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Title of the paper

The Effect of Deployment Policy Design on the Lock-In of Innovative Technologies – A Model of Alternative Policy Design Scenarios and the Case of the Solar PV Feed-In Tariff in Germany

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Abstract

Technology deployment policies are key to bringing early-stage technologies to the market. Their design is decisive in determining which technologies are selected by markets, but its mechanism remains underexplored. Here we develop an empirically-calibrated agent-based model to show how deployment policy design, particularly the technology specificity and application specificity, influences technology selection in the case of the solar PV feed-in tariff in Germany. Our results show that offering different tariffs for different applications may create niches for competition between technologies, while neutral and technology-specific remuneration schemes most often result in the dominance of one technology. Thus, it is important for policymakers to understand technology selection and learning mechanisms before opting for a policy design in order not to prematurely prevent the diffusion of immature technologies.

Keywords: Agent-based modelling, deployment policy design, application specificity, technology specificity, technology selection, solar PV, technology

1 Introduction

Climate change mitigation requires the implementation of an effective policy mix including carbon pricing and complementary technology deployment policies (Van Benthem, Gillingham, and Sweeney 2008; Bergh 2013; Bertram et al. 2015). The latter are necessary to account for market failures, such as learning feedbacks (Van Benthem, Gillingham, and Sweeney 2008), and to increase economic long-term efficiency by introducing low-carbon technologies to the market (van den Bergh et al. 2006).

For renewable energy technologies, deployment policies have played a crucial role for capacity additions and hence to drive these technologies down their learning curves (Couture and Gagnon 2010; Fouquet and Johansson 2008; Hoppmann, Huenteler, and Girod 2014; Menanteau, Finon, and Lamy 2003). Solar photovoltaics (PV), for instance, has seen a steep increase in global deployment from 1.4 to 227 GW in the period between 2000 and 2015 (REN21 2011, 2016) accompanied by a cost decrease of about 99.4% in the past four decades (Trancik et al. 2015).

While literature has shown that the design of such deployment policies is decisive for their success in terms of inducing cost reductions (Kemp and Pontoglio 2011; Lipp 2007), it also suggests that poor policy design may lead to unintended dominance of one or a few technologies (Hoppmann, Huenteler, and Girod 2014; Schmidt et al. 2016b). Two aspects however remain unexplored on deployment policy design and technology selection. First, the specific mechanisms of how distinct design features of deployment policies act on technology selection remain unexplored in the literature. Second, the discussion on policy design mainly focuses on the extent to which renewable electricity generation technologies should be specifically supported disregarding the fact that, within these main technology categories, there again exist various subtechnologies. The solar PV technology, for instance, may be subdivided into its major subtechnologies, crystalline silicon (c-Si) and thin film[1] (Hoppmann et al. 2013).

We address this research gap by exploring the influence of the design of the German solar PV feed-in tariff on the selection of the two main solar PV subtechnologies. The analysed design features include the technology specificity and application specificity, as well as the overall level of support as sensitivity parameter. For this purpose, we develop an empirically-calibrated agent-based model, thereby also contributing to the emerging research field of ex-post models for policy design evaluation (Rai and Henry 2016). The modelled agents represent investors conducting investment assessments and choosing between the two available solar PV subtechnologies. We hence obtain information on the subtechnology selection under specific policy design scenarios. The German policy is a particularly interesting case for it is widely acknowledged to have been the first and foremost driver of global solar PV deployment in the 2000s and therefore the main reason for the substantial decrease in solar PV prices during that period (Jacobsson and Lauber 2006; Peters et al. 2012; Trancik et al. 2015).

Our results suggest that policy design has great influence on technology selection. Most policy design scenarios lead to the dominance of one or the other technology. However, policymakers can extend the period of competition between technologies by offering specific support for applications within which several technologies can compete. This also applies for technology-specific policy design, but only if the tariff differential between the technologies reflects their cost differential. The analysed case also suggests that policymakers may dynamically manage and adapt the support scheme in order to prevent premature lock-in. Finally, even though we focus on solar PV in the present study, the findings are also important to inform policy design for emerging low-carbon technologies, such as battery storage.

2 The role of policy design in technology selection, the case of Germany

Scholars employ the term policy design in different ways. Here, we use it as the low-level operationalisation of the policy instrument. While deployment policies and feed-in tariffs in particular may consist of many instrument design features (Jacobs 2014; Mendonça 2007), we focus on the ones deemed important for technology diffusion and technology selection by the literature. Technology selection hereby represents the choice for a specific technology among alternatives. It largely depends on the competitiveness of the different technological options and is closely interrelated to technology diffusion in the way that selection of one technology leads to the increased deployment and hence diffusion of this technology on the market. The abovementioned policy features include the technology specificity (Azar and Sandén 2011; Schmidt et al. 2016a) of the policy instrument, the application specificity (Schmidt et al. 2016a), and the level of support (Ashford, Ayers, and Stone 1985; Kemp and Pontoglio 2011). By focusing on these features, we also contribute to the debate about picking winners. In this debate, the advocates for technology-neutral support schemes, such as a carbon tax, argue that markets should choose the winner amongst competing technologies (Krugman 1996; Marchant 2009). Conversely, proponents for technology-specific deployment policies contend them to be necessary complements of carbon pricing in order to offer a level playing field to different early-stage technologies and avoid premature technological lock-in (van den Bergh et al. 2006; Bertram et al. 2015; Gillingham and Sweeney 2012; Jaffe, Newell, and Stavins 2005; Sandén and Azar 2005; Schmidt et al. 2016b). Technology-specific policy instruments directly foster the deployment of individual or groups of technologies. Importantly, they may be technology-specific to a greater or lesser extent (Azar and Sandén 2011; Schmidt et al. 2016b). The renewable portfolio standard (RPS) enacted in several states of the U.S., for instance, did not differentiate between renewable energy technologies, while the feed-in tariff in Germany offered different support for the various renewable energy technologies, such as wind or solar

PV, but was particularly unspecific at the subtechnology level. This level is the focus of our study, as we analyse the effect of different levels of technology specificity on the selection of subtechnologies.

The application specificity of a policy instrument has only recently entered the discussion and refers to deployment policies differentiating between applications of a multi-purpose technology (Schmidt et al. 2016b). Here, an application is defined as a technology use case offering the opportunity for value creation to a specific user group. Different applications may consist, for instance, of onshore and offshore wind installations or the use of batteries for different grid services. Even though neutral at the subtechnology level, the German solar PV feed-in tariff was actually application-specific discerning rooftop installations from large-scale open space installations between 2004 and 2011[2] (Figure 1) (Hoppmann, Huenteler, and Girod 2014).

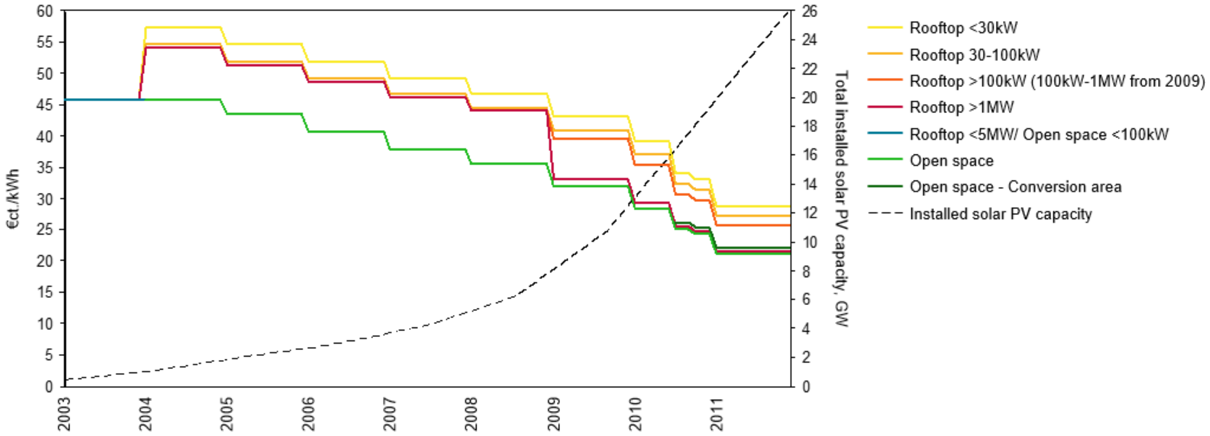


Figure 1. Development of solar PV feed-in tariffs and total installed capacity in Germany in the analysed period between 2003 and 2011 (BMWi 2016b; Bundesgesetzblatt 2000, 2004, 2008, 2011).

Finally, we use the level of support, i.e. the granted tariff (Jacobs 2014; Mendonça 2007; Rogge and Reichardt 2016), as sensitivity against the above design features. The level of support has been shown to be one of the most decisive factors for technology deployment (Jenner, Groba, and Indvik 2013; Mendonça 2007). It therefore opens the window of opportunity for technology selection. We vary the overall compensation levels and adjust the technology specificity or application specificity of the feed-in tariff by varying the compensation for the different subtechnologies or applications.

3 Methodology

3.1 General Approach

The agent-based model assesses the influence of technology specificity, application specificity, and the level of support of the German feed-in tariff on the selection of the two major subtechnologies in two iterative steps.

In the first step, we calibrate our model in such a way to simulate total historical solar PV diffusion in Germany and the shares of the two subtechnologies. To do so, we use empirical data from Germany for the period between 2003 and 2011, such as historical module prices, the application and size of actually-built installations and the feed-in tariff they received. The analysed years encompass the period when the German feed-in tariff generously and successfully supported rooftop as well as open-space installations and Germany was the global leader in capacity additions (Figure 1) (Trancik et al. 2015).

In the second step, we use the calibrated model for different policy designs, i.e. we apply alternative policy scenarios with varying feed-in tariff levels for the subtechnologies and applications to analyse their effects on technology selection. Scenario 1 represents the historical application-specific and technology-neutral tariff, Scenario 2 represents an application-neutral and technology-neutral tariff, and Scenarios 3 represents an application-neutral but technology-specific tariff (Table 1). Sub-scenarios exist for the variations of individual elements, such as the rooftop or crystalline-silicon tariffs. In both steps, potential bounded-rational solar PV investors, i.e. the model's agents, take investment decisions for individual installations based on the net present value (NPV), which represents the expected earnings from the installation in the future at today's value. The NPV largely depends on module cost and balance of system

(BOS) cost as well as the received feed-in tariff. Based on their assessment, the agents decide either to invest in an installation with one of the subtechnologies or not to invest at all.

The number of iterations per modelled year is defined as the number of historically-built installations for the calibration step. Conversely, in the second step, the number of investment decisions per year – whether positive or negative - from the calibration step is used. At the end of every year, the reduction in module and BOS cost thanks to the capacity additions are assessed based on the historical learning curves. In our model, we do not consider effects from markets external to Germany on the module and BOS prices.

Table 1. Overview of the analysed scenarios. The baseline tariff refers to the historical tariff for open space installations. See a graphical representation of the sensitivities in Figure A. 1.

Scenario	Design features *Sub-technology*	Design features *Application*	Operationalisation	Sensitivity
1 (Base case)	Neutral	Specific	Historical tariff	
1a	Neutral	Specific	Historical tariff	Variation of rooftop tariff between -10% and +10%
1b	Neutral	Specific	Historical tariff	Variation of open space tariff between -10% and +10%
2	Neutral	Neutral	Baseline tariff for both applications and sub-technologies	Variation of total tariff between -10% and +10%
3a	Specific	Neutral	Baseline tariff for c-Si, 5% higher tariff for thin film	Variation of thin film tariff between -10% and +10% of baseline
3b	Specific	Neutral	Baseline tariff for thin film, 5% higher tariff for c-Si	Variation of c-Si tariff between -10% and +10% of baseline

3.2 Model

3.2.1 Agent-based modelling rationale

We employ an agent-based model to simulate the investment decisions of different agents. This approach is suitable for the purpose of this study since it manages to capture non-linear innovative diffusion processes at the individual level, explicitly taking into account the heterogeneity, the decision-making processes, and the interactions of the different agents (Kiesling et al. 2012). Here, the heterogeneity of actors is characterised by the different preferences for application and size of the installation by different investors, such as homeowners, farmers, and institutional investors (Dewald and Truffer 2011).

The model consists of two steps. The first one, called “Calibration step”, is used to calibrate the model to simulate historical solar PV diffusion in Germany, while the second step, called “Alternative policy scenario (APS) step” uses the calibrations to analyse how the technology selection changes under different feed-in tariff design scenarios.

The two steps work in a similar fashion consisting of two modules called “Investment decision module” and “Price curve module” (see Figure 2). In the Investment decision module, one year is modelled at a time. It starts with potential investors, i.e. this model’s agents, selecting an installation to assess the investment attractiveness. An installation is defined by its size and application. In the Calibration step, agents select installations from a pool of the historically-built installations in the specific year, while in the APS step the agents randomly select the installation from a distribution based on all historical installations built in the analysed timeframe (see the distributions and functions in Figure A.3 and Table A. 1). This distribution is assumed to proportionally represent the actual surfaces available for solar PV installations in Germany.

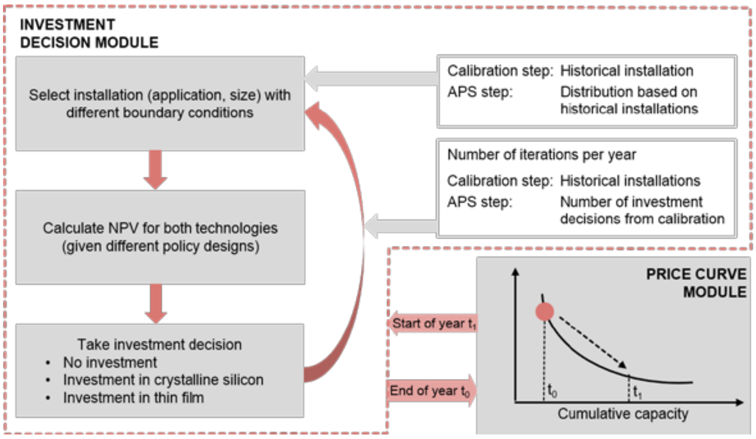


Figure 2. Iterative structure of the model.

The investment attractiveness of the specific installation is analysed for both subtechnologies using the net present value (see below for more details on the assessment of the investment attractiveness). The agent then decides whether to invest at all (NPV≥0) and, if so, in which subtechnology (maximum NPV). Then, the model moves either to a new agent taking an investment decision or to the Price curve module when it has reached the number of annual investment decisions. In the Calibration step, this is achieved when positive investment decisions have been taken for all historical capacity additions of the specific year. In the APS step on the other hand, the number of annual investment decisions is determined by the number of all investment decisions - whether positive or negative - taken for this year in the Calibration step (Table A. 2). In the Price curve module, the annual capacity additions are introduced in the historical price curves for the respective subtechnology as well as for the BOS and the module and BOS prices are determined for the next year.

3.2.2 Operationalisation of agents' investment decisions

The decision-making process of investing into a specific installation is based on the net present value (NPV) of the potential installation. The NPV is the sum of the discounted cash flows over the investment lifetime minus the initial investment (see equation (1)) and represents the expected future earnings at today's value (Brealey and Myers 2000). It therefore allows for easy comparison between different investment options, which are, in this study, the two solar PV subtechnologies thin film and crystalline silicon.

$$NPV = -I_{t=0} + \sum_{t=1}^{T} \frac{CF_t}{(1+r)^t} \quad (1)$$

where $I_{t=0}$ represents the initial investment cost, r the discount rate, CF_t the net cash flow in year t, and T the duration of the investment. The investment cost depends on the size of the installation and the module and BOS cost. Since the size is here defined as the installed capacity, BOS costs are increased by 20% for thin film given its lower efficiency (Fraunhofer ISE 2015) and the need for more BOS equipment. With increasing project size, we assume the module costs to linearly decrease thanks to economies of scale (Figure A. 2d). The annual cash flows are the difference between the revenues and expenses (see equation (2)).

$$CF_t = E_t FiT_t - O\&M_t \quad (2)$$

where E_t is the energy produced by the installation in year t, FiT_t the tariff paid in year t for the produced energy, and $O\&M_t$ the cost for the operation and maintenance of the installation. Values are based on literature (Table A. 3). The annually produced energy is randomly picked from a truncated normal distribution in order to account for the different solar irradiation exposures of the installations due to their different latitudinal location as well as the roof inclination in the case of rooftop installations.

3.2.3 Assumptions and stylised facts

Bounded-rational NPV calculation. We assume the actors to have bounded rationality due to the cost they incur to gather and process complete information (Simon 1972). We account for this in two ways. On the one hand, we introduce a parameter based on the bias towards crystalline-silicon installations. This is justified by the fact that German installation companies less often offer the thin-film technology in their portfolio (Bundesverband Solarwirtschaft 2013). Furthermore, we assume this technology-specific bias to be greater for small-scale rooftop investors, such as homeowners, than for large-scale rooftop and open-space investors. This is justified in the way that, due to their larger investment volume, institutional investors and large project developers have a higher incentive to acquire information about different offers, and that solar PV module producers are likely to closely work with such agents (Dewald and Truffer 2011). Homeowners, on the other hand, are assumed to rely more on their local installation companies that obtain complete installation packages from PV system suppliers (Dewald and Truffer 2011).

On the other hand, for each investment decision, the module price is randomly picked from a truncated normal distribution. This way, we account for the fact that agents have limited knowledge about the cheapest module price due to the transaction cost that gathering complete information would incur.

Ceteris paribus. The model, *ceteris paribus,* analyses the implications of the changing deployment policy designs on technology demand. We assume the supply to remain the same as in the historical case. Hence, we restrict the model to interactions over the price curves. In other words, interactions and feedbacks of the effect of a new hypothetical, historically-divergent deployment policy on the innovation system are not modelled. The effects of external events such as the silicon shortage observed between 2006 and 2009 (van Sark et al. 2007) and capacity additions in other countries are for instance always assumed to hold in any historically diverging paths. We justify this assumption that, with spendings of 20 billion EUR in the analysed timeframe (BMWi 2016a), Germany was not only the forerunner in annual PV capacity additions but also in cumulative PV capacity (Trancik et al. 2015). At the same time, Germany was one of the few countries with a stable policy and therefrom resulting constant growth rates (Trancik et al. 2015), hence offering a fruitful environment for PV producing and installing companies to learn from earlier experiences. It is therefore valid to assume that a slower development in Germany would have slowed down global solar PV capacity development and therefore price decreases.

3.3 Data

Data on historical installations is used twofold in the model. First, it represents input parameters from which agents pick individual installations in the Calibration and APS steps. To do so, it is subdivided into applications and, for the APS step, additionally aggregated into a normal distribution. Second, subdivided into subtechnologies, the data is used to verify the validity of the results from the Calibration step.

The data is obtained from a consumer organisation that archives original raw data from the network operators and makes it publicly available (EnergyMap 2014). Since most data from before 2009 is not categorised according to the application of the installation (see Figure A. 3a), we apply machine learning to assign applications to the uncategorised data. To do so, the classified data from 2009 to 2012 is used to build a classification algorithm based on the highly scalable naïve Bayes classifier. This classifier builds on the principle of Bayes' theorem which uses prior knowledge to describe the probability of an event (James et al. 2014). Here, a subset of the classified data is used to train the Bayes classifier. It is assumed that the distribution within a size class is approximately constant. The accuracy of the classifier is tested with another subset of the already classified data using Cohen's kappa, a coefficient measuring the observer agreement for categorical data (Landis and Koch 1977). Kappa statistics of 0.24 were obtained for the accuracy evaluation, which can be considered a fair agreement (Landis and Koch 1977). Finally, the Bayes classifier is applied to the unclassified data from 2003 to 2011 with the simulation input data containing 1,102,601 installations (see result of the application classification in Figure A. 3b).

The historical shares of the thin-film and crystalline-silicon subtechnologies is obtained by combining different data sources on the German and world market and validated with German solar PV experts (Figure A. 4).

4 Results

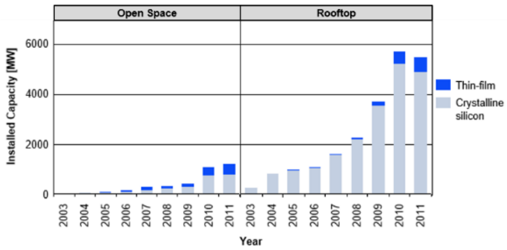
The modelling results for the different scenarios are displayed in Figure 3 including graphs for the diffusion of the two subtechnologies per application for the scenario operationalisation on the left-hand side and heat maps displaying how the shares of the subtechnologies develop under sensitivity analyses.

The results for Scenario 1, which represents the historical case, show that on the one hand crystalline silicon diffuses more extensively, especially in rooftop installations (Figure 3a.1). On the other hand, within the open-space application, competition between the two subtechnologies is prevalent. Yet, rooftop sees larger capacity additions and the prevalently selected technology in the rooftop application therefore becomes dominant also in open-space applications. Turning to Scenario 1a, Figure 3a.2 displays the sensitivity of technology selection patterns under varying rooftop tariffs. They suggest that lowering the rooftop tariffs leads to dominance of the thin-film subtechnology thanks to spillover effects from the open-space application to the rooftop application. Spillover effects are positive externalities, such as BOS cost reductions, induced by capacity additions which improve the business case for both subtechnologies within both applications (Battke et al. 2016). Contrarily, with increasing tariffs for rooftop, crystalline silicon becomes dominant. The results for Scenario 1b displayed in Figure 3a.3 suggest that variation of the open-space tariff leads to more competition, and which subtechnology is finally dominating is determined only very late. Increasing of the open-space tariffs results in final dominance of thin film, whereas decreasing open-space tariffs respectively foster the selection of crystalline silicon. Overall, the analysis of Scenario 1 indicate that the German policymaker operated at the edge of lock-in but managed to keep competition up.

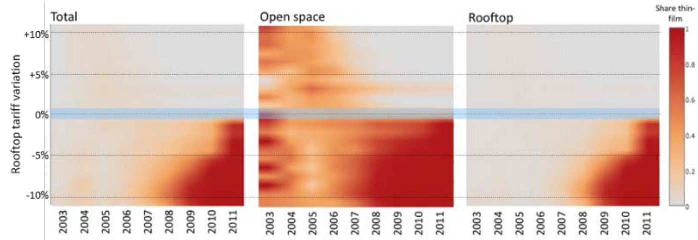
Turning to Scenario 2, the results displayed in Figure 3b.1 suggest that thin film is the dominating subtechnology in this application-neutral and technology-neutral policy configuration. Yet, thanks to its historical predominance, crystalline silicon is the subtechnology of choice for rooftop installations in the first period before spillover effects induce a switch to thin film. Increasing the overall tariffs does not induce any changes in the selection patterns (see Figure 3b.2). However, when decreasing the tariffs beyond a threshold (beyond -5% in the present case), crystalline silicon becomes dominant. This suggests that, at very low overall tariffs, total diffusion is low in such a way that learning and spillover effects do not occur, and investors stick to the initially more prevalent subtechnology. It is noteworthy that, with the overall tariffs being lower in Scenario 2 than in Scenario 1, the total diffusion of both subtechnologies is also lower.

Finally turning to Scenario 3, we find that, for most tariff combinations, thin film is the dominant subtechnology even if crystalline silicon receives more support (Figure 3c.1, Figure

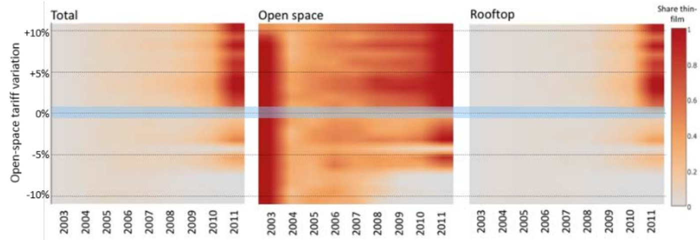
a.1) Scenario 1 (Base case). Historical application-specific feed-in tariff.



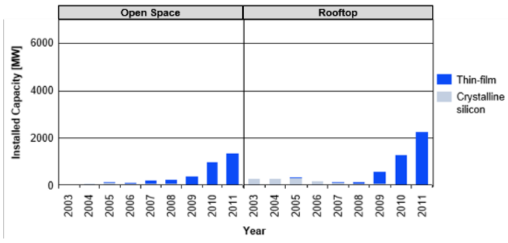
a.2) Scenario 1a. Variation of rooftop tariff. Constant open-space tariff.



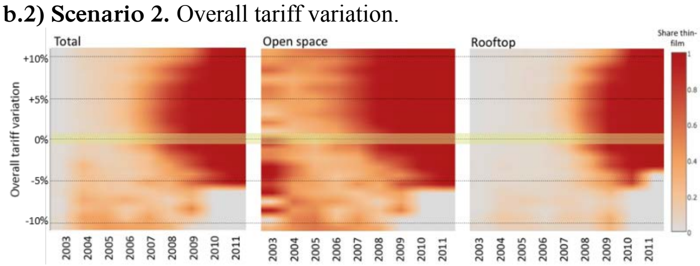
a.3) Scenario 1b. Variation of open-space tariff. Constant rooftop tariff.



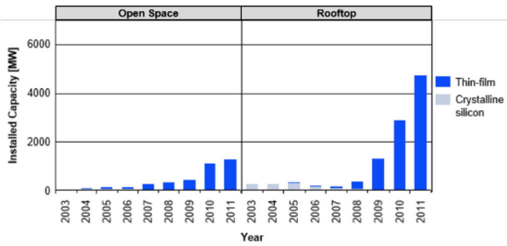
b.1) Scenario 2. Technology-neutral, application-neutral feed-in tariff.



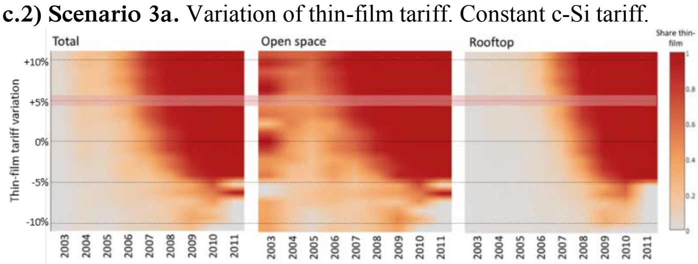
b.2) Scenario 2. Overall tariff variation.



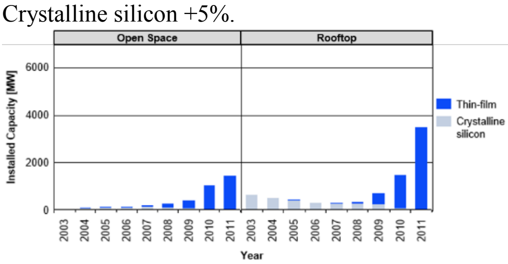
c.1) Scenario 3a. Subtechnology specific, application-neutral feed-in tariff.
Thin film +5%.



c.2) Scenario 3a. Variation of thin-film tariff. Constant c-Si tariff.



c.3) Scenario 3b. Subtechnology specific, application-neutral feed-in tariff.
Crystalline silicon +5%.



c.4) Scenario 3b. Variation of c-Si tariff. Constant thin-film tariff.

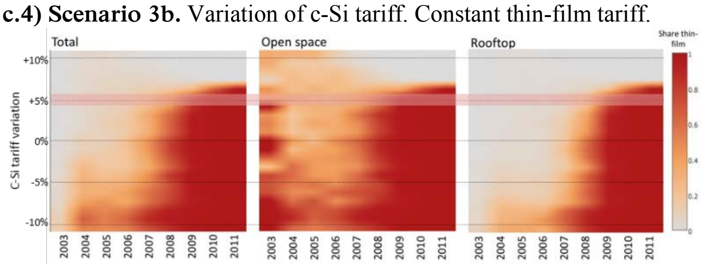


Figure 3. Modelling results of the analysis of policy design effects on technology selection. a.1,b.1,c.1,c.3) The graphs indicate the total diffusion of the two subtechnologies for the specific operationalisations of the scenarios summarised in Table 1. a.2,a.3,b.2,c.2,c.4) The heat maps show total shares of thin film and crystalline silicon for tariff variations between -10% and +10%. The lines in the heat maps indicate the tariffs used for the left-hand side graphs.

3c.3). Only in the case of crystalline silicon receiving an at least 8%-higher tariff than thin film, overall lock-in to crystalline silicon is observed (see Figure 3c.2 and Figure 3c.4). These results imply that spillover effects for the BOS cost between the two subtechnologies are advantageous for thin film. Thus the deployment of crystalline silicon, especially in rooftop installations, improves the business case for thin film to the point that it actually replaces crystalline silicon. The comparison of the heat maps of Scenario 2 and Scenario 3a (Figure 3b.2 and Figure 3c.2) suggests that increased tariffs for thin film does not induce substantial changes in selection patterns but simply accelerates lock-in to thin film.

Overall, the results show higher competition within the open-space application. For rooftop on the other hand, one technology is usually dominating, but shifts from one subtechnology to the other, from rooftop to thin film, happen when spillover effects from open space are large.

5 Discussion and Conclusion

As our analysis demonstrates, policy design is very influential not only for technology selection but also for total technology diffusion. As expected, the level of support is the decisive factor in terms of overall technology diffusion, i.e. diffusion increases with increasing tariffs and vice versa. For technology selection, the mechanisms are more complex.

As our results indicate, dominance of one or the other subtechnology is the most likely case for the analysed scenarios. This means that, at the end of the analysed period, one subtechnology is used for all capacity additions under most design scenarios. Thin film is thereby more prevalent even in the case of high initial adoption of crystalline silicon thanks to spillover effects and decrease in cost of BOS. It is shown that a neutral policy design, which does not specifically support technologies or applications, results in the dominance of the technology that manages to become more competitive very quickly. The results of the technology-specific policy design suggest that directly supporting one or another technology does not necessarily lead to dominance of the supported technology. In fact, the support differential between the technologies needs to be sufficiently large and hence reflect the cost differential of the technologies in order to avoid dominance of the technology that is more efficient in the short term.

While our results show little competition within the rooftop application, the open-space application offers a level playing field for both subtechnologies to gain market shares. Thus by supporting specific applications, policymakers can create niches to stir competition between different technologies and not prematurely pick winners. In the present case of Germany, expanding the feed-in tariff to larger open-space installations in 2004 helped to overcome the early dominance of crystalline silicon and the recurring adaptations of the policy design managed to keep a competitive environment where both technologies could thrive.

Our insights can be extended to other multi-purpose technologies, such as batteries (Stephan et al. 2016). Before picking a winner or let the market pick a winner, policymakers can make use of technologies being competitive in different applications and, by designing application-specific deployment policies, effectively offer a level playing field for many technologies (Schmidt et al. 2016b). Thus, learning effects can be fostered for all early-stage technologies, and the ultimately most efficient technologies may then be selected by the markets at a later point. However, our results also show that competition between technologies within and across applications and the risk of ending up with one dominant technology at the outset need to be understood when designing deployment policies. Though changes in competitiveness between technologies happen gradually, i.e. one technology does not become prevalent from one moment to the next. This allows policymakers to dynamically manage and adapt the policy design if necessary.

Our analysis offers three contributions: First, with the agent-based model, we methodologically contribute to the emerging but still scarce number of ex-post models for policy design evaluation hence offering a tool to better understand the mechanisms between design elements and technology selection. Second, our empirical contribution consists of collecting, processing, and using data on the application and subtechnology of historical solar PV installations in Germany, as well as the speed at which a specific technology can become dominant in a given policy configuration. Third, we contribute to the policy debate by proving the relevance of application specificity in indirectly influencing technology selection and its potential to maintain a competitive environment for several technologies, as well as poorly designed technology-specific policies may not result in the desired outcome.

Future research on forward-looking models that account for technology selection and lock-in could provide important inputs for the effective design of deployment policies to introduce new low-carbon technologies to the market in order to help mitigate climate change.

6 Acknowledgements

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7 Endnotes

[1] In our analysis, we focus on two mature solar PV subtechnologies, crystalline silicon and thin film. It is important to note that these subtechnologies are rather technology concepts, each of which again consists of variants of these concepts featuring similar characteristics, such as working principle, efficiency, production process and cost.

Crystalline silicon. In the crystalline-silicon subtechnology, we include monocrystalline silicon as well as polycrystalline silicon cells. Their manufacturing starts with the fabrication of pure silicon ingots from metallurgical silicon followed by the slicing of these ingots into wafers with a thickness of approximately 200µm (IRENA and IEA-ETSAP 2013). These wafers are then assembled into modules. Crystalline silicon is the solar PV technology with the highest efficiency and hence offers more capacity per surface area than other subtechnologies. Ribbon silicon, which is also a wafer-based technology, is not considered in this study due to its low market shares (Hering 2012).

Thin film. In thin film, we include cell technologies of various materials, such as amorphous silicon, cadmium telluride, and copper indium gallium diselenide. The manufacturing process, common to all these cell technologies, consists of vapour deposition of the photoactive material on a substrate, such as conductive glass, and subsequent washing, cutting, and sealing of the final module (Sartorius 2005). Thanks to the vapour deposition process, the absorbing layers of thin film PV do not exceed thicknesses of 1μm (Sartorius 2005) which allows for large material savings compared to crystalline silicon. Furthermore, the energy requirements for thin-film cell and module production are lower than for crystalline silicon (Fraunhofer ISE 2015). These two factors constitute the competitive advantage of thin film in terms of production cost per capacity. Yet, this advantage is compensated by the lower efficiency of thin film compared to crystalline silicon.

In this study, we do not consider other solar PV subtechnologies, such as dye-sensitised solar cells or organic PV, due to their immaturity and low market penetration.

[2] We focus on the German feed-in tariff between 2003 and 2011. While this was the period of very strong market growth, public support of solar PV deployment already started much earlier and is still ongoing (Hoppmann, Huenteler, and Girod 2014; Jacobsson and Lauber 2006). The predecessors of the analysed feed-in tariff were implemented in the 1990s in the form of an early technology-neutral feed-in tariff, the Electricity Feed-in Law, complemented by the 1000-roof programme (Hoppmann, Huenteler, and Girod 2014; Jacobsson and Lauber 2006). While the former did not trigger any considerable solar PV deployment due to its very low remuneration, the 1000-roof programme was more successful offering an investment grant for small-scale rooftop solar PV installations of up to 70% of the investment cost. Supplemented by various initiatives on the municipal level, it induced an increase of installed solar PV capacity from 2 MW in 1990 to 70 MW in 1999 (BMWi 2016b). In 2000, the Renewable Energy Act (EEG) replaced the Electricity Feed-in Law and introduced cost-reflective and technology-specific tariffs (Hoppmann, Huenteler, and Girod 2014; Jacobsson and Lauber 2006). For solar

PV, one tariff was offered for rooftop installations with capacities up to 5 MW and small-scale open-space installations up to 0.1MW during a period of 20 years. An annual degression path of the tariffs of 5% was introduced to account for learning effects. In combination with the successor of the 1000-roof programme, the 100,000-roof programme, the new support scheme had a considerable effect on growth rates of solar PV capacity additions resulting in a total installed capacity of 435 MW in 2003 (BMWi 2016b; Hoppmann, Huenteler, and Girod 2014). The amended EEG implemented in 2004 brought major changes by removing the size caps for solar PV installations and increasing the remuneration for the rooftop application while also differentiating between different installation sizes within the rooftop application (Hoppmann, Huenteler, and Girod 2014). This increase in support led to an even larger boom in solar PV deployment between 2004 and 2008 resulting in massive price reductions and a total installed capacity of 6,120 MW in 2008 (BMWi 2016b). Technology and power producers earned high profits thanks to the fact that the automatic annual degression rate could not keep up with the unforeseen extent of learning effects. In order to limit social costs, the EEG was therefore amended anew in 2009 introducing a flexible degression and changing the size differentiation within the rooftop application. In 2010, another amendment followed immediately reducing the tariffs even further due to the influx of cheap solar PV panels from China. Finally, the amendments implemented since 2012 have changed the focus of the EEG away from merely increasing the solar PV deployment to ensuring smooth integration of solar electricity into the grid and the market (Hoppmann, Huenteler, and Girod 2014). For this reason and also because of other countries jumping on the bandwagon of comprehensive solar PV deployment support, we terminate our analysis in 2011 when total installed solar PV capacities had reached 25,429 MW (BMWi 2016b).

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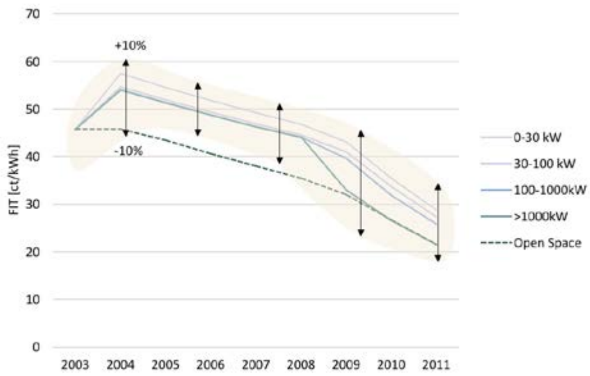
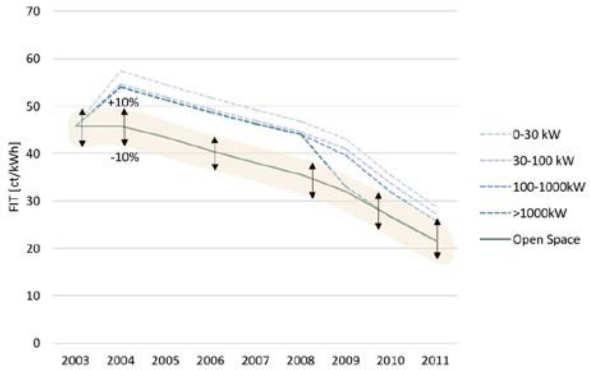
A Appendix

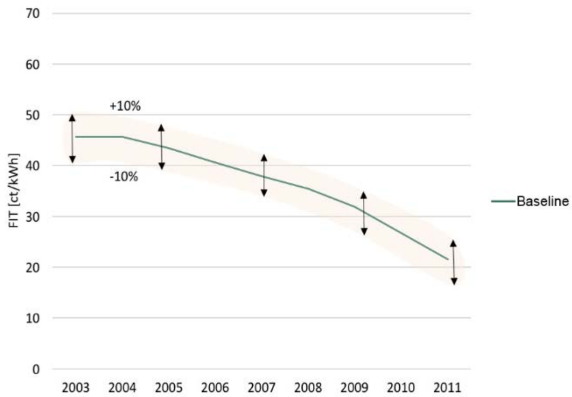
a) Scenario 1a



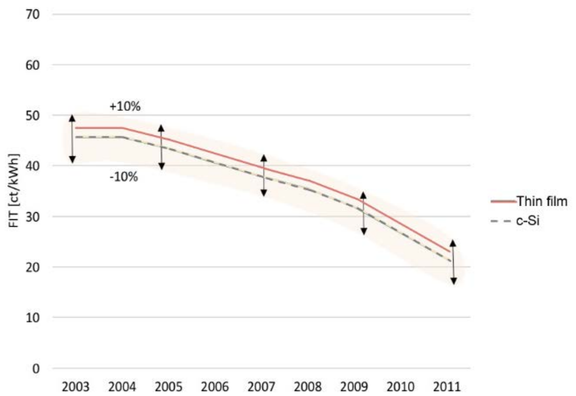
b) Scenario 1b



c) Scenario 2



d) Scenario 3a



e) Scenario 3b

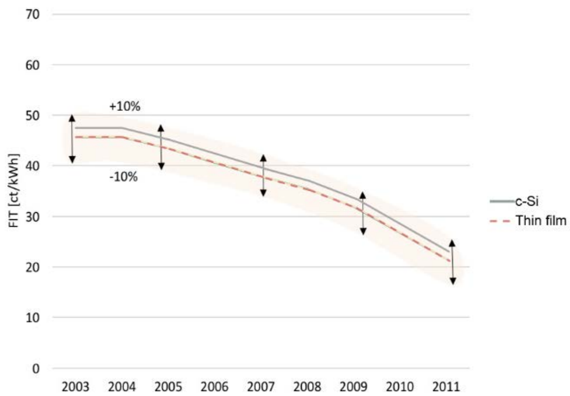
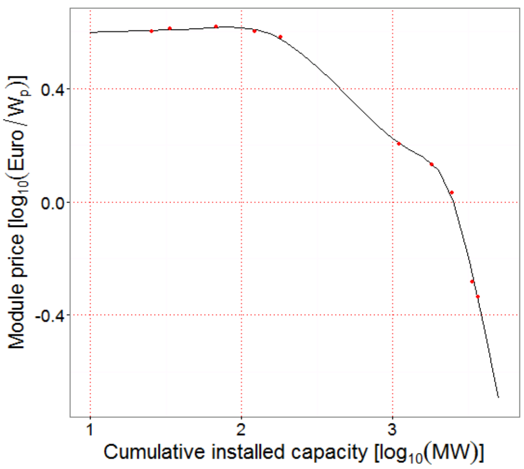
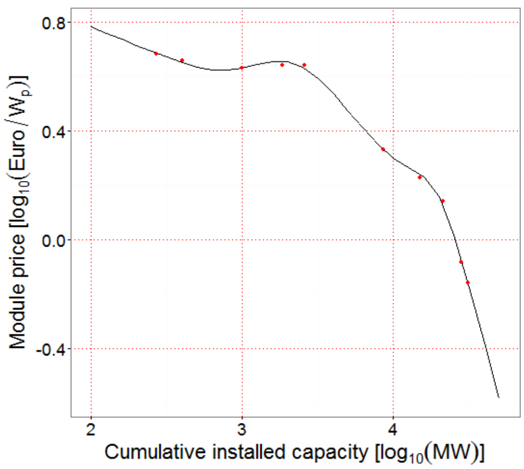


Figure A. 1. Variations (in beige) of the tariffs in the three alternative policy scenarios. a) In Scenario 1a, the historical rooftop feed-in tariffs (beige area) are varied between -10% and +10%, the historical open-space tariff staying the same. b) In Scenario 1b, the historical open-space feed-in tariff is varied (beige area), the historical rooftop tariffs staying the same. c) In Scenario 2, the baseline tariff (which corresponds to the historical open-space tariff) is given to all applications and subtechnologies and varied between -10% and +10% (beige area). d) In Scenario 3a, crystalline silicon is remunerated with the baseline tariff, thin film with a 5%-higher tariff. The sensitivity is analysed by varying the tariff for thin film between -10% and +10% of the baseline tariff (beige area). e) In Scenario 3b, thin film is remunerated with the baseline tariff, crystalline silicon with a 5%-higher tariff. The sensitivity is analysed by varying the tariff for crystalline silicon between -10% and +10% of the baseline tariff (beige area).

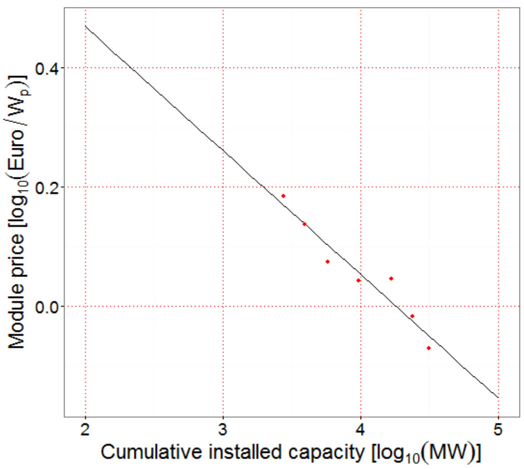
a) Thin-film price curve



b) Crystalline-silicon price curve



c) BOS price curve



d) Economies of scale

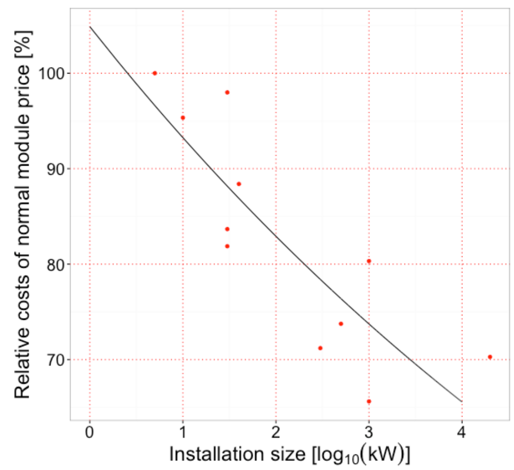


Figure A. 2. Historical price curves for a) thin film, b) crystalline silicon, and c) balance of system (BMUB 2007; BMWi 2011, 2014; Bundesverband Solarwirtschaft 2013; EnergyMap 2014; Fraunhofer ISE 2015; Hering 2011, 2012; IRENA 2015), and e) economies of scale (BMWi 2011, 2014; Bundesverband Solarwirtschaft 2013). See overview of functions in Table A. 1.

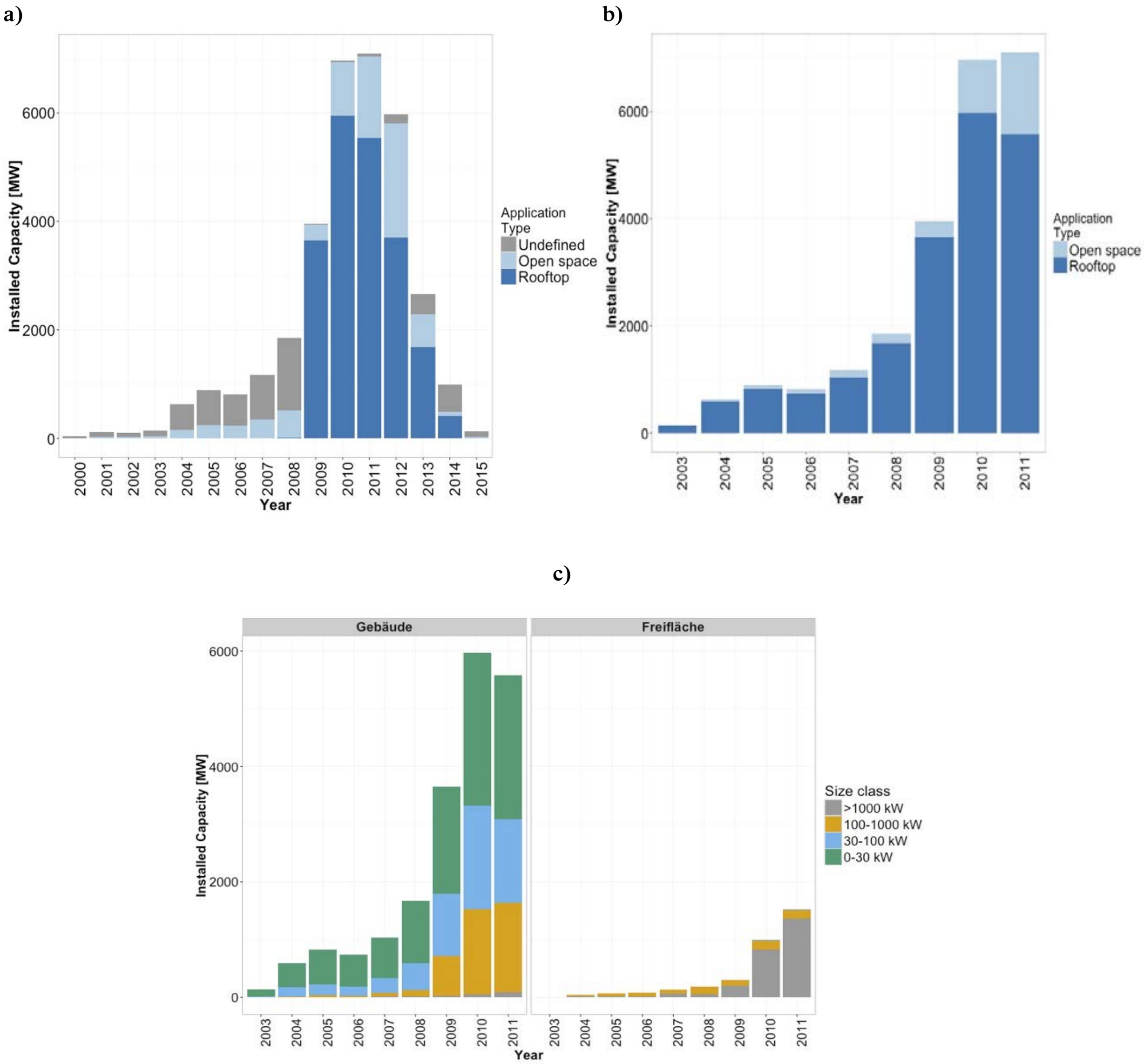


Figure A. 3. Data on historically built installations in Germany. a) Original data including unclassified installations (EnergyMap 2014). b) Data with distribution of different applications after classification process. c) Simulation input data differentiated by size classes within the rooftop (Gebäude) and open-space (Freifläche) applications.

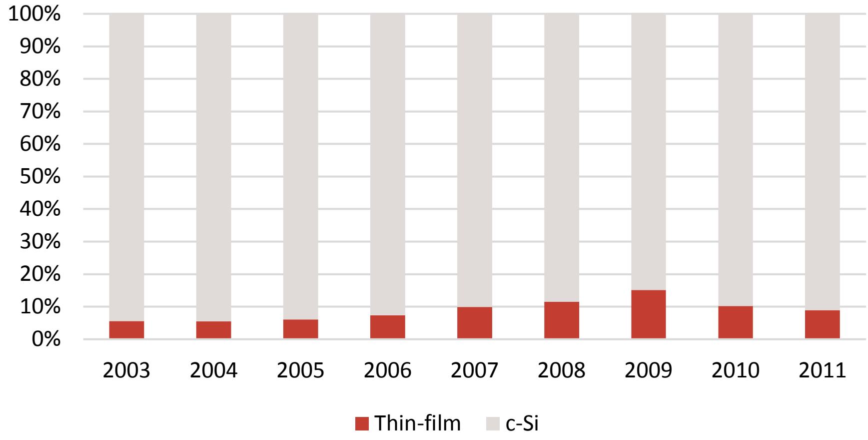


Figure A. 4. Historical shares of thin-film and crystalline-silicon solar PV in Germany for the analysed years, 2003-2011. Data aggregated from different sources including German and world market data (Bundesverband Solarwirtschaft 2013; EnergyMap 2014; Fraunhofer ISE 2015; Hering 2012).

Table A. 1. Overview of the different functions used in the model

Model function	Method	Result	Sources
Price curve thin film	Regression splines 4 knots, log/log	See Figure A. 2a	(BMUB 2007; BMWi 2011, 2014; Bundesverband Solarwirtschaft 2013; EnergyMap 2014; Fraunhofer ISE 2015; Hering 2011, 2012; IRENA 2015)
Price curve c-Si	Regression splines 4 knots, log/log	See Figure A. 2b	(BMUB 2007; BMWi 2011, 2014; Bundesverband Solarwirtschaft 2013; EnergyMap 2014; Fraunhofer ISE 2015; Hering 2011, 2012; IRENA 2015)
Price curve BOS	Linear Regression No knots, log/log	See Figure A. 2c	(BMUB 2007; BMWi 2011, 2014; Bundesverband Solarwirtschaft 2013; EnergyMap 2014; Fraunhofer ISE 2015; Hering 2011, 2012; IRENA 2015)
Module price thin film	Truncated normal distribution	**Mean** = derived from price curve **Sd** = 0.15*mean **Lower limit** = 0.4*mean **Upper limit** = 1.4*mean	(Bundesverband Solarwirtschaft 2013)
Module price c-Si	Truncated normal distribution	**Mean** = derived from price curve **Sd** = 0.15*mean **Lower limit** = 0.4*mean **Upper limit** = 1.4*mean	(Bundesverband Solarwirtschaft 2013)
Annually-generated power	Truncated normal distribution	**Mean** = 943.96 **Sd**= 133.61 **Lower limit** = mean – 2*Sd **Upper limit** = mean + 2*Sd	(EnergyMap 2014)
Economies of scale	Linear regression Log/linear scale	**ES (S)** = $104.87 \cdot S^{-0.051}$ See Figure A. 2d	(BMWi 2011, 2014; Bundesverband Solarwirtschaft 2013)

Table A. 2. Investment decisions per category from calibration step.

Category		2003	2004	2005	2006	2007	2008	2009	2010	2011
Roof-top	*0-30kW*	832,007	76,241	95,151	83,904	72,297	104,480	156,174	217,033	227,467
	30-100kW	1,669	5,407	6,246	4,884	6,340	10,931	23,275	35,964	28,338
	0.1-1MW	53	184	290	238	440	779	3,118	6,785	6,809
	> 1MW	0	0	0	0	2	4	27	38	49
Open Space	*0-30kW*	0	0	0	0	0	0	389	731	348
	30-100kW	0	0	0	0	0	0	87	70	53
	0.1-1MW	10	181	221	239	208	348	170	318	282
	> 1MW	0	9	14	15	32	29	86	271	349

Table A. 3. Model input values and sources.

Parameter	Unit	Value	Comments and sources
Module cost	EUR/W_p	See comments	The yearly updated output of the price curve (see Figure A. 2a,b) is used as input in a normal distribution function from which a value is randomly chosen (see Table A. 1 for more details on the distribution function). Sources: (BMUB 2007; BMWi 2011, 2014; Bundesverband Solarwirtschaft 2013; EnergyMap 2014; Fraunhofer ISE 2015; Hering 2011, 2012; IRENA 2015)
Balance of system cost	EUR/W_p	See comments	The yearly updated output of the price curve (see Figure A. 2c) is used as input in a normal distribution function from which a value is randomly chosen (see Table A. 1 for more details on the distribution function). Sources: (BMUB 2007; BMWi 2011, 2014; Bundesverband Solarwirtschaft 2013; EnergyMap 2014; Fraunhofer ISE 2015; Hering 2011, 2012; IRENA 2015)
Annually generated power	kWh/Wp	See comments	For every investment decision, a value is randomly chosen from a calibrated normal distribution (Table A. 1 for more details on the distribution function). Due to its lower efficiency, the normal distribution is 20% lower for thin film. Source: (EnergyMap 2014)
Duration of investment	Years	20	Between 2003 and 2011, the feed-in tariff in Germany is paid for 20 years (Bundesgesetzblatt 2000, 2004, 2008, 2011).
Project size	W_p	See comments	The selected installation's size is an empirical model input (see distribution of sizes in Figure A. 2c).
Feed-in tariff	EUR/Wh	See Table A. 4	See Table A. 4. Sources: (Bundesgesetzblatt 2000, 2004, 2008, 2011)
Annual O&M cost	EUR	10% of investment cost	
Inflation rate	%	1	
Discount rate	%	4	
Cumulative thin film capacity in Germany before 2003	MW_p	25.45	(EnergyMap 2014)
Cumulative c-Si capacity in Germany before 2003	MW_p	268.7	(EnergyMap 2014)

Table A. 4. Historical German feed-in tariffs between 2003 and 2011 as used in the simulation in [EURcts./kWh] (Bundesgesetzblatt 2000, 2004, 2008, 2011).

Category		**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Roof-top	*0-30kW*	45.70	57.40	54.53	51.80	49.21	46.75	4301	35.40	28.74
	30-100kW	45.70	54.60	51.87	49.28	46.82	44.48	40.91	33.68	27.33
	0.1-1MW	45.70	54.00	51.30	48.74	46.30	43.99	39.58	31.87	25.86
	> 1MW	45.70	54.00	51.30	48.74	46.30	43.99	33.00	26.57	21.56
Open space		45.70	45.70	43.42	40.60	37.96	35.49	31.94	26.72	21.59