MASTER THESIS

Spreading the use of responsive adjustment mechanisms for renewable energy deployment policies: An agent-based modelling cross-country evaluation

Spring Semester 2018

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The present work was submitted on 5 September 2018 to
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Acknowledgements

Firstly, I would like to express my sincere gratitude to Alejandro Núñez Jiménez and Christof Knoeri for the continuous support on this project. Thanks for your guidance and valuable feedback throughout the whole time. Additionally, I want to thank the whole SusTec team and in particular my friends from the Master Students' room. I appreciate your interest in my work and your support throughout the development of this project. Thanks to Pascal Kuhn for his valuable feedback and thanks to professors Volker Hoffmann and Robert Pitz-Paal for supervising this Master Thesis.

Most importantly, I want to thank my family, who has always supported me in all my projects, no matter how far that would take me from them.

Abstract

Deployment policies proved to effectively stimulate the diffusion of renewable energies. Yet, the adjustment of incentives to evolving technology costs remains a challenge. A previous study suggested novel policy designs, which automatically adjust the incentives based on control theory principles, to produce a more effective and cost-efficient feed-in tariff for photovoltaics (PV) than the historical policy in Germany. However, policy transfer between countries sometimes leads to policy failure. Thus, the reproducibility of the suggested achievements in jurisdictions comprising different economic, social or environmental contexts remains unclear. Especially for technologies such as solar PV, the transfer of deployment policies from one country to another could be particularly risky. They often combine rapidly evolving technology costs, influenced by global and local learning rates, and an attractiveness heavily influenced by local factors, such as irradiation. This study assesses if the new mechanisms can repeat the improvements upon historical policies in Switzerland and Spain. Therefore, it employs an agent-based model of the socio-technical system for solar PV in each country. The results state that the analyzed design can reliably achieve a higher deployment with significantly lower costs per installed capacity than the simulated historical policies in each country. It can curb, yet not fully avoid the historically occurred boom and bust cycles in Spain. The results show that different overall deployment targets as well as different initial incentive levels do not compromise the policy’s cost efficiency when using the new suggested policy design. However, they stress that a later deployment generally allows for higher cost-efficient policies. The novel policy design could offer policy makers a reliable new tool for designing future deployment policies under different conditions that effectively accelerate the diffusion of technologies to mitigate climate change without becoming too costly. As it becomes less critical to decide upon the right initial level of incentives or a suitable target for overall deployment, the novel design could encourage governments to apply deployment policies in the future.

Keywords: Renewable energy policy, responsive incentive adjustments, agent-based model, solar photovoltaics, feed-in tariff.

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II List of Acronyms

Abbreviation	Description
PV	Photovoltaics is a term that generally covers the conversion of light into electricity but often is used to refer to a power system that supplies solar power by means of photovoltaics.
Wp	Watt peak is a measure unit of electrical power that refers to the nominal power output of a photovoltaic device under standard test conditions.
kWh	Kilowatt hour is a measure unit of energy often used for electricity.
GHI	Global horizontal irradiation is the total (sum of direct and diffuse) irradiance coming from the sun on a horizontal surface on earth.
FITs	Feed-in tariffs constitute financial incentives offered by policy makers to renewable energy producers that normally include a long-term contract that pays a fixed and above-market price per unit of energy.
MKF	Additional costs financing (German: Mehrkostenfinanzierung) is the feed-in remuneration policy for renewable energies in Switzerland that came into force in January 2005 and was replaced by the KEV in January 2009.
KEV	Feed-in remuneration at cost (German: Kostendeckende Einspeisevergütung) is the feed-in remuneration policy for renewable energies in Switzerland that came into force in January 2009.
EIV	One-time investment subsidy (German: Einmalvergütung) constitutes an alternative to the KEV in Switzerland since 2014 that pays renewable energy producers a one-time subsidy for building a renewable energy system.
GDP	Gross domestic product is the monetary value of all final goods and services produced in a specific time within the borders of a country.
NPV	Net present value is the current value of a future difference in cash inflows and cash outflows for a given discount rate over a period of time.
IRR	Internal rate of return describes the discount rate that makes the NPV to zero. In this thesis, this refers to the average NPV of an investment in a PV system by households.
EUR	Euro is the official currency of the European Union.
CHF	Swiss franc (German: Schweizer Franken) is the official currency of Switzerland.
ABM	Agent-based models enable to simulate the actions of autonomous agents in order to assess their effects on the system as a whole.
ODD	ODD protocol (i.e. overview, design principles, details) constitues a standard protocol for describing agent-based models.
PDA	Personal degree of attraction defines an agent’s general affinity in this study for a solar PV investment in the ABM.

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1 Introduction and research question

"The impacts of climate change affect all regions around the world and are expected to intensify in the coming decades" (European Comission 2018a). Contributing to approximately 25% of global greenhouse gas emissions, the production of electricity and heat is here of particular importance (IPCC 2014). However, the global energy usage is expected to increase by 28% until 2040 compared to the level of 2015 (U.S. EIA 2017). Thus, an immediate rethinking of how to supply this growing demand in the future is inevitable to prevent the potentially disastrous consequences, which scientists and experts predict for our planet earth.

Renewable energy technologies are key to decarbonizing the generation of electricity. They have shown an exponential growth in the past two decades, mainly driven by public policies and rapid cost reductions (Fraunhofer ISE 2018). Yet, they still reveal a vast potential to exploit.

While deployment policies that encourage adoption through economic incentives, generally have proven to be effective, their cost efficiency remains criticized (Frondel et al. 2010). By fostering adoption, policies trigger technology cost reductions through learning effects, inducing even more deployment. However, if incentives are not adjusted accordingly, lower technology prices may offer unreasonably high returns for investors that reduce the policy's cost efficiency. In order to retain the effectiveness of deployment policies while ensuring their cost efficiency a continuous adjustment of the incentive level to environmental influences in general and the evolution of the technology costs in particular is needed. However, systematic evidence on how to achieve this goal is missing in both literature and practice.

A previous study evaluated new mechanisms based on control theory principles to adjust policy incentives (Nuñez-Jimenez et al., forthcoming). The results suggested the designs could produce more effective, cost-efficient and more reliable deployment policies than adjustments used in the German feed-in tariff (FIT) policy for solar photovoltaics (PV) from 2000 to 2016.

However, historical experiences have shown that policy transfer between jurisdictions can lead to policy failure, especially when copied to countries with different economic, societal or environmental contexts (Dolowitz and Marsh 2000; Stone 2017; James and Lodge 2016). In general, many countries need to deploy renewables at a very large scale in order to comply with the Paris Agreement of limiting the increase of global average temperature well below 2°C and to ensure emissions to peak as soon as possible (European Comission 2018b). While the new design could constitute a policy to be employed across countries, the reproducibility of the suggested achievements in Germany into other jurisdictions remains an open question. Spain's deployment policy of solar PV exemplified this general issue as it oriented the design towards the historical German mechanism, which is well known for having performed quite successful overall (del Rio 2014). However, after a period of moderate adoption, the country experienced an unprecedented surge in the deployment of solar PV installations in 2008. When policy makers introduced abrupt and retroactive incentive adjustments as a response to escalating and unsustainable policy costs, the Spanish solar PV market experienced a sudden breakdown and was not able to recover (del Rio 2014).

Especially for technologies such as solar PV, the transfer of deployment policies from one country to another could be particularly risky. They often combine rapidly evolving technology costs, influenced by global and local learning effects, and an attractiveness heavily influenced by local factors, such as irradiation and electricity prices. Other upcoming technologies, such as batteries, could display similar patterns. This reveals the necessity of evaluating the suggested mechanisms under different environmental and societal conditions and especially in cases where historical support policies were not as successful as in Germany but faced distinctive difficulties. This Master Thesis assesses the suggested policy design by comparing its effectiveness and cost efficiency to simulated historical policy outcomes. Its goal is to answer the following research questions:

RQ 1: Could responsive adjustment mechanisms have prevented inefficient or ineffective deployment policies in different countries exposed to different conditions?

RQ 2: How is the performance of responsive adjustment mechanisms driven by their policy configuration, namely the magnitude of overall policy targets, the deployment timing and the initial incentive conditions?

The answers indicate if (1) the novel design could offer policy makers a universal tool for designing future deployment policies that effectively accelerate the diffusion of technologies without becoming too costly, even if the policies get applied in different contexts. In addition, they reveal if (2) the new mechanisms can limit the influence of the policy's configuration on the policy's success. This could make the application of the new design less critical and governments more likely to apply deployment policies in the future to mitigate climate change.

Therefore, this study employs an agent-based model of the socio-technical system for solar PV in Switzerland and Spain. The model incorporates individual decision-making based on: economic profitability, environmental and technical considerations, the available information on solar PV and the impact of social interactions. It manages to reproduce historical deployment patterns during the 2004-2016 period in Switzerland and the 1996-2016 period in Spain by simulating each country's historical policy. The model enables to evaluate if the new policy design could have prevented the experienced boom and bust cycle of deployment in Spain and if a policy continuation could have been ensured with reasonable costs for the society. Additionally, it is assessed if and at what cost the new policy designs could have steered the Swiss market as steady as in history, but only by adjusting the level of incentives and without the assistance of the historically implemented caps on policy costs.

The remainder of this thesis is structured as follows: Chapter 2 provides an introduction into renewable energy policy and diffusion models. Subsequently, chapter 3 summarizes the case selection combined with a brief overview of the historical policy designs. Chapter 4 contains an explanation of the methodology applied, which is used to test the scenarios of chapter 5 to answer the research questions. The results of these scenarios are illustrated in chapter 6 and subsequently discussed in chapter 7. The limitations of the employed model are stated in chapter 8. Finally, chapter 9 concludes by summarizing previous chapters, stressing the main findings of the study, and providing suggestions for future research.

2 Literature Review and Theoretical Background

In literature, the majority agrees that deployment policies are necessary for most new renewable energy technologies to become competitive in the near future (Ibanez-Lopez et al. 2017; Hoppmann et al. 2013; Jenner et al. 2013). Generally, an increase in production capacity offers learning effects that reduce the capital cost (Wand and Leuthold 2011). However, a missing competitiveness of a technology limits deployment and inhibits technological improvements.

In 2016, 126 jurisdictions worldwide had deployment policies for renewable energies in place to encourage adoption. Two-thirds used a feed-in tariff (FIT) scheme that guarantees above-market prices for the electricity sold (REN21 2017). Others fostered the demand for renewable energy technologies by reducing the initial investment costs for investors (e.g., through investment subsidies), or by mandating a specific amount of electricity production from a certain technology in the future (e.g., through renewable portfolio standards) (REN21. Renewables 2015 - Global Status Report 2015; Solangi et al. 2011; Sarzynski et al. 2012).

Several studies have developed models in order to understand the effect of deployment policies on the diffusion of technical renewable energy innovations (Chapter 2.1). However, only few have dealt with the question of how to effectively perform incentive adjustments of deployment policies that need to comply with evolving technology costs (Chapter 2.2). In addition, several studies have investigated the performance of historical deployment policy designs and have compared policies across countries. Nevertheless, only little research has been done on the question of how the performance of a particular policy design is influenced by its area of application or its specific policy configuration (Chapter 2.3).

2.1 Renewable energy policy and diffusion models

A first introduction to the scope, applications, methodology and content of energy system models has been given by Hoffman and Wood (1976). Besides an insight into strategic planning and policy analysis, they already addressed the question of predicting the direction as well as the magnitude of a response to an intervention in energy policies (Hoffman and Wood 1976). Generally, literature distinguishes between “bottom-up” models and “top-down” models, due to their conceptual structure.

“Bottom-up” models normally take specific technologies for the energy generation into account. Representatives of this category are linear programming models such as MARKAL (Fishbone and Abilock 1981) with its consecutive descendent, TIMES (Loulou and Labriet 2008), and MESSAGE (Schrattenholzer 1984). Recently, agent-based models that have gained in importance within the category of “bottom-up” models dealing with the diffusion of renewable energies. In most cases, they only address the diffusion of one specific technical energy innovation and focus on understanding the technology adoption process in order to analyze the impact of the underlying policy design.

In contrast, as they focus on macroeconomics, the following models are often described as "top-down" models: MERGE (Manne et al. 1995), ABARE (Hinchy 1996), DICE/RICE (Nordhaus and Noyer 1999) and GEM-E3 (Capros 2003). The studies assess the impacts of climate change policies. Due to their macro approach, they do not include a detailed consideration of different technologies and are thus not able to model or evaluate technology specific policy measures.

Grubb et al. (1993) find a major difference between the two approaches outlined before. The technology-oriented "bottom-up" engineering models often deduced reduction of greenhouse gas (GHG) emissions could to be achievable with net cost savings. In contrast, economic "top-down" models mostly stressed that goals such as stabilizing fossil-fuel carbon emissions already resulted in relatively high costs for the economy.

In order to assess the impact of changing incentives on adoption, a profound understanding of the technology’s diffusion and its drivers in the market is crucial. This thesis investigates the performance of a policy adjustment mechanism targeting one individual technology, explicitly solar photovoltaics (PV). Thus, understanding the decision-making process of individuals whether to invest in a solar PV system and the influence of financial incentives in particular is of major importance. While the general diffusion of innovations has long been investigated, several studies particularly focus on the adoption of renewable energy technologies.

Everett M. Rogers (1963), who published "Diffusion of Innovations” in the middle of the 20th century, is regarded as the father of diffusion research. Besides his qualitative and explanatory theory, mathematical models for consumer durables (Bass 1969) and even a specific approach for the spread of technical innovations (Mansfield 1961) have already been developed around the same time. The diffusion of technologies is generally characterized by the interplay of a large number of actors (e.g. policy makers and firms), networks (formal and informal), and institutions (e.g., norms, values or regulations) within a socio-technical system (Carlsson and Stankiewicz 1991; Edquist 2009). Large-scale diffusion or adoption of a new technology occurs cumulatively over time, and emerges out of decision-making of individuals (Rogers 2003). According to the Diffusion of Innovations Theory (DOI), the adoption of a new technology is, among other things, based on its relative advantage, compatibility, and ease of use. If it is technologically and economically superior to what the individual is currently using, if it fits with the individual's lifestyle, if it is simple to use and affordable, it is more likely to be adopted (Rogers 2003).

In order to forecast the diffusion of renewable energies, such as solar PV, or to assess the influence of different support policies on adoption, studies have modeled the decision-making process of individuals. There are several well-established social psychological theories to explain consumers' acceptance of new technologies, such as the technology acceptance model (TAM) (Davis 1989), the model of goal-oriented behavior (MGB) (Perugini and Bagozzi 2001), the social cognitive theory (SCT) (Locke 1987), the motivation model (MM) (Vallerand 1997) or the Theory of Planned Behavior (TPB) (Ajzen 1991). They all take into account different factors that drive the decision of individuals. With regard to the diffusion of renewable energies and explicitly the case of solar PV, studies often refer to financial aspects (Pearce and Slade 2018; Iachini and Borghesi 2015; Palmer et al. 2015; Robinson et al. 2013), environmental aspects (Schelly 2014; Rai and McAndrews 2012; Palmer et al. 2015; Iachini and Borghesi 2015), the opinion from peer-to-peer interaction (Islam 2014; Rai and McAndrews 2012; Zhao et al. 2011; Robinson et al. 2013) or the influence of media (Zhao et al. 2011; Schelly 2014) as main factors.

In combination with the general theories, they often show two different approaches on how to determine these main parameters on the decision to adopt. Rai and McAndrews (2012), Schelly (2014) and Islam (2014) use survey data to qualify the most important parameters and in the latter case also quantify their relative importance among each other. Conversely, models of a second category build their qualitative choice of parameters on findings of previous literature and afterwards use a calibration step to determine their relative importance. The calibration step is applied to quantitatively weight the parameters until the results of the modeled diffusion process match with historical data.

A selection of models applying one of the two mentioned approaches is shown in Table 2.1.

Table 2.1: Studies addressing the diffusion of solar photovoltaic

Reference	Type of Research	Focus of Research	Regional focus	Technology price evolution	Time Scope[a]
(Pearce and Slade 2018)	Agent based model	Evaluating the effect of support schemes on adoption of small-scale PV	Great Britain	Exogenous	2010-2016 / (2022)
(Iachini and Borghesi 2015)	Agent based model	Evaluating the effect of social and economic factors on adoption of residential PV	Emilia-Romagna region of Italy	N/A	2007-2013
(Palmer et al. 2015)	Agent based model	Evaluating the effect of support schemes on adoption of resid. PV	Italy	Exogenous	2006-2011 / (2026)
(Robinson et al. 2013)	Agent based model	Reproducing historical real-world residential PV diffusion data by simulating spatially-resolved adoption	Austin, Texas, USA	Exogenous	2005-2008 / (2012)
(Zhao et al. 2011)	Two-level hybrid Agents based model	Evaluating the effect of support schemes and policy regulations on residential PV	Tuscon, Arizona, USA	Exogenous	(20 years)
(Grau 2014)	Analytic model	Reproducing historical real-world small-size PV installations and assessing different adjustment mechanisms against multiple scenarios for PV system price developments	Germany	Exogenous	2009-2013 / (2016)
(Yaquob et al. 2014)	System dynamics model	Discussing the development of resilient and responsive feed in tariff policy	Germany	Endogenous	(2009-2014)
(Islam 2014)	Discrete choice experiments and an innovation diffusion model	Predicting the adoption time probabilities of solar PV by households	Ontario, Canada	[-]	(10 years)
(Rai and McAndrews 2012)	Survey of residential owners of solar PV systems	Understanding the experience of PV adopters in selecting and installing residential PV systems	Texas, USA	[-]	[-]
(Schelly 2014)	Interviews with early adopters	Understanding the motivation of homeowners to adopt residential solar PV	Wisconsin, USA	[-]	[-]

Note: This is by no means an exhaustive list; further examples, also addressing other technologies than solar PV can be found in e.g.: (Cantono and Silverberg 2009), (Ibanez-Lopez et al. 2017), (P. Denholm, E. Drury, and R. Margolis 2009), (Sorda et al. 2013) and (Zhang and Nuttall 2011). (a) While the time scope generally refers to the modeled period for which historical data was used for training and calibration purposes, the period in parenthesis was predicted by the model without any reference data for verification.

2.2 Adjustment of deployment policies

The need to adjust incentives as technology costs evolve is present in theory (Alizamir et al. 2016; Créti and Joaug 2012; Wand and Leuthold 2011) and practice (Sijm 2002; European Comission 2013). Yet, there lacks an agreement on how to perform these adjustments accordingly. They are necessary to achieve planned deployment targets, while avoiding excessive costs that could strain public resources to the point of compromising the policy's continuity (Hoppmann et al. 2014a). Wand and Leuthold (2011) further argue that incentive adjustments are important to ensure deployment following a certain and controllable course over time. This would allow exploiting learning effects of new technologies optimally.

In most cases, incentive levels in history were only revised periodically or as a response to low adoption or growing costs (Hoppmann et al. 2014a; Kreycik et al. 2011). Quite often, this resulted in major consequences for the continuity of the policy. For example, favored by falling technology prices but steady incentives, Italy experienced a boom in solar PV installations from 2007 to 2010. Only later in 2011, when the scheduled revision took place, policy makers, astonished by annual payments over 6 billion euros, stopped the policy (del Rio 2014; Di Dio et al. 2015).

To avoid past incidents in policy outcomes, responsive adjustment mechanisms have gained attention in theory and practice. In order to automatically update policy incentive levels, these mechanisms follow a predefined procedure that responds to the evolution of certain policy outcomes. They are considered a promising tool to ensure the adaptation of incentive levels to the effect of technological learning (Klein et al. 2008), to limit policy costs (Kreycik et al. 2011), and to increase the cost efficiency of deployment policies (Mendonça et al. 2009).

In practice, responsive adjustment mechanisms have already been applied. Back in 2007, California incorporated an adjustment mechanism that reduced incentives for solar PV in the event that installation capacity surpassed predefined targets (California Public Utilities Commission 2017). A similar measure was adopted by the United Kingdom in 2016 (Department of Energy & Climate Change, UK 2015). In 2008, Spain introduced automatic FIT reductions based on periodic deployment calls (del Rio 2014). Germany introduced an annual flexible degression depending on deployment targets in 2009 (Clearingstelle, EEG, KWKG 2008) and increased the qualifying period to monthly adjustments in 2012 (Clearingstelle, EEG, KWKG 2012).

Policy makers in the past interpreted the application of responsive adjustment mechanisms in a variety of ways and with different degrees of success (Klein et al. 2008). Yet, quantitative evaluations that investigate the question of how to improve upon historical alternatives is missing. This analysis is of particular importance with regard to policy designs targeting technologies such as battery storage or electric vehicles, whose evolution of costs show a similar behavior as the costs of solar PV (Kittner et al. 2017; Nykvist and Nilsson 2015).

Given the above displayed list of studies in Table 2.1, there already exists a profound understanding within the literature of how financial incentives shape the decision process of renewable energy adopters. However, so far only few studies have evaluated quantitatively the design of responsive adjustment mechanisms for deployment policies that could set the level of incentives for adopters in a suitable way.

Building upon the agent-based model of the adoption of small-scale solar PV systems in Great Britain over the period of 2010-2016, Pearce and Slade (2018) further assess if a similar or higher cumulative installed capacity could have been achieved at a lower cost. Therefore, they implement logical, simple degression strategies for the FIT (e.g. a linear or percentage reduction at regular intervals), possibly in combination with deployment caps. They find out that a simple linear degression and a responsive FIT adjustment based on deployment caps would have achieved a higher cost efficiency than in history. In addition, responsive adjustments would have ensured a higher reliability of policy outcomes (Pearce and Slade 2018).

Extending its analytic model to simulate weekly installations of PV systems up to 30 kWp in Germany since 2009, Grau (2014) evaluates different FIT adjustment mechanisms against multiple scenarios for PV system price developments. Thereby the focus of the analysis lies on the impact of (1) degression frequency, (2) adjustment flexibility, and (3) qualifying period. He concludes that responsive FIT schemes with frequent tariff adjustments and short qualifying periods steer adoption towards deployment targets most effectively. Furthermore, he states that monthly flexible degressions had been able to even reach the targets in the case of large and sudden price changes (Grau 2014).

Yaquob and Yamaguchi (2014) study a responsive adjustment mechanism that maintains a constant profitability for adopters of rooftop solar PV in Germany between 2009 and 2014. They identify that more frequent adjustments ensure a higher cost efficiency and reliability of the policy but show slower deployment as investment rushes are prevented (Yaquob et al. 2014).

This research project extends previous knowledge. We test our novel adjustments responsive not only to deployment but also to policy costs and additionally investigate their impact on the uncertainty of policy outcomes. Therefore, the overall model incorporates social, behavioral, and non-economic factors that better represent how incentive adjustments influence the adoption decision-making process of individuals (Rai et al. 2016; Jager 2006). Differentiating the effects of global and national technological learning, we incorporate the feedback of policy outcomes on the evolution of technology costs. Besides small installations, this research also accounts for medium and large systems, covers a long time span including the early years of the policy, and explores different temporal distributions of policy targets.

2.3 Performance of renewable energy deployment policies

Previous literature studied historically employed deployment policies across countries with respect to their similarities and differences in configurations and evaluated their performance (see Table 2.2). Yet, an understanding of how the performance of a particular policy design is influenced by its area of application or its specific configuration remains elusive.

While renewable energy policies in the European Union tend to converge and become more similar (Kitzing et al. 2012) critics claim that better policy coordination mechanisms are still pending (Reboredo 2015). They would facilitate the substitution of non-renewable for renewable energy sources as variations in support schemes generally constitute barriers for cooperation (Klinge Jacobsen et al. 2014). Contributing to this effort, first approaches to coordinate or even harmonize renewable energy policies have long been around (Ragwitz et al. 2011; Klinge Jacobsen et al. 2014; Jansen 2011; Gustav Resch et al. 2013), with the Directive 2009/28/EC even on an inter-European level (European Parliament 2018).

While a transnational conformity of renewable energy deployment policies in particular is still missing, the general application of equal policy designs in different jurisdictions revealed risks (Evans and Buller 2017; James and Lodge 2016; Stone 2017). Especially when copying policies to countries with different economic, social, or environmental contexts experience has shown that policy transfer can lead to policy failure (Dolowitz and Marsh 2000). The diffusion of renewable energy technologies in general, but especially certain technologies such as solar PV or newly emerging technologies like battery storage or electric vehicles might react particularly sensitive to these context parameters. They show rapidly developing technology costs, combining global and local influences, and an attractiveness heavily influenced by local factors such as irradiation or electricity prices. In addition, and besides their possible economic profitability under the support of deployment policies, new innovative technologies are products that have shown to sometimes be adopted from individuals just out of conviction (Schelly 2014; Rai and McAndrews 2012). However, the degree of environmental concerns or the financial possibilities to allow for such economically nonviable investments might differ across societies.

Current research confirms the influence of local factors on the outcome of deployment policies. Despite their convergence in designs, studies still certify renewable energy policies in different countries in Europe large differences in effectiveness and efficiency (Guidolin and Mortarino 2010; Mitchell et al. 2006; Haas et al. 2011a; Jansen 2011) (see Table 2.2). For the particular case of solar PV, Jenner et al. (2013) show the interaction between a policy design and local factors such as electricity price and electricity production cost to be a relevant determinant of renewable energy deployment.

Recent studies mostly compared the performance of different policy designs across countries. This makes a distinction of occurred performance differences between those caused by differences in policy designs and those caused by different societal and environmental circumstances in the areas of application difficult (see Table 2.2). Even analyses that consider similar policy designs, such as only FIT remuneration schemes (Jenner et al. 2013), still focus on the individual policies that had been in place in history across countries. These historical policies showed differences among their configurations. In particular, they differed with respect to the implementation of FIT adjustments over time, the main object of investigation this thesis is looking at.

Besides the general design of a policy and its area of application, literature stresses the particular policy configuration as well as the policy execution to be of crucial importance when it comes to policy performance. While Haas et al. (Haas et al. 2011a) point out that the decision upon specific policy features cannot be neglected, Grubler (2012) generally stresses the warning of historical energy transition research of moving “too fast, too big and too early”.

One major issue of FIT policies discussed in theory and visible in practice is the question of how to set the initial level of incentives. Policy makers (European Comission 2005), as well as current researchers (Islam 2014; Rai and McAndrews 2012) are convinced of the necessity to offer potential adopters financial support that ensures investments to be within the range of profitability. Otherwise, and besides some early adopters that might consider the economics not that important (Schelly 2014), a reasonable and widespread diffusion of the technology will not occur. However, the current method of calculations as well as the cost elements taken into account in the process of setting national support levels vary greatly (European Comission 2005, 2013). Policy makers in practice are often divided if tariffs are too low or too high (Department of Energy & Climate Change, UK 2015). Responsive adjustment mechanisms suggest a new approach of how to deal with this issue over time as they do not rely on estimating the technology costs or the profitability of adopters. However, the European Commission stressed that besides the adjustment of tariffs one major issue lies within the difficulty of how to initially set appropriate feed-tariff levels (European Comission 2013).

The effects of the uncertainty in setting initial incentive levels were quite visible in practice: Many countries, including Germany, Spain and France experienced distinct periods of no adoption at the beginning of their deployment policies for solar PV due to too low incentive levels. After some time, policy makers decided upon a sudden raise to effectively foster deployment (see Figure 10.1, A.1). Other countries, such as Great Britain or Switzerland, already realized shortly after the policy’s start that their initially provided incentives might have been too generous and soon performed drastic incentive cuttings (see Figure 10.1, A.1).

The general issue of what level of incentives to start a policy with is present in theory and practice. Yet, agreement on how to do it remains elusive. While for example Alizamir et al. (2016) qualitatively discuss how the level of profitability for adopters should generally decrease over time to ensure a high cost-efficient policy, the quantitative effect of different incentive levels on the early diffusion phase of a technology remains questionable.

This thesis gives answers to these questions. It evaluates the achievements of the same novel responsive mechanisms in different countries. It focusses not only on a case that has shown a quite satisfying policy outcome such as Germany, but on countries comprising different environmental and societal contexts, especially countries that showed quite inefficient or ineffective deployment policies in the past. For this purpose, this thesis applies the mechanisms to the case of Spain and Switzerland that faced distinctive sets of problems in history. Furthermore, it explicitly assesses the influence of different policy configurations in each context. This study quantitatively analyzes the impact of different initial incentive levels on the outcome of a policy using the suggested novel mechanisms. It approaches the warnings of moving “too fast, too big and too early” and investigates the ability of the new design to deal with different overall policy targets and a different deployment timing.

Table 2.2. Studies evaluating renewable energy policy performances across countries

Reference	Technology focus	Performance criteria applied	Policy designs investigated	Regional focus	Results
(Jenner et al. 2013)	Wind and Solar PV	Effectiveness as a function of ROI	Historical FIT policy	EU-26	FIT has driven solar PV deployment; no robust evidence that FIT has driven wind depl. in EU
(Dong 2012)	Wind	Effectiveness	Historical FIT policy and Renewable Portfolio Standard (RPS)	53 countries around the world	FIT performs better than RPS regarding cumulative deployment
(Jansen 2011)	No particular technology focus	Efficiency	Implementation of new Renewable Energy Quota System	Norway, Sweden, Netherlands	Harmonisation could improve current Policy Inefficiency
(Haas et al. 2011a)	No particular technology focus	Effectiveness and Efficiency	Historical policies without separating them	EU-27	Design criteria of policy more important than general policy design
(Guidolin and Mortarino 2010)	Solar PV	Effectiveness	Historical policies without separating them	11 countries around the world	Large differences in historical policy effectiveness
(Butler and Neuhoff 2008)	Wind	Effectiveness and Efficiency	Historical FIT policy (DE) and Project + Tradable Green Certificate scheme (UK)	Germany and UK	FIT reduces costs to consumers and result in larger deployment
(Mitchell et al. 2006)	No particular technology focus	Effectiveness	Historical FIT policy (DE) and Renewable Obligation (E+WAL)	Germany and England+Wales	FIT is more effective and reduces risk for adopters more effectively
(Harmelink et al. 2006)	No particular technology focus	Effectiveness	Historical policies without separating them	EU-15	Additional policies needed to achieve set RE-EU targets
(European Comission 2005)	Wind, Biogas, small-scale Hydro, Solar PV	Effectiveness	Historical policies without separating them	EU-15	Different effectiveness across historical policies

Note: This is by no means an exhaustive list; further examples can be found in e.g. (Menanteau et al. 2003) and (Haas et al. 2011b).

3 Research Case

The research project aims at contributing to the improvement of renewable energy support policies. It analyzes novel responsive adjustment mechanisms for the incentives of deployment policies and evaluates their performance under different conditions in the cases of Switzerland and Spain.

For this purpose, it first focuses on the policy mechanism of feed-in tariffs (FIT). With a high impact on the historical deployment of renewable energies and a widespread use, FIT policies offer a good data availability. In addition, they can be considered a good proxy for any deployment policy based on economic incentives, even for upcoming technologies, such as rebates for electric vehicles or investment subsidies for residential battery storage.

Second, with rapidly decreasing costs, solar photovoltaics (PV) offers a well-suited basis for evaluating the performance of the novel responsive mechanisms under particularly demanding conditions. The technology will also remain relevant as a case of application for deployment policies in the future. In addition, with its modularity and a cost evolution, dependent on global and local factors, it largely complies with the expected characteristics of future technologies such as batteries.

3.1 Rationale for focus on feed-in tariffs schemes

FITs constitute financial incentives offered by policy makers to renewable energy producers. Policies using FITs normally include a long-term contract that pays a fixed price per kWh (kilowatt hour) of energy produced. The level of the FITs is generally above the wholesale electricity market price to compensate producers for the higher investment costs that usually come along with renewable energy technologies.

Quite often, FITs are considered the most effective policy at stimulating the rapid development of renewable energy sources (Couture and Gagnon 2010; Zhao et al. 2011; Kreycik et al. 2011; Lesser and Su 2008). Exemplarily, this effectiveness could be seen in pioneering countries such as Germany, where the Renewable Energy Sources Act (Erneuerbare Energien Gesetz, EEG) based on FITs has been especially successful for solar PV and other renewable energy technologies as measured by market growth (Wand and Leuthold 2011).

FITs can be considered a good proxy for any deployment policy based on economic incentives defined by an administration. Despite the prevailing effectiveness of FIT policies in most cases, studies are divided with regard to their cost efficiency (Frondel et al. 2010). However, most deployment policies for renewable energies rely on FIT remuneration schemes (REN21 2017). Additionally, for the support of new technologies, such as e.g. battery storage or electric vehicles, there is no indication that deployment policies based on economic incentives similar to FITs will be replaced in the near future.

3.2 Rationale for focus on solar PV technology

Since costs for solar panels generally experience a particularly fast decrease over time (Candelise et al. 2013; Hernández-Moro and Martínez-Duart 2013) solar PV offers an especially demanding environment to evaluate the new suggested adjustment mechanisms for incentives. In order to ensure the cost efficiency of deployment policies, while retaining their effectiveness, the adjustment of incentives as technology costs evolve is one of the key challenges (Wand and Leuthold 2011; Créti and Joaug 2012; Sijm 2002; Alizamir et al. 2016). Solar PV is a modularly built technology, which makes prices dependent on global and local learning effects. Additionally, the attractiveness of the technology is heavily influenced by its area of application comprising different irradiation or electricity prices. Simultaneously, the rapid price evolution of solar PV might be similar to the one of future technologies, as for example batteries or electric vehicles.

Furthermore, solar PV is expected to remain a case of application for deployment policies as the technology still offers a tremendous potential to exploit in the future. The technology directly uses solar power that is compared to geothermal and tidal energy by far the biggest source of renewable energy (World Energy Council 2013). The solar PV technology has broken new records in the recent past. During 2016 solar power was the fastest-growing source of new energy worldwide. It grew by 50%, reaching over 74 GWp and is expected to keep this leading position in the near future (IEA - International Energy Agency 2017a).

3.3 Case selection – objects of investigation

This thesis performs a cross-country comparison of the novel responsive adjustment mechanisms to gather a more precise understanding of whether, and if so, how different contexts influence its applicability and performance. It extends the investigations done in the German case to two further countries whose selection process is outlined in the following.

To select well suited research cases for answering our research question this chapter carries out a high-level preselection process of all countries around the world (Chapter 3.3.1), followed by a more detailed analysis of the resulting shortlist (Chapter 3.3.2). The preselection ensures a minimum scope of technological adoption, the applicability of the modeled adoption decision process and the existence of the investigated policy design in history. The country-specific analysis then sheds light on historical policy performances in order to select interesting cases that indicate particularly demanding conditions to test the new policy design in.

3.3.1 High-level country preselection

In order to pass the high-level preselection process (see Table 3.1), countries need to fulfill the following three necessary criteria:

a) Above minimum cumulative [1 GWp] and per capita [100 Wp] installed solar PV capacity in the considered country to ensure an adequate basis for investigation
b) European country to ensure the applicability of the modeled adoption decision process
c) Historical application of a FIT policy for solar PV

This study evaluates novel adjustment mechanisms by comparing their performance to historical policy outcomes. First, by referring to findings in literature, this thesis models the adoption decision of individuals in a certain country and calibrates the model against historical patterns. Then, while keeping the same decision rationales, we expose the potential adopters to a different policy design to evaluate the resulting policy outcome under the novel mechanisms.

a.) The larger the data basis for modeling the adoption the more accurate the modeled decision rationales. The spread of solar PV is a process of diffusion that generally emerges from the sum of individual decisions. Analyzing a country where more individuals in total, as well as a higher share of individuals participated in the process increases the certainty of actually representing the distinctive, country specific decision rationales.

Thus, we only focus on the biggest solar PV markets in 2016 with a "total cumulative installed capacity above or equal to 1 GWp", leaving 23 countries in the short-list (see Table 3.1). As a reference of magnitude, the two biggest nuclear reactors in the world are in the "Chooz Nuclear Power Plant" in France with a peak net electrical capacity of around 1.5 GWp each (WDR 2017). This criterion avoids the investigation of a fairly small country or even a city state, such as Monaco, were the limited data basis of only a few overall installations complicates to model a representative and generalizable decision-making process of adopters.

Additionally, we limit the considered 23 countries within the first selection to those with an "average installed capacity per capita of above 100 Wp". As a reference of magnitude, the energy expenditure during sleeping hours is around 90 and 75 watts for men and women respectively (Garby et al. 1987) or 100 watts for a classic light bulb. The second criterion avoids the investigation of a deployment driven by just a few individuals in a big country, such as India, whose decision criteria might not be representative and generalizable for the whole country.

b.) Additionally, we only focus on European countries where the assumption of common decision-making processes, following the influencing factors identified in current literature is more likely to hold true.

c.) Given that we analyze a FIT policy design for the case of solar PV, countries need to have applied such a policy in history, in order to have a reference to compare and calibrate the model to.

Our preselection process (see Table 3.1) results in 8 countries undergoing a more detailed investigation hereafter, namely **Germany, Italy, Great Britain, France, Spain, Czech Republic, Switzerland** and **Austria**.

Table 3.1: High-level country preselection

Criterion	**a)**	**a)**	**b)**	**c)**
Country	**Cumulative installed solar PV capacity** **2016 [GWp]**	**Per capita installed solar PV capacity** **2016 [Wp / capita]**	**European country**	**Nationwide FIT support scheme for solar PV**
China	**78.07**	56	NO	N/A
Japan	**42.75**	**334**	NO	N/A
Germany	**41.22**	**504**	**YES**	**YES**
United States	**40.3**	**126**	NO	N/A
Italy	**19.28**	**324**	**YES**	**YES**
Great Britain[a]	**11.63**	**178**	**YES**	**YES**
India	**9.01**	7	NO	N/A
France	**7.13**	**111**	**YES**	**YES**
Australia	**5.9**	**248**	NO	N/A
Spain	**5.49**	**118**	**YES**	**YES**
South Korea	**4.35**	86	NO	N/A
Belgium	**3.42**	**303**	**YES**	NO
Canada	**2.72**	76	NO	N/A
Greece	**2.6**	**232**	**YES**	N/A
Thailand	**2.15**	31	NO	N/A
Czech Republic	**2.1**	**198**	**YES**	**YES**
Netherlands	**2.1**	**124**	**YES**	NO
Switzerland	**1.64**	**197**	**YES**	**YES**
Chile	**1.61**	91	NO	N/A
South Africa	**1.45**	26	NO	N/A
Taiwan	**1.38**	59	NO	N/A
Romania	**1.3**	65	**YES**	N/A
Austria	**1.08**	**124**	**YES**	**YES**

Note: Bold characters indicate that the country meets the criterion in the respective category for the high-level country preselection. The grey shade indicates that the country meets all three criteria for the high-level country preselection. (a) Due to the negligible amount of solar PV installations in Northern Ireland and given its non-consideration within the support scheme in the United Kingdom, Great Britain is evaluated on a non-State level.

3.3.2 Country specific final selection and definition of policy effectiveness and efficiency

For the performance assessment of the historical deployment policies, we apply an effectiveness and an efficiency criterion. Although a policy's success is hard to grasp and not clearly defined in theory or practice, different ways to measure the performance of a policy have been discussed in previous literature. Referring to this literature, we decide upon one definition for each criterion, for policy effectiveness and for policy efficiency. We apply both criteria to all countries of the high-level country preselection and finally choose two countries based on the results as further research cases for this study.

3.3.2.1 Policy effectiveness

For the assessment of a policy's effectiveness, studies propose to compare either the cumulative or the annually added capacity with a certain reference value of either a pre-set installation or generation target (Butler and Neuhoff 2008; Harmelink et al. 2006) or a previously determined installation or generation potential for a country (European Comission 2005). The results of these suggestions are highly dependent on the choice of the target or reference value and the reasoning behind these choices might distort the results. To avoid this, we keep the effectiveness criterion quite simple and limit it to **"per capita installed solar PV capacity"**, already used in the high-level country preselection.

3.3.2.2 Policy efficiency

Referring to a policy's efficiency, Menanteau et al. (2003), Haas et al. (2011b) and Frondel et al. (2010) determine the cumulative capacity, the added annual generation per capita or the amount of CO_2 avoided, relative to the cost involved. Oriented towards Menanteau et al. (2003), we define the efficiency criterion also as a cost efficiency criterion estimating the policy's **"cumulative installed solar PV capacity per overall FIT policy cost"**.

3.3.2.3 Limitations of chosen criteria

The definitions of our criteria reveal certain limitations. Thus, the final classification of policy characteristics is only meant to reveal countries whose historical deployment policies have shown extreme outcomes. This might offer indications of a country with particularly demanding conditions. It does not constitute a final statement upon better or worse policy designs. By choosing a capita specific characteristic value for the effectiveness, we comply with the different overall sizes of countries. However, as already targeted by the approaches in literature, this does not consider the variety of potentials countries might offer, such as suitable sites for systems or irradiation intensity. Besides driving the effectiveness of a policy, these deviations in potentials might also heavily influence the policy's cost efficiency. In general, the implementation of e.g. a certain PV capacity under better conditions, such as a sunnier region should expected to be feasible with less overall costs. Furthermore, a delayed deployment to times when PV prices had already decreased due to learning effects from other countries should also require less financial support.

3.3.2.4 Assumptions and calculation basis for efficiency criterion

While the historical deployment and a country's population directly reveal the defined effectiveness of a policy, the calculations estimating the cost efficiency as defined within the criteria are built upon the following simplified assumptions:

1) The calculation only considers the cost of paid FITs; no other subsidy mechanism is taken into account even if it might have also been in place in history.
2) If no other information is available, all installations that were built during an active FIT policy are assumed to have been remunerated by this support mechanism.
3) Policy costs are interpreted as the difference between paid FITs and a national solar PV specific wholesale electricity price at sun peak hours (11 am – 4 pm).
4) Policy costs include all payments that are expected to be performed during the entire eligible period of guaranteed remuneration of each country.

In most cases, this method of cost calculations differs from the ones used by governments, which often do not include already pledged but not yet performed future payments to solar generators. However, given different timings of deployment and different shares of payments still outstanding, the chosen approach ensures a better comparability across countries.

Explicitly, the policy cost efficiency is defined as the cumulative installed capacity throughout the policy's active period but before December 2016, divided by the total support costs of the FIT scheme until December 2016.

$$\text{Policy cost efficieny} = \frac{\text{Cumulative installed capacity [Wp]}}{\text{Poliy costs [EUR]}} \qquad \text{(Eq. 1)}$$

The total policy costs include the support costs for all installations built in a given month, summed up over the entire active period of the policy but before December 2016.

$$\text{Policy costs [EUR]} = \sum_{\text{month = poliy start month}}^{\text{min[policy end month; Dec 2016]}} \text{Policy costs}_{\text{month}} \text{ [EUR]} \qquad \text{(Eq. 2)}$$

The total support costs for installations built in a given month ($\text{Cap}_{\text{month}}$) include all remuneration costs for the expected energy produced over the entire guaranteed payment period of the considered country (Pay. Period) allocated to the month of adoption.

$$\text{Poliy costs}_{\text{month}} \text{ [EUR]} =$$

$$\sum_{\text{year=1}}^{\text{Pay. Period}} \frac{\text{Cap}_{\text{month}}\text{[kWp]} \bullet \text{Solar capacity factor} \left[\frac{\text{kWh}}{\text{kWp}\bullet\text{a}}\right] \bullet \text{Remuneration costs} \left[\frac{\text{EUR}}{\text{kWh}}\right]}{(1 + \text{Government discount rate})^{\text{year}}} \qquad \text{(Eq. 3)}$$

The costs for remuneration derive from the difference between the FIT at the month of the adoption and the wholesale electricity market price. Until 2017, the wholesale electricity price paid for energy produced by solar PV is estimated as the average yearly day-ahead-auction wholesale electricity price between 11 am and 4 pm in each country, representing the time for sun peak hours. Afterwards, a yearly price increase of 1.5% is assumed (Hoppmann et al. 2014b).

$$\text{Remuneration costs}\left[\frac{\text{EUR}}{\text{kWh}}\right] = \text{Feed-in tariff}_{\text{month}}\left[\frac{\text{EUR}}{\text{kWh}}\right] - \text{Wholesale electricity market price}_{\text{year}}\left[\frac{\text{EUR}}{\text{kWh}}\right] \quad \text{(Eq. 4)}$$

A summary of the used data and its sources can be found in the appendix (see A.1).

Figure 3.1 shows an overview of the eight countries from the high-level preselection process displaying the estimations on historical policy performance with regard to the defined effectiveness and efficiency criteria. It reveals a relatively heterogeneous picture across countries. For the effectiveness, we can observe values varying between just over 100 Wp/capita in France and Spain to more than 500 Wp/capita in Germany. Partially explainable by the countries' population sizes, the overall cumulated installed solar PV capacity per country lies in a wide interval from just over 1 GWp in Austria to over 40 GWp in Germany.

With regard to the efficiency criterion, Switzerland is listed twice. While the uncommented label assumes all installations to receive a feed-in remuneration, the corrected label considers that this assumption does not hold true. Given policy cost caps in the Swiss policy design, a significant amount of installations did not get any feed-in remuneration. However, their installation was performed during the policy's active period, most likely motivated by the hope of future remuneration. Consequently, these installations are included in the effectiveness as they actually were installed, but they do not drive up the corrected policy costs as they did not receive any feed-in remuneration (for further information see Chapter 3.3.4).

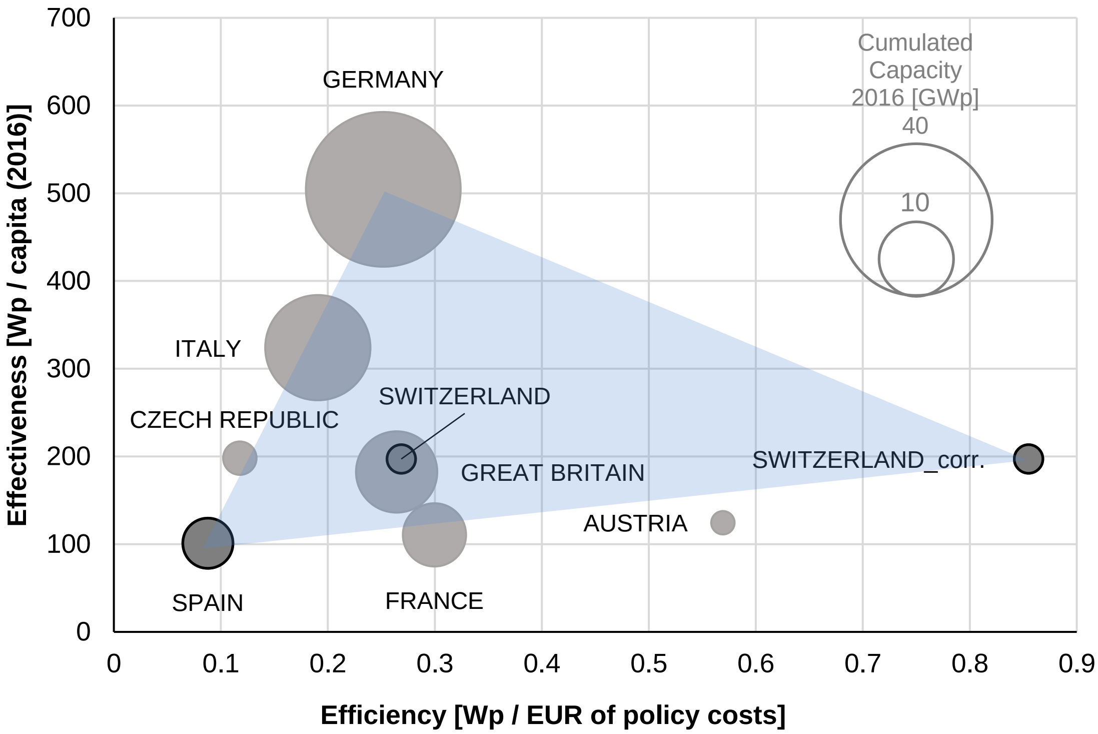
Finally, regarding the cost efficiency, Spain and the Czech Republic stand out negatively. Both show a relatively low installation capacity per EUR of policy costs of 0.09 Wp/EUR and 0.12 Wp/EUR respectively. In contrast, Austria and the corrected policy estimation for Switzerland stand out positively. Both deployment policies in these countries show relatively high cost efficiencies of 0.57 Wp/EURa and 0.85 Wp/EUR.

Based on the results we select Spain and Switzerland as the research cases of this study to evaluate the new responsive adjustment mechanisms. This allows us to cover a wide range of estimated historical policy performances (see Figure 3.1).

Among all eight countries, **Spain** shows the lowest historical policy effectiveness and the lowest policy efficiency. Additionally, it indicates to be an interesting case with a particularly demanding environment. The literature states Spain as the most famous case of a failed support policy for solar PV that ended up in an immediate shutdown of the policy after periods of dramatic difficulties (del Rio 2014; European Environment Agency 2014b). We would thus like to see if by the use of the new policy design, the Spanish PV market could have been controlled in a more sustainable way. Explicitly we want to test, if the experienced installation boom of 2008 could have been prevented and if a policy continuation could have been ensured with reasonable costs for the society.

In contrast, the historical policy in **Switzerland** reveals an outstanding cost efficiency, despite showing similarly little effectiveness. However, this cost efficiency was only achieved thanks to many installations that did not receive any feed-in remuneration from the government. Besides many PV systems that were built without getting remunerated, even more interested adopters, awaiting a release of financial support, did not perform their investment. The rush from interested investors that refrained from the investment due to insufficient funds even increased throughout the years (Bundesamt für Energie BFE). Consequently, this restrictive policy design with its policy cost caps might have constituted a bottleneck for adoption. Given the demand for support largely exceeding the provision of funds, one might suspect that even for lower incentive levels the entire provided financial resources could have been transformed into solar PV installations. In sum, we would thus like to assess if and at what cost the new policy design that remunerates all interested adopters, could have steered the Swiss market similar to history but only by adjusting the level of incentives and without caps on policy costs.

Although qualitative particularities of the individual policies are only discussed for the two selected countries, an overview for all eight countries can be found in the appendix (see A.2).



Note: Cumulative installed capacity in 2016 is taken from IEA PVPS (2017c). The values for the efficiency are generally based on the defined assumptions for the estimation of policy costs of Chapter 3.3.2. For countries that do not have the euro, monthly exchange rates are used to convert policy costs into euros (boerse.de). Switzerland is additionally listed in a corrected version (SWITZERLAND_corr.) given the knowledge that one of the defined assumptions did not hold true (see Chapter 3.3.2.4).

Figure 3.1. Effectiveness-efficiency – Historical policy mapping across countries

3.3.3 Summary of historical policy design and environmental conditions in Spain

With around 46 million inhabitants, a population density of 93 people per square kilometer and an overall size of 505’990 square kilometers, Spain is the fourth biggest country as well as the sixth biggest economy in Europe, measured by gross domestic product (GDP) (United Nations 2018). Given the geographical location, fixed PV systems in Spain achieve an average yield of 1461 kWh/kWp (European Comission 2016) that could be increased by around 30-40% by the use of two-axis tracking systems (Huld et al. 2008; Eke and Senturk 2012).

Spain introduced its Electricity Sector Law in 1997 (Real Decreto 54/1997) but first uncoupled their FITs for solar PV from the prevailing electricity price in January 2004. In 2012 the support policy for new solar PV systems came to a complete moratorium (del Rio 2014). While there was no limitation on solar PV systems remunerated until September 2008, Spain introduced capacity quotas on the amount of installed capacity receiving remuneration in October 2009 that lasted until the policy’s end in 2012.

The FIT paid to each project was the one that was in place at the date of installation and constant for the total funding period of a system. Initially, in 2004, support was guaranteed for the whole lifetime of the plant declining after some years but was finally adjusted to 28 years for plants built under RD661/2007. For plants built since December 2008, the overall funding period was limited to 25 years (del Rio 2014).

3.3.4 Summary of historical policy design and environmental conditions in Switzerland

With just over 8 million inhabitants and a population density of 196 people per square kilometer on an overall size of only 41’285 square kilometers, Switzerland is only the 31st biggest country, but still the eight biggest economy in Europe, measured by GDP (United Nations 2018). On average, PV systems in Switzerland can achieve a yield of 950 kWh/kWp (pronovo 2018).

In Switzerland the first nationwide FIT policy, named "additional costs financing" (MKF, Mehrkostenfinanzierung) came into force in January 2005 (Bundesamt für Energie BFE) that was changed to a “feed-in remuneration at cost” (KEV, kostendeckende Einspeisevergütung) in January 2009.

With the introduction of the KEV, Switzerland also introduced policy cost caps that limited the available KEV fund for each year. In order to ensure that these caps were respected, potential operators of renewable electricity plants needed to apply for KEV payments by registering on a waiting list. This implied that there were a limited number of projects that could be financed per year. The waiting list was ordered by registration dates, independent of whether an installation had already been built or not. When new funds were provided, projects with the earliest registration dates were released for remuneration first. However, there was no certainty about the provision of new funds in the future. Eventually, during 2017 no new funds for the KEV were provided and in 2018 the KEV was completely stopped. Until December 2016, 11’563 PV installations with a capacity of 526 MWp had been accepted and released for the KEV and had started to receive the feed-in remuneration. However, another 35’028 projects with a capacity of 2’105 MWp were still registered on the waiting list and were still awaiting their release for the KEV, which never happened afterwards. In particular, over 1’000 MWp of these waiting projects were already installed in the meantime and were already producing energy, most of the times sold to the local electric utility for a price far below the FIT in place. After the KEV was finally stopped, the government started to pay those already implemented projects a one-time investment subsidy (EIV, Einmalvergütung) instead of the expected feed-in remuneration as a compensation. However, this one-time compensation was significantly below the payments investors would have received within the KEV (Bundesamt für Energie BFE).

Generally, the FIT paid to each project with the benefit of having gotten released for the KEV was the one that was in place at the date of installation and constant for the total eligible period of remuneration. As FITs decreased over time, investors with an earlier installation date thus received higher incentives per kWh of energy produced throughout their entire eligible period of remuneration. However, the eligible period for remuneration did not start before a project was released for remuneration within the KEV. Then, the period latest ended after 25 years for systems that were installed until the end of 2013 and after 20 years for systems that were installed afterwards, counted from the date of the installation of a project. Furthermore, payments were not performed retroactively for energy produced before the eligible period started. Thus, if a system was installed before its release, the meantime between installation and release for the KEV shortened the total funding period of remuneration (Bundesamt für Energie BFE).

Consequently, interested investors were facing the following situation: An early installation without immediate remuneration bears the risk of building a system that only receives remuneration during a shortened and not precisely foreseeable funding period or at worst receives no remuneration at all. However, in the case of remuneration it ensures payments based on a relatively high FIT. Alternatively, the postponement of an installation until the project gets released for remuneration avoids the above-mentioned uncertainties but would receive a future FIT that is not foreseeable and most likely significantly lower (pronovo 2018).

4 Methodology

In order to test the performance of the novel responsive adjustment mechanism, we need to evaluate its interplay with and its impact on the evolution of a country's solar photovoltaic (PV) deployment system. Performing experiments in the real world would be extremely slow and costly. Therefore, we need to formulate a simplified representation of the real system that we can then experiment on (Railsback and Grimm 2012, p. 4).

4.1 Rationale for Agent Based Modelling

Agent-based models (ABMs) offer a wide set of characteristics that are favorable in our case:

AMBs are able to model micro-based behavior of individuals in order to explain marcro-level phenomena (Bonabeau 2002). The diffusion of solar PV is a process of emergence that arises from the interaction and response of individual economic actors (i.e. agents) to the behavior of each other and their environment (Railsback and Grimm 2012). ABMs allow to model system-level dynamics, such as technological learning of solar PV, which is driven by the agents' behavior but also influences their decisions (Schaeffer et al.; Bollinger and Gillingham 2014). The framework of ABMs allows to simulate heterogeneous agents with unique and individual preferences and characteristics (Palmer et al. 2015; Rai and Robinson 2015). This complies with the diversity of potential solar PV adopters in a market.

Furthermore, ABMs account for spatial resolution. Usually, agents do not interact with all other agents but only with a limited selection. Thus, the social network of an agent, determining the interactions with other agents, is at least partially driven by the agent's geographical location (Railsback and Grimm 2012; Bollinger and Gillingham 2012). A number of studies have shown that particularly in the diffusion of solar PV peer effects exist and the information by word of mouth of major importance is (Bollinger and Gillingham 2012; Linder 2013; Richter 2013; Rai and Robinson 2013). Furthermore, the integration of GIS-data (geographic information systems) allows for greater precision by exposing agents to realistic environmental influences, such as in our case to precise solar radiation values (Robinson et al. 2013).

Additionally, given the stochastic nature of ABMs, they also offer the possibility of estimating how the adjustment mechanisms influence the variability of policy outcomes. Moreover, the dynamic structure, being an essential characteristic of a diffusion process over time, is already implemented in the model's framework (Dawid 2006). Consequently, ABMs show to be a suitable tool to be used for the desired purpose and to account for most characteristics specifically applying to our object of investigation.

4.2 Model description

The model description is oriented towards the main aspects of the ODD protocol (i.e. overview, design principles, details), a standard protocol for describing ABMs (Grimm et al. 2010; Grimm et al. 2006). The protocol is chosen in order to make the model description more understandable and complete, thereby supporting its reproducibility. Within the following three sections we present an overview and the purpose of the model (see Chapter 4.2.1), introduce the model entities and their state variables (see Chapter 4.2.2), as well as spatial and temporal scales of the model (see Chapter 4.2.3), and outline key processes and scheduling (see Chapter 4.2.4).

4.2.1 Purpose of the model and model overview

4.2.1.1 Purpose

The purpose of our model is to represent the historical socio-technical evolution in a country's solar PV market. This allows to enhance system understanding of the technology adoption process and to evaluate the performance of novel responsive adjustment mechanisms for the feed-in tariff (FIT).

4.2.1.2 Overview

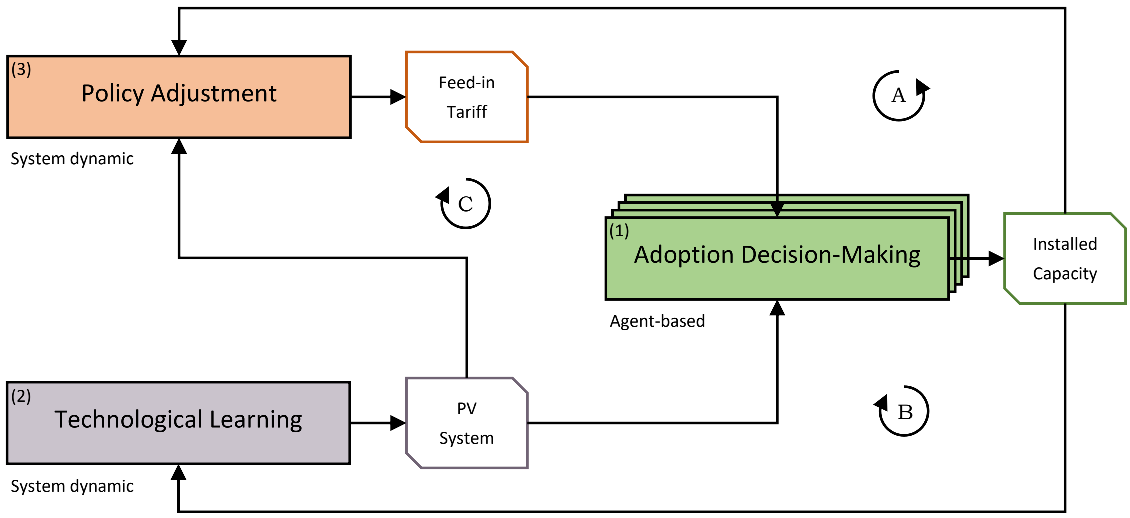
Figure 4.1 shows a simplified process structure of the model, giving an overview of its general logic. The key output measures of the model are deployment dynamics (i.e. monthly installed capacity, overall installed capacity) and costs of policy measures (i.e. monthly policy costs, overall policy costs). The model is mainly composed of three subparts that are executed in a recurring sequence: (1) The adoption decision-making of the model's agents, (2) the resulting technological learning of solar PV, and (3) the policy adjustment mechanism.

First, every potential solar PV adopter – residential, commercial and industrial, and utility-scale agents – undergoes a decision-making process of whether to install a solar PV system or not. Therefore, the agent first needs to develop the idea of an installation. This procedure is modeled as a weighted linear combination of the actors' personal awareness of the technology ($Awareness_j$), the information situation with regard to solar PV ($ArticlesPV_t$), the fraction of actors that have installed a PV system in the country ($Peers_t$) and the country's average profitability of an investment in a solar PV system in the given month (IRR_t). The weighting of each factor is determined during the calibration of the model.

Once an agent has developed the idea to install solar PV, it computes the net present value (NPV) of adopting solar PV and defines the investment to be attractive if the NPV is non-negative or if the agent represents a residential agent whose environmental awareness is extraordinarily high. All systems that are considered attractive by the agent are executed, except for projects for which remuneration is not immediately available. For example, this can be the case due to policies' cost caps as they had been implemented in Switzerland or policies' deployment caps as they had been implemented in Spain between 2009 and 2011. In this case, the agent in Spain does not install but undergoes the whole process again in the next month. In contrast, given the possibility to register on a waiting list for remuneration in Switzerland, the agent facing this situation in Switzerland, undergoes an additional decision-making process evaluating a potential postponement of the investment. Therefore, it compares the expected NPV of an immediate investment with the expected NPV of a postponement, taking into account a certain risk aversion of the agent. In the event of a postponement, the solar PV system is implemented as soon as remuneration is offered to the agent by the policy.

Second, the price of solar PV progresses down the technology's learning curve according to national and worldwide demand from adopters. Solar PV modules are widely considered a global product whose technological learning depends on global deployment. In contrast, the cost evolution of the balance of system, namely inverters and installation services, relies to a large extent on a regional learning process (Schaeffer et al.; Bollinger and Gillingham 2014). Our model considers this by employing one global experience curve for solar PV modules, and one national experience curve for non-module components of the system.

Finally, the responsive policy mechanism calculates the adjustment of the FIT for the following month, based on two variables. Therefore, it determines the deviation of one of the key output measures, deployment or costs, to predefined policy targets. It considers the deviation for the current month and the deviation on a cumulative basis over all months since the policy started.



Note: The three modules of our ABM: (1) adoption decision-making, (2) technological learning and (3) policy adjustment, influence each other directly and through feedback loops. The FIT and installed capacity (A) connect policy adjustment and adoption decision-making. Typically, as the FIT increases, it encourages more adoption raising the installed capacity, which in turn triggers the adjustment of the FIT. The installed capacity and PV system price (B) connect adoption decision-making and technological learning. As installed capacity grows, the technology progresses down its experience curve lowering PV system prices. In turn, lower prices facilitate more adoption, closing the loop. Finally, the FIT, installed capacity and PV system price (C) connect policy adjustment and technological learning. As a higher FIT leads to growing installed capacity by promoting adoption, technological learning pushes down PV system prices. This indirectly influences the policy adjustment through adoption decision-making as policy targets are defined in terms of deployment or policy costs.

Figure 4.1. Agent-based model process structure of solar PV adoption

The costs of the policy are defined as the expenditures by the government within the FIT scheme over the whole period of years of guaranteed payments, allocated to the month of the adoption (see Equation 5). Explicitly, only the difference between the FIT at the month of adoption and the wholesale electricity price is considered. Until 2017, the wholesale electricity price paid for energy produced by solar PV is estimated as the average yearly day-ahead-auction wholesale electricity price between 11 am and 4 pm in each country, representing the time for sun peak hours. Afterwards, a yearly price increase of 1.5% is assumed (Hoppmann et al. 2014b). For the government's historical discount rate, the interest rate of the countries' historical bonds in the month of adoption are used. In most cases, this method of calculation differs from the ones used by governments, as they often do not include already pledged but not yet performed future payments to solar generators. While our method hinders a direct comparison to historical policy cost data, it facilitates the comparability among different countries as it considers the different timings of deployment.

Policy costs [local currency] =

$$\sum_{\text{year}=1}^{\text{Pay. Period}} \frac{(\text{FIT}_0 - \text{Wholesale electricity market price}_{\text{year}}) \cdot \text{Electricity generation} \cdot (1 - \text{Self-consumption})}{(1 + \text{Government discount rate})^{\text{year}}} \tag{Eq. 5}$$

4.2.2 Entities and state variables

The model only comprises two hierarchical levels: (i) individual agents and (ii) the observer defining the conditions the individual actors are exposed to.

(i) Every individual agent represents a potential solar PV investor in the respective country. Agents are assigned to representing households, commercial and industrial actors and utility-scale actors. Based on their actor type and based on historical country specific data, every agent is assigned a certain PV size it might consider building. It owns a different self-consumption rate, pays a different electricity price, receives a different level of incentives and owns a different production factor [Mean 0.9, Standard deviation 0.2], which accounts for the heterogeneity of each installation (e.g., orientation, tilt, shading).

Furthermore, every agent owns socio-demographic variables, such as PV awareness as a normal distribution but limited to positive values [Mean 0.5, Standard deviation 0.2] and a discount rate, including a randomly assigned delta to the cost of capital for each agent type [Mean 0, Standard deviation 1].

(ii) The higher hierarchical level in the model is the observer, a system-level entity, responsible for global time-keeping, policy characteristics (i.e. setting FIT levels, determining PV information) and technology characteristics (i.e. PV efficiency). Additionally, it tracks the output variables of the overall population of agents such as policy cost and deployment.

Table 4.1: Main variables of potential adopters by type and country

Country	Type of adopter	System size [kWp][a]	Solar self-consumption rate[b]	Electricity rate	Discount rate[c]	Incentive[d]
Switzerland	*Residential*	0-30 kWp	30%[e]	Historical rates for households.[f]	Historical lending rate.[g]	100%
	Commercial and Industrial	30-100 kWp	20%[e]	Hist. rates for small/medium industry.[f]	Historical lending rate.[g]	85%
	Utility-scale	100-1,000 kWp	40%[e]	Historical rates for big industry.[f]	Historical lending rate.[g]	80%
Spain	*Residential*	0-20 kWp	30%[e]	Historical rates for households.[f]	Historical lending rate.[g]	100%
	Commercial and Industrial	20-100 kWp	20%[e]	Hist. rates for small/medium industry.[f]	Historical lending rate.[g]	95%
	Utility-scale	100-5,000 kWp	0%[e]	Historical rates for big industry.[f]	Historical lending rate.[g]	90%

(a) The relative frequency of the different sizes within the range for each type of adopter follows the distribution of remunerated solar PV systems within the KEV between 2006 and 2016 in Switzerland (Bundesamt für Energie BFE) and registered solar PV systems at the ministry for ecological transformation in Spain (Gobierno de España, Ministerio para la Transición Ecológica.) respectively. The size ranges reflect a consolidated version of the different categories considered by the KEV in Switzerland and by the Royal Decree 661/2007 in Spain respectively. **(b)** Solar self-consumption rate is the fraction of electricity generated from the solar PV system that is consumed by the adopter. **(c)** The historical lending rate for each adopter type is added to the individual discount rate of each agent. **(d)** Fraction of the incentive received by each adopter type if the novel responsive adjustment mechanism is active. Values are derived from the historical capacity weighted average of incentive fractions for each category within the policy of each country. For model calibration the real historical values are used. **(e)** The self-consumption rate of each agent is randomly assigned from a normal distribution with the above mean, an assumed standard deviation of 0.05 and truncated between zero and one for each adopter type. The values of the mean are adopted from studies within the German market (Fraunhofer ISE 2018). For utility-scale agents in Spain the self-consumption rate is set to zero, given the size of installations and the almost exclusive application of ground-mounted systems in this category. **(f)** Estimated monthly electricity rates based on historical values, please see appendix A.5. **(g)** Historical lending rates based on long-term loans interest rates, please see appendix A.6.

4.2.3 Scale, temporal and spatial resolution

4.2.3.1 Scale

Optimally, we would represent every potential solar PV investor in reality by exactly one agent in the model. However, given computational power constraints this is not expedient, especially not for representations of large-scale systems like a country's solar PV adoption process. Thus, the model contains consistent "resize-population" scaling parameters that scale the number of agents implemented and allow for shorter simulation times.

The model revealed that scaling works well for agent-groups with a rather large number of actors such as households in Spain. For these groups, the agent scale may be increased up to 1:2000 without significant effects on the results of the model. This scaling factor would indicate that every 2000th potential solar PV investor in reality, is represented by one agent in the model. In contrast, the robustness of the calibration for large scaling factors is more problematic for groups with less agents, e.g. utility-scale actors in Switzerland. During the calibration, and in the further scenarios of the model, the following scaling factors are used:

Table 4.2: Number of agents and scaling factors of potential adopters by type and country

Country	Type of adopter	Number of estimated agents	Model scaling factor	Number of modeled agents due to rescaling
Switzerland	*Residential*	1445850[a]	1:200	7229
	Commercial and Industrial	457395[b]	1:50	9147
	Utility-scale	30937[c]	1:2	15468
Spain	*Residential*	18252800[a]	1:2000	9126
	Commercial and Industrial	7532271[b]	1:500	15064
	Utility-scale	99697[c]	1:5	19939

(a) Number of owner-occupied households in Spain (Instituto Nacional de Estadística) and Switzerland (Bundesamt für Statistik) in 2014 respectively. **(b)** Average number of firms, except insurance activities of holdings and electricity and finance firm in Switzerland and Spain in 2014 (Eurostat). **(c)** Average number of electricity, financial and insurance firms in Switzerland (Bundesamt für Statistik) and Spain (Eurostat) in 2014.

4.2.3.2 Temporal distribution

One time step in the model refers to one month in reality, being the shortest time period that is considered between two FIT adjustments. The underlying data allows the model to start earliest in 1991 and to run until the end of 2016. The actual running period is country dependent and oriented towards the time period of historical policy activity (see Chapter 4.2.4.1).

4.2.3.3 Spatial resolution

The model's agents are distributed according to the number of residential buildings in the countries' regional subdivisions, namely by the cantons in Switzerland (Bundesamt für Statistik) and the autonomous communities in Spain respectively (Instituto Nacional de Estadística), thus receiving a distinctive annual irradiation based on their location (NASA).

The patches of the model are the spatial grid units, limited within each country's borders. The scaling of patches depends on the overall size of the country. In the Swiss model, we employ geographical patches of 10 per 10 kilometers and in Spain of 15 per 15 kilometers. In addition to their coordinates, every patch carries a variable defining the country's region and is allocated to the local irradiation intensity as global horizontal irradiation (GHI) derived from satellite data (NASA).

4.2.4 Scheduling and process overview

In the following, the main procedure is presented. It is repeated after the initialization of the model once every month. The procedure goes through its three modules in the following order: (1) evaluate adoption, (2) update technological change and (3) adjust deployment policy (if the policy is active). The model's simulation period runs from January 2004 for Switzerland and from January 1996 for Spain until December 2016 for both cases.

4.2.4.1 Scheduling

This thesis aims at evaluating the performance of novel policy mechanisms. Thus, in order to have a reference scenario to compare with and to ensure optimal data availability and accuracy during the analysis only past periods are modeled. However, given some future parameter assumptions (i.e. electricity prices, global installation capacities, etc.) the model could be used to forecast future developments. In general, the accuracy of a model increases with its simulated timeframe used for model calibration. However, the positive influence of an extended timeframe decreases when a time extension does not provide additional information. Simultaneously, longer simulation periods drive up computing times. Consequently, we start the simulation latest when a substantial solar PV deployment occurred in history but before the first FIT policy of that country came into force.

In Switzerland the first nationwide FIT policy, named "additional costs financing" (Mehrkostenfinanzierung) came into force in January 2005 (Bundesamt für Energie BFE). At this time, total installations accounted for approximately 25 MWp, only making up 1.5% of total installations at the end of 2016 with around 1660 MWp. Consequently, in order to additionally allow for a short lead time of one year, the simulation time for Switzerland starts in January 2004. In comparison, Spain's Electricity Sector Law was first introduced in 1997 (Law 54/1997). With only around 1 MWp, the installed capacity in 1997 was, compared to 4690 MWp at the end of 2016, negligible. Again, including a short lead time, the simulation time for Spain starts in January 1996.

4.2.4.2 Process overview

The basic algorithms of the model are based on theory and previous studies. At the beginning of the procedure, time-keeping and monitoring variables are adjusted. Potential adopters then evaluate whether they want to install solar PV or not. Afterwards, according to the already installed capacity, the price of solar PV systems decreases using a global experience curve for PV modules and a national experience curve for non-module costs. Finally, in the case of policy activity, the adjustment mechanism modifies the FIT of the deployment policy depending on the deviation to predefined policy targets.

4.2.4.3 Consumers' adoption decision-making

Every actor undergoes the following decision-making process every month in order to decide upon the investment in a solar PV system. Following the natural process of such a decision, it is implemented as consecutive steps. (a) While the first step depicts whether an actor develops the general idea to install PV, (b) the agent afterwards determines if it considers the investment economically attractive. (c) In the case of policy cost caps and a current stop for new systems being accepted for remuneration, the actor finally decides whether to install the system immediately or to postpone the investment until new remuneration is accessible. The last step (c) only applies to agents in Switzerland.

4.2.4.3.1 (a) Determine project idea

The determine project idea procedure consists of a gate keeper function that ensures that not all actors constantly consider a solar PV project investment. Therefore, every agent owns a personal degree of attraction (PDA_j) that defines the agent's affinity for a solar PV investment. It is modeled as a weighted linear combination of four factors: the actors' personal awareness of the technology ($Awareness_j$), the information situation with regard to solar PV ($ArticlesPV_t$), the fraction of actors that have installed a PV system in the country ($Peers_t$) and the country's average profitability of an investment in a solar PV system in the given month (IRR_t).

$$PDA_j = k_{awareness} \cdot Awareness_j + k_{info} \cdot ArticlesPV_t + k_{peers} \cdot Peers_t + k_{advantage} \cdot IRR_t > \widehat{PDA}_{threshold} \qquad \text{(Eq. 6)}$$

The indices indicate whether the factors vary over time *t* and/or between agents *j*. All four factors ($Awareness_j$, $ArticlesPV_t$, $Peers_t$, IRR_t) take values between zero and one, and are weighted according to the results of the model calibration (see Chapter 4.3.1). The weights ($k_{awareness}$, k_{info}, k_{peers}, $k_{advantage}$) need to be greater than zero. Consequently, an agent's personal degree of attraction (PDA_j) also can only take on positive values. Only if an agent's personal degree of attraction PDA_j is greater than a certain global threshold $\widehat{PDA}_{threshold}$, the agent is considered having the idea of a solar PV investment and proceeds to the next step (b). Consequently, if its personal degree of attraction is below the threshold, the agent is not considered having the idea in this month and undergoes the procedure starting at step (a) in the next period again. Given its linear dependency, the threshold $\widehat{PDA}_{threshold}$ is fixed to a value of 0.5.

The PV awareness reflects the individual attitude and knowledge of the technology, triggering PV affine actors to enter the process earlier than PV averse consumers. This can be understood as a combination of factors, besides others, driven by e.g. an adopter's technological affinity or environmental awareness. Literature states that for certain adopters the interest and curiosity in solar PV being an innovative electricity generation technology played a key role for their investment (Schelly 2014). Additionally, interviews and surveys stressed environmental concerns or the reduction of the impact on the environment by using renewable energy sources to be very important in an adopters' decision-making processes (Schelly 2014; Rai and McAndrews 2012). Each agent is assigned a constant environmental awareness level between zero and one, following a truncated normal distribution of mean 0.5 and standard deviation 0.2.

The available information represents how much new and cumulated content on solar PV is accessible through news articles. In 1969, Bass (1969) already proposed a product diffusion model indicating the adoption process being influenced by an external effect, mainly referring to mass media, and an internal effect referring to word-of mouth or the neighborhood effect (see below). These two main types of communication channels have later been confirmed by Jager (2006) and Rogers (2003) and also applied in modeling solar PV adoption processes (Zhao et al. 2011). The available information each month is the sum of the news articles published that month about solar PV and the cumulative number of articles on the topic, which both evolve according to the deployment of solar PV in the considered country and the rest of the world. The functions to calculate the number of articles have equal weight and were fitted from empirical data on articles about solar PV in the considered country since 1990 (see appendix A.7).

The peer-effect represents the proportion of adopters of solar PV within the country. The theoretical foundation of interpersonal communication among agents being an important component of an innovation's diffusion process in general was already given by Rogers (2003). Since then, a number of studies have shown that particularly in the diffusion of solar PV peer effects exist (Bollinger and Gillingham 2012; Linder 2013; Richter 2013; Rai and Robinson 2013). Even the questions of how and why peer effects influence the decision to adopt has been subject of recent research (Curtius et al. 2018). Besides this, most studies investigating the adoption of solar PV also include mechanisms to account for this characteristic (Palmer et al. 2015; Robinson et al. 2013; Zhao et al. 2011). Although researchers found out that the influence of this effect is often driven by the geographical proximity between agents (Islam 2014; Rai and McAndrews 2012; Schelly 2014), due to computational power restraints, we currently depict the effect on a national basis. Defined as the fraction of actors that have already installed a PV system in the respective country, and thus being a global, instead of an agent-specific variable, it drives down model complexity and allows for shorter computation time.

The perceived advantage represents the improving chances to develop the idea to adopt a technology as this becomes a more attractive investment. Several studies have shown the economic profitability being of major importance for the decision-making process of an investor (Islam 2014; Rai and McAndrews 2012). The variable rests on the assumption that more advantageous investment options enjoy more active sharing of information about it through word of mouth. This is modeled by the internal rate of return of a solar PV investment for an average household in the respective country.

4.2.4.3.2 (b) Determine Project Profitability

Once an agent develops the idea to install solar PV, it evaluates whether adoption makes economic sense. It is implemented as a net-present-value (NPV) calculation, being a function of investment costs, avoided electricity purchasing costs, operation and maintenance costs, received revenues due to FIT payments and the guaranteed payment period for incentives and is calculated in the national currency (Cur.) of the considered country.

$$\text{NPV}_{\text{PV}}\ [\text{Cur.}] =$$

$$- \text{Investment cost [Cur.]} + \sum_{\text{year}=0}^{\text{Pay. Period}} \frac{\text{Avoided costs [Cur./yr] - O\&M costs [Cur./yr] + FIT revenues [Cur./yr]}}{(1 + \text{discount rate})^{\text{year}}} \quad \text{(Eq. 7)}$$

In principle, every agent that has determined the potential idea of an investment undergoes this economic evaluation and only defines the installation to be economically attractive if its expected project NPV is non-negative (i.e. the internal rate of return of adopting exceeds the agent's discount rate). Alternatively, residential agents (i.e. households) will install solar PV regardless of its economics if their environmental awareness is extraordinarily high and greater than a country specific and calibrated awareness threshold ($\widehat{\text{Awa}}_{\text{threshold}}$) (see Chapter 4.3.1).

Surveys found out that for some adopters an interest in technical innovation and the enjoyment of the technical aspects of energy systems combined with environmental concerns were of higher importance than the economics. As a result, some of the adopters, mostly private individuals, even invested despite a lack of profitability for their solar PV system (Schelly 2014). Additionally, history proved that some early adopters pioneered the uptake of solar PV at a time when doing so was uneconomic.

Given that the available information of solar PV (ArticlesPV_t), the proportion of adopters in the country (Peers_t) and the perceived advantage of the investment (IRR_t) are global variables, agents with the highest awareness level get the idea of a potential investment first. Due to this strong linkage, it is ensured that high aware agents with a personal awareness above the threshold will install earlier in time, and before all other agents with an awareness level below the threshold. Consequently, the implemented exemption for households of investing despite missing profitability is well suited for representing the early adopters as stressed by literature and visible in historical data.

However, in the case the agent's awareness is below the threshold for early adopters, it considers, a project specific non-negative NPV as a precondition for the final system installation. The investment costs are calculated as the product of the size of the system (agent's own characteristic), the price of solar PV and the scale effect.

$$\text{Investment cost [Cur.]} = \text{System size [kWp]} \cdot \text{PV system price [Cur./kWp]} \cdot \text{Scale effect [-]} \quad \text{(Eq. 8)}$$

The scale effect reduces the price of solar PV as the system size grows larger based on historical observations. The scale effect is set according to a reference system of size 10 kWp for which the price remains unchanged (i.e. the scale effect is one). For systems smaller than 1 kWp it is kept constant at 1.2. For systems greater than 1 kWp the scale effect is defined by the following function (Haelg, L., Waelchli, M. & Schmidt, T. S.):

$$\text{Scale effect [-]} = 1.1246 \cdot \text{System size [kWp]}^{-0.051} \quad \text{(Eq. 9)}$$

Avoided costs derive from the avoided consumption of electricity from the grid and are a function of the self-consumption rate for the solar generation, the electricity price, and the solar electricity generation itself. Operation and maintenance costs are estimated to be around 1.5% of the cost of the solar system (Peters et al. 2012).

$$\text{Avoided costs [Cur./yr]} = \text{Self-consumption [-]} \cdot \text{Solar generation [kWh/yr]} \cdot \text{Electricity price [Cur./kWh]} \quad \text{(Eq. 10)}$$

Revenues from policy incentives are a function of the FIT, the self-consumption rate for the solar generation, and the solar electricity generation.

$$\text{FIT revenues [EUR/yr]} = (1 - \text{Self-consumption [-]}) \cdot \text{Solar generation [kWh/yr]} \cdot \text{FIT}_0 \text{ [EUR/kWh]} \quad \text{(Eq. 11)}$$

The solar electricity generation is a function of the irradiation in the location of the agent, the size of the system, the performance ratio (PR) (i.e. the ratio between AC output and DC nominal power, set at 0.85) (Fraunhofer ISE 2018), and a production factor, which accounts for the heterogeneity of each installation (e.g., orientation, tilt, shading). Each agent has a production factor randomly assigned from a normal distribution of mean 0.9 and standard deviation 0.2.

$$\text{Solar generation [kWh/yr]} = \text{Irradiation [kWh/kWp]} \cdot \text{System size [kWp]} \cdot \text{PV PR [-]} \cdot \text{Production factor [-]} \quad \text{(Eq. 12)}$$

As mentioned above, if the NPV is non-negative, the agent considers the investment to be attractive. If besides its attractiveness, also sufficient funds for remuneration are available in the given month and for the considered project, the agent installs the system.

In Spain, if there are not sufficient remaining funds provided by the government, due to the policy’s deployment cap between 2009 and 2011, the agent refrains from the investment in this period and undergoes the whole procedure starting at step (a) in the next period again.

In Switzerland, if there are not sufficient remaining funds provided by the government, due to the policy’s cost cap, the agent undergoes the following decision-making step (c). It determines whether to install the system in the current month without immediate remuneration or to postpone the investment until new funds are available.

4.2.4.3.3 (c) Decide upon investment postponement

As mentioned in Chapter 3.3.4, under certain circumstances an immediate installation, despite missing immediate remuneration, could be economically advantageous over the postponement of the investment. However, for similar expected returns of both options, immediate investment versus investment postponement, we expect agents to postpone their installation to avoid the risk of an immediate investment featuring the uncertainty of future remuneration. This is supported by an individual's risk aversion that is a fundamental element in standard theories of asset valuation (Pratt 1964) and a desirable goal when it comes to investment decisions (Klos et al. 2005).

Consequently, taking this into account, the agent in our model only decides for the immediate installation in the following cases: (i) if the expected NPV for the immediate installation is positive, while the expected NPV for the postponement is negative or (ii) if the expected NPV for the immediate investment exceeds the expected NPV for the postponement by a certain percentage (see Eq. 13). If one of the two requirements hold true, the agent immediately installs its system and registers on the waiting list in the hope of receiving remuneration for the already built system in the future. The threshold value of 13.6% was derived within the overall model calibration (see Chapter 4.3.1).

$$\frac{NPV_{PV,\ immediate\ expected}}{NPV_{PV,\ postponed\ expected}} - 1 > \widehat{NPV}_{threshold} \qquad \text{(Eq. 13)}$$

In all other cases, the agent does not install its system in the current month. However, it also registers the not yet built project on the waiting list and installs its system as soon as sufficient funds are available and its project is released for remuneration. Although during the time between the registration date and the final installation date PV prices as well as FIT levels might have changed, the agent does not review the economic viability of its project before final installation. This is justified by the high bureaucratic burden for the registration process in history (pronovo 2018). For the sake of simplicity, the agent only has the two mentioned options, whose decision is taken in the same month as the initial idea generation. Installing the system at some point between the initial idea generation and the release of funding for the project is not considered as an option.

An agent undergoing the decision process assumes to face the same waiting time as the adopter that so far waited the longest between project registration and final release of its project remuneration. New demand for the remuneration of new projects constantly exceeded the supply of new financial funding provided by the government throughout the years in history (pronovo 2018). Consequently, the registered capacity on the waiting list, as well as the necessary waiting time, also grew continuously.

The expected NPV for an immediate installation($PV_{PV,\ immediate\ expected}$) but without immediate remuneration considers the current investment costs, the avoided electricity purchasing costs and the operation and maintenance costs during all years, from the current date until the end of the payment period. They are calculated using the same approach as in step (b) (see Chapter 4.2.4.3.2). The future FIT revenues are only taken into account for the shortened funding period, starting after the expected waiting time but again only lasting until the end of the payment period.

$$\text{NPV}_{\text{PV, immediate expected}} =$$

$$- \text{Inv. cost}_0 + \sum_{\text{year}=0}^{\text{Pay. Period}} \frac{\text{Av. costs - O\&M costs}}{(1+\text{discount rate})^{\text{year}}} + \sum_{\text{year=expected waiting time}}^{\text{Pay. Period}} \frac{\text{FIT rev}_0}{(1+\text{discount rate})^{\text{year}}} \quad \text{(Eq. 14)}$$

The future FIT revenues are based on the current FIT level of the date of installation.

$$\text{FIT}_0 = (1\text{-Self-consumption}) \bullet \text{Solar generation} \bullet \text{FIT}_0 \quad \text{(Eq. 15)}$$

The expected NPV for a postponed installation ($\text{NPV}_{\text{PV, postponed expected}}$) estimates the future investment costs and takes into account the expected future FIT revenues, starting after the expected waiting time but this time lasting until end of a guaranteed payment period, postponed by the expected waiting time. The operation and maintenance cost are estimated to be around 1.5% of the expected cost of the solar system (Peters et al. 2012). The avoided electricity purchasing costs still follow the same approach as in step (b) (see Chapter 4.2.4.3.2) and are based on the current electricity price that is not projected into the future.

$$\text{NPV}_{\text{PV, postponed expected}} =$$

$$- \text{Inv. cost}_{\text{expected waiting time}} + \sum_{\text{year=expected waiting time}}^{\text{Pay. Period + expected waiting time}} \frac{\text{Av. costs - O\&M costs + FIT rev}_{\text{expected waiting time}}}{(1 + \text{discount rate})^{\text{year}}} \quad \text{(Eq. 16)}$$

The agent estimates the future investment cost and the future FIT as a relative share of today's values. Thereby, it assumes the relative change that these values have experienced over the duration of the expected waiting time in the recent past, to occur by the same percentage over the duration of the upcoming waiting time. For example, if the agent expects its waiting time to be 1 year and if PV prices have decrease by 10% during last year, it expects the PV prices to again decrease by 10% during the next year.

$$\text{Inv. cost}_{\text{expected waiting time}} = \text{Inv. cost}_0 \bullet \frac{\text{Inv. cost}_0}{\text{Inv. cost}_{0\text{ - expected waiting time}}} \quad \text{(Eq. 17)}$$

$$\text{FIT rev}_{\text{expected waiting time}} = (1 \text{ - Self-consumption}) \bullet \text{Solar generation} \bullet \text{FIT}_{\text{expected waiting time}} \quad \text{(Eq. 18)}$$

$$\text{FIT}_{\text{expected waiting time}} = \text{FIT}_0 \bullet \frac{\text{FIT}_0}{\text{FIT}_{0\text{ - expected waiting time}}} \quad \text{(Eq. 19)}$$

4.2.4.4 Technological learning

The evolution of cumulative deployment in the respective country constitutes an endogenous output variable of the model, determined by the agents' adoption each month. The cumulative installed capacity in the rest of the world is given by historical data (IEA PVPS - International Energy Agency 2017c). The price decrease of solar modules, following a global experience curve is determined by the sum of both cumulative deployments. However, the price decrease of non-module elements (e.g. installation, inverter, balance of system) is only defined by the country's respective cumulative deployment, and thus follows a national experience curve. Both cases and countries are modeled using one-factor experience curves based on the historical price development of residential solar PV systems and solar modules in the respective country (IEA PVPS - International Energy Agency 2017b, 2017a). The curves are fitted through least squares with the errors weighted by the monthly installations. This results in learning rates of 22% for modules and 9% for non-module components in Spain and learning rates of 21% for modules and 11% for non-module components in Switzerland.

To avoid excessive sensitivity of the experience curves, the learning effect is capped at 2% per month. The cap is based on an observed maximum annual price decrease of around 22% in Germany as a reference country with good data availability (IEA - International Energy Agency 2017b).

4.2.4.5 Policy adjustment

We study two different adjustment criteria in respect of which the mechanism calculates the monthly incentive adjustments: deployment – based on the capacity installed each month and policy costs – based on the total support costs calculated following Eq. 5.

While historical FIT policies sometimes only waited one month between two incentive adjustments (Clearingstelle, EEG, KWKG 2012), the revisions of FITs normally were performed less frequently. For example, in the early phase of Spain's support policy, the revision of remuneration levels was only scheduled once every year (del Rio 2014). However, experience has taught policy makers that this regularity was not sufficient to react to the fast evolution of solar PV prices (Sijm 2002). Also previous studies found that responsive FIT schemes with more frequent tariff adjustments reach deployment targets most effectively (Zhao et al. 2011). Nevertheless, literature also agrees that adjustments should not happen too frequently in order provide a certain security to project investors (Kreycik et al. 2011). Although more frequent than monthly adjustments would most likely further increase the stability of policy outcomes, weekly or even daily changing FIT levels would not give potential adopters enough time to take reasonable economic decisions on the basis of constantly changing remuneration levels.

The mechanisms employ an algorithm based on control theory principles, which calculates a non-predetermined modification of the FIT every month. The modification is based on the deviation of the policy outcome from predefined targets. The deviation is measured as the distance between a deployment or policy cost target and the model's actual installed capacity or policy expenditure. Deployment: the policy defines monthly policy targets and the mechanism responds to the evolution of the monthly installed capacity. Policy costs: the policy sets monthly cost objectives and the mechanism tracks how support costs (i.e. including future payments) evolve each month. The deviation is positive if the system falls short of the policy target and negative if the system exceeds it.

According to the direction and distance of the deviation, the algorithm aims at simultaneously correcting the previous month's deviation (proportional correction) and the cumulative deviation since the beginning of the policy (integrative correction). The sum of these two individual corrections then determines the adjustment of the incentive level.

Given its reactive and automated behavior, the functional principle of the adjustment mechanism constitutes a major change compared to historical policy designs that attempted to predict the pace of technological learning or used fixed adjustments (Kreycik et al. 2011; Grau 2014). For example, if we used a deployment adjustment criterion and there were a deviation since the beginning of the policy (excluding the previous month) of +100 MWp and the deviation for the previous month were -20 MWp, then, the proportional correction would be proportional to -20 MWp and the integrative correction would be proportional to +80 MWp. The resulting adjustment of the policy incentive is the sum of the two corrections scaled by their proportionality constants (Eq. 20).

$$FIT_{\#month} = FIT_{\#month-1} + k_p \bullet e_{\#month-1} + k_i \bullet \sum_{t=1}^{\#month-1} e_t \qquad \text{(Eq. 20)}$$

Where *e* stands for the deviation between the actual and the targeted deployment or policy cost for the month *#month*. The proportionality constants k_p and k_i were calibrated for each adjustment criterion to minimize the monthly deviations (see Chapter 4.3.1).

Within Chapter 5 we define different scenarios employing the two adjustment criteria and comprising different overall policy targets, different starting conditions for the policy incentives and different temporal distributions of targets.

4.3 Model and mechanism calibration

In order to ensure the model's accurate representation of the dynamics of solar PV adoption in each country and to achieve optimal results for the adjustment of incentives, the model's calibration parameters as well as the mechanism's proportionality constants need to be calibrated.

4.3.1 Model calibration

The model's key output measure deployment is calibrated against the historical evolution of cumulative installed capacity in the respective country. Furthermore, given the existence of the waiting list for remuneration, the Swiss model is simultaneously calibrated against a second, artificial pattern that we define as the intended installation capacity of adopters. It is defined as the sum of cumulative historical deployment and the installation capacity that was registered on the waiting list that had not yet been installed.

This general procedure can be referred to as "pattern oriented modeling" (Grimm et al. 2005) that determines the model's calibration parameters. They are derived separately for the model of each country. While in Switzerland, the calibration parameters of all three steps apply, the Spanish model only constitutes the calibration parameters of step (a) and (b).

In step (a), the development of the idea to install, the threshold for the agent's personal degree of attraction to develop the idea to install ($\widehat{PDA}_{threshold}$) is set to a value of 0.5, given its linear dependency. Thus, the weighing factors defining the strength of the following four influences on the agents' personal degree of attraction constitute model calibration parameters:

- the influence of the actors' personal awareness of the technology → $k_{awareness}$
- the influence of the information situation with regard to solar PV → k_{info}
- the influence of the fraction of actors that have installed a PV system in the country → k_{peers}
- the influence of the average profitability of an investment in a solar PV system → $k_{advantage}$

Step (b), the determining of the project profitability, is a purely economic evaluation without the need of calibration, whereas the threshold to skip the economic evaluation for highly aware agents constitutes a calibration parameter:

- the awareness threshold to skip the economic evaluation → $\widehat{Awa}_{threshold}$

In step (c), only relevant for the Swiss model, the threshold, determining the decision upon an investment postponement also constitutes a calibration parameter:

- the threshold to decide upon the invest. postponement → $\widehat{NPV}_{threshold}$

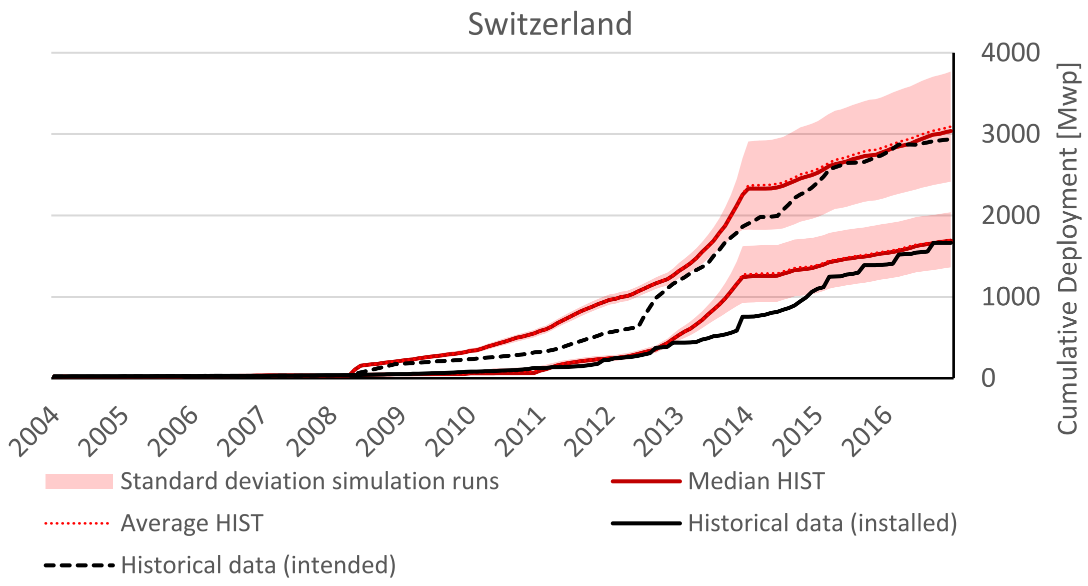
In a first phase, the approximate weights were estimated by trial and error, in order to find the general region of the values, where the modeled deployment pattern was similar to cumulative installed capacity in history. The final selection of weights was performed by minimizing the sum of the monthly deviations from historical values to the median of sets of 100 simulation runs (see Table 4.3).

Since the models are based on stochastic processes (e.g., the distribution of the environmental awareness among agents), that generate a unique behavior for each simulation run of the model, we need to consider the statistical properties of a number of simulation runs to derive reliable conclusions. Sets of 100 model runs allowed for a statistically representative distribution of model outcomes for one scenario, while limiting computational requirements to an acceptable extent. Their median values deviate less than 5% above or below from the median that we would observe from a set with 1,000 simulation runs.

Table 4.3: Model calibration parameters for Switzerland and Spain

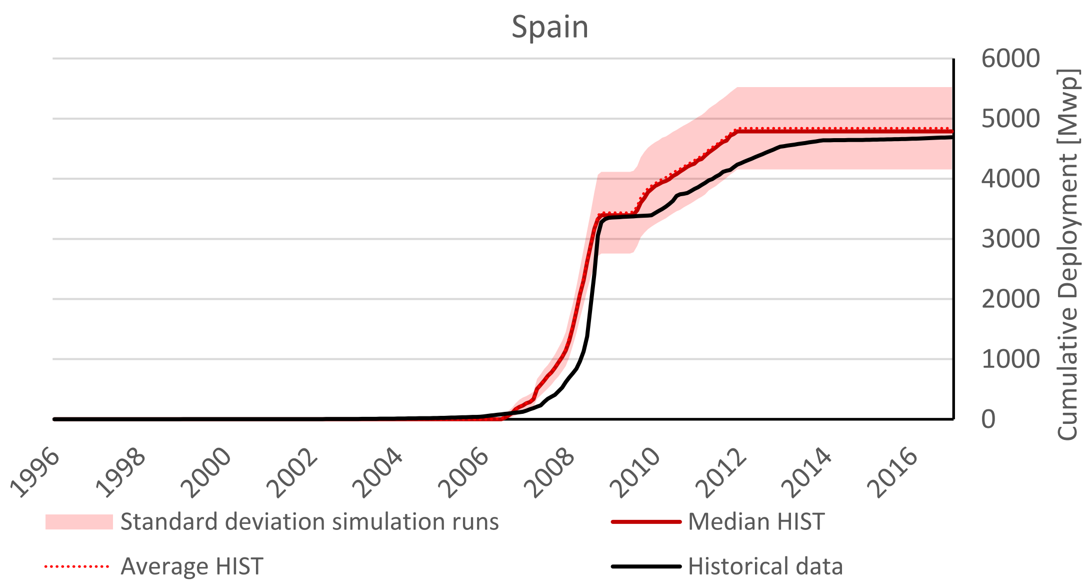
Country	**Step (a)** Determine project idea	**Step (b)** Determine Project Profitability	**Step (c)** Decide upon investment postponement
Switzerland	$k_{awareness}$ = 0.491 k_{info} = 0.089 k_{peers} = 1.07 $k_{advantage}$ = 0.047 $\widehat{PDA}_{threshold}$=0.5	$\widehat{Awa}_{threshold}$= 0.99[b]	$\widehat{NPV}_{threshold}$ = 0.136
Spain	$k_{awareness}$ = 0.488 k_{info} = 0.0428 k_{peers} = 0.8 $k_{advantage}$ = 0.5 $\widehat{PDA}_{threshold}$=0.5	$\widehat{Awa}_{threshold}$=0.99[b]	-

(a) Given the linear combination of factors within the development of the idea inequation, one factor was initially fixed; here the threshold for the agent's personal degree of attraction $\left(\widehat{PDA}_{threshold}\right)$ to a value of 0.5. (b) This qualifies around 0.1% of all households to be early adopters, due to their awareness above the calibrated threshold. While in the simulated policy in Switzerland, 4.5% of all households adopted solar PV until 2016, only 0.13% of households in Spain adopted solar PV until 2016.



Note: Simulated results are based on 1,000 simulation runs.

Figure 4.2. Simulated and historical cumulative deployments for 2004-2016 in Switzerland



Note: Simulated results are based on 1,000 simulation runs.

Figure 4.3. Simulated and historical cumulative deployments for 1996-2016 in Spain

The model does not consider potential psychological influences on adoption. This could be the reason, why it overestimates the general deployment between 2009 and the end of 2011 in Spain. In Spain, economic profitability was still given for many projects in history as well as in the simulation after October 2008, despite the reduction of incentives. However, given the additional introduction of even retroactive policy measures for already existing solar PV plants, as a response from policy makers to the installation boom, some potential adopters might have experienced a loss of reliance in promised political commitments (del Rio 2014). Furthermore, deployment in the model experiences a sudden stop from 2012 onwards, given the moratorium of incentives. While deployment in history also grinds to a halt towards 2014, some installations were still performed after the policy's end. The delayed completion of these laggard projects, whose decision and implementation might have already started before 2012, or installations that were decided upon without the existence of incentives, cannot be displayed by the model.

4.3.2 Mechanism calibration

Besides the general calibration of the model to match historical deployment, the adjustment mechanisms need to be calibrated. Given the control theory approach the mechanisms require the setting of one proportionality constant for each of the correction terms: proportional (k_p) and integrative (k_i). The values of these constants define the sensitivity of the incentive adjustments with regard to the model's deviations from the policy targets in the previous month (proportional correction) and the cumulative deviation since the policy start (integrative correction). As higher values create larger corrections, the mechanism's ability to adjust the policy incentives to evolving technology costs increases, while the stability of incentives decreases.

As soon as the system does not precisely follow its policy targets for some time, we are facing a trade-off between minimizing the absolute deviations from monthly policy targets and the deviation from the overall policy target. Under the condition of achieving the overall policy target, a temporary excess of deployment can only be corrected by allowing for a consecutive and undesired temporary shortfall on installations (e.g. all deployment in the early years and zero afterwards). Thus, we opt for a compromise that allows for an approximate achievement of the overall policy target, while avoiding phases of extremely high or low installations and simultaneously trying to minimize fluctuations of incentives.

As different countries are exposed to different contexts and residents show a different sensitivity to the determined factors driving adoption, each country needs a separate calibration of its adjustment mechanisms. In addition, depending on the applied adjustment criterion, deviations are measured in different units resulting in different magnitudes (e.g. deployment in MWp or policy costs in million EUR/CHF). Thus, each adjustment criterion also requires a different calibration of the adjustment mechanism. Finally, a further calibration was necessary for different overall targets, to align the sensitivity of incentive corrections (see Table 4.4).

Table 4.4: Proportionality constants for incentive adjustment mechanisms

Country	Adjustment criterion	k_p	k_i	Unit
Switzerland	For achievement of historical key policy outcomes			
	Deployment	$2.0 \cdot 10^{-4}$	$2.0 \cdot 10^{-6}$	[ΔCHF_{FIT} / $MWp_{deviation}$]
	Policy cost	$8.0 \cdot 10^{-5}$	$1.0 \cdot 10^{-5}$	[ΔCHF_{FIT} / millllion $CHF_{deviation}$]
	For achievement of 500 W/capita in deployment[a]			
	Deployment	$6.0 \cdot 10^{-4}$	$5.0 \cdot 10^{-5}$	[ΔCHF_{FIT} / $MWp_{deviation}$]
Spain	For achievement of historical key policy outcomes			
	Deployment	$7.0 \cdot 10^{-5}$	$4.0 \cdot 10^{-5}$	[ΔEUR_{FIT} / $MWp_{deviation}$]
	Policy cost	$2.0 \cdot 10^{-5}$	$4.0 \cdot 10^{-6}$	[ΔEUR_{FIT} / millllion $EUR_{deviation}$]
	For achievement of 500 W/capita in deployment[a]			
	Deployment[b]	$7.0 \cdot 10^{-5}$	$4.0 \cdot 10^{-5}$	[ΔEUR_{FIT} / $MWp_{deviation}$]

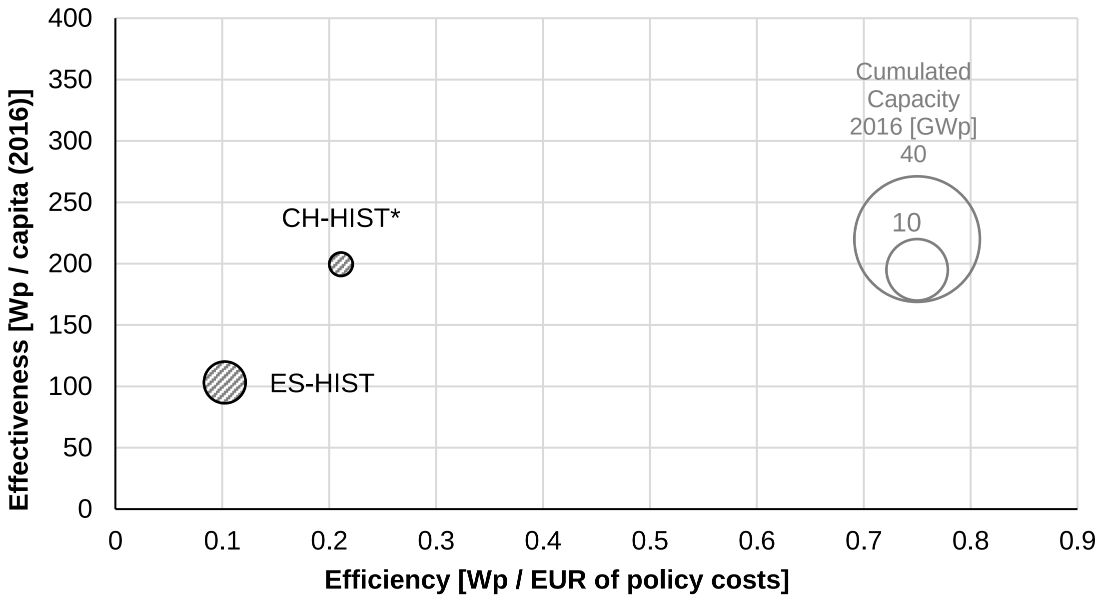
(a) The overall deployment goal in the second set of scenarios is aligned with the capita specific historical deployment in Germany in 2016 of 500 W/capita (see Chapter 5.1.2 and 5.2). (b) For Spain, the proportionality constants for the achievement of the historical key policy deployment outcome was also suitable for the achievement of the increased target.

5 Scenarios

This thesis evaluates a novel adjustment mechanism that automatically modifies the policy incentives each month, namely the feed-in tariff (FIT) level, depending on the deviation from installation capacity or policy costs to predefined policy targets. In contrast to historical policy designs, the studied responsive mechanisms neither attempt to predict the pace of technological learning, nor use fixed adjustments. Instead, they utilize control theory principles to determine each month's correction of the FIT level (La Hoz et al. 2010).

In the first part of our analysis (1), we evaluate if the responsive adjustment mechanisms could have achieved a more cost-efficient policy and an increase in the policy's effectiveness compared to historical policies. In the second part (2), we assess the influence of different policy configurations on the ability of the new policy design to accurately achieve its targets and test their influence on the policy's cost efficiency. We explicitly test different overall deployment targets, different initial incentive conditions and a different deployment timing.

The main model outputs of all scenarios are the diffusion of the technology (i.e. installed capacity of solar photovoltaics (PV)) and the policy costs (i.e. the sum of support costs for each adopter during 20 years of the FIT). Using these measures, we (1) compare the outcome of simulated policies using the new mechanisms to the simulated historical policy outcomes in Spain and Switzerland (see Figure 5.1 below). Then, we (2) compare different scenarios comprising the three mentioned variations in policy configurations among each other and with respect to a base scenario. In compliance with the model's calibration, we employ the median outcome of 100 simulations to account for the randomness of the adoption process.



Note: Values are based on model outcomes for simulated historical policies in Switzerland and Spain (for more info see 5.1.1).

Figure 5.1. Simulated historical policy outcomes in Switzerland and Spain

5.1 Increasing cost efficiency and effectiveness of historical policies

For our first part of the analysis (1) we start with (a) testing the mechanisms under conditions close to history and aim for a similar overall deployment or for similar overall policy costs as simulated for the historical policies. Then, given that historical conditions were not necessarily desirable, we (b) detach the targets for our new policy design from historical outcomes and aim for a higher effectiveness as achieved by historical policies, measured in cumulative deployment.

5.1.1 Improving policies within historical conditions

In order to ensure the comparability to the historical policies, our mechanism's activity is restricted to the period when historical policies had a FIT with independent and fixed incentive levels in place. While Switzerland directly started its FIT policy with independently set incentives in January 2005 (Bundesamt für Energie BFE), Spain first decoupled their incentive levels from the average retail electricity price in January 2004. While in Switzerland the feed-in remuneration policy was still in place at the end of 2016, Spain's support policy for new solar PV systems already came to a complete moratorium in 2012 (del Rio 2014).

We define the overall policy goals as the historical deployment or estimated policy cost and distribute them throughout the months that the policy is active. Additionally, for each type of target, deployment and policy cost, we study two temporal distributions of monthly targets: a linear one, resulting in a quadratic function for cumulative targets, and a logistic one, resulting in an s-shaped curve for cumulative targets.

The logistic distribution of deployment targets is set to closely mimic the historical evolution of installations but with a smoother distribution over time, avoiding individual temporal deployment peaks. The peak-month of the s-curve of cumulative targets is adjusted to ensure that the distribution reaches 50% of its overall target at the same time as in history. Additionally, the steepness is set to mirror that of the historical evolution in the considered country. As an alternative, we further explore a linear distribution of deployment targets, being a typical distribution of targets defined by policy makers in history (Instituto para la Diversificación y Ahorro de la Energía (IDAE) 2011). For policy cost targets, the overall goal distribution is identical to the one for deployment targets.

In both cases, the overall targets are set to the historical deployment and estimated policy costs in Spain and Switzerland for installations built until 2016. In Switzerland, cumulative deployment of 1.66 GWp in 2016 is rounded up to 1.7 GWp and in Spain rounded up from 4.69 GWp to 4.7 Gwp (see Table 5.1 below).

For the cost targets that simultaneously serve as the reference to compare the achievements of the new policy design with, both countries reveal some challenges regarding the definition of policy costs. Switzerland ended up only paying around 32% of all installations built until December within the expected feed-in remuneration scheme, while others were left with a significantly lower one-time investment subsidy after they had already built their PV system (see Chapter 3.3.4) (Bundesamt für Energie BFE). Spain introduced certain policy measures that ex post cut the expected and promised financial support to adopters as they retroactively shortened the initially guaranteed eligible period for remuneration or retroactively implemented caps on the maximum remunerated operating hours. In both countries, these decisions obviously allowed to reduce the final policy costs at the investors' expense. Instead, our new policy design does not offer these possibilities. It does not allow for any retroactive policy changes and assumes (1) all installed PV systems to be paid by the feed-in remuneration scheme for (2) all energy fed into the grid (3) over a 20 years period. To allow for a rather fair comparison, we estimate the historical policy costs a government had faced if it had applied the same conditions. The model estimates the historical policy costs within the historical simulated policy scenarios (CH-HIST* / ES-HIST, see Chapter 4.3.1 and Table 6.1) the same way it also calculates the policy costs for the scenarios applying the new policy design (see Eq. 5)

For Spain, the historical policy costs estimated by the model (EUR 46.65 billion) only deviate by 5.3% from the estimated actual historical policy costs for installations built until 2016 in Spain based on government data (EUR 44.24 billion) (Comisión Nacional de los Mercados y la Competencia (CNMC) 2018). Thereby we referred to "Retribución Regulada", only considering the difference between the paid FIT and the wholesale electricity price as final policy costs (see Eq. 5).

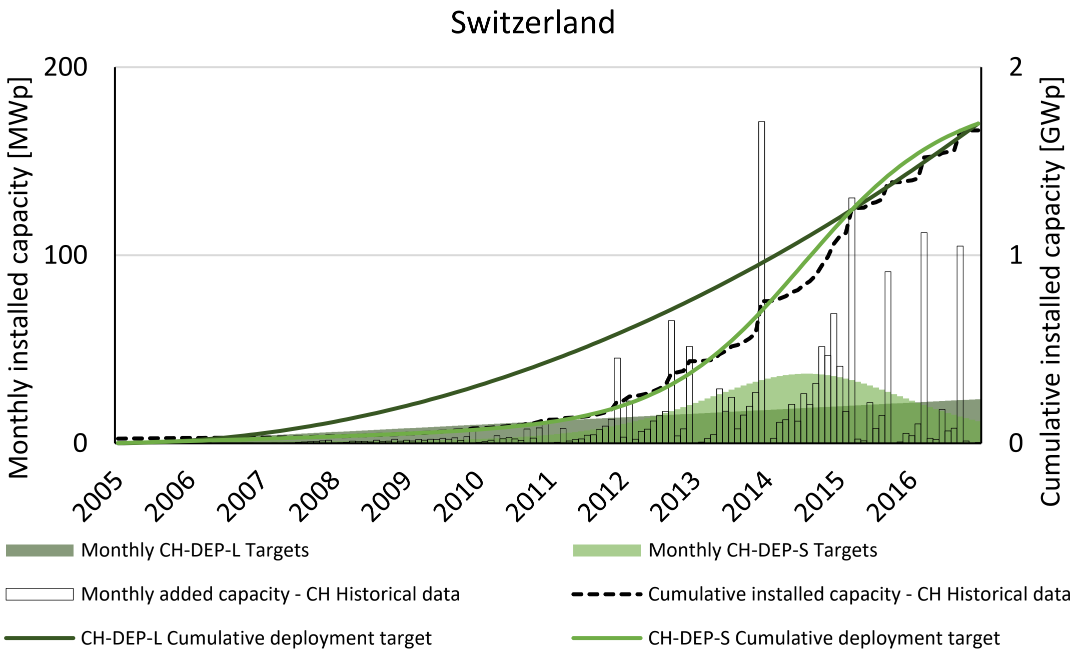
For Switzerland, as there is no cost data available for our considered assumptions, we refer to the historical policy costs estimated by the model (EUR 7.75 billion / CHF 8.6 billion). A more detailed discussion on this topic dealing with different approaches of how to calculate historical policy costs in Switzerland can be found in the Appendix (see A.10).

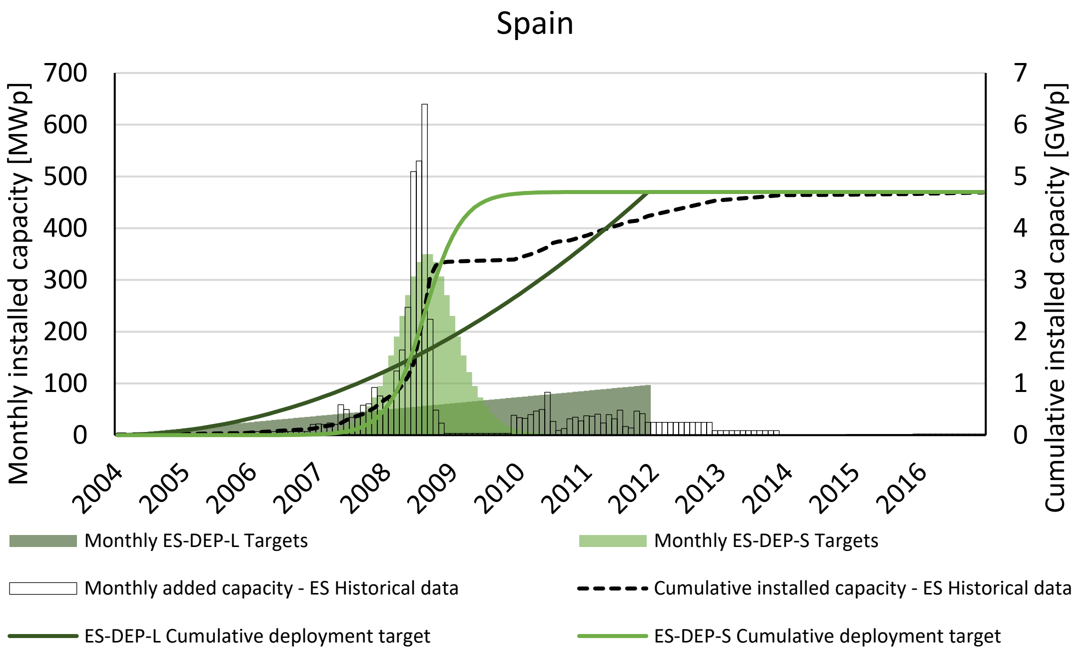
Including the simulation of the historical policies and accounting for the two temporal distributions of deployment and policy cost targets, ten scenarios are evaluated (see Table 5.1). Figure 5.2 shows the temporal distributions of deployment targets compared to history. The initial FIT at the beginning of the policy's active period for residential adopters is set to the historical value: EUR 0.1 per kWh (CHF 0.15 per kWh) in January 2005 in Switzerland and EUR 0.4 per kWh in January 2004 in Spain. Commercial and utility-scale agents consistently receive a fraction of the residential FIT according to historical relations (see Table 4.1).

Table 5.1: Target summary – Improving policies within historical conditions

Scenario	Policy target	Overall target	Temporal distribution of monthly targets	Additional parameters
CH-HIST	Historical FIT / Deployment	[-]	[-]	[-]
CH-DEP-L	Deployment	1.7 GWp[b]	Linear	[-]
CH-DEP-S[a]			Logistic	Peak month Jul 2014, steepness 0.085
CH-COST-L	Policy cost	EUR 7.75 billion (CHF 8.60 billion)	Linear	[-]
CH-COST-S[a]			Logistic	Peak month Jul 2014, steepness 0.085
ES-HIST	Historical FIT / Deployment	[-]	[-]	[-]
ES-DEP-L	Deployment	4.7 GWp[b]	Linear	[-]
ES-DEP-S[a]			Logistic	Peak month Aug 2008, steepness 0.3
ES-COST-L	Policy cost	EUR 46.65 billion	Linear	[-]
ES-COST-S[a]			Logistic	Peak month Aug 2008, steepness 0.3

(a) The logistic distribution of monthly targets results in the evolution of cumulative deployment or policy costs following an s-curve, which is why mechanisms using this distribution are referred to with '-S'. (b) Watt peak (Wp) is a measure unit of electrical power that refers to the nominal power output of a solar PV device under standard test conditions. (c) To allow for a better comparison, results are generally displayed in EUR. However, the policy cost targets for the Swiss model are defined in CHF, given that the model is running in CHF.





Note: Given the step in the cumulative deployment curve in Spain, the steepness of the target curve was set to most accurately represent the major uptake of deployment around 2008.

Figure 5.2. Target distribution – Improving policies within historical conditions

5.1.2 Increasing effectiveness of historical policies

We study scenarios that evaluate if the responsive adjustment mechanism could have ensured a higher effectiveness of policy outcomes than in history (see Table 5.2). We set a consistent active period that runs from January 2005 to December 2016 in both Switzerland and Spain to reduce the influence of a different policy timing on the effectiveness of the policy.

We take Germany as a reference case being the most effective country in terms of installed capacity per capita. We test if the new policy design could have made other countries equally effective and evaluate how this would have affected the policy's cost efficiency. We set the overall deployment target to a value for each country that would ensure a specific effectiveness per capita of 500 W, comparable to the one in Germany in 2016. The distribution of targets also imitates the historical deployment distribution in Germany between 2000 and 2016. We consider a logistic distribution of deployment with the peak month of installations after 65% of the policy's active period and a steepness for the s-curve of 0.07. The initial FIT in January 2005 is automatically calculated by the model to ensure an internal return rate of 0% for the solar PV investment of an average residential agent in the respective country. Figure 5.3 shows the resulting distribution of deployment targets over time compared to history.

Table 5.2. Target summary – Increasing effectiveness of historical policies

Scenario	Policy Deployment Target	Initial FIT[b]	Additional parameters
Base Scenario	Capacity per capita as in DE 2016 (500 W/capita)	FIT starting value for profitability indifference	Similar goal distribution as deployment in history in DE
CH-BASE	4'100 MW	IRR = 0%	Peak month Nov 2012, steepness 0.07
ES-BASE	23'200 MW	IRR = 0%	Peak month Nov 2012, steepness 0.07

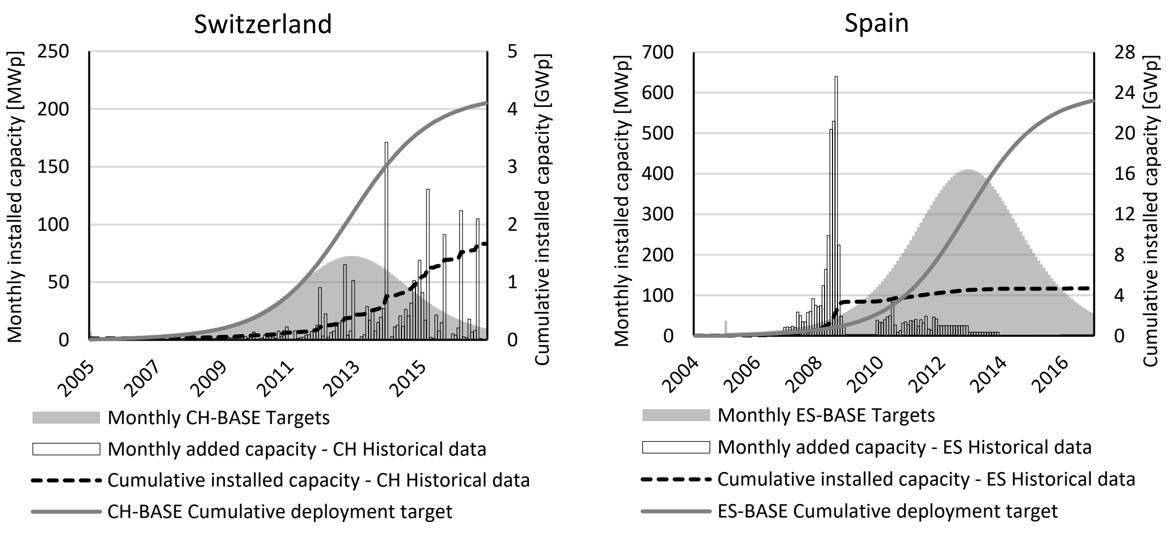


Figure 5.3. Target distribution – Increasing effectiveness of historical policies

5.2 Evaluating influence of overall policy targets, initial incentives and deployment timing

In our second part of the analysis we explore how much the configuration of the policy – overall deployment targets, initial incentive levels, deployment timing – hinders or facilitates achieving a more effective or cost-efficient policy than in the base scenario (see Figure 5.4 and Table 5.3).

First, we increase and decrease the overall deployment target by ±20%, while keeping the initial incentive conditions to a level that on average ensures a 0% internal return rate for residential adopters, the peak month in November 2012 and the steepness of the s-curve for cumulative deployment to 0.07.

Second, while keeping the overall deployment target to the values of the base-scenarios, we increase and decrease the initial incentive conditions to a level that on average ensures an initial internal return rate of ±2% for residential adopters. The distribution of targets remains the same.

Third, while keeping the overall deployment target to the values of the base-scenarios and the initial incentive conditions, we modify the distribution of deployment targets by shifting the peak month and accordingly adjust the steepness of the s-curve. For simulating an earlier deployment, monthly installations already peak after 50% of the policy's active period, in January 2011, while for a later deployment, monthly installations only peak after 80% of the policy's active period, in August 2014. In order to still achieve the overall deployment targets within the given period, the steepness of the s-curve for a later deployment is increased to 0.09 and the steepness for an earlier deployment accordingly decreased to 0.05.

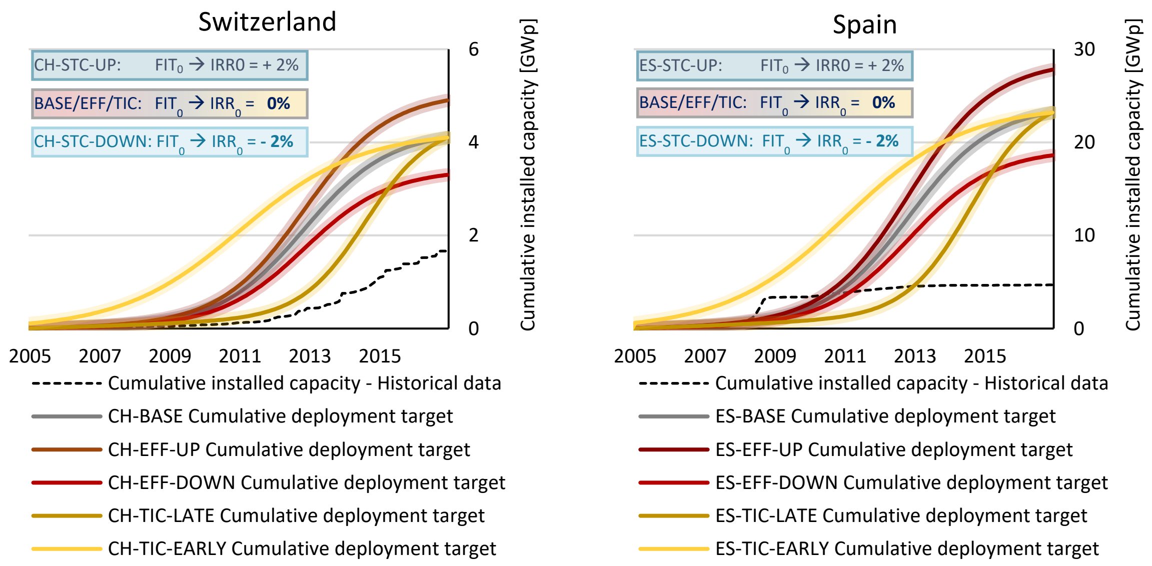


Figure 5.4. Target distribution – Influence of policy targets, initial incentives and timing

Table 5.3: Target summary – Influence of policy targets, initial incentives and timing

Scenario	Policy Deployment Target	Initial FIT	Additional parameters
Base Scenario[a]	Capacity per capita as in DE 2016 (500 W/capita)	FIT starting value for profitability indifference	Similar goal distribution as deployment in history in DE
CH-BASE[a]	4'100 MW	IRR = 0%	Peak month Nov 2012, steepness 0.07
ES-BASE[a]	23'200 MW	IRR = 0%	Peak month Nov 2012, steepness 0.07
Effectiveness Evaluation	±20% change in capacity per capita (600 W/capita 400 W/capita)	FIT starting value for profitability indifference	Similar goal distribution as deployment in history in DE
CH-EFF-UP CH-EFF-DOWN	4'900 MW 3'300 MW	IRR = 0%	Peak month Nov 2012, steepness 0.07
ES-EFF-UP ES-EFF-DOWN	27'800 MW 18'600 MW	IRR = 0%	Peak month Nov 2012, steepness 0.07
Starting Conditions Evaluation	Capacity per capita as in DE 2016 (500 W/capita)	FIT starting value for deviating average internal return rate	Similar goal distribution as deployment in history in DE
CH-STC-UP CH-STC-DOWN	4'100 MW	IRR = +2% IRR = -2%	Peak month Nov 2012, steepness 0.07
ES-STC-UP ES-STC-DOWN	23'200 MW	IRR = +2% IRR = -2%	Peak month Nov 2012, steepness 0.07
Timing Evaluation	Capacity per capita as in DE 2016 (500 W/capita)	FIT starting value for profitability indifference	±15% change in peak month, ±0.02 change in steepness
CH-TIC-LATE CH-TIC-EARLY	4'100 MW	IRR = 0%	Peak month Aug 2014, steepness 0.09 Peak month Jan 2011, steepness 0.05
ES-TIC-LATE ES-TIC-EARLY	23'200 MW	IRR = 0%	Peak month Aug 2014, steepness 0.09 Peak month Jan 2011, steepness 0.05

(a) While the BASE-scenarios have already been analyzed within phase one they are still listed here as they serve as a reference.

6 Results

This chapter first presents the results from part 1 of the analysis (see Chapter 6.1), followed by the results from part 2 of the analysis (see Chapter 6.2). The results are generally based on the median values of 100 model runs, as this has also been the criteria used for the model calibration to account for the randomness of the adoption process. The Swiss model is running in CHF to ensure that adopters are also taking the investment decisions in their national currency. However, the resulting costs of the model are all converted into EUR to allow for a better comparison across countries. The policy costs that are generally allocated to the month of adoption are converted by the monthly historical exchange rate of the corresponding month (boerse.de).

6.1 Increasing cost efficiency and effectiveness of historical policies

6.1.1 Improving policies within historical conditions

In both countries, all adjustment mechanisms, whether following deployment or policy cost goals and whether distributing targets linearly or logistically, successfully steer adoption towards the historical deployment and policy cost with a deviation of less than 10% from their policy targets. Apart from the linear distribution of targets in Spain, they all manage to improve the certainty about policy outcomes over the simulated historical policy (see Table 6.1).

In Switzerland, all adjustment mechanisms manage to increase largely and even double the cost efficiency of the simulated historical policy (i.e. at a lower policy cost per unit of installed capacity). Due to the removal of the overall deployment limit, the mechanisms following cost targets even achieve a doubling of historical deployment in Switzerland without increasing the simulated historical policy costs. In Spain, mechanisms with linearly distributed policy targets manage to reach their goals more cost-efficiently than the simulated historical policy. In contrast, the logistic distributions of targets show lower cost efficiencies than the simulated historical scenario.

Thus, deployment policies using the analyzed adjustment mechanisms tend to achieve their targets more reliably than the simulated historical policies. However, doing so more cost-efficiently would depend on the formulation and distribution of the policy targets and the country they are applied in.

Table 6.1 shows the median effectiveness and cost efficiency of each scenario and the simulated historical policies. The overview allows us to evaluate the relative change of these key values for policies using the suggested new responsive policy design compared to simulated historical outcomes. Figure 6.2 shows the temporal evolutions of the median feed-in tariff (FIT) and annual installations for each scenario in each country. They compare adjusting incentives to deployment or policy cost targets distributed linearly (DEP-L, COST-L) or logistically (DEP-S, COST-S).

Table 6.1: Key policy outcomes – Improving policies within historical conditions

Scenario	Total Installed Capacity (median) [GWp]	Total Policy Cost (median) [bn EUR]	Policy Cost Efficiency (median) [Wp / EUR]
CH-HIST*	1.66 (-0.3,+2.2)	7.75 (-1.19,+3.05)	0.21 (-0.02,+0.01)
CH-DEP-L	1.84 (-0.05,+0.06)	3.97 (-0.15,+0.14)	0.46 (-0.01,+0.01)
CH-DEP-S	1.76 (-0.06,+0.06)	3.9 (-0.28,+0.29)	0.45 (-0.03,+0.02)
CH-COST-L	3.37 (-0.13,+0.15)	7.28 (-0.08,+0.19)	0.46 (-0.01,+0.02)
CH-COST-S	3.77 (-0.13,+0.2)	7.55 (-0.06,+0.13)	0.50 (-0.01,+0.02)
ES-HIST	4.79 (-0.9,+1.3)	46.65 (-9.6,+14.2)	0.10 (-0.004,+0.004)
ES-DEP-L	4.79 (-0.6,+2.1)	39.92 (-1.9,+6.5)	0.12 (-0.01,+0.03)
ES-DEP-S	5.12 (-0.2,+0.7)	64.15 (-2.9,+9.6)	0.08 (-0.004,+0.003)
ES-COST-L	7.58 (-1.0,+4.6)	48.94 (-3.6,+18.1)	0.16 (-0.01,+0.03)
ES-COST-S	4.16 (-0.3,+0.6)	50.40 (-1.9,+10.5)	0.08 (-0.005,+0.004)

Note: The median value from 100 simulations is reported together with the distance to the upper and lower boundaries of the interval around the median covering 90% of the simulations. The mean of each policy outcome of each mechanism in standard letters is statistically different from the simulated historical scenario (CH-HIST* / ES-HIST) with a confidence level exceeding 99.999% according to a two-tailed t-test robust to heteroskedaticity. The confidence level for values in italics is 95% or higher and for underlined values between 60% and 85%.

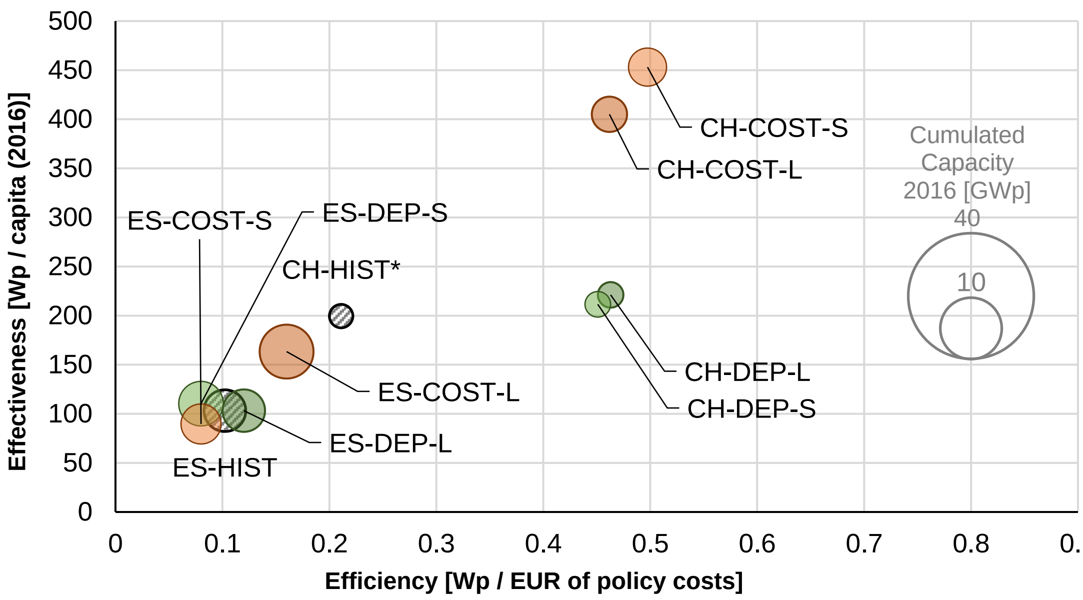


Figure 6.1. Effectiveness-efficiency – Improving policies within historical conditions

Distributing policy targets logistically – matching the historical evolution of deployment

In Switzerland, both logistic distributions of policy targets (CH-DEP-S / CH-COST-S) more than double the simulated historical cost efficiency (CH-HIST*). They manage to steer deployment to the overall goal with significantly lower FIT levels than in history throughout the entire policy period (see Figure 6.2, top). Given the removal for the overall deployment limit, the scenario containing a logistic distribution of cost targets (CH-COST-S) even manages to more than double deployment with similar costs compared to the simulated historical policy. Thereby, it also achieves a higher cost efficiency than the scenario with logistically distributed deployment targets (CH-DEP-S).

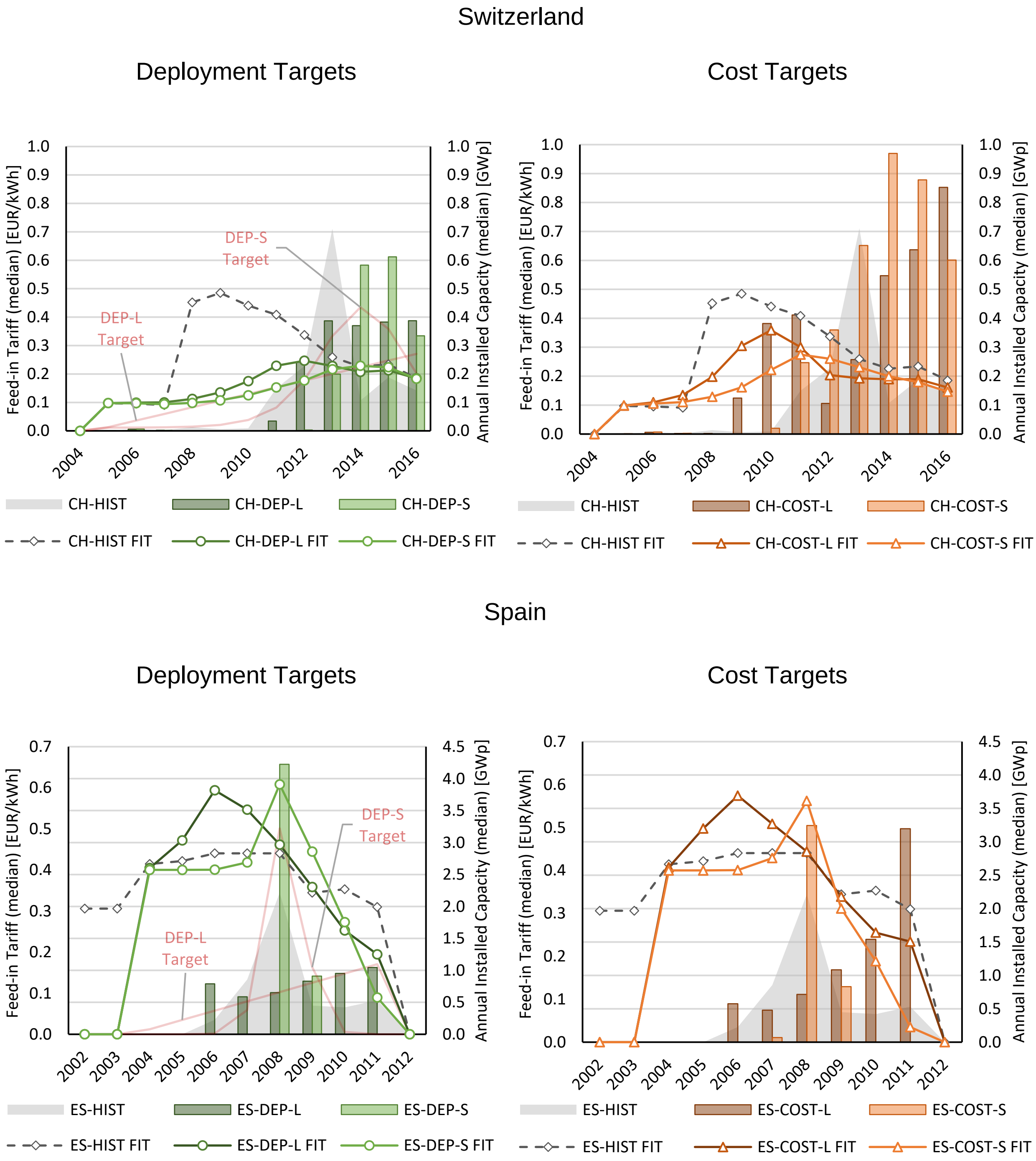
In contrast, mimicking the historical boom and bust cycle of deployment in Spain fails to increase the cost efficiency of the simulated policy (ES-HIST). This applies to deployment targets as well as to policy cost targets (ES-DEP-S / ES-COST-S). Due to cumulative policy targets following a strict s-curve, the mechanisms even aim at achieving an earlier deployment of the historical installations that occurred after 2009 (see Figure 5.2 and Figure 6.2, bottom).

Targeting a different evolution of deployment than history by distributing goals linearly

In Switzerland, the mechanisms with a linear distribution of targets (CH-DEP-L / CH-COST-L), whether following deployment or cost targets, both manage to double the simulated historical cost efficiency of the policy (CH-HIST*). Again, given the removal for the overall deployment limit, the scenario with a linear distribution of cost targets (CH-COST-L) even manages to more than double deployment with similar costs compared to the simulated historical policy. Yet, despite the removal in the deployment restriction, the scenario with a linear distribution of cost targets (CH-COST-L) cannot outperform the linear distribution of deployment targets (CH-DEP-L) as it experiences a temporary overshoot in adoption (see Figure 6.2, top).

In Spain, both linear distributions (ES-DEP-L / ES-COST-L) of policy targets allow for an increase in cost efficiency compared to history because they ensure a more even distribution of monthly deployment targets. Additionally, they allow for a temporal shift of average installations to a later period, confronting adopters with lower solar photovoltaic (PV) prices. This allows for deployment at lower incentive levels (see Figure 6.2, bottom left). Given the removal for the overall deployment limit, the scenario with linearly increasing cost targets (ES-COST-L) even outperforms the scenario with linearly increasing deployment targets as it achieves a higher effectiveness, as well as an increase in efficiency.

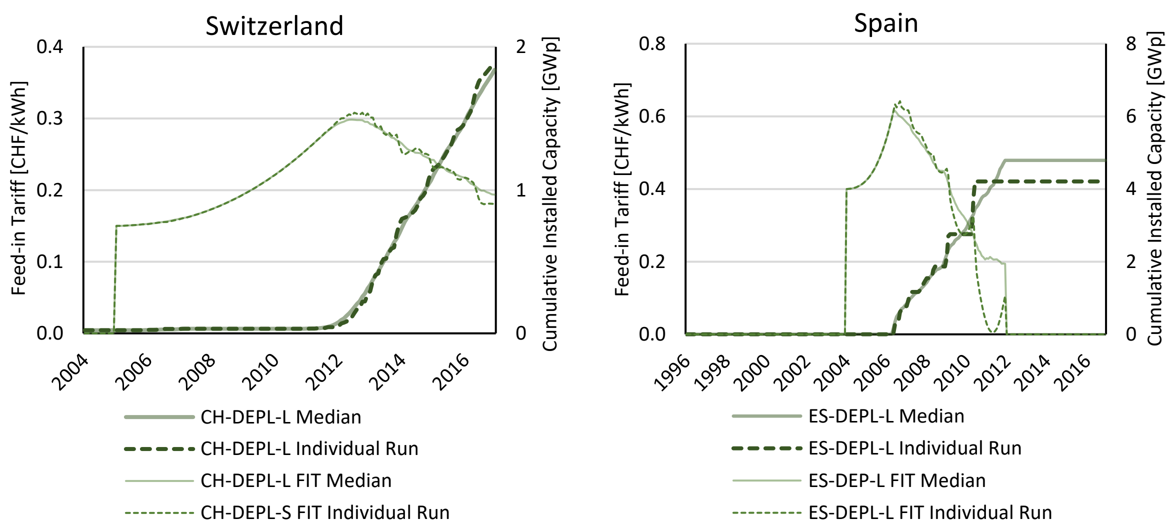
While the new policy designs manage to achieve the set targets in Spain already within the first years, it does not manage to foster deployment in Switzerland in the early years at all. Starting at a relatively low incentive level of only 0.1 EUR/kWh (0.15 CHF/kWh) in 2005, the adjustment mechanism requires a certain time until the first installations are built in Switzerland. A further investigation of the impact of different initial incentive levels is performed in the second part of our analysis (see Chapter 6.2.2).



Note: The left Figures compare the median FITs, annual installed capacities and deployment targets of the designs using a deployment adjustment criterion, with linear (CH-DEP-L / ES-DEP-L) and logistic (CH-DEP-S / ES-DEP-S) distributions of targets to the historical policy scenarios (CH-HIST / ES-HIST). The Figures on the right compare the median FITs and annual installed capacities of the designs using a policy cost adjustment criterion, with linear (CH-COST-L / ES-COST-L) and logistic (CH-COST-S / ES-COST-S) distributions of targets to the historical policy scenario (CH-HIST / ES-HIST).

Figure 6.2. Temporal evolutions – Improving policies within historical conditions

The results show that the novel adjustment designs are able to steer adoption to the defined targets. While in Switzerland this can be achieved with a relatively low volatility of incentives over time, the mechanisms in Spain need to introduce sudden and large changes in the FIT (see Figure 6.3). This effect is a peculiarity of the Spanish market. Going into the details of the simulations, one can observe that deployment tends to boom mainly driven by just a few relatively big installations. This complies with the occurrences in history. In contrast to other countries characterized by a high share of residential and roof-mounted systems, 98% of the installed capacity of solar PV in Spain consists of ground-mounted large-scale systems (ASIF - Asociación de la industria fotovoltaica 2009).



Note: (1) The analysis of incentive fluctuations in Switzerland refers to CHF, being the currency a Swiss investor would be looking at. The incentives converted into EUR would create fluctuations due to the changing exchange rate, which would distort the message of this figure. (2) The scaling of agents in the model artificially strengthens the effect of just a few big PV systems already explaining a large installation boom. For example, if one agent with a 1 MWp PV system belongs to an agent type group scaled by the factor 10, this one agent in the model represents 10 investors in reality. Instead of possibly having one of those investors each month getting the idea to install in reality, the model would on average only simulate one idea every 10 months as there are 10 times less agents of this agent type in the model than in reality. However, every 10 months this one investment then accounts for 10 installations in reality. Thus, instead of having 1 MWp of deployment every month, the model simulates 10 MWp of deployment but only every 10 months. Consequently, the model overestimates the fluctuations in incentives driven by large installations compared to how distinct they would appear in reality under the use of the new policy design.

Figure 6.3. Incentive fluctuations for individual simulation runs

6.1.2 Increasing effectiveness of historical policies

In both countries, Switzerland and Spain, the responsive adjustment mechanism successfully achieves a similar capita specific effectiveness as the historical policy in Germany (see Table 6.2 and Figure 6.4). While it allows to make the Spanish policy nearly as cost-efficient as the estimated historical German one, Switzerland can achieve an even more cost-efficient policy than in Germany.

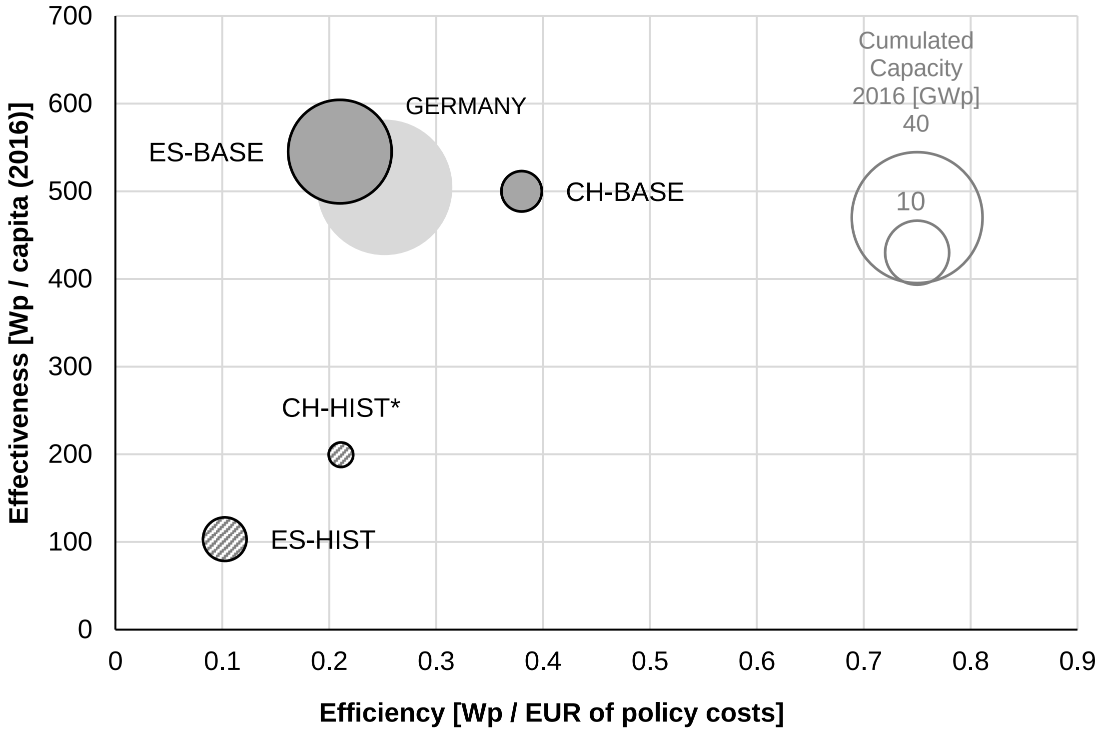
While in Switzerland the mechanism accurately achieves the defined deployment goal, it exceeds its target by nearly 10% in Spain. In Switzerland, despite shifting the average installation dates of deployment to earlier periods than in history, the mechanism still achieves an 80% higher cost efficiency than the simulated historical policy (CH-HIST*). However, given the increase in effectiveness of around 160% from 1.6 GWp in history to 4.16 GWp, the simulated historical policy costs increase by 35% from EUR 7.75 billion in the historical simulation to EUR 10.5 billion.

In Spain, the mechanism more than doubles the cost efficiency compared to the simulated historical policy from 0.1 Wp/EUR to 0.21 Wp/EUR. It fosters deployment especially between 2012 and 2016, a period when the solar PV market in history was more or less stagnating in Spain (see Figure 6.5, incl. note). Given the efficiency increase, an effectiveness increase of more than 400% from 4.7 GWp in history to 25.3 GWp can be achieved with policy costs only rising by around 150% from EUR 46.65 billion in history to EUR 120 billion.

Table 6.2. Key policy outcomes – Increasing effectiveness of historical policies

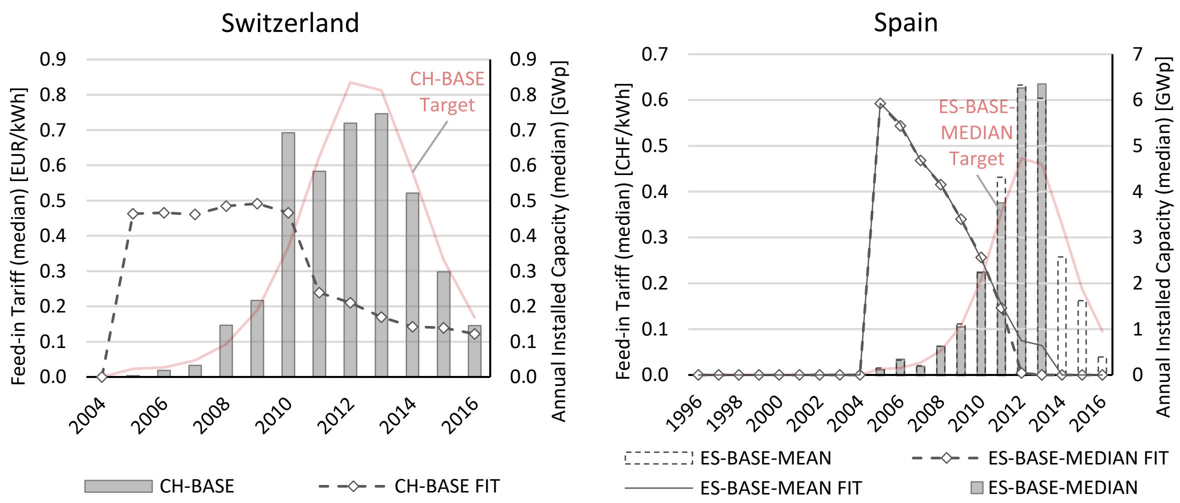
Scenario	**Total Installed Capacity (median)** [GWp]	**Total Policy Cost (median)** [bn EUR]	**Policy Cost Efficiency (median)** [Wp / EUR]
CH-BASE	4.16 (-0.02,+0.02)	10.52 (-0.44,+0.77)	0.38 (-0.09,+0.03)
ES-BASE	25.30 (-2.4,+5.2)	120.00 (-15.9,+28)	0.21 (-0.02,+0.03)

Note: The median value from 100 simulations is reported together with the distance to the upper and lower boundaries of the interval around the median covering 90% of the simulations.



Note: The graph shows the median from 100 simulations.

Figure 6.4. Effectiveness-efficiency – Increasing effectiveness of historical policies



Note: Given the high fluctuations in the FIT level and accordingly in the deployment in Spain, the median values distort the evolutions at first sight. Although from 2014-2016 the FIT for the median is at 0 EUR/kWh and does not display any deployment, incentives were temporary above 0 EUR/kWh and deployment did occur as visible in the mean values.

Figure 6.5. Temporal evolutions – Increasing effectiveness of historical policies

6.2 Evaluating influence of overall policy targets, initial incentives and deployment timing

Table 6.3. Key policy outcomes - Influence of policy targets, initial incentives and timing

Scenario	**Total Installed Capacity (median)** [GWp]	**Total Policy Cost (median)** [bn EUR]	**Policy Cost Efficiency (median)** [Wp / EUR]
CH-BASE	4.16 (-0.02,+0.02)	10.52 (-0.44,+0.77)	0.38 (-0.09,+0.03)
ES-BASE	25.30 (-2.4,+5.2)	120.00 (-15.9,+28)	0.21 (-0.02,+0.03)
CH-EFF-UP	4.96 (-0.02,+0.07)	12.67 (-0.7,+1.01)	*0.38* (-0.1,+0.03)
CH-EFF-DOWN	3.36 (-0.01,+0.03)	8.60 (-0.29,+0.43)	*0.38* (-0.09,+0.02)
ES-EFF-UP	31.04 (-3.5,+5)	149.5 (-18.5,+36.5)	0.20 (-0.02,+0.02)
ES-EFF-DOWN	19.96 (-1.8,+4.2)	90.30 (-13.1,+23.6)	0.22 (-0.02,+0.02)
CH-STC-UP	<u>4.16</u> (-0.02,+0.03)	11.04 (-0.52,+0.72)	0.36 (-0.09,+0.03)
CH-STC-DOWN	<u>4.16</u> (-0.02,+0.02)	10.32 (-0.47,+0.42)	0.39 (-0.09,+0.03)
ES-STC-UP	<u>25.57</u> (-2.8,+4.7)	<u>120.50</u> (-15.5,+26.4)	<u>0.21</u> (-0.01,+0.02)
ES-STC-DOWN	<u>24.98</u> (-2.2,+5.7)	<u>120.50</u> (-17.4,+25.5)	<u>0.21</u> (-0.02,+0.02)
CH-TIC-LATE	4.18 (-0.04,+0.29)	8.39 (-0.22,+0.31)	0.49 (-0.1,+0.02)
CH- TIC-EARLY	4.86 (-0.75,+1.44)	44.46 (-10.45,+12.2)	0.1 (-0.04,+0.03)
ES-TIC-LATE	26.43 (-3.8,+10.2)	<u>121.00</u> (-26.7,+48.9)	0.23 (-0.04,+0.03)
ES-TIC-EARLY	24.80 (-1.9,+3.0)	163.00 (-15.0,+17.9)	0.15 (-0.01,+0.01)

Note: The median value from 100 simulations is reported together with the distance to the upper and lower boundaries of the interval around the median covering 90% of the simulations. The mean of each policy outcome in standard letters is statistically different from the base scenario (CH-BASE / ES-BASE) with a confidence level exceeding 99.999% according to a two-tailed t-test robust to heteroskedaticity. The confidence level for values in italics is 95% or higher and for underlined values between 60% and 85%.

6.2.1 Evaluating the influence of different overall targets

Similar to the previous scenarios, the responsive adjustment mechanism accurately achieves different deployment targets in Switzerland, while it tends to exceed the overall targets in Spain by around 10%. In Spain, the absolute, as well as the relative overshoot increases with more ambitious goals. In both cases, different overall deployment targets do not compromise policy efficiency and remain relatively constant at 0.38 Wp/EUR in Switzerland and 0.21 Wp/EUR in Spain (see Table 6.3 and Figure 6.6).

In both countries, the mechanism accurately ensures the incentive differences required to achieve different overall deployment goals. Visually apparent in Figure 6.6, the differences in the FIT across scenarios are more distinct in Switzerland. While the median FIT between higher and lower overall deployment targets in Switzerland experiences a temporary gap of up to 0.1 EUR/kWh, incentives in Spain do not separate more than 0.02 EUR/kWh across scenarios (see Figure 6.6, right).

In the early years, the results show higher deployment generally requiring higher incentives. For the late years, this does not hold true and one can even see higher deployment despite lower incentives for scenarios with more ambitious goals compared to those with less ambitious goals. Reflected by the crossing of FIT evolutions over time, the scenario ensuring more early installations can profit more from market adjustments afterwards. Higher deployment in an initial policy phase allows for a better utilization of especially national technological learning, driving down investment costs and enhancing the presence of the technology for future adopters in later years (see Figure 6.6, right). The model takes this into account within the learning curve for the technology, the information effect and the peer-effect, driven by either cumulative installed capacity or the number of installations.

In general, for all three policy configurations the reliability of policy outcomes is much higher in Switzerland than in Spain. While the key policy outcomes, overall deployment and overall policy cost, of all 100 simulation runs end up within a quite narrow range in Switzerland, the results in Spain show a significantly more scattered picture (see Figure 6.6, Figure 6.7 and Figure 6.8, left).

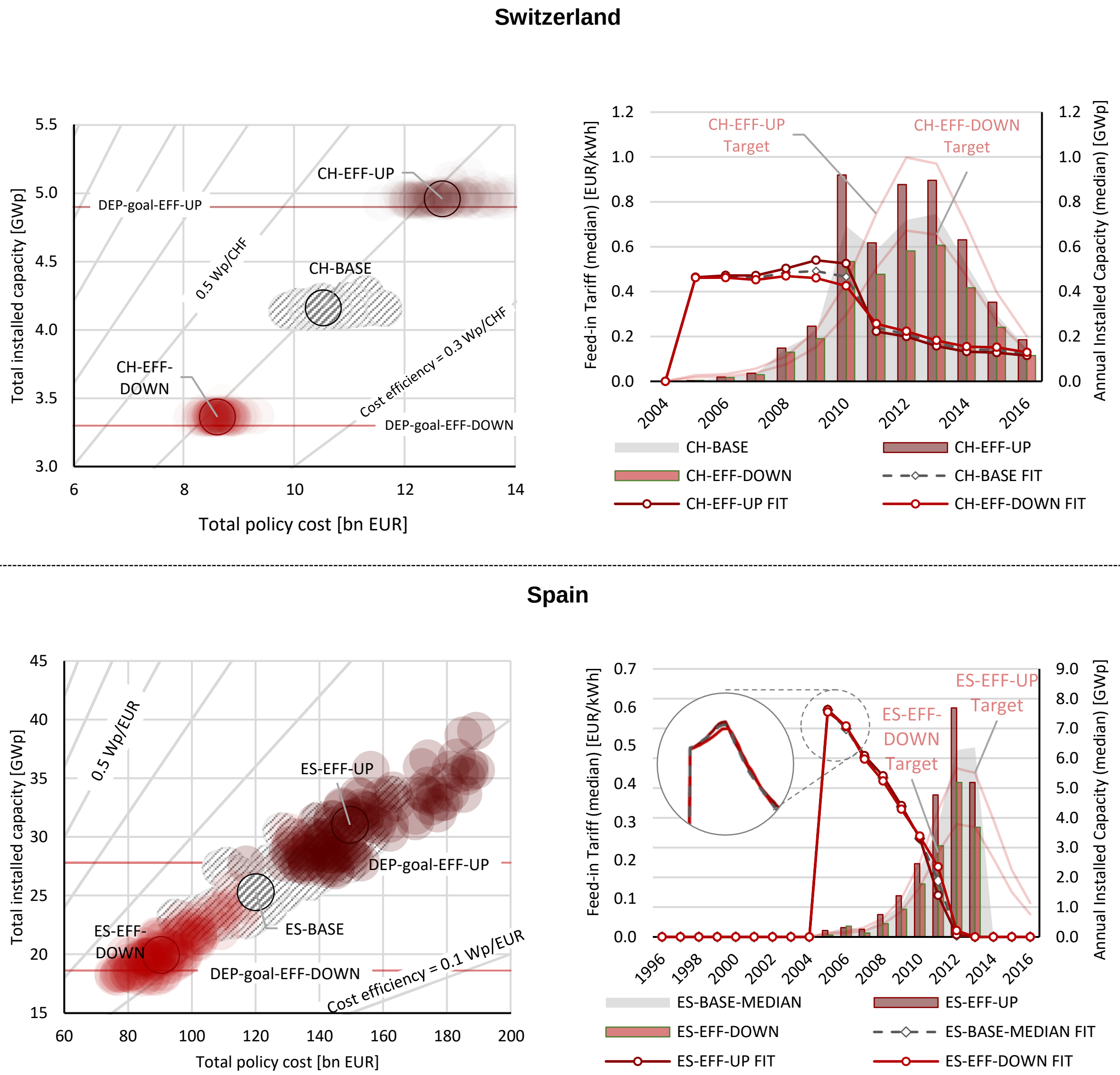


Figure 6.6. Comparison of total installed capacity and total policy costs and temporal evolutions of scenarios – Evaluation of different overall deployment targets

6.2.2 Evaluating the influence of initial incentive conditions

Owing to the responsive adjustment mechanism, different initial incentive conditions do not appear to have a significant influence on the overall final deployment. While in Switzerland the mechanism accurately achieves the overall deployment goal, in Spain, independently of the initial incentive levels, it exceeds the goal to the same extent as in the Base-scenario (see Table 6.3 and Figure 6.7).

While there is also no significant difference regarding policy efficiency between scenarios in Spain, the studied different initial incentive conditions do only have little influence on policy efficiency in Switzerland. Within the studied scenarios, the responsive mechanism proves the ability to deal with different initial incentive levels for equal policy targets by adjusting them in an early policy stage and to ensure a unified evolution of tariffs across scenarios afterwards.

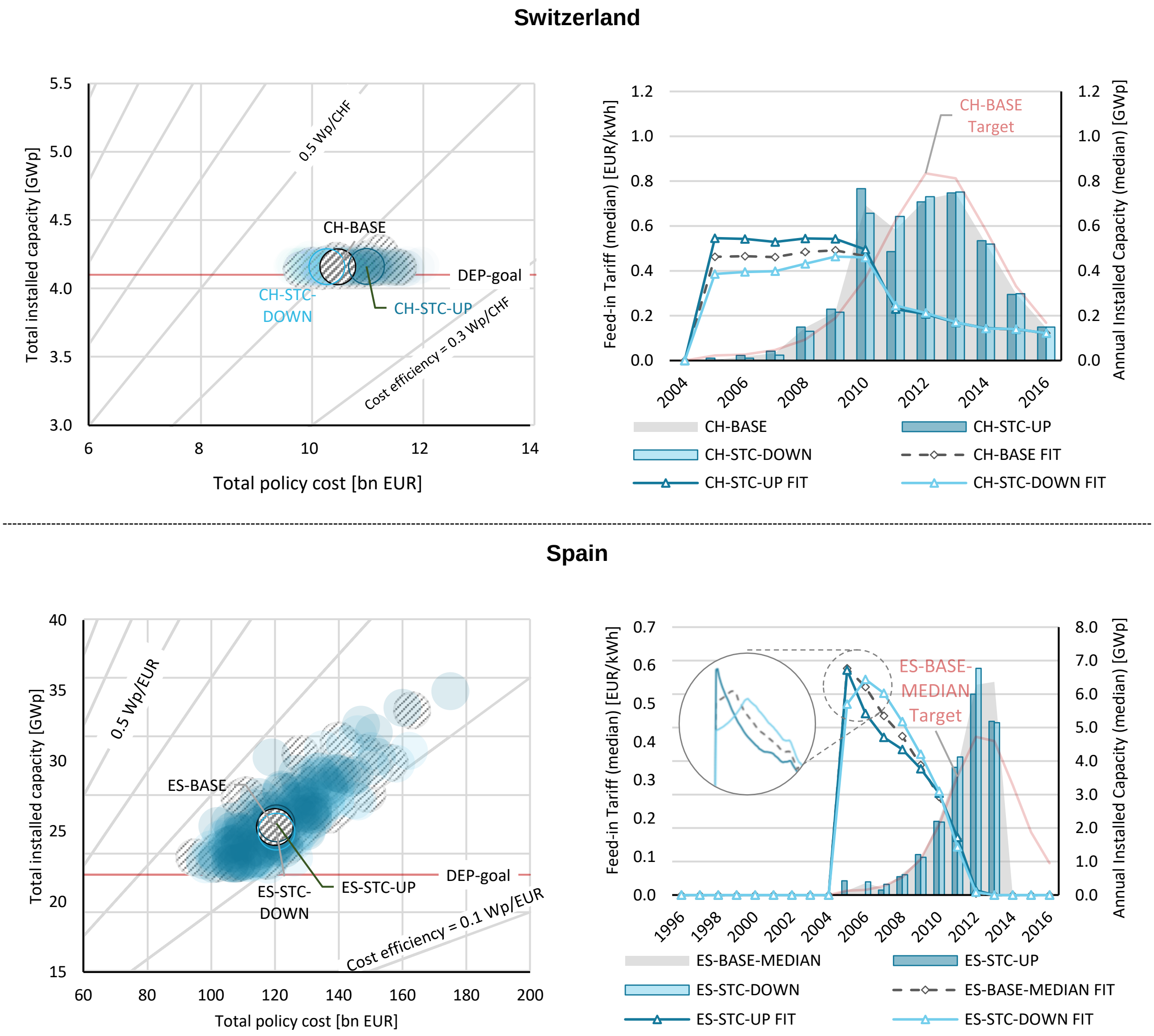


Figure 6.7. Comparison of total installed capacity and total policy costs and temporal evolutions of scenarios – Evaluation of different initial incentive conditions

6.2.3 Evaluating the influence of deployment timing

Except for the scenario of an early deployment in Switzerland, the responsive mechanism manages to steer the markets for different deployment timings to the defined goals with a similar accuracy as in the base scenario. Moreover, a later deployment generally offers cost reductions and thus an increase in the policy's cost efficiency (see Table 6.3 and Figure 6.8).

In Switzerland, trying to keep up with the targeted fast adoption ramp-up for an early deployment (CH-TIC-EARLY), the mechanism sharply drives up the incentives. However, diffusion misses the policy targets and incentives increase further. After still falling short on the targets for a couple of years, the market eventually experiences a severe adoption overshoot. By then, incentives have already reached a level where the responsive mechanism is not anymore able to take countermeasures fast enough in order to bring the market back under control (see Figure 6.8, top right). Consequently, given the temporarily high incentives especially during the adoption boom, policy costs escalate and the policy efficiency collapses from 0.38 Wp/EUR in the base scenario (CH-BASE) down to 0.1 Wp/EUR. In contrast, an initial raise of incentive levels by around 0.1 EUR/kWh in Spain (ES-TIC-EARLY) is already sufficient to foster the increased targeted adoption in the early policy phase (see Figure 6.8, bottom right). Nevertheless, the necessary increase of incentives expectedly reduces the policy's cost efficiency significantly from 0.21 Wp/EUR in the base scenario (ES-BASE) down to 0.15 Wp/EUR.

While a later targeted deployment generally offers the possibility of cost reductions across all scenarios, the extent to which the cost efficiency of policies can be increased varies. In Switzerland, the postponement of deployment (CH-TIC-LATE) allows to foster the majority of installations after incentives have experienced a distinctive drop around 2010. Simultaneously, incentives in the late years do not require to be much higher as in the base scenario (CH-BASE) in order to still achieve more ambitious deployment targets. This allows for an increase of 29% in the policy's cost efficiency from 0.38 Wp/EUR in the base scenario up to 0.49 Wp/EUR. In contrast, incentives require to be significantly higher than in the base scenario (ES-BASE) in order to ensure high deployment in the late years in Spain (ES-TIC-LATE). Thus, the cost efficiency can only be increased by around 10% from 0.21 Wp/EUR in the base scenario up to 0.23 Wp/EUR, although the majority of deployment is shifted to later times.

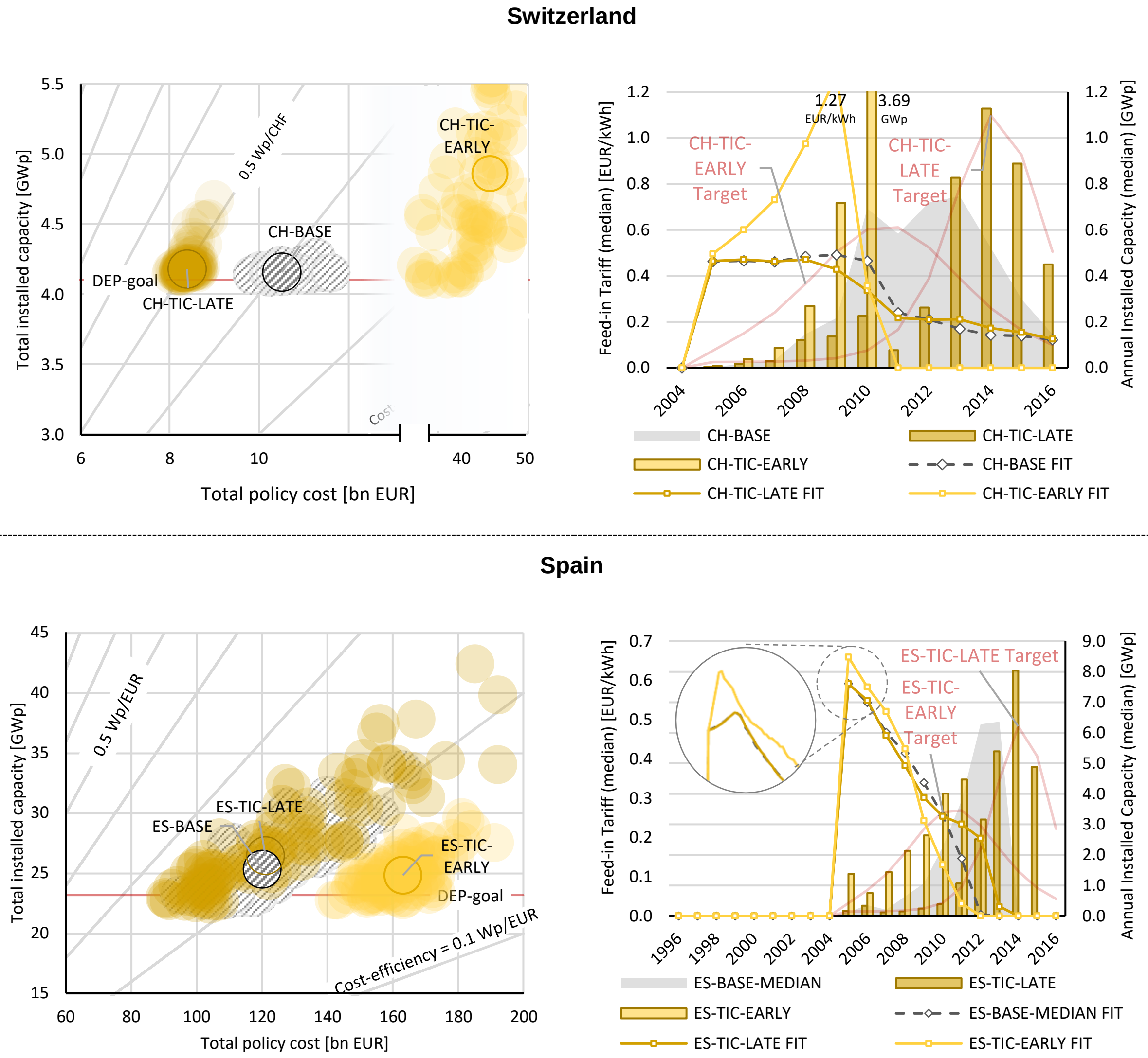


Figure 6.8. Comparison of total installed capacity and total policy costs and temporal evolutions of scenarios – Evaluation of different deployment timing

7 Discussion

This study reveals how a new design for adjusting incentives can prevent low solar photovoltaic (PV) deployment achieved by historical policies in Switzerland and Spain. Simultaneously, it can significantly reduce the costs per installed capacity compared to the simulated historical policies.

First, the results show that adjusting incentives according to more evenly distributed policy targets can curb the historically occurred boom and bust cycles in Spain and can achieve more cost-efficient deployment policies. By distributing policy cost targets linearly (ES-COST-L), Spain could have increased its overall deployment of 4.79 GWp solar PV by an additional 2.8 GWp (+58%) while only spending EUR 2.2 billion (+5%) more than in the simulated historical policy scenario (ES-HIST) (see Table 6.1 and Figure 6.1). In contrast, the new designs do not achieve cost reductions by trying to mirror the extreme and undesired historical evolution of installations in Spain, characterized by a short adoption surge, instantly followed by a deployment collapse. Thus, for appropriately defined targets, the designs reveal a novel approach of how to tackle the major issue of an uncontrolled and sudden boom in adoption, historically present in countries such as Italy or the Czech Republic (see Figure 10.1, A.1).

Second, the new policy design can accurately steer a market that in history was regulated by policy cost caps, only by offering a suitable level of feed-in tariffs (FITs) and without using additional measures. In Switzerland, for logistically distributed deployment targets (CH-DEP-S), the new mechanism manages to more than double the cost efficiency of the simulated historical policy from 0.21 Wp/EUR (CH-HIST*) to 0.45 Wp/EUR (see Table 6.1 and Figure 6.1). By offering consistently lower incentives, it achieves a similar deployment of 1.76 GWp, while only spending 50% of the simulated historical costs. Rephrased, despite a reduction in incentives, policy makers in Switzerland could have ensured an even higher deployment as in history without exceeding their provided financial support. Hence, continuously met policy caps indicate unnecessarily generous incentive levels. Additionally, the new design could make the use of policy caps under certain conditions generally dispensable, avoiding their drawbacks of possibly arising cost inefficiencies and a limited access to funds for investors.

Third (see Chapter 6.1.2), the novel policy design accurately achieves different predefined policy goals and can reliably increase the effectiveness and cost efficiency of simulated historical policies. This enables policy makers to define their final policy goals in advance while handing over the adjustment of incentives to the novel mechanisms without being concerned about escalating costs. Using the new design, Switzerland and Spain could have both achieved a similar deployment of around 500 Wp/capita as Germany until 2016. It furthermore would have allowed the Spanish policy to become nearly as cost-efficient and the Swiss policy to become even more cost-efficient than the estimated German one (see Figure 6.4). For a logistic distribution of deployment targets, Switzerland (CH-BASE) could have installed 4.16 GWp (+150%) for total policy costs of EUR 10.52 billion (+35%). Spain (ES-BASE) could have achieved an overall deployment of 25.3 GWp (+430%) for total policy costs of EUR 120 billion (+157%), doubling the simulated historical cost efficiency (ES-HIST) from 0.1 Wp/EUR to 0.21

Wp/EUR (see Table 6.2). Applied in new deployment policies, the novel design could thus ensure the rapid spread of future key technologies in order to address the issue of climate change effectively while cost-efficiently.

A further analysis of scenarios revealed (1) the distinct tendency of more cost-efficient policies when deployment targets focus on later years, even when using the responsive adjustment mechanisms. However, the novel design manages to strongly (2) limit the influence of different initial incentive conditions and (3) different overall deployment targets on the obtained policy efficiency as well as on the accuracy of achieving the predefined overall policy targets.

First (see Chapter 6.2.3), the results show that higher deployment targets in later years generally offer the possibility for cost reductions. However, the financial benefits of a later diffusion become particularly present if a certain exploitation of early market developments is ensured. A later deployment that shifts the peak month from November 2012 nearly two years ahead to August 2014 (CH-TIC-LATE) increases the cost efficiency of the base scenario in Switzerland (CH-BASE) by 29% from 0.38 Wp/EUR to 0.49 Wp/EUR. However, the study reveals the cost efficiency increase of a later deployment in Spain (ES-TIC-LATE) to only account for 10% compared to the base scenario (ES-BASE) from 0.21 Wp/EUR to 0.23 Wp/EUR. The benefits of e.g. national technological learning were limited in the Spanish scenario, given that deployment was not effectively fostered in the early years. However, delaying installations can undermine the environmental benefits of deploying renewable technologies, despite the increase in the cost efficiency of the policies. While the later deployment in Spain (ES-TIC-LATE) allows for an increase in cost efficiency of 10% compared to the base scenario (ES-BASE), it misses out on 27% of avoided CO_2-equivalent emissions from other electricity generation sources until 2016 (see Table 10.4 in A.12).

Depending on the conditions the responsive adjustment mechanism is applied in, the novel design either manages or fails to ensure a fast adoption ramp-up for an early deployment. While the Spanish market responds relatively sensitively and almost instantly to a small rise in the FIT, the Swiss market misses high initial policy targets even for fairly generous incentive levels. Thus, the mechanism provides the ability to adjust incentives in a suitable way in order to steer the market accordingly, if a market itself allows for a quick and strong immediate uptake with reasonable incentive levels. However, the responsive mechanisms cannot steer adoption single-handedly towards the policy targets by only adjusting the incentives, if non-economic barriers (e.g. scarce information) in a market do not allow for such an uptake, despite high financial returns. In the latter, when non-economic barriers weaken, the high incentives eventually might induce a surge in installations as the technology becomes better known and adopters start influencing their neighbors. Along with the discussed difficulties of a fast adoption ramp-up for an early deployment from the demand side, the realizability from a supply perspective might create an additional bottleneck. The fast and widespread diffusion of a technology that is quite new in a national market requires a timely development of a specific industry to provide infrastructure enabling such an abrupt market uptake, e.g. PV hardware supply and installers.

Especially for the support of new technologies, policy makers should keep in mind that forcing a too fast adoption ramp-up bears risks, as the market might not be able to keep up with the fast pace. However, a continuous postponement of renewable deployment due to cost advantages misses its actual purpose of achieving environmental objectives. Instead, an early introduction of support with responsive policy adjustments and moderately increasing deployment targets over time minimizes the risk of uncontrollable adoption and ensures timely environmental benefits.

Second (see Chapter 6.2.2), within the tested spectrum, the mechanism shows the ability to overcome the issue of how to set the initial incentive level, a concern that policy makers, not being able to refer to historical experiences, faced often. With the novel policy design, it becomes less critical to introduce the right level of incentives as they get automatically adjusted, which could make governments more likely to apply deployment policies in the future. However, initiating a policy with too cautiously set incentives, far below a level that could make an investment for adopters profitable, risks to lead to a start-up time with no deployment. Depending on the settings of the mechanisms, the adjustment towards suitable incentives would require a certain time until the targeted adoption occurs. Eventually, as the policy has fallen short on its targets for some time, policy makers would have to allow the adoption to exceed the defined targets in the later years in order to still achieve the overall goal. Alternatively, trying to make up for the deficit in initial deployment, a temporary but drastic overshoot could occur deteriorating the policy’s cost efficiency (see Figure 6.2, top right).

Third (see Chapter 6.2.1), the results show that different overall deployment targets can be accurately achieved and do not necessarily compromise the costs per installed capacity when using the responsive mechanisms. This demonstrates the potential of the new design to avoid future deployment policies similarly missing their intended targets as in history (Kreycik et al. 2011; del Rio 2014; Ragwitz et al. 2011). Simultaneously, from a policy cost efficiency view, the results show that policy makers should not be afraid of setting ambitious goals.

Overall, the results show that the novel adjustment designs are able to steer adoption to the defined targets in Spain but only by introducing sudden, large changes in the FIT as a response to occasionally coinciding installations of big plants (see Figure 6.3). This tendency complies with historical occurrences. Spain experienced over 70% of its deployment until October 2008 in just six months, making the pattern for cumulative installations resemble one big step function that abruptly stopped by the drastic incentive cuts and the introduction of deployment caps. While the new policy design cannot satisfyingly overcome this issue, it allows to smooth these effects and to reduce the size of the steps without using additional measures such as caps but by ensuring a faster adjustment of incentives than in history. However, this missing consistency in incentive levels might discourage adoption as it inhibits the planning security for project investors whose project implementation might exceed the qualifying period between two adjustments of one month. The findings still reveal the need to further refine the mechanism for such extreme cases. A possible solution approach could be the uncoupling of utility-scale adopters and the residential market by setting independent incentives for different system sizes, combined with deployment caps for utility-scale systems.

8 Limitations

This study has several limitations that offer promising avenues for future research: First, the model is limited with regard to how it was calibrated. Optimally, it would be validated against data not used for calibration. However, given the recursive working principle of the adoption process, influenced by the evolution of previous periods, one cannot just use a random subset of data for calibration. Instead, one would need to validate the outcome of later periods against the calibration of earlier periods. As technological diffusion is a process of emergence, consulting a shorter time span as used for the calibration in order to leave room for validation data would reduce its accuracy. Since the availability of historical data for the adoption of solar photovoltaics (PV) is limited, a possible validation can only be done in the near future.

Second, the model is built on a number of simplifications and assumptions, mainly due to the lack of empirical data. The main simplifications are (a) the limited representation of adoption decision-making, (b) the missing consideration of inertia and expectations about technology prices or policy incentives and (c) the limited representation of technological change.

(a) The model designs a unitary decision-making process that is primarily based on literature findings tailored for private adopters, while industrial investors might follow a different and more economically driven approach. Moreover, by modeling a time invariant adoption, the model cannot represent a change in decision rationales of investors over time. However, especially in Switzerland interviews with the local PV industry revealed a growth in environmental awareness driving the decision for an adoption, sometimes even defying economic rationality (Rottmann 5/9/2018b, 5/9/2018a). Yet, the model only takes this bounded rationality for some early adoptions into account. Due to limited data, the environmental awareness of potential adopters is assumed to be distributed in the same manner in Switzerland and Spain, despite indications that this may not be accurate. (b) Moreover, the model does not account for inertia. Any changes in the market are immediately taken into consideration by potential adopters that implement their decision by immediately building a solar PV system, neglecting any construction times. In addition, expectations about future technology prices and policy incentives may impact the timing of the adoption of the technology. Although historical incentive adjustments in reality have sometimes even been performed on a monthly basis, the influence of such regular adjustments regarding the required planning security of investors remains unclear. (c) Furthermore, the model is limited in the detail at which it represents technological change. The experience curve of a technology may evolve differently under alternative policy designs and deployment patterns and might experience sudden changes due to unexpected external influences.

Third, the model is suspiciously sensitive to changes in the weighting factors for the idea generation of adoption. Small value changes generate strong changes in diffusion (see A.9).

Fourth, the study is limited in its technological scope to solar PV. While it overcomes the issue of how the new policy designs perform under different conditions, the transferability of findings to other technologies e.g. energy storage or electric mobility, remains obscure.

9 Conclusion

This study reveals how a novel design for adjusting incentives can prevent low effectiveness deployment policies in different countries, while simultaneously increasing the policies' cost efficiency. The new mechanisms achieve more ambitious solar photovoltaic (PV) deployment targets in Switzerland and Spain while significantly reducing the costs per installed capacity compared to the simulated historical policies in each country. While a later deployment favors more cost-efficient policies, different overall deployment targets as well as different initial incentive levels do not compromise the policy's cost efficiency when using the studied policy design.

The analyzed adjustment mechanisms use an algorithm based on control theory principles, which calculates a non-predetermined modification of the policy incentives every month based on the deviation of the policy from predefined policy targets. In an attempt to represent the complex diffusion process of solar photovoltaics under the influence of changing incentives, this study implements an agent-based model (ABM) for both Switzerland and Spain. It incorporates individual decision-making based on: economic profitability, environmental and technical considerations, the available information situation on solar PV, and the impact of social interactions. The model manages to reproduce historical deployment patterns during the 2004-2016 period in Switzerland and the 1996-2016 period in Spain by simulating each country's historical policy.

In Spain, the results show that by adjusting incentives according to linearly distributed policy cost targets (ES-COST-L), which avoids the historically boom-and-bust installations cycle, a 60% higher cost efficiency could have been achieved compared to the simulated historical policy. In Switzerland, a market that was subject to policy cost caps, the adjustment mechanism proves to accurately steer solar PV adoption towards the historical deployment, exclusively by setting a feed-in tariff (FIT) consistently lower than in history. In addition, the new design manages to achieve a similar specific deployment of around 500 Wp per capita as in Germany in 2016 for both countries, if the overall deployment goals are set accordingly. Moreover, the mechanism achieves that level of deployment in Spain at a similar cost efficiency as estimated for Germany, while being more cost-efficient in Switzerland.

The results show that delayed deployment targets tend to lower policy costs. Additionally, they reveal that an unnaturally rapid and forced deployment ramp-up for early installations risks an adoption overshoot that deteriorates the policy's cost efficiency. However, the new mechanisms reduce the importance of setting the right initial level of incentives by subsequently adjusting them accordingly. Finally, the new design allows to accurately achieve different deployment targets without compromising the cost efficiency of the policy.

The novel design reconfirms its ability to improve upon the simulated historical policies. From a policy cost efficiency view, the results show that policy makers should not be afraid of setting ambitious deployment goals when using the new mechanisms. The novel design could thus ensure the rapid spread of future key technologies in order to address the issue of climate change without becoming too costly. Under certain conditions, the new mechanisms could make the use of policy deployment or cost caps dispensable as they offer a new approach of how to tackle the major issue of an uncontrolled and sudden boom in adoption. As it becomes less critical to introduce the right level of incentives, the novel policy design could make governments more likely to apply deployment policies in the future.

Beyond the limitation in the degree of detail regarding technological change and adoption decision-making, implementations of the new policy design targeting other technologies offer a promising avenue for future research. This is particularly interesting, as the methodology offers the possibility to inform the design of future deployment policies, e.g. in the field of energy storage or electric mobility.

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V Appendix

A.1. Values for historical policy performances across countries

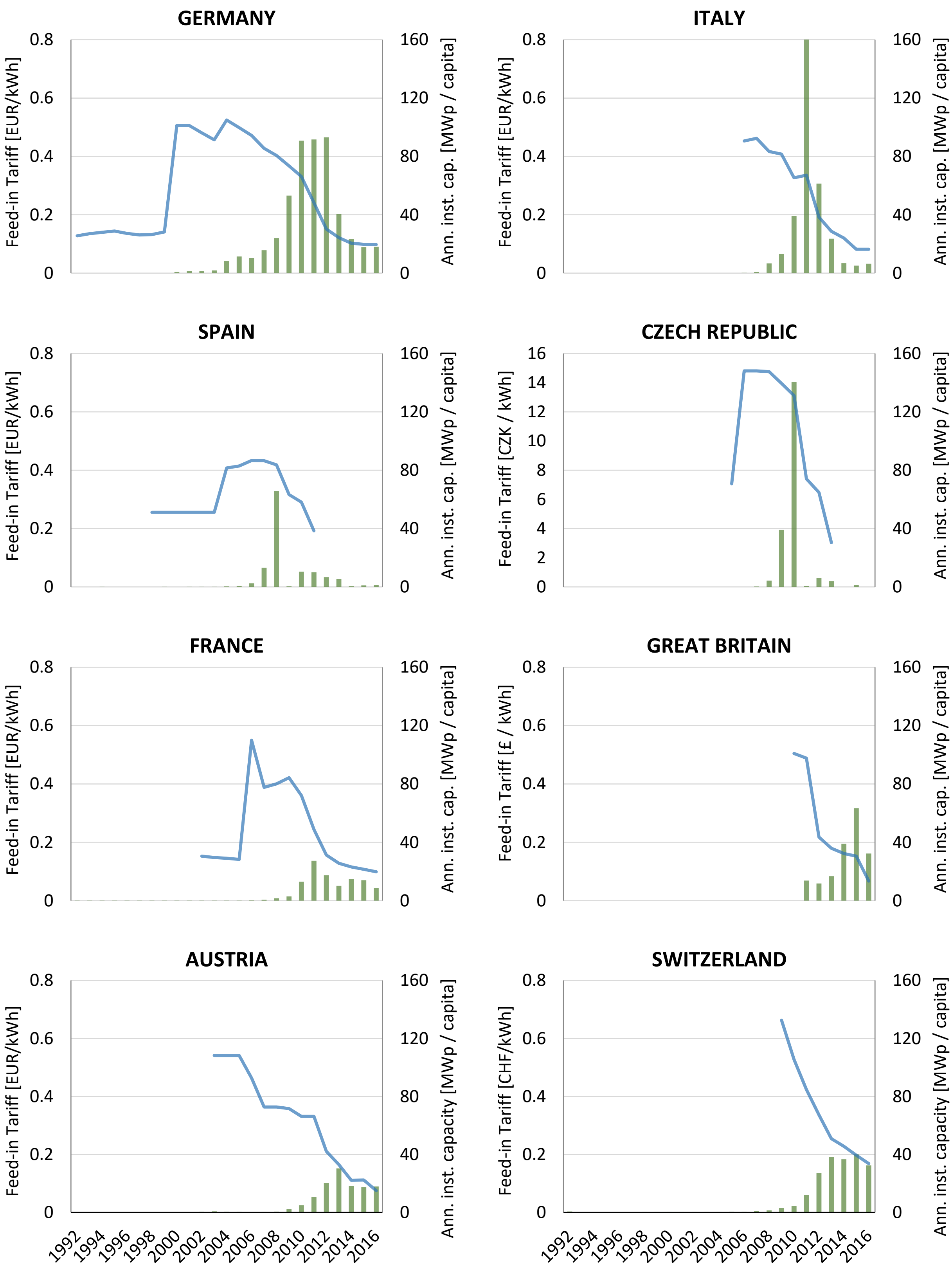
Table 10.1. Sources for values used in policy assessment across countries

Country	Installation Capacity[a]	Feed-in tariff[b]	Wholesale electricity prices
Germany	(IEA PVPS - International Energy Agency 2017c)	(Bundesnetzagentur 2018)	(EPEX SPOT SE 2018)
Italy	(Instituto Nazionale di Economia Agraria 2013)	(MSE 2005 2005) (MSE 2007 2007) (MSE 2010 2010) (MSE 2011 2011) (MSE 2012 2012)	(GSE Gestore Servizi Energetici)
Great Britain[a]	(Pearce and Slade 2018)	(Pearce and Slade 2018)	(NORD POOL 2018)
France	(IEA PVPS - International Energy Agency 2017c)	(HESPUL 2018)	(EPEX SPOT SE 2018)
Spain	(del Rio 2014)	(del Rio 2014)	(OMIE - Operador del Mercado Ibérico de Energía - Polo Español 2018)
Czech Republic	(IEA PVPS - International Energy Agency 2017c)	(Energy Regulatory Office 2018)	(pxe 2018)
Switzerland	(Bundesamt für Energie BFE)	(Bundesamt für Energie BFE)	(EPEX SPOT SE 2018)
Austria	(OeMAG)	(OeMAG)	(EPEX SPOT SE 2018)

(a) If available within the source, monthly data was taken for the calculation of policy costs for the efficiency criterion defined in Chapter 3.3.2. Otherwise, yearly data was uniformly distributed across the months for each year. (b) If available within the installation data, the monthly policy cost was separately calculated for different categories of solar PV systems. Otherwise one average FIT for all installations of that month was taken that was weighted by the proportion of each system category on the total installed capacity (see Figure 10.1).

The solar capacity factors, displaying the average expected produced energy with a solar photovoltaic (PV) system, are, apart from the Swiss value (pronovo 2018) taken from the (European Comission 2016). The discount rate employed to bring future costs of the policy supports to the month of adoption is represented by the interest rate of government long-term interest rates for all countries from the (OECD 2018).

Figure 10.15 on the following page shows the evolution of the capita specific annual installed solar PV capacity in [MWp/capita] and the evolution of the average FIT level in several countries between 1992 and 2016.



Note: The displayed FIT level presents the average FIT payed to solar PV adopters in each year and country. It is weighted by the proportion of each system category on the total installed capacity, considered by the policy in the given year, and the according FIT level of the category.

Figure 10.1: Historical deployment and feed-in tariff patterns over time across countries

A.2. Qualitative evaluation of historical policies

GERMANY:

The German feed-in tariff (FIT) system for solar photovoltaic (PV) power is famous for being a highly effective and widely copied policy instrument targeted at fostering the diffusion and development of renewable energy technologies. Despite short periods of excess remuneration, windfall profits for the PV industry, the general criticism of too high costs for the society and the responsibility for rising electricity prices, it is overall considered a successful policy (Lesser and Su 2008, p. 984; Hoppmann et al. 2014a, p. 1426).

ITALY:

Due to high costs for its support program, Italy introduced a register for new PV systems in 2011 to put a cap on the amount of support granted to PV systems. Furthermore, the support scheme in 2012 already aimed at quickly decreasing the level of the feed-in payments , since grid parity was reached around 2011 (Palmer et al. 2015). Some people argue, that overall the confused Italian energy policy is responsible for the collapse of the PV market in Italy since July 2013 (Di Dio et al. 2015, p. 101).

CZECH REPUBLIC:

As a result of favorable market conditions, supported by a decline in solar PV prices and a slow reaction of policy makers, the Czech Republic became the country with the fourth largest newly installed solar PV capacity in 2010. Therefore, several changes were introduced that significantly deteriorated market conditions. A windfall profit tax of 26% on FITs was imposed at the end of 2009, followed by a complete stop of FIT payments for solar PV from 2014 onwards. These policy adjustments, being the response to the escalating costs of the support scheme, created a lack of policy consistency and strong yearly fluctuations in installations (European Environment Agency 2014a, p. 3).

FRANCE:

Besides the main support mechanism, the FIT scheme, France offers a broad range of direct and indirect support policies for solar PV installations, such as capital subsidies, income tax credits or special green mortgages, promoting PV. Apart from slight modifications in its policy, such as the elimination of FIT support for non-building mounted PV systems in 2016, the support policy of France has not risen that much attention in the recent past (IEA PVPS - International Energy Agency 2016).

GREAT BRITAIN:

In October 2011, the government of Great Britain announced the reduction of FIT levels by more than 50% from 12 December 2011. However, due to a challenge by Friends of the Earth and two PV installers, a high court ruling prohibited such a drastic cut in FIT levels with only a few weeks' notice. Consequently, the FIT was reinstated at a higher level and upheld until March 2012. In general, the number of solar PV installations was predicted to reach 780'000 by 2020 but already exceeded this number in 2016 (Pearce and Slade 2018). As a result, and following the UK general election, the FIT scheme was paused from 15 January to 8 February 2016. After this interruption, deployment caps were introduced to limit installations (Ofgem 2016).

AUSTRIA:

In Austria, the support schemes for solar PV have shown some discontinuity. They were more or less continuously under discussion and experienced a yearly change, which allows private users and investors only short time planning. However, compared to other countries, the support policy of Austria has not risen that much attention in the recent past beyond its national borders (University of applied sciences (FH Technikum Wien) 2016).

A.3. Historical solar photovoltaic installations data

The model refers to historical solar photovoltaic (PV) installations data for Switzerland (Bundesamt für Energie BFE) and for Spain (del Rio 2014), as well as for the rest of the world from the perspective of each country (IEA PVPS - International Energy Agency 2017c). In order to derive the data for the rest of the world we subtract Switzerland's or Spain's cumulative installed capacity respectively from the world's total.

To transform yearly data into monthly data, the yearly installation capacity is linearly distributed for each of the year's month within each year from 1991 to 2016 for world data and uniformly distributed from 1991 to 2005 for Switzerland's data and from 1991 to 2006 for Spain's data.

From 2006 onwards monthly data for Switzerland is estimated based on the registered installations within the KEV (pronovo 2018). From 2007 onwards monthly data for Spain is adopted from previous literature (del Rio 2014).

The linear distribution determines the installed capacity each month so that the sum of all months of one year equals the installed capacity that year and the slope of the linear distribution approximates the slope of the exponential curve described by the yearly data. For example, if in a certain year around 12 GWp were installed, instead of distributing them uniformly among the twelve months of the year (12 ÷ 12 = 1 GWp), the linear distribution allocates installations mimicking the growth in installations observed in the yearly data, that could exemplary result in lower installations in January than in December. This approach helps avoiding large jumps from one year to another.

A.4. Solar photovoltaic experience curves

The experience curve used in the model is fitted using the historical prices and cumulative installation capacity in Switzerland (IEA PVPS - International Energy Agency 2017b) and Spain (IEA PVPS - International Energy Agency 2017a) through least squares with the errors weighted by the monthly installations. While deteriorating the fitting for early years, this approach improves the fitting of the experience curve for the years where large amounts of solar photovoltaics (PV) were installed. The results provide a learning rate for modules of 21.08% in Switzerland and 21.99% in Spain and for all other elements of 11.4% in Switzerland and 9.2% in Spain.

The historical solar PV prices are calculated as being composed of module prices and prices for all other elements. The distribution of costs between module and other costs evolve over time: in Switzerland as well as Spain from 65% of the price determined by modules in 1991 to just 40% in 2016 following the historical development observed in the data (IEA PVPS - International Energy Agency 2017b, 2017a).

Values of years that are not given in the historical data are linearly extrapolated from closest existing yearly data points. To transform the yearly data into monthly data, the missing data points are linear extrapolations from their closest available data points. To allow some monthly variability in prices, each monthly price is allowed to fluctuate randomly by ±3% from the value of the linear extrapolation.

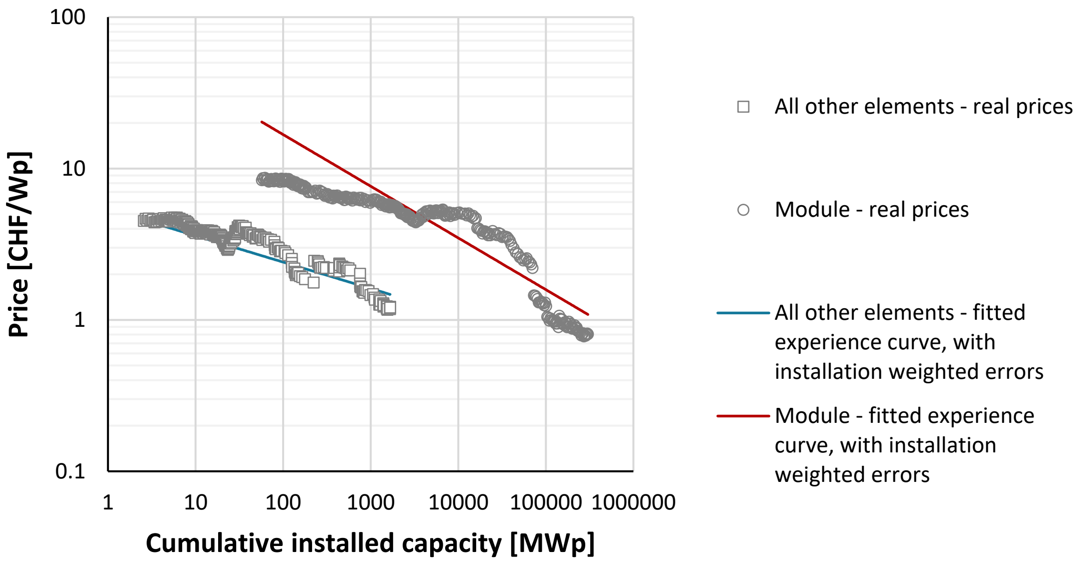
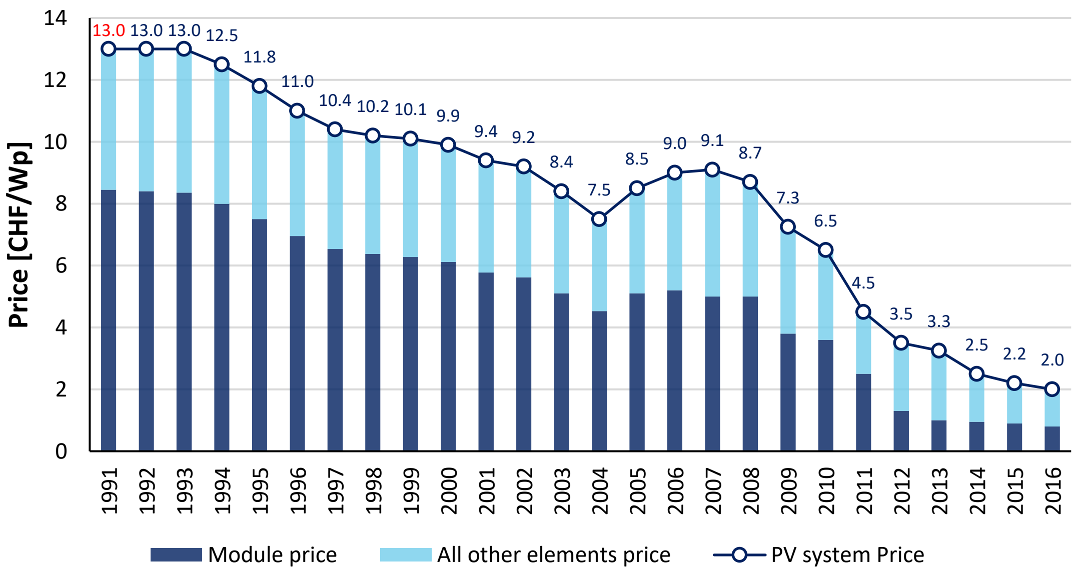


Figure 10.2. Fitted experience curves to historical solar PV prices in Switzerland



Note: Values in red are estimated PV system prices. Data based on (IEA PVPS - International Energy Agency 2017b).

Figure 10.3. Historical solar PV price evolution in Switzerland for 1991-2016

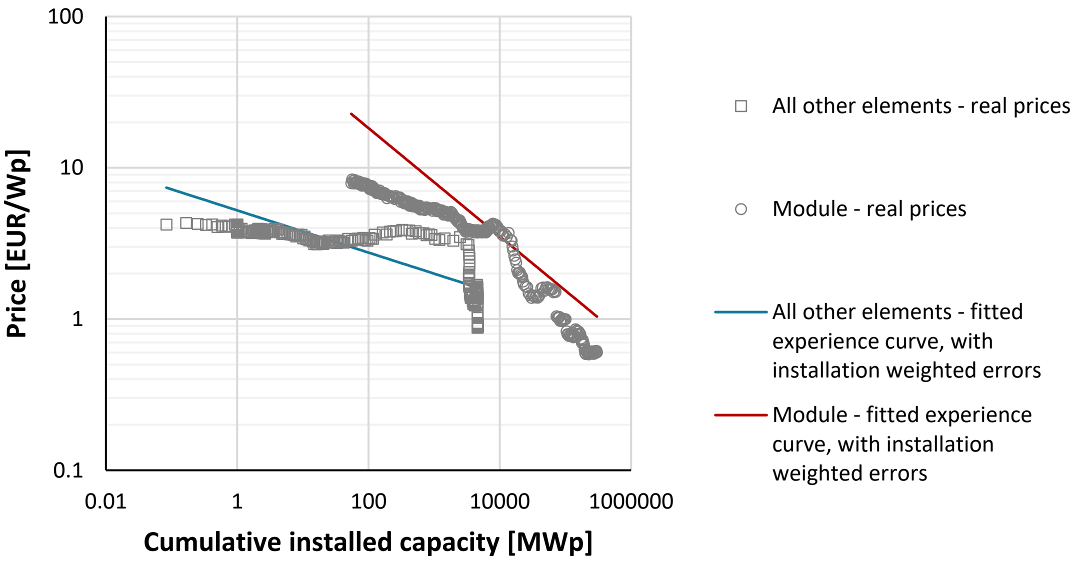
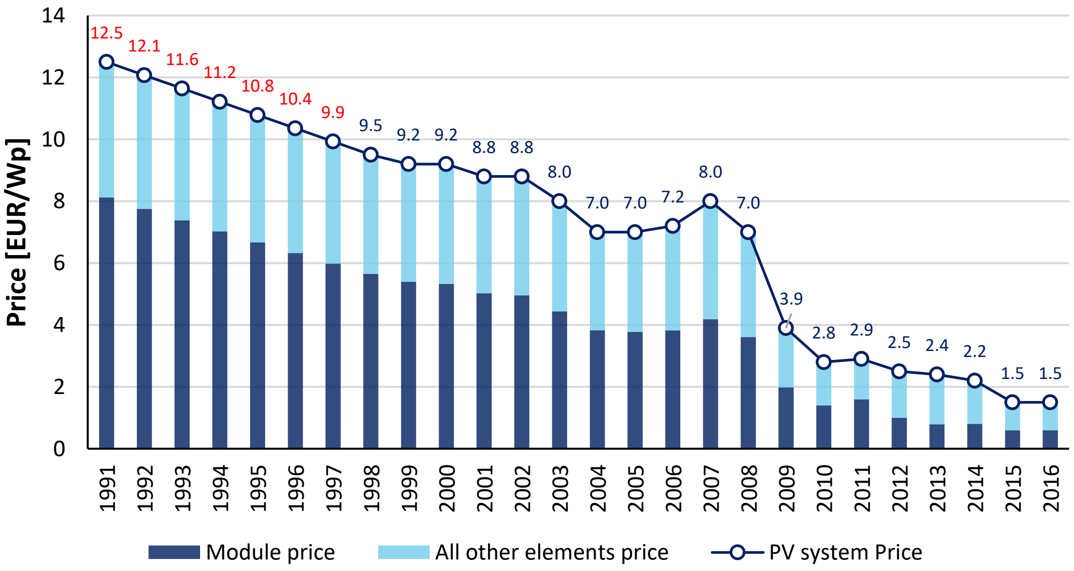


Figure 10.4. Fitted experience curves to historical solar PV prices in Spain



Note: Values in red are estimated PV system prices. Data based on (IEA PVPS - International Energy Agency 2017a).

Figure 10.5. Historical solar PV price evolution in Spain for 1991-2016

A.5. Electricity rates and wholesale electricity market price

For Switzerland, between January 1991 and April 2000, monthly electricity prices for residential agents (including all taxes and levis) are linearly extrapolated from annual data. From June 2000 until December 2016 there is monthly data available (Bundesamt für Statistik). Monthly electricity prices for commercial (i.e. 150 MWh/a, max. 60 kW) and utility-scale agents (i.e. 1500 MWh/a, max. 430 kW) (excluding VAT and other recoverable taxes and levies) from January 1991 until April 1993 are extrapolated into earlier times by using the value of April 1993 and the residential electricity prices as a proxy for the relative change of prices over time. Between May 1993 and December 2016 there is monthly data available (Bundesamt für Statistik).

For Spain, monthly electricity prices for residential agents (including all taxes and levis) as well as for commercial (160 MWh/a, max. 100 kW) and utility-scale agents (2000-20000 MWh/a) are linearly extrapolated from biannual data for the whole period between 1991 and 2016 (Eurostat).

Between 1992 and 2016, the wholesale electricity price paid to solar generators is estimated as the average yearly day-ahead-auction wholesale electricity price between 11 am and 4 pm in each country, representing the time for sun peak hours (EPEX SPOT SE; OMIE - Operador del Mercado Ibérico de Energía - Polo Español 2018). Finally, between 2017 and 2045, the wholesale electricity prices are assumed to increase annually by 1.5% (Peters et al. 2012).

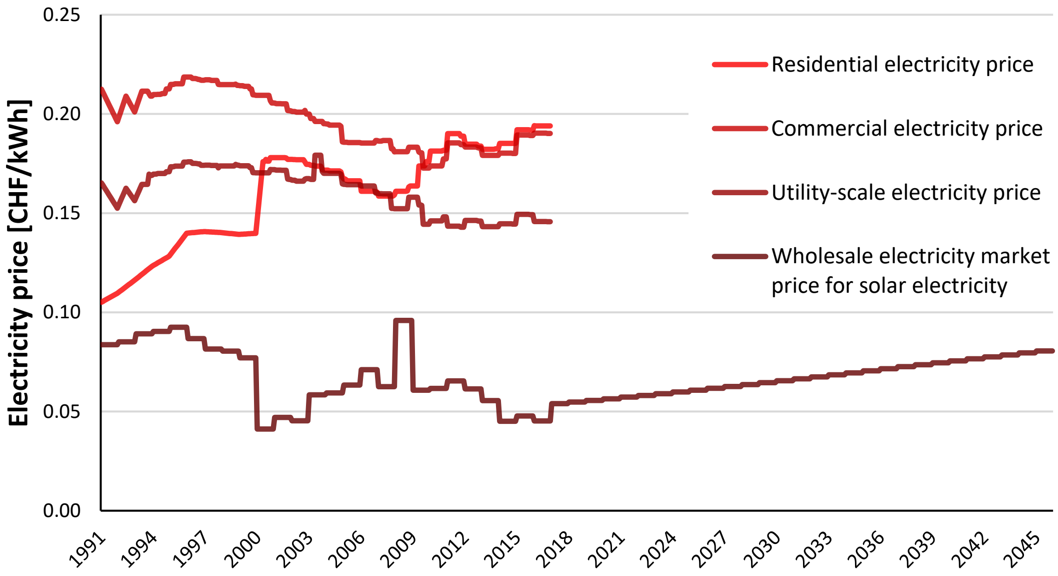


Figure 10.6. Electricity prices for potential adopters and wholesale electricity market prices for solar electricity in Switzerland

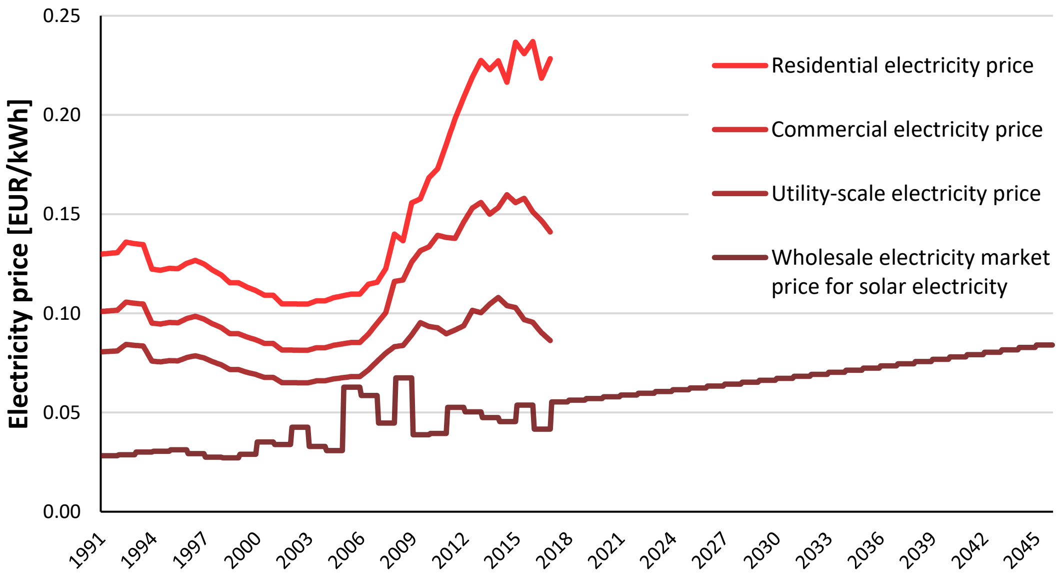


Figure 10.7. Electricity prices for potential adopters and wholesale electricity market prices for solar electricity in Spain

A.6. Discount rates and bonds

The discount rate for each agent type is represented by the historical cost of capital for different individuals and corporations in Switzerland and Spain.

In Switzerland, the discount rate of agents is represented by the historical average lending rates for fixed-interest investment loans and a credit amount of 50’000 – 100’000 CHF for residential agents, 100’000 – 500’000 CHF for commercial and industrial agents and 1 million – 5 million CHF for utility-scale agents (SNB - Schweizer Nationalbank 2018).

In Spain, the discount rate of agents is represented by historical average lending rates for consumer credits and other loans with a duration of more than five years. Residential agents are estimated by referring to values for households, commercial and industrial agents by referring to values for small and medium-sized enterprises and utility-scale agents by referring to values for non-financial cooperations (BDE - Banco de España).

The discount rate employed to bring future costs of the policy supports to the month of adoption is represented by the interest rate of Swiss and Spanish government long-term interest rates (OECD 2018).

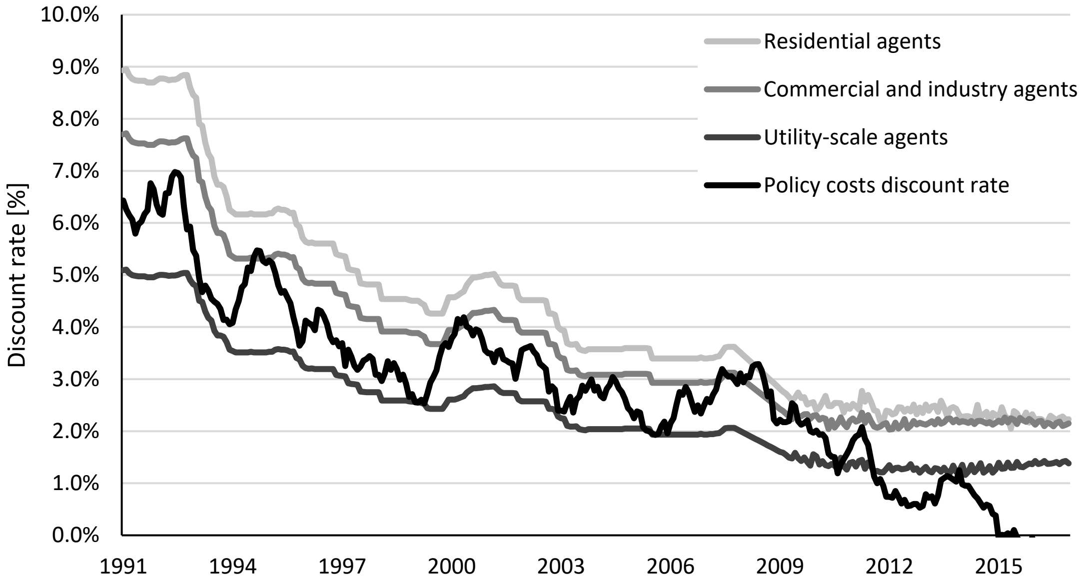


Figure 10.8. Evolution of discount rates for each type of agent and the discount rate for policy costs calculations in Switzerland

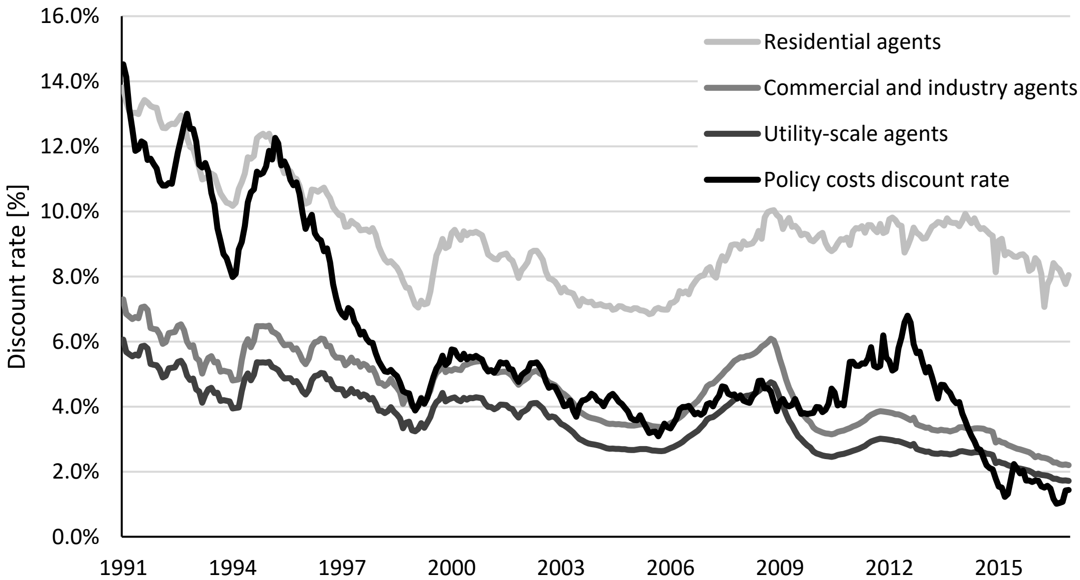


Figure 10.9. Evolution of discount rates for each type of agent and the discount rate for policy costs calculations in Spain

A.7. Information on solar photovoltaics

For the available information and media attention to solar photovoltaics (PV), the number of news articles on solar PV is used as a proxy. The historical evolution of news articles on solar PV is based on the number of articles matching the following search of keywords in the LexisNexis database for international as well as Swiss or Spanish media outlets:

Switzerland

“solar photovoltaics” OR "solar PV" OR "photovoltaic" OR "sonnenenergie" OR "sonnenkraft" OR "solarenergie"

Spain

"solar photovoltaics" OR "solar PV" OR "photovoltaic" OR "energía solar" OR "energía del sol" OR "energía fotovoltaica"

The news articles on solar PV are normalized using the maximum number of articles published (1088 articles in 2012 in Switzerland and 3299 articles in 2016 in Spain). Although the number of news articles published each month in Switzerland decreased after 2012, in the following years, the variable is kept constant at one as it represents how readily available news articles on solar PV are. Thus, we argue that the availability of articles on solar PV can get saturated but not decrease. The cumulative articles on solar PV are normalized by the maximum value of the series (8,484 articles in 2016 in Switzerland and 27,961 articles in 2016 in Spain). The normalized curves are fitted to a logistic function using least square errors. The information variable used in the model is a combination of functions with equal weight.

Switzerland

$$\text{New articles } [0,1] = -174.30 + \frac{175.31}{1 + \exp\left(-3.46 \cdot 10^{-5} \cdot \text{Cumulative installed capacity in the world} - 5.15\right)} \quad \text{(Eq. 21)}$$

$$\text{Cumulative articles } [0,1] = -154.20 + \frac{155.24}{1+\exp\left(-9.19 \cdot 10^{-6} \cdot \text{Cumulative installed capacity in the world} - 5.01\right)} \quad \text{(Eq. 22)}$$

Spain

$$\text{New articles } [0,1] = -501.91 + \frac{502.77}{1+\exp\left(-8.21 \cdot 10^{-5} \cdot \text{Cumulative installed capacity in the world} - 6.30\right)} \quad \text{(Eq. 23)}$$

$$\text{Cumulative articles } [0,1] = -154.20 + \frac{155.24}{1+\exp\left(-9.19 \cdot 10^{-6} \cdot \text{Cumulative installed capacity in the world} - 5.01\right)} \quad \text{(Eq. 24)}$$

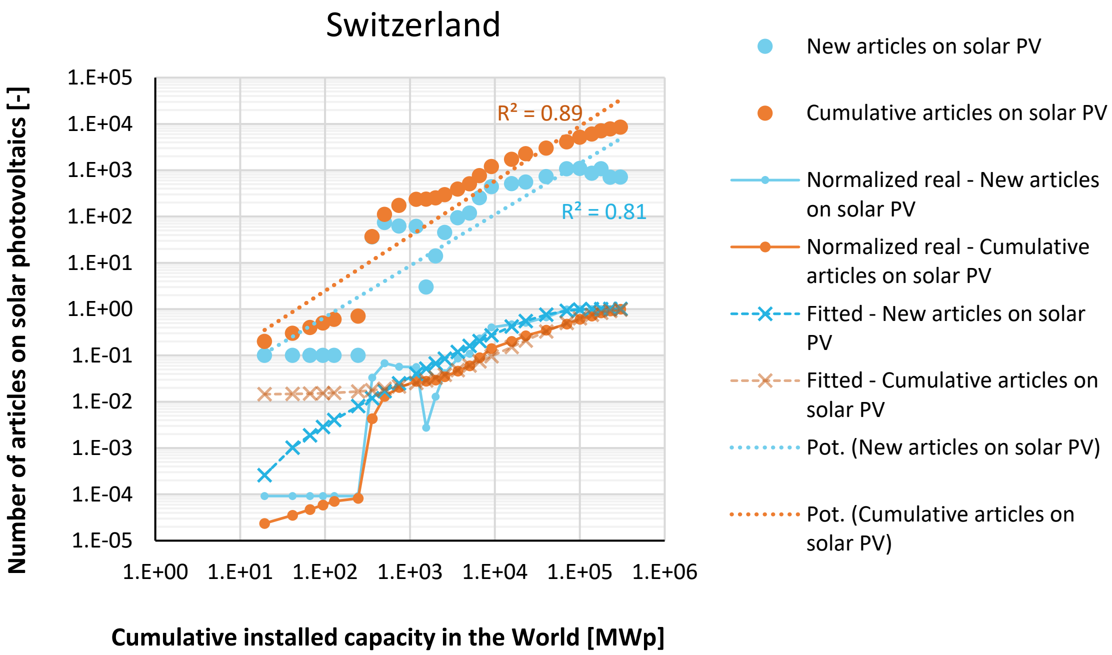


Figure 10.10. Evolution of number of new and cumulative articles on solar PV for Switzerland and cumulative installed capacity in the world. Data collected from LexisNexis

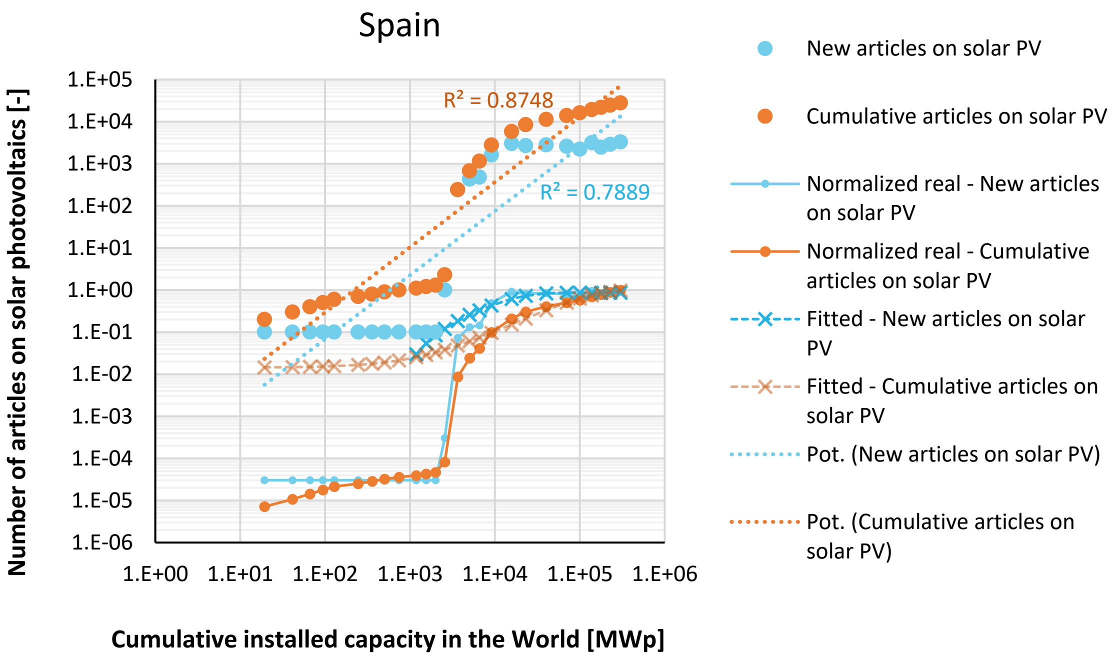


Figure 10.11. Evolution of number of new and cumulative articles on solar PV for Spain and cumulative installed capacity in the world. Data collected from LexisNexis

A.8. Scale effect on solar photovoltaic prices

Larger solar photovoltaic (PV) systems benefit from substantial economies of scale, mainly associated with the costs of inverters, installation, and balance of system elements. This effect has been widely studied before (Ossenbrink 2017; Haelg, L., Waelchli, M. & Schmidt, T. S.). We apply the results from Haelg et. al. (forthcoming) who used a log linear regression of the relation between the system size and the system price for Germany and assume a similar scale effect in Switzerland and Spain. After comparing the relation with other references (Ossenbrink 2017), we adopted it after shifting it to make the scale effect one for systems of 10 kWp, used as a reference for the price of solar PV. Due to the power form of the scale effects, it grew excessively large for values closer to zero. Thus, a fixed scale effect of 1.2 is used to approximate the scale effect on system sizes below 1 kWp.

$$\text{Scale effect} = 1.1246 \cdot \text{System size [kWp]}^{-0.051}$$

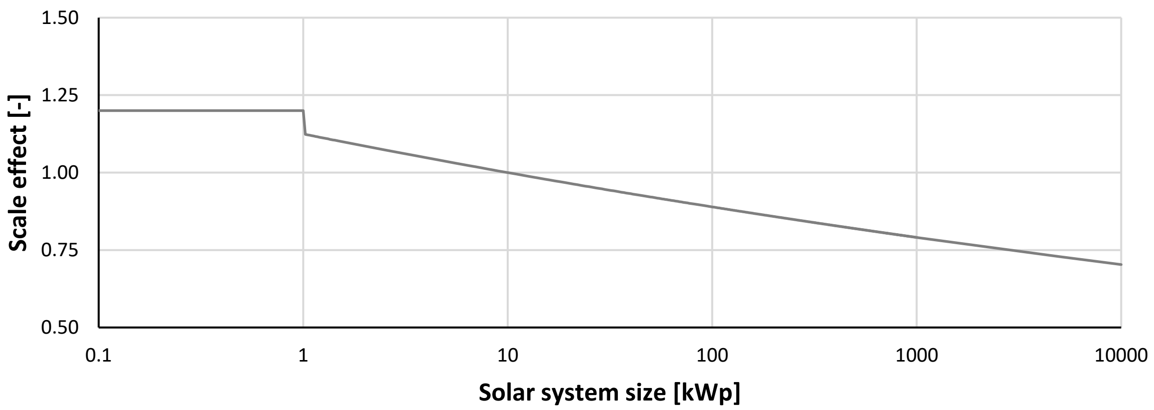


Figure 10.12. Economies of scale for solar photovoltaic systems

A.9. Model robustness check results

Table 10.2. Robustness check results of model calibration parameters

Country	Calibration parameter	Final parameter setting	Parameter variation by -10%	Cumulative capacity in Dec 2016 [GWp]	Parameter variation by +10%	Cumulative capacity in Dec 2016 [GWp]
Switzerland	*Final parameter settings*[a]			1.6049		1.6049
	$k_{awareness}$	0.0491	0.04419	3.1584 (-80.32%)	0.05401	3.4860 (+117.21%)
	k_{info}	0.089	0.0801	1.4374 (-10.43%)	0.0979	1.9285 (+20.17%)
	k_{peers}	1.07	0.963	1.4598 (-9.04%)	1.177	1.8550 (+15.59%)
	$k_{advantage}$	0.047	0.0423	1.6186 (+0.85%)	0.0517	1.6392 (+2.14%)
	$\widehat{Awa}_{threshold}$	0.99	0.891	1.673 (+0.83%)	1.089	1.5567 (-6.23%)
	$\widehat{NPV}_{threshold}$	0.136	0.1224	1.6300 (+1.57%)	0.1496	1.5780 (-1.67%)
Spain	*Final parameter settings*[a]			4.7872		4.7872
	$k_{awareness}$	0.488	0.4392	0.0010 (-99.98%)	0.5368	870.1983 (+18077%)
	k_{info}	0.0428	0.03852	3.9097 (-18.33%)	0.04708	5.7128 (+19.33%)
	k_{peers}	0.8	0.72	4.6694 (-2.46%)	0.88	4.7110 (-1.59%)
	$k_{advantage}$	0.5	0.45	3805.8 (-20.50%)	0.55	5469.5 (14.25%)
	$\widehat{Awa}_{threshold}$	0.99	0.891	4760.2 (-0.56%)	1.089	4617.05 (-3.55%)

Note: Each individual calibration parameter variation was performed for 100 simulation runs and with all other calibration parameters kept constant at their final value from the initial calibration. (a) The cumulative capacity for the final parameter settings of the initial calibration step with 1000 simulation runs serve as the reference values for the parameter variations.

A.10. Discussion on historical Policy Costs in Switzerland

In Switzerland, given the policy's complexity and missing clarity of policy costs, we differentiate between three cost approaches (see Table 10.3 and Figure 10.13). CH-HIST$_{2016}$: policy costs for granted payments in 2016. CH-HIST$_{exp.}$: actually expected final policy costs for all installations until the end of 2016. CH-HIST*: estimated policy costs if all historical installations until 2016 had received the announced feed-in remuneration for the entire guaranteed payment period and from the date of their installation on. CH-HIST* is the one we consider to be the fairest comparison to how the new policy design performs, which is why it is chosen as a reference scenarios in this Thesis.

CH-HIST$_{2016}$: This approach only takes into account payments to installations that already had gotten a confirmation of remuneration by the end of 2016. Every adopter that got accepted within the compensation program was granted remuneration for 25 years if its system was installed until the end of 2013 and for 20 years if its system was installed afterwards (Bundesamt für Energie BFE). Consequently, these payments include both remuneration for already produced energy by the end of 2016 and remuneration for future energy production that falls into the guaranteed remuneration period of the respective adopters.

As a reference for this scenario, historical policy cost data, only including the KEV payments for installations until December 2016, is available. With an estimated policy costs of CHF 2.58 billion based on government data (pronovo 2018), our simulated policy costs from the model for CH- HIST$_{2016}$ of CHF 2.55 billion (see Table 10.3) not even deviate by 2%.

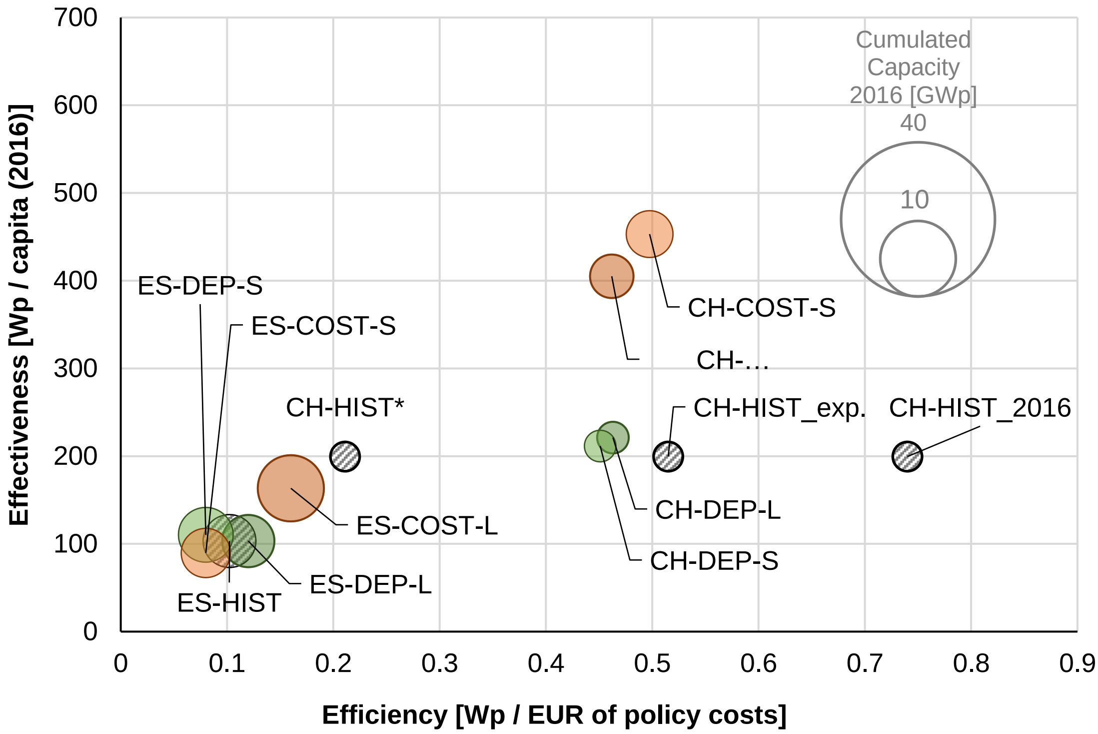
CH-HIST$_{exp.}$: This approach extends CH-HIST$_{2016}$ by including expected retroactive one-time investment subsidies (within the EIV) to all installations that were already built before the end of 2016 but still had been registered on the waiting list without having received and financial support yet. In 2017, no new financial resources for the initial remuneration design were provided by the government and no new adopters were accepted in the scheme. Additionally, at the beginning of 2018 the initial design of the feed-in policy came to its final moratorium. Instead, the Swiss government retroactively started to pay one-time investment subsidies as a compensation to the initially expected feed-in tariffs (FITs) to adopters. However, this only comprised a part of the total payments an adopter would have received in the form of a feed-in remuneration over the years. Although at times of this study not all payments had already been performed, it is expected that in the near future all adopters that had installed their solar photovoltaic (PV) system until the end of 2016 will have received this compensation (Bundesamt für Energie BFE).

CH-HIST*: This calculation is the one considered for comparison in the thesis. It displays an approach where all historical installations that were built until the end of 2016 in Switzerland would have received the announced feed-in remuneration for their entire guaranteed payment period and from the date of their installation on. Here, only systems that actually were installed in history are considered. A historical scenario without limitations in the number of adopters that could get accepted for the feed-in remuneration most likely would have experienced a further increase in the number of installations. However, this has not been analyzed.

Table 10.3. Discussion on historical policy costs in Switzerland

Scenario	Total Installed Capacity (median) [GWp]	Total Policy Cost (median) [bn]	Policy Cost Efficiency (median) [Wp / EUR]
CH-HIST$_{2016}$	1.66 (-0.3,+2.2)	EUR 2.23 (-0.2,+0.8) (CHF 2.55)	0.74 (-0.16,+0.78)
CH-HIST$_{exp.}$	1.66 (-0.3,+2.2)	EUR 3.29 (-0.47,+2.28) (CHF 3.76)	0.52 (-0.09,+0.17)
CH-HIST*	1.66 (-0.3,+2.2)	EUR 7.75 (-1.19,+3.05) (CHF 8.6)	0.21 (-0.02,+0.01)

Note: The median value from 100 simulations is reported together with the distance to the upper and lower boundaries of the interval around the median covering 90% of the simulations. The mean of each policy outcome of each mechanism in standard letters is statistically different from the historical scenario (CH-HIST$_{exp.}$ / ES-HIST) with a confidence level exceeding 99.999% according to a two-tailed t-test robust to heteroskedaticity. The confidence level for values in italics is 95% or higher and for underlined values between 60% and 85%.



Note: These values are based on model outcomes for simulated historical policies in Switzerland and Spain.

Figure 10.13. Effectiveness-efficiency mapping - Discussion on historical policy costs

All tested adjustment mechanisms (CH-DEP-S / CH-DEP-L / CH-COST-S / CH-COST-L) would have nearly doubled the cost efficiency compared to the scenario where all historical installations until the end of 2016 in Switzerland would have received the announced feed-in remuneration for the entire guaranteed payment period and from the date of their installation on (CH-HIST*) (see discussion in Thesis).

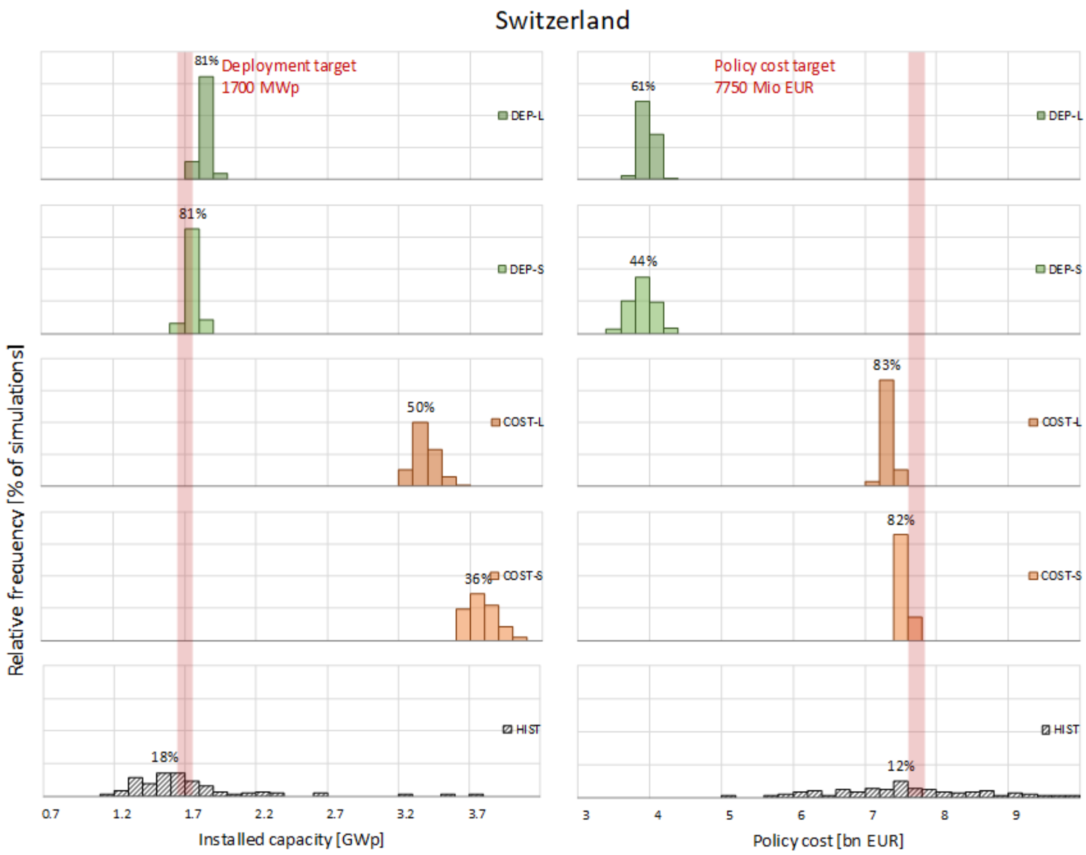
Instead, compared to a scenario that only takes into account payments to installations that already had gotten a confirmation of remuneration by the end of 2016 (CH-HIST$_{2016}$) the new policy designs obviously fails to increase the cost efficiency. Here it competes against a scenario that has seen most of its installations not having received any financial support yet.

However, our mechanism only shows a slightly less cost-efficient policy, if one compares it to the actually expected final policy costs the Swiss government will probably be facing for installations performed until the end of 2016 (CH-HIST$_{exp.}$). This means, that the novel responsive mechanisms could have e.g. achieved a similar deployment as in history while simultaneously keeping policy costs at bay without the use of additional policy measures such as policy cost caps as used in history. Additionally it would have ensured a fairer distribution of funds as it had remunerated all adopters based on the same and coherent feed-in policy design.

A.11. Improving policies within historical conditions – reliability of policy outcomes

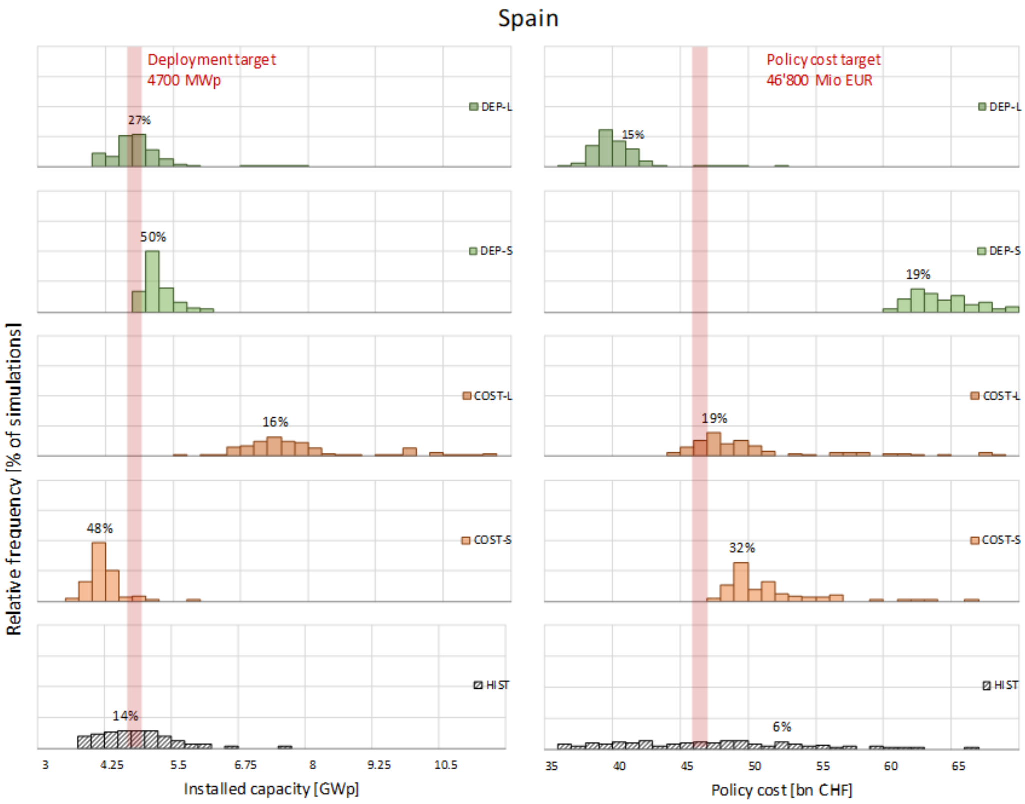
Figure 10.14 and Figure 10.15 compare the distributions of total installed capacities and policy costs across scenarios. The results show that the certainty about the outcomes of future deployment policies could greatly improve by adjusting incentives using a responsive mechanism based on control theory in Switzerland and Spain.

In both countries, adjusting incentives according to deployment or policy cost targets produces policies that deviate only slightly from their diffusion or policy cost goals. The outcomes derive from simultaneously correcting the monthly and cumulated deviations to predefined policy targets. In short, they result from estimating the incentive adjustment each month using control theory principles. The manual ad hoc adjustments of incentives in history, temporary combined with flexible degressions in Spain (HIST) produce the most scattered policy outcomes in both countries.



Note: Distribution of total installed capacity in GWp (left) and total policy cost in billions of EUR (right) of the 100 simulation runs conducted for each adjustment mechanism design in Switzerland.

Figure 10.14. Reliability of policy outcomes, Switzerland – Improving policies within historical conditions



Note: Distribution of total installed capacity in GWp (left) and total policy cost in billions of EUR (right) of the 100 simulation runs conducted for each adjustment mechanism design in Spain.

Figure 10.15. Reliability of policy outcomes, Spain – Improving policies within historical conditions

A.12. Evaluating influence of deployment timing – Ecological assessment of results

Besides the economic aspects, considered within the cost efficiency criterion, the influence of our three policy configurations (different timing, effectiveness and initial incentive conditions) on ecological aspects requires further investigation. The widespread diffusion of renewable energies is generally motivated by their positive impact on the environment, often measured in emission reductions, explicitly in saved amounts of CO_2 equivalents. While our analyses especially showed a shift in deployment to later times offering the possibility of cost reductions, postponed installations simultaneously miss out on early emission reductions (see Table 10.4).

Table 10.4. Ecological emission savings – Evaluating the influence of deployment timing

Scenario	Additional emissions savings compared to BASE-scenario[a] (tonnes CO_2eq)					
	until 2016		until 2020		until 2030	
ES-EFF-UP	+13‘720‘578	(+19.85%)	+26‘205‘269	(+21.10%)	+57‘416‘997	(+21.93%)
ES-EFF-DOWN	-14‘789‘946[b]	(-21.39%)	-26‘425‘888	(-21.28%)	-55‘515‘744	(-21.20%)
ES-TIC-LATE	-18‘977‘331	(-27.45%)	-16‘519‘974	(-13.30%)	-10‘376‘582	(-3.96%)
ES-TIC-EARLY	+20‘698‘874	(+29.94%)	+19‘607‘283	(+15.79%)	+16‘878‘307	(+6.45%)
CH-EFF-UP	+452‘771	(+18.90%)	+823‘333	(+19.19%)	+1‘749‘736	(+19.39%)
CH-EFF-DOWN	-442‘802	(-18.49%)	-802‘068	(-18.70%)	-1‘700‘233	(-18.84%)
CH-TIC-LATE	-675‘065	(-28.18%)	-656‘455	(-15.30%)	-609‘928	(-6.76%)
CH-TIC-EARLY[c]	+1‘674‘341	(+69.90%)	+1‘992‘337	(+46.44%)	+2‘787‘328	(+30.88%)

Note: Scenarios evaluating different initial incentive conditions are not listed as they do not significantly differ from the base case with regard to the average installation date and thus do not have a relevant impact on different emission savings. **(a)** Values are calculated based on average electricity-specific CO_2 equivalent emission factors for grid electricity (ES: 320 g-CO_2eq/kWh$_{el}$ (Subdirección General de Planificación Energética y Seguimiento 2016), CH: 120.87 g-CO_2eq/kWh$_{el}$ (Bundesamt für Energie BFE)), annual yields of 950 kWh$_{el}$/kWp in Switzerland (Bundesamt für Energie BFE) and 1700 kWh$_{el}$/kWp in Spain (Comisión Nacional de los Mercados y la Competencia (CNMC) 2018) and assume the technological lifetime for all solar PV systems built until 2016 to last until 2030. **(b)** Negative values indicate the amount of CO_2 equivalent emissions in tonnes less saved than in the BASE-scenario. **(c)** Note, that the cumulative installed capacity for the CH-TIC-EARLY scenario exceeds the one from the CH-BASE scenario, as the policy significantly misses its target, which influences the values for saved emissions overproportionately.

While the scenario of a later deployment in Spain (ES-TIC-LATE) allows for an increase in cost efficiency of 10% it misses out on 27% of reduced emissions until 2016 and still on 13% of emission reductions until 2020 compared to the base scenario (ES-BASE). A change in overall deployment targets that keep the average date of installation constant across scenarios, obviously allow for consistently more or less saved emissions in the order of their target differences, here around ±20%.