historical values; see 13 in SI (Eurostat 2017c, 2017d).

^k Historical lending rates based on long-term loans at interest rates ranging from 1.4% to 9.6%; see 14 in SI (Deutsche Bundesbank 2017).

2.1.4.2.1. Getting the idea

Agents develop the idea of installing PV when the weighted sum of four variables exceeds a threshold of 0.5 (see equation (2) and SI). The variables represent: (1) peer effects, measured by the fraction of adopters among the agent's neighbors within a radius of 1 km (Müller and Rode 2013); (2) available information, simulated as the available news articles about PV through an empirically derived relation with deployment (see 15 in SI); (3) environmental awareness, as a constant awareness between 0 and 1 from a truncated normal distribution; and (4) the attractiveness of investing in PV, as the IRR for the average household adopter (Rai and Robinson 2015). All four variables range between 0 and 1, and their weights k_{peers} , k_{info} , $k_{awareness}$, $k_{attractive}$ are model calibration parameters

$$k_{peers} \cdot \left(\frac{PEERS_{PV_{i,t}}}{PEERS_i} \right) + k_{info} \cdot PVINFO_t + k_{awareness} \cdot PVAWE_i + k_{attractive} \cdot PVIRR_t > 0.5. \quad (2)$$

$$WP_{i,t} = \begin{cases} \text{if } NVP(FIT = 0)_{i,t} > 0 \text{ then } NVP(FIT)_{i,t} - NVP(FIT = 0)_{i,t} \\ \text{if } NPV(FIT = 0)_{i,t} \leq 0 \text{ then } NPV(FIT)_{i,t} \end{cases} \quad (9)$$

2.1.4.2.2. Economic evaluation

Agents with the idea of adopting perform an economic evaluation calculating the net present value of their installation, and adopt if it is not negative (see equation (3))

$$NPV_{i,t} = -INV_{i,t} + \sum_{year=0}^{year=20} \frac{AC_{i,t} - O\&M_{i,t} + FITR_{i,t}}{(1 + D_i)^{year}} \geq 0. \quad (3)$$

Alternatively, highly environmentally aware agents—about 1.8% of the model's population—represent innovators who skip the economic evaluation and adopt as soon as they developed the idea (Rogers 1995). The environmental awareness threshold is a calibration parameter.

Agents estimate investment costs $INV_{i,t}$ according to: its system's size $PVSIZE_i$, PV prices $PVPRICE_t$, and scale effects SE_i (see equations (4) and 16 in SI).

$$INV_{i,t} = PVSIZE_i \cdot PVPRICE_t \cdot SE_i, \quad (4)$$

$$SE_i = 1.1246 \cdot PVSIZE_i^{-0.051}. \quad (5)$$

Avoided costs $AC_{i,t}$ from self-consumption SC_i and revenue from policy incentives $FITR_{i,t}$ are positive cash flows that depend on the solar generation

GEN_i , the electricity prices $EP_{i,t}$, and the FIT_t (see equations (6), (7)). Annual operation and maintenance costs are the only negative cash flow, assumed to be 1.5% of the investment costs (Hoppmann *et al* 2014b).

$$AC_{i,t} = SC_i \cdot GEN_i \cdot EP_{i,t}, \quad (6)$$

$$FITR_{i,t} = (1 - SC_i) \cdot GEN_i \cdot FIT_t. \quad (7)$$

Solar generation depends on the irradiation at the agent's location SUN_i , the system size, the performance ratio $PVPR$ (assumed to be 0.85), and the agent's production factor $PVPF_i$ that accounts for heterogeneity across installations (e.g. shade) (see equation (8)) (Fraunhofer ISE 2017).

$$GEN_i = SUN_i \cdot PVSIZE_i \cdot PVPR \cdot PVPF_i. \quad (8)$$

2.1.4.3. Windfall profits

Any incentives inducing or increasing a positive $NPV_{i,t}$ are windfall profits $WP_{i,t}$ because they are not required to motivate adoption (see equation (9)).

2.1.4.4. Technological learning

PV system prices comprise module and non-module elements. Module prices follow an experience curve that depends on the simulated deployment in Germany, and the historical deployment in the rest of the world (Schaeffer *et al* 2004, IEA-PVPS 2018, Kavlak *et al* 2018). Non-module prices (e.g. balance of system, installation) follow another experience curve that depends only on the simulated installations in Germany. Based on historical data, we estimated learning rates of 20.3% for modules and 10.2% for non-module elements, and limited price reductions to below 2% per month (see 11 in SI). Random $\pm 5\%$ oscillations around the experience curve represent noise in price signals.

2.1.5. Model calibration and robustness tests

The model was calibrated to the historical cumulative installations in Germany between 1992 and 2016 (see 4 in SI). The calibration parameters were the k_{info} , $k_{awareness}$, $k_{attractive}$ weights (k_{peers} is linearly dependent so they sum up to 1), and the environmental awareness threshold, restricted to above 0.88 so innovators are fewer than 3% of agents (Rogers 1995). The entire space of calibration parameter combinations was examined. The selected parameters closely replicate the historical evolution (see table 2 and figure 2). Because of the ABM's stochastic inputs, results were derived from 60 simulation-runs batches, which

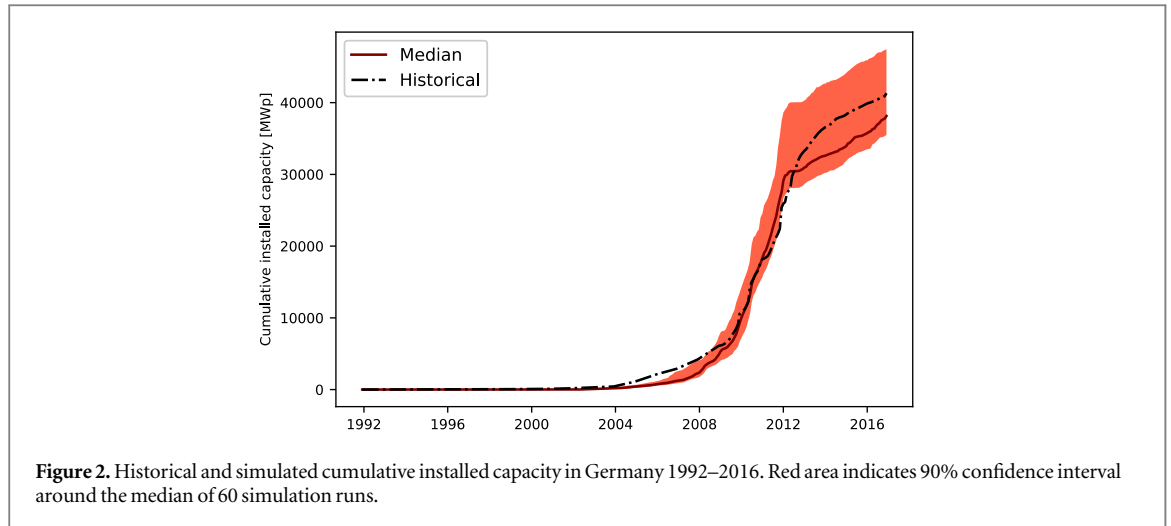


Table 2. Calibrated, adimensional parameters of model.

Calibration parameter	Calibrated value	Value range
k_{info}	0.19	[0,1]
$k_{\text{awareness}}$	0.49	[0,1]
$k_{\text{attractive}}$	0.11	[0,1]
<i>Environmental awareness threshold</i>	0.90	[0.88,1]

deviate 2% or less around the mean of a 1000-simulation-runs sample (see 4 in SI).

A sensitivity analysis to variations of the calibration parameters is available (see 6 in SI), as well as robustness tests to: variations of policy parameters (see 7 in SI), policy goals (see 8 in SI) and their temporal distributions (see 9 in SI), and the impact of solar deployment on wholesale and retail electricity prices (see 10 in SI). These analyses support the robustness of the qualitative implications of this study.

2.2. Policy scenarios

We simulate the historical policy scenario, which contains the historical FIT, and seven policy scenarios with designs inspired by control theory (see table 3).

We evaluate three policy designs inspired by control theory that automatically adjust incentives. In contrast to historical mechanisms, these designs do not attempt to predict the pace of technological learning, and refrain from using predefined adjustments (Kreycik *et al* 2011, Grau 2014). Instead, they calculate an incentive adjustment each month using a PID (proportional, integrative, and derivative) mechanism.

Each design employs different variables to calculate the adjustments depending on how policy targets are defined. Deployment (DEP) and policy cost (COST) targets set an overall goal (i.e. a deployment level or a budget). Profitability (IRR) targets, however, set a desired internal return rate for the average household adopter in Germany (see table 1), who receives an annual solar yield of 950 kWh/kWp (Fraunhofer

ISE 2017), and maintain that target constant throughout the policy's duration.

All three designs employ the same PID algorithm, which is a basic and extensively used tool from control engineering. The algorithm's objective is to correct the deviation from monthly policy targets e_t , measured as the difference between the actual and the targeted monthly installed capacity, policy costs, or profitability to adopters, depending on the policy targets. The algorithm tries to simultaneously correct the previous month's deviation (i.e. proportional correction), compensate for the cumulative deviation since the policy began (i.e. integrative correction), and reduce the growth in the deviation over the following month (i.e. derivative correction). The FIT adjustment is the weighted sum of these corrections (see equation (10)). A set of proportionality constants was defined for each design (see section 2.2.1).

$$FIT_t = FIT_{t-1} + k_p \cdot e_{t-1} + k_i \cdot \sum_{m=1}^{m=t-1} e_m + k_d \cdot (e_{t-2} - e_{t-1}). \quad (10)$$

For deployment and policy-cost targets, we assess two ways of distributing the overall targets PT throughout the policy's duration: *linear distribution* ($-L$), which increases targets by the same amount every month, trying to benefit from lower technology costs in later years (see equation (11)), and *bell-shaped distribution* ($-B$), which aims to exploit the typical s-shaped pattern of the diffusion of innovations (see equations (12a) and (12b) and figure 3).

$$PT(\text{linear})_t = t \cdot \frac{PT}{\sum_{t=0}^{t=n} t}, \quad (11)$$

$$PT(\text{bell})_t = CUMPT_{t+1} - CUMPT_t, \quad ((12a))$$

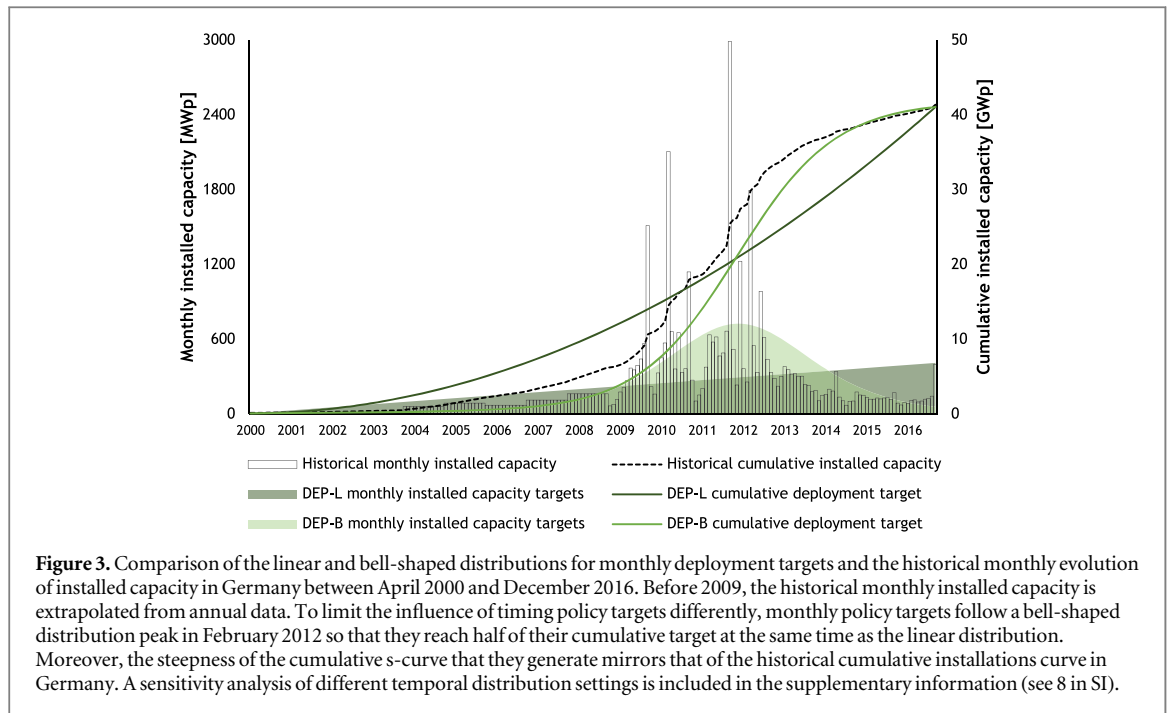


Table 3. Summary of the simulated scenarios.

Scenario	Policy target	Overall target	Temporal distribution of monthly targets
HIST ^a	Historical policy	[-]	[-]
DEP-L	Deployment	41 GWp ^b	Linear
DEP-B			Bell-shaped ($k = 0.07$, $t_{peak} = 142$)
COST-L	Policy cost	€115 billion	Linear
COST-B			Bell-shaped ($k = 0.07$, $t_{peak} = 142$)
IRR-5%	Profitability	5% IRR	Uniform
IRR-7%		7% IRR	
IRR-9%		9% IRR	

^a The historical scenario includes the ‘1000 Solar Roofs’ program with 70% investment subsidies (1992–1993) and the ‘100 000 Solar Roofs’ program with 1.91% rate loans (1999–2003), the costs of which are not accounted for due to their small size. The different adjustment mechanisms in the historical scenario are detailed in the SI (see 2 in SI).

^b Watt peak (Wp) is a measurement unit of electrical power that refers to the nominal power output of a photovoltaic device under standard test conditions in direct current. A sensitivity analysis to overall policy targets is included in the supplementary information (see 8 in SI).

Table 4. Policy parameters for each design.

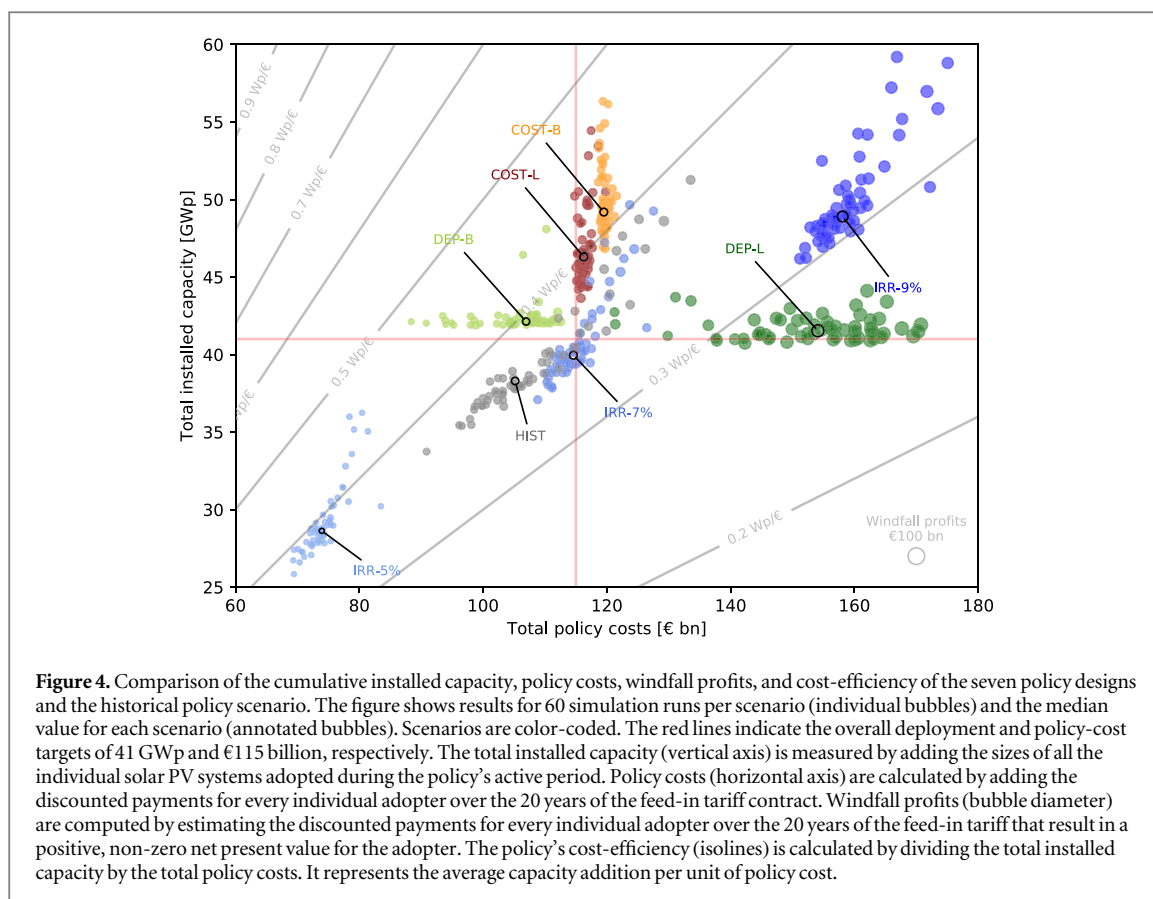
Policy targets	Unit	k_p	k_i	k_d
Deployment	[€/kWh per MWp]	$4.00 \cdot 10^{-5}$	$2.00 \cdot 10^{-6}$	$1.00 \cdot 10^{-8}$
Policy cost	[€/kWh per € million]	$9.00 \cdot 10^{-6}$	$4.00 \cdot 10^{-7}$	$1.00 \cdot 10^{-7}$
Profitability	[€/kWh]	3.40	0.01	1.00

$$CUMPT_t = \frac{PT}{(1 + \exp(-k \cdot (t - t_{peak})))} \quad ((12b))$$

To limit the influence of timing policy targets differently, t_{peak} is set to 142 (i.e. February, 2012) so both distributions reach 50% and 100% of their overall goals simultaneously. The steepness of the cumulative s-curve k is 0.07 based on historical data from

Germany. We decided against uniformly distributed targets because early results indicated high policy costs.

We compare the designs to a historical policy scenario that simulates the mechanisms and ad-hoc adjustments to Germany’s FIT between 2000 and 2016 (see table S7 in SI). We defined the deployment and policy-cost goals according to the historical policy outcomes of 41 GWp of PV and €115 billion of total costs (own estimation) by 2016 (Frondel *et al* 2010,



Bundesnetzagentur 2017b), while using three profitability targets. In all cases, FIT contracts last for 20 years and the initial level is the historical one: 0.5062 €/kWh (German Parliament 2000).

2.2.1. Setting of policy parameters

Analogous to designs employed historically (e.g. German Parliament 2008, California PUC 2017), the policy designs require certain parameters to be defined. In particular, three proportionality constants for each design's PID algorithm because they employ different targets. The parameters selected (1) achieved a median deviation from the overall policy goals below 5%, and (2) minimized deviations from monthly targets (see table 4, and section 5 in SI). We explored the whole parameter space through iterative runs of our model, building upon the practice of incorporating models to policy-making (e.g. European Commission 2019).

3. Results

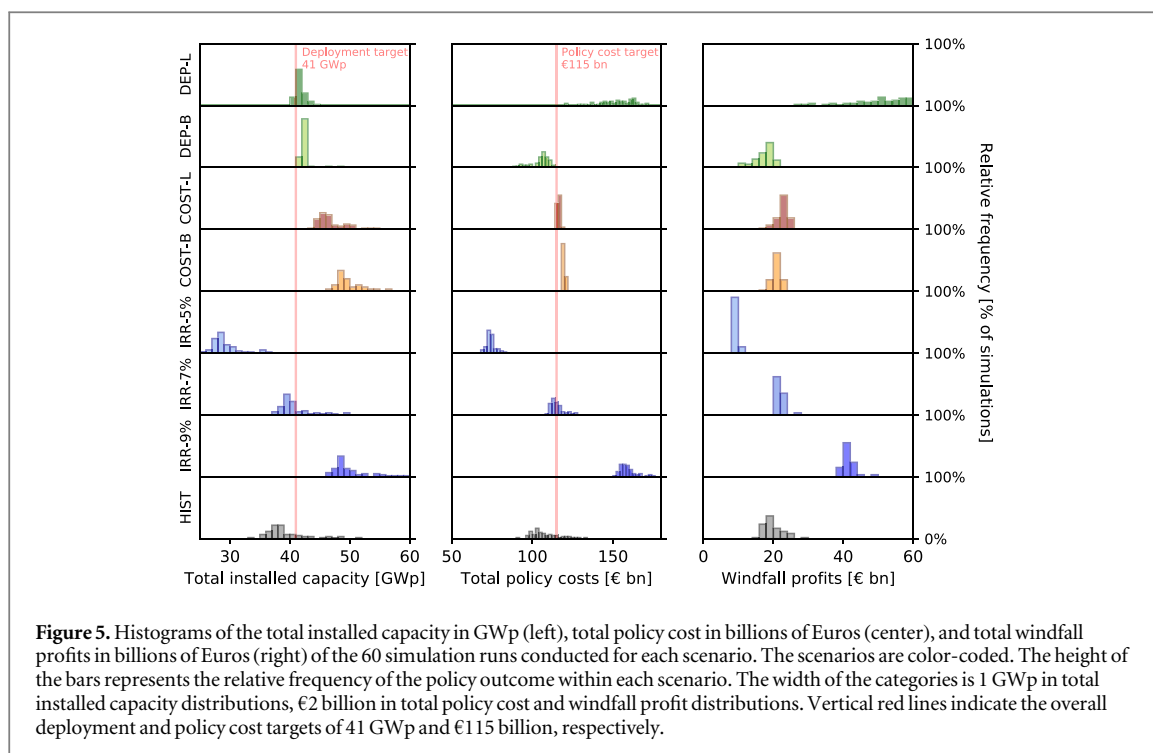
We find that the policy designs inspired by control theory are effective in steering adoption towards the policy targets, and markedly reduce uncertainty about policy outcomes. However, not every scenario is more cost-efficient (i.e. has a higher installed capacity per unit of policy cost) than the historical policy scenario. These results imply that small details in the design of the adjustment mechanism could have large impacts over policy outcomes.

3.1. Impact of policy design on windfall profits

Figure 4 shows the total installed capacity, policy cost, and windfall profits of all individual runs and the median of each scenario. It also indicates the lines of constant cost-efficiency. Our results demonstrate that there is no fixed correlation between the amount spent on subsidies (i.e. policy cost) and the technology's deployment (i.e. installed capacity). Rather, the policy design for adjusting incentives heavily influences this relationship—and, thus, the policy's cost-efficiency.

Adjusting incentives according to deployment or policy-cost targets leads to a decoupling between final installations and the cost of the policy. For instance, the DEP-B scenario achieves the same installed capacity as DEP-L, but at much lower policy costs. Similarly, COST-L and COST-B have similar policy costs but different ranges of installed capacities. In contrast, adjusting incentives in order to maintain constant profitability for adopters produces a relation between policy costs and installed capacity that depends on the targeted rate of return. The lower the profitability targeted, the larger the gains in installed capacity per additional unit of policy cost, but also the lower the total deployment (e.g. IRR-5%).

All scenarios show the expected relation between windfall profits and policy cost-efficiency, with bubble sizes decreasing as they approach the upper-left corner of figure 4 (i.e. as the policy's cost-efficiency increases). However, not all designs proved equally good at reducing windfall profits. Adjusting incentives following



policy cost targets produces more cost-efficient outcomes because the mechanism reacts to increases in windfall profits more strongly than if it followed deployment or profitability targets. Public funds spent on windfall profits are determined by the product of installations and revenues to adopters above those needed to induce them to invest. Thus, windfall profit expenses grow in two cases: (1) if installations increase while the FIT already provides excess revenues; or (2) if profitability rises so that revenues to adopters surpass those needed to induce adoption and installations do not fall. A policy design that responds to changes in installations primarily reacts to the first case, while a design tracking profitability mainly reacts to the second. Only a design following policy costs responds to both cases, because more windfall profit expenses directly impact policy costs regardless of what drives their increase. Although low profitability targets also limit windfall profits, they induce limited deployment, which diminishes the policy's effectiveness.

3.2. Impact of policy design on uncertainty about policy outcomes

Figure 5 compares installed capacities, policy costs, and windfall profits across scenarios. The results show that adjusting incentives using a design inspired by control theory could markedly reduce uncertainty over the outcomes of deployment policies.

Adjusting incentives according to changes in installations or policy costs produces policies that deviate only slightly from their targets. Adjusting to changes in the profitability for adopters produces policies that restrict windfall profits around a value that increases with higher profitability targets. The PID

algorithm produces these outcomes by simultaneously addressing the monthly and cumulative deviations and trying to prevent their growth. However, this mechanism does not limit uncertainty about policy outcomes that are not specifically targeted by the policy design (e.g. policy costs in DEP scenarios). Moreover, there are important differences between designs that respond to the same policy variable, due to the different temporal distributions of policy targets (e.g. DEP-L and DEP-B).

Notably, the historical mechanisms and ad-hoc adjustments to Germany's feed-in tariff (HIST) produce the most scattered policy outcomes (see figure 5). This highlights how uncertain the outcome of the scheme was, and how much the novel designs could improve upon it.

3.3. Impact of temporal distributions of targets on policy cost-efficiency

Figure 6 shows the temporal evolutions of the median FIT and monthly installations for each scenario. The results highlight the influence of the temporal distribution of policy targets for achieving cost-efficient deployment policies.

For the deployment and policy-cost scenarios, policy targets distributed linearly caused surges in installations, during which adopters receive generous windfall profits, which determined the lower cost-efficiencies of these scenarios compared to those with bell-shaped distributed targets (see DEP-L, COST-L in figures 6(a), (b)). The non-economic factors that influence the behavior of the agents in our model explain this phenomenon. In the early years of the policy, non-economic variables such as information about the

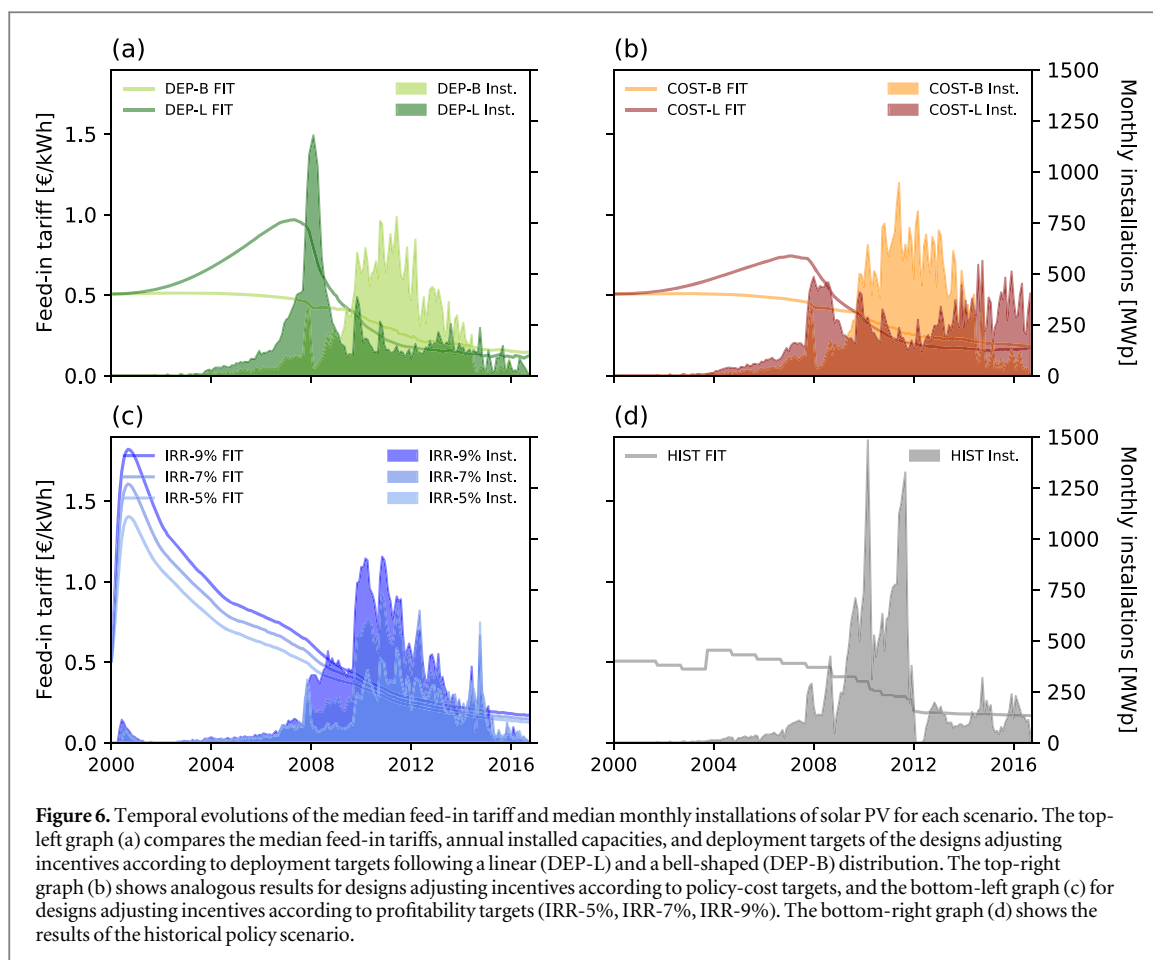


Figure 6. Temporal evolutions of the median feed-in tariff and median monthly installations of solar PV for each scenario. The top-left graph (a) compares the median feed-in tariffs, annual installed capacities, and deployment targets of the designs adjusting incentives according to deployment targets following a linear (DEP-L) and a bell-shaped (DEP-B) distribution. The top-right graph (b) shows analogous results for designs adjusting incentives according to policy-cost targets, and the bottom-left graph (c) for designs adjusting incentives according to profitability targets (IRR-5%, IRR-7%, IRR-9%). The bottom-right graph (d) shows the results of the historical policy scenario.

technology and peer effects have a low impact because PV installations are rare. The policy designs try to compensate for this by increasing the FIT in order to encourage enough adoption to meet the monthly targets. However, since the economic attractiveness of solar PV is just one of the four factors determining whether agents develop the idea to adopt, the FIT needs to increase very substantially to have a big enough influence on the agents. As the months go by, more information becomes available, peer effects become stronger, and the very high incentives lead to deployment overshoots. The behavior observed in our model is analogous to historical experiences in countries such as Italy and Spain (Del Río and Mir-Artigues 2014, Di Dio *et al* 2015).

4. Discussion and policy implications

This study shows how new policy designs for adjusting incentives could draw inspiration from control theory to keep deployment policies effective and cost-efficient, while reducing uncertainty over their outcomes.

First, our results show that adjusting incentives specifically according to the evolution of policy costs can produce more cost-efficient deployment policies. Prior research focused on mechanisms that tracked the evolution of deployment or profitability for

adopters (Leepa and Unfried 2013, Grau 2014, Yaqub and Yamaguchi 2015, Pearce and Slade 2018). However, we find that, compared to the historical policy scenario (HIST) (not to historical data), in the best case, Germany could have saved over €320 million (−11.7%) per gigawatt-peak installed by adjusting incentives in response to policy costs with targets distributed following a bell curve (COST-B).

Second, this study suggests that responsive policy designs based on control-theory principles can significantly reduce uncertainty over the outcomes of future deployment policies. With such designs, policy outcomes deviated by less than 5% from their targets for 93% of the simulations—in stark contrast to the historical policy simulations, which, on average, were 40% off their annual targets of 3000 MWp between 2012 and 2016 (BMW 2014, Bundesnetzagentur 2017a). This should instil confidence in the ability of future policies to meet their targets. However, our results highlight a need for limiting uncertainty about policy outcomes these designs do not respond to (e.g. policy costs in DEP scenarios), for example, through caps. In addition, responsive adjustments to incentives could diminish the ability of investors to predict their evolution, and increase investor's perception of risk (Polzin *et al* 2019). Policymakers could lessen this tradeoff by transparent and timely communication about the policy design and incentive adjustments.

Third, our study reveals the decisive role of the temporal distribution of policy targets, and highlights the limitations of economic incentives in driving early adoption. When there are non-economic barriers to the diffusion of a technology, as research has shown e.g. for electric cars, attempting an ambitious ramp-up through subsidies alone could lead to costly adoption surges and jeopardize the whole policy (Ragwitz and Steinhilber 2014, De Rubens *et al* 2018). To address this, future policies could employ gradually rising targets and exploit synergies with non-economic instruments such as information campaigns.

Overall, this analysis overcomes the limitations of previous studies and bears relevant policy implications, for instance, for deployment policies targeting energy storage, electric vehicles, or renewable heating (IRENA *et al* 2018). As subsidy schemes are scrutinized to determine whether they are proving ineffective or inefficient (Wee *et al* 2018, Jenn *et al* 2018), our findings can help to improve their cost-efficiency and reduce uncertainty over their outcome.

Our model is limited in the representation of technological change and adoption decision-making, and in its scope. Future research might consider investigating how market dynamics influence pricing, and how expectations may change agents' behaviour. For example, if agents could form expectations, they might postpone their investments if they foresee that PV prices will reduce faster than incentives, or accelerate their adoption otherwise. Although we would anticipate our results to remain qualitatively similar, since the policy designs adjust incentives in response to how deployment evolves, we believe this question deserves further analysis. To test the robustness of our findings, further research could also study other countries, policies and technologies.

Acknowledgments

The authors declare no competing interests. We are thankful to Hendrik Clausdeinken, Petrisa Eckle, Bastien Girod, David Grosspietsch, and Annegret Stephan, and to participants in the NEST-2017 and IST-2017 conferences who provided valuable comments on previous versions of this work. This research is part of the activities of CREST and FEED&D Swiss Competence Centers for Energy Research financially supported the Swiss Innovation Agency: Innosuisse.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID iDs

Alejandro Nuñez-Jimenez  <https://orcid.org/0000-0002-1505-9772>

Christof Knoeri  <https://orcid.org/0000-0003-0355-1011>

Joern Hoppmann  <https://orcid.org/0000-0002-1820-6600>

References

- Alizamir S, de Véricourt F and Sun P 2016 Efficient feed-in-tariff policies for renewable energy technologies *Oper. Res.* **64** 52–66
- BMWi 2014 *Act on the Development of Renewable Energy Sources (Renewable Energy Sources Act - RES Act 2014)* (<http://bmwi.de/Redaktion/EN/Downloads/renewable-energy-sources-act-eeg-2014.html>)
- BMWi 2016 *2017 Revision of the Renewable Energy Sources Act*
- Bollinger B and Gillingham K 2014 Learning-by-Doing in Solar Photovoltaic Installations SSRN (<https://doi.org/10.2139/ssrn.2342406>)
- Bundesnetzagentur 2017a *Data from the Installations Register* (https://bundesnetzagentur.de/EN/Areas/Energy/Companies/RenewableEnergy/InstallationsRegister/InstallationsRegister_node.html)
- Bundesnetzagentur 2017b *Figures, Data and Information on the EEG* (https://bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/ErneuerbareEnergien/ZahlenDatenInformationen/zahlenunddaten-node.html)
- California PUC 2017 *California Solar Initiative Program Handbook* (http://gosolarcalifornia.ca.gov/documents/CSI_HANDBOOK.PDF)
- Créti A and Jouag J 2012 *Let the Sun Shine : Optimal Deployment of Photovoltaics in Germany* (<https://hal.archives-ouvertes.fr/hal-00751743>)
- Deutsche Bundesbank 2017 *Money and Capital Markets—Time Series Database Statistics* (https://www.bundesbank.de/dynamic/action/en/statistics/time-series-databases/time-series-databases/743796/743796?treeAnchor=GELD&statisticType=BBK_ITS)
- Dijkgraaf E, van Dorp T and Maasland E 2014 On the effectiveness of feed-in tariffs in the development of photovoltaic solar SSRN *Electron. J.* (<https://doi.org/10.2139/ssrn.2541588>)
- Di Dio V, Favuzza S, La Cascia D, Massaro F and Zizzo G 2015 Critical assessment of support for the evolution of photovoltaics and feed-in tariff(s) in Italy *Sustain. Energy Technol. Assess.* **9** 95–104
- De Rubens G Z, Noel L and Sovacool B K 2018 Dismissive and deceptive car dealerships create barriers to electric vehicle adoption at the point of sale *Nat. Energy* **3** 501–7
- del Río P and Mir-Artigues P 2012 Support for solar PV deployment in Spain: some policy lessons *Renew. Sustain. Energy Rev.* **16** 5557–66
- Del Río P and Mir-Artigues P 2014 A cautionary tale: Spains solar PV investment bubble *Int. Inst. Sustain. Dev.*
- European Commission 2019 EU Commission Competence Center on Modelling (<https://ec.europa.eu/jrc/en/modelling>)
- Eurostat 2017a *Business demography* (<http://ec.europa.eu/eurostat/web/structural-business-statistics/entrepreneurship/business-demography>)
- Eurostat 2017b *ef_oluft Land use: number of farms and areas of different crops by type of farming (2-digit)* (http://ec.europa.eu/eurostat/web/products-datasets/-/ef_oluft)
- Eurostat 2017c *Electricity prices for domestic consumers Energy Price Stat.* (http://ec.europa.eu/eurostat/statistics-explained/index.php/Energy_price_statistics#Electricity_prices_for_household_consumers)

- Eurostat 2017d Electricity prices for industrial consumers Energy Price Stat. (http://ec.europa.eu/eurostat/statistics-explained/index.php/Energy_price_statistics#Electricity_prices_for_household_consumers)
- Fraunhofer ISE 2017 *Recent Facts about Photovoltaics in Germany* (<https://ise.fraunhofer.de/content/dam/ise/en/documents/publications/studies/recent-facts-about-photovoltaics-in-germany.pdf>)
- Fronzel M, Ritter N, Schmidt C M and Vance C 2010 Economic impacts from the promotion of renewable energy technologies: the German experience *Energy Policy* **38** 4048–56
- German Census 2014 Statistische Ämter des Bundes und der Länder Zensus 2011 Database (<https://zensus2011.de>)
- German Parliament 2000 Renewable Energy Sources Act (<https://web.archive.org/web/20160921012408/http://bmub.bund.de/fileadmin/bmu-import/files/pdfs/allgemein/application/pdf/res-act.pdf>)
- German Parliament 2008 Gesetz für den Vorrang Erneuerbarer Energien (Renewable Energy Sources Act 2009) (https://clearingstelle-eeg-kwkg.de/files/EEG_2009_Urfassung_juris.pdf)
- Grau T 2014 Responsive feed-in tariff adjustment to dynamic technology development *Energy Econ.* **44** 36–46
- Gürtler K, Postpischil R and Quitzow R 2019 The dismantling of renewable energy policies: the cases of Spain and the Czech Republic *Energy Policy* **133** 110881
- Haas R *et al* 2004 How to promote renewable energy systems successfully and effectively *Energy Policy* **32** 833–9
- Haelg L, Waelchli M and Schmidt T S 2018 Supporting energy technology deployment while avoiding unintended technological lock-in: A policy design perspective *Environ. Res. Lett.* **13** 104011
- Hoppmann J, Huenteler J and Girod B 2014a Compulsive policy-making - The evolution of the German feed-in tariff system for solar photovoltaic power *Res. Policy* **43** 1422–41
- Hoppmann J, Volland J, Schmidt T S and Hoffmann V H 2014b The economic viability of battery storage for residential solar photovoltaic systems - a review and a simulation model *Renew. Sustain. Energy Rev.* **39** 1101–18
- IEA-PVPS 2018 *2018 Snapshot of Global Photovoltaic Markets* (http://iea-pvps.org/fileadmin/dam/public/report/statistics/IEA-PVPS_-_A_Snapshot_of_Global_PV_-_1992-2016_1_.pdf)
- IRENA, IEA and REN21 2018 *Renewable Energy Policies in a Time of Transition* (http://iea.org/publications/freepublications/publication/IRENA_IEA_REN21_Policies_2018.pdf)
- Jenn A, Springel K and Gopal A R 2018 Effectiveness of electric vehicle incentives in the United States *Energy Policy* **119** 349–56
- Jenner S, Groba F and Indvik J 2013 Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries *Energy Policy* **52** 385–401
- Kavlak G, McEnerney J and Trancik J E 2018 Evaluating the causes of cost reduction in photovoltaic modules *Energy Policy* **123** 700–10
- Klein A, Pfluger B, Held A, Ragwitz M, Resch G and Faber T 2008 *Evaluation of Different Feed-in Tariff Design Options: Best Practice paper for the International Feed-in Cooperation* (http://renewwisconsin.org/policy/ARTS/MISC Docs/best_practice_paper_2nd_edition_final.pdf)
- Kreycik C, Couture T D and Cory K S 2011 Innovative Feed-In Tariff Designs that Limit Policy Costs *Technical Report NREL/TP-6A20-50225* (<https://doi.org/10.2172/1219216>)
- Leepa C and Unfried M 2013 Effects of a cut-off in feed-in tariffs on photovoltaic capacity: evidence from Germany *Energy Policy* **56** 536–4
- Li L, Liu J, Zhu L and Zhang X-B 2019 How to design a dynamic feed-in tariffs mechanism for renewables—a real options approach *Int. J. Prod. Res.* **7543** 1–15
- Mendonça M, Jacobs D and Sovacool B 2009 Advanced FIT design options *Powering the Green Economy: The Feed-in Tariff Handbook* (London: Earthscan) pp 39–56
- Müller S and Rode J 2013 The adoption of photovoltaic systems in Wiesbaden, Germany *Econ. Innov. New Technol.* **22** 519–35
- NASA 2016 NASA surface irradiation database (<https://eosweb.larc.nasa.gov/sse/>)
- Netztransparenz.de 2019 Annual Accounts Overview of Renewable Energy Sources Act (<https://netztransparenz.de/EEG/EEG-Konten-Uebersicht>)
- OECD 2017 Long-term interest rates Mon. Monet. Financ. Stat. (http://stats.oecd.org/Index.aspx?DataSetCode=MEI_FIN)
- Pearce P and Slade R 2018 Feed-in tariffs for solar microgeneration: policy evaluation and capacity projections using a realistic agent-based model *Energy Policy* **116** 95–111
- Polzin F, Egli F, Steffen B and Schmidt T S 2019 How do policies mobilize private finance for renewable energy?—A systematic review taking an investor perspective *Appl. Energy* **236** 1249–68
- Ragwitz M and Steinhilber S 2014 Effectiveness and efficiency of support schemes for electricity from renewable energy sources *WIREs Energy Environ.* **3** 213–29
- Rai V and Robinson S A 2015 Agent-based modeling of energy technology adoption: empirical integration of social, behavioral, economic, and environmental factors *Environ. Model. Softw.* **70** 163–77
- Rogelj J *et al* 2018 Mitigation pathways compatible with 1.5 °C in the context of sustainable development *Global Warming of 1.5 °C. IPCC Special Report 3: Ch 2 IPCC*
- Rogers E M 1995 *Diffusion of Innovations* (New York: The Free Press)
- Schaeffer G J *et al* 2004 *Learning from the Sun—Analysis of the use of experience curves for energy policy purposes* (<http://ecm.nl/docs/library/report/2004/c04035.pdf>)
- Schiera D S, Minuto F D, Bottaccioli L, Borchiellini R and Lanzini A 2019 Analysis of rooftop photovoltaics diffusion in energy community buildings by a novel GIS- and agent-based modeling co-simulation platform *IEEE Access* **7** 93404–32
- Schwarz M, Ossenbrink J, Knoeri C and Hoffmann V H 2019 Addressing integration challenges of high shares of residential solar photovoltaics with battery storage and smart policy designs *Environ. Res. Lett.* **14** 074002
- Sijm J P M 2002 The performance of feed-in tariffs to promote renewable electricity in European countries *Project ECN Report* 34016026
- Spanish Parliament 2008 *Royal Decree 1578/2008 BOE-A-2008-15595* (<https://boe.es/eli/es/rd/2008/09/26/1578>)
- Vaishnav P, Horner N and Azevedo I L 2017 Was it worthwhile? Where have the benefits of rooftop solar photovoltaic generation exceeded the cost? *Environ. Res. Lett.* **12** 094015
- Wand R and Leuthold F 2011 Feed-in tariffs for photovoltaics: learning by doing in Germany? *Appl. Energy* **88** 4387–99
- Wee S, Coffman M and La Croix S 2018 Do electric vehicle incentives matter? Evidence from the 50 US states *Res. Policy* **47** 1601–10
- Winkler J, Magosch M and Ragwitz M 2018 Effectiveness and efficiency of auctions for supporting renewable electricity—What can we learn from recent experiences? *Renew. Energy* **119** 473–89
- Yaquob A A and Yamaguchi K 2015 Dynamic feed in tariff price adjustments for the rooftop PV market in Germany *Proc. 33rd Int. Conf. Syst. Dyn. Soc.* pp 1–20