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LETTER

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

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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 Joua 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, Kreyck 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 (Haeg 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).
unique values for production factor, environmental awaremess, 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).

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.

Policy costs arise from the difference between the FIT$_i$ 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 $DG_i$ 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).

\[
PC_{i,t} = \frac{\sum_{year=1}^{20} (FIT_i - EPW_{year}) \cdot GEN_{i,year} \cdot (1 - SC_i)}{(1 + DG_i)^{year}}.
\]  

Figure 1. Schematic representation of the agent-based model. The ABM’s modules: (A) policy adjustment, (B) adoption decision-making, and (C) technological learning influence each other directly and through feedback loops. Loop (I) (dotted, red line) connects policy adjustment and adoption decision-making. A higher feed-in tariff encourages adoption, which triggers the responsive adjustment of the feed-in tariff. Loop (II) (dotted, grey line) connects adoption decision-making and technological learning. As installed capacity grows, the technology progresses along the experience curve, lowering prices and, in turn, increasing adoption. Loop (III) (dotted, blue line) connects policy adjustment and technological learning. A higher feed-in tariff leads to more installed capacity, which pushes technology prices along their experience curve. This influences the policy adjustment directly or through the adoption decision-making module. The model includes exogenous variables such as the historical evolution of PV deployment in the rest of the world, which influences technological learning and adoption.
Table 1. Main attributes of agents according to their category.

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

\(^a\) 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 \(k_{\text{peers}}, k_{\text{info}}, k_{\text{awareness}}, k_{\text{attractive}}\) are model calibration parameters:

\[
k_{\text{peers}} \left( \frac{\text{PEERSPV}_{i,t}}{\text{PEERS}_{i}} \right) + k_{\text{info}} \cdot \text{PVINFO}_{i} + k_{\text{awareness}} \cdot \text{PVAWE}_{i} + k_{\text{attractive}} \cdot \text{PVIRR}_{i} > 0.5.
\]


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))

\[
\text{NPV}_{i,t} = -\text{INV}_{i,t} + \sum_{\text{year}=0}^{20} \left( \frac{\text{AC}_{i,t} - \text{O&M}_{i,t} + \text{FITR}_{i,t}}{(1 + D_{i})^{\text{year}}} \right) \geq 0.
\]

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 \(\text{INV}_{i,t}\), according to: its system’s size \(\text{PVSIZE}_{i}\), PV prices \(\text{PVPRICE}_{i}\), and scale effects \(\text{SE}_{i}\) (see equations (4) and 16 in SI).

\[
\text{INV}_{i,t} = \text{PVSIZE}_{i} \cdot \text{PVPRICE}_{i} \cdot \text{SE}_{i}.
\]

\[
\text{SE}_{i} = 1.1246 \cdot \text{PVSIZE}_{i}^{-0.051}.
\]

Avoided costs \(\text{AC}_{i,t}\) from self-consumption \(\text{SC}_{i}\) and revenue from policy incentives \(\text{FITR}_{i,t}\) are positive cash flows that depend on the solar generation \(\text{GEN}_{i}\), the electricity prices \(\text{EP}_{i,t}\), and the \(\text{FIT}_{i}\) (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).

\[
\text{AC}_{i,t} = \text{SC}_{i} \cdot \text{GEN}_{i} \cdot \text{EP}_{i,t},
\]

\[
\text{FITR}_{i,t} = (1 - \text{SC}_{i}) \cdot \text{GEN}_{i} \cdot \text{FIT}_{i}.
\]

Solar generation depends on the irradiation at the agent’s location \(\text{SUN}_{i}\), the system size, the performance ratio \(\text{PVPR}\) (assumed to be 0.85), and the agent’s production factor \(\text{PVPF}_{i}\) that accounts for heterogeneity across installations (e.g. shade) (see equation (8)) (Fraunhofer ISE 2017).

\[
\text{GEN}_{i} = \text{SUN}_{i} \cdot \text{PVSIZE}_{i} \cdot \text{PVPR} \cdot \text{PVPF}_{i}.
\]

2.1.4.3. Windfall profits

Any incentives inducing or increasing a positive \(\text{NPV}_{i,t}\) are windfall profits \(\text{WP}_{i,t}\) because they are not required to motivate adoption (see equation (9)).

\[
\text{WP}_{i,t} = \begin{cases} \text{if } \text{NPV}(\text{FIT} = 0)_{i,t} > 0 \text{ then } \text{NPV}(\text{FIT})_{i,t} - \text{NPV}(\text{FIT} = 0)_{i,t} \\ \text{if } \text{NPV}(\text{FIT} = 0)_{i,t} \leq 0 \text{ then } \text{NPV}(\text{FIT})_{i,t} \end{cases}
\]

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, Kavkavl 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 ±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 \(k_{\text{info}}, k_{\text{awareness}}, k_{\text{attractive}}\) weights (\(k_{\text{peers}}\) 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
Environmental awareness simulation runs 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).

$$FIT_t = FIT_{t-1} + k_p \cdot e_{t-1}$$

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

(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).

$$PT(\text{linear})_t = t \cdot \frac{PT}{\sum_{t=0}^{\infty} t}.$$  

(11)

$$PT(\text{bell})_t = CUMPT_{t+1} - CUMPT_t.$$  

((12a))
To limit the influence of timing policy targets differently, \( t_{\text{peak}} \) is set to 142 (i.e. February, 2012) so that 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, Figure 3. Comparison of the linear and bell-shaped distributions for monthly deployment targets and the historical monthly evolution of installed capacity in Germany between April 2000 and December 2016. Before 2009, the historical monthly installed capacity is extrapolated from annual data. To limit the influence of timing policy targets differently, monthly policy targets follow a bell-shaped distribution peak in February 2012 so that they reach half of their cumulative target at the same time as the linear distribution. Moreover, the steepness of the cumulative s-curve that they generate mirrors that of the historical cumulative installations curve in Germany. A sensitivity analysis of different temporal distribution settings is included in the supplementary information (see 8 in SI).

\[
CUMPT_i = \frac{PT}{(1 + \exp(-k \cdot (t - t_{\text{peak}}))},
\]

\((12b))\)
Figure 4. Comparison of the cumulative installed capacity, policy costs, windfall profits, and cost-efficiency of the seven policy designs and the historical policy scenario. The figure shows results for 60 simulation runs per scenario (individual bubbles) and the median value for each scenario (annotated bubbles). Scenarios are color-coded. The red lines indicate the overall deployment and policy-cost targets of 41 GWp and €115 billion, respectively. The total installed capacity (vertical axis) is measured by adding the sizes of all the individual solar PV systems adopted during the policy’s active period. Policy costs (horizontal axis) are calculated by adding the discounted payments for every individual adopter over the 20 years of the feed-in tariff contract. Windfall profits (bubble diameter) are computed by estimating the discounted payments for every individual adopter over the 20 years of the feed-in tariff that result in a positive, non-zero net present value for the adopter. The policy’s cost-efficiency (isolines) is calculated by dividing the total installed capacity by the total policy costs. It represents the average capacity addition per unit of policy cost.

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

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.
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
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, Yaquob 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 (BMWi 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 Steinhi1ber 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.

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Data availability

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

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References

Alizamir S, de Véricourt F and Sun P 2016 Efficient feed-in-tax policies for renewable energy technologies Oper. Res. 64 52–66
Bundesnetzagentur 2017a Data from the Installations Register (https://bundesnetzagentur.de/EN/areas/Energy/Companies/RenewableEnergy/InstallationsRegister/installation_node.html)
Bundesnetzagentur 2017b Figures, Data and Information on the EEG (https://bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/ErneuerbareEnergien/ZahlenDatenInformationen/zahlennuulddaten-node.html)
Créti A and Jouag J 2012 Let the Sun Shine : Optimal Deployment of Photovoltaics in Germany (https://hal.archives-ouvertes.fr/hal-00751743)
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, Noed 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
Eurostat 2017b ef_olufi 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_olufi)


Frondel 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 1048–56


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 108811

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


Jenner S, Groba F and Indvik J 2019 The dismantling of renewable energy policies: the cases of Spain and the Czech Republic Energy Policy 133 108811


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


NASA 2016 NASA surface irradiation database (https://eosweb.larc.nasa.gov/sse/)


Ragwitz M and Steinhalber S 2014 Effectiveness and efficiency of support schemes for electricity from renewable energy sources WIREs Energy Environ. 3 213–29


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


Sijm J P M 2002 The performance of feed-in tariffs to promote renewable energy in European countries Project EGN Report 34016026


Vaishnav P, Horner N and Azvedo I L 2017 Was it worthwhile? Where have the benefits of rooftop solar photovoltaic generation exceeded the cost? Environ. Res. Lett. 12 094015


