Let the sun shine: optimal deployment of photovoltaics in Germany

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Abstract

The widespread use of subsidies in the form of feed-in tariffs to foster the diffusion of photovoltaics is recently being rediscussed in several countries. However, the difficulty to target tariffs may create a misalignment between profitability and installed capacity of panels. Our analysis tackles this issue. First, we set a discrete choice investment model with feed-in tariffs. Second, on the basis of that microeconomic model, we calculate optimal trajectories of feed-in tariffs and installed capacity that minimize subsidy costs for the government. The model is calibrated to study the diffusion process of photovoltaics in Germany and to simulate its future developments, showing distortions with respect to the optimal deplyoment path in terms of feed-in tariffs, installed capacity and cost trajectories.

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1 Introduction

During 2011, 14.2 GW of PV panels were installed resulting in 35 GW total photovoltaic (henceforth, PV) capacity worldwide, with OECD countries more than doubling their 2010 installations (OECD, 2012). Germany, Italy, USA, Japan and France, representing more than 87% of the world market, lead the diffusion process. The success of these countries can be explained by an early implementation of support policies (in Germany and Japan) or a more recent but intensive subsidization program (notably in Italy, France and USA). However, some bubbles have significantly disrupted market growth, as for instance in Spain. Germany experienced a similar problem but to a lesser extent, following the recent redefinition of the national Renewable Energy Act (Erneuerbare-Energien-Gesetz, henceforth EEG).[1]

Despite this fast diffusion process as well as several technological breakthroughs, PV price remains high. The levelized cost[2] of a unit of PV electricity ranges from 0.16 - 0.35 €/kWh, depending on its location as well as on the size and type of PV system used (EPIA Report, 2011). Investment costs are largely driven by the cost of modules, which in turn depends on refined silicon. The cost of modules, however, is steadily declining due to strong competition between manufacturers (Grau et al., 2011). In 2010 the average price of modules was about 1,6 €/Watt, almost 20% lower than the corresponding figure in 2009 which was itself 35% lower than in 2008 (IEA-PVPS, 2011b).

Economic analysis of PV deployment process has gained importance during the last decade. Two bunches of models have been used: adoption and learning approach on one side, and technological diffusion dynamics on the other.

The adoption approach describes the evolution of PV system price, according to the learning curve. This latter informs about the speed at which the price falls as installed capacity doubles (Wright, 1936) and remains the main tool for forecasting PV market growth (Nemet, 2005), despite some limitations such as sensitivity to data, or interaction with complex produc-

[1] The EEG Act was designed to encourage cost reductions based on improved energy efficiency from economies of scale over time. It came into force in the year 2000 and was the initial spark of a strong development of renewable energies.

[2] The "levelized cost of electricity" is equivalent to the total output of the PV system over its entire lifetime, divided by the total cost of installation and maintenance. This definition of the PV price does not take into account the intermittence or the gain in terms of avoided energy dissipated through the grid, as in Borenstein (2008).

tion technologies (McDonald and Schrattenholzer, 2001).

Models on diffusion of innovations explain the drivers of PV deployed. They are often described by "S-curves", making reference to general trends in technology diffusion, as in Geroski (2000) or Kishore and Rao (2010). Guidolin and Mortarino (2010) apply the Bass model to the PV sector in several countries finding that Germany, Japan, UK are at a mature stage; Australia, Canada, France are a steadily growing market. Extreme cases are represented, on the one hand, by Italy and Spain that started investing in this sector recently, and on the other, by Austria and The Netherlands that have overtaken the peak of installed power.

However, previous theoretical literature neglects the existence of subsidies and feed-in tariffs (henceforth FITs).that are actually crucial for PV development.[3] In fact, subsidizing PV increases the share of renewable energy and fosters grid parity.[4] A large body of empirical evidence suggests that adoption models should take into account the impact of subsidies to better explain the path of installed capacity. Indeed, support policies for renewables deeply change projects net present value and thus strongly encourage deployment, as shown by Dusonchet and Telaretti (2010) who calculate the value of investments in different European countries.[5] Hoz et al (2003) as well as Klein and Faber (2008) point out the lack of levers for the Spanish government in the task of achieving a PV target capacity without going over. The report by Charpin and Trink (2011) analyzes the case of France in a

[3]FITs are a premium rate paid for electricity fed back into the electricity grid from a designated renewable electricity generation source. FITs can be applied in two forms: *gross FITs* - whereby all electricity generated from a renewable source is purchased from the generator at a generous price, with the generator buying-back any electricity they need to use from the grid; or *net FITs* - whereby only unused or surplus electricity is purchased from the generator. Either of these FITs can be applied as a static subsidy, or can gradually decrease over time.

[4]Grid parity occurs when solar cells are able to produce electricity at a cost lower than the price of retail electricity purchased from the network, excluding grants and special rates. After reaching this threshold, the industry will survive without any subsidy, which is the main criterion for economic maturity.

[5]According to Dusonchet and Telaretti (2010), when FITs do not cover full investment costs, the impact of subsidies is very limited (as in the Netherlands, Luxembourg, Finland, Ireland and Sweden). FITs effectiveness can be weak because either the target for PV installation is too low (as in Austria) or FITs values are guaranteed for a limited time span (which happends in Cyprus, Luxembourg and the Netherlands), or even the administrative procedures are too complicated (as in Greece and France). In the same line, Zhang and Hamori (2011) also provide empirical evidence by examining subsidies offered in Japan. They show that installation costs have a negative effect on PV system adoption, whereas public subsidies as well as housing investment and environmental awareness among residents have positive effects.

similar vein. The two latter studies point out a drawback also discussed by Hansen and Percebois (2010): the risk that production responds in excess or in default when the energy policy objective is not clearly announced or readjusted too often.

Our paper adds to existing models along two main directions. First, we adapt a standard discrete choice model to take into account government subsidies together with technology diffusion and learning as PV investment drivers. Second, we calculate the optimal level and dynamic path of FITs for a given target of installed capacity, minimizing public subsidy costs, under the constraint that the evolution of PV demand is determined by the discrete choice model we set up. Our non-linear optimal control model, linking installed capacity targets to FITs, is calibrated it on German data, from 1998 to 2009, and then numerically solved.

Model simulations and forecast allow us to characterize three phases of PV development in Germany: initial growth (2000-2006), stability (2007-2012) and maturity (2013-2020). We show that a 2020 target of 70GWp of installed PV capacity would have required an initial value of FITs equal to 1.4€/kWh, well above the highest tariff observed so far in European countries. Total costs of the FITs program are then calculated. To our knowledge, this kind of evaluation has never been performed.[6] We find that reaching 70 GW in 2020 costs $67 * 10^9$€ in the optimal scenario. If we constrain the FITs to the actual cap, that is 0.6€/kWh, subsidy costs increase of nearly 55% compared to the total FITs bill obtained in the optimal scenario. We then move to a scenario based on reality, and we show the distortions created by the German policy. According to our model calibrations, FITs costs reached $121 * 10^9$€ up to 2009, that is approximately the double of the optimal (unconstrained) costs as calculated from 2001 to 2020. With respect to other analyses on the German case, in particular the Berger's (2010) report, we forecast a smoother PV price decrease and a faster reduction in FITs, which, according to our simulations, would be phased out in 2017.

The paper is organized as follows. We set up an adoption model that encompasses the impact of FITs (Section 2) which is then used to calculate optimal subsidies (Section 3) calibrated on German data (Section 4). A widespread evaluation of the German policy as well as a forecast of PV market growth are then performed. We briefly conclude (Section 5) by

[6] Wüstenhagen and Bilharz (2006) explain the impact of German policy on the deployment of renewable energy. Green power marketing driven by customer demand, on the other hand, has had limited measurable impact. Jacobsson and Lauber (2006) finds that, up to 2003, total amounts of subsidies to PV in Germany amounted to 2.7 billion euros.

suggesting some extensions of the model which are left for further research.

2 Discrete choice with feed-in tariffs, diffusion and learning

We consider a discrete yearly time scale t. A representative consumers is assumed to invest by equity or by debt. At time t, the representative consumer has a utility function U_t and has to make a binary choice (Ben-Akiva and Lerman 1985; Train, 2009).

If he chooses to invest, his utility function will be the sum of the observed (V_{1t}) and unobserved utility modeled by a random variable (X_1):

$$U_{1t} = V_{1t} + X_1. \tag{1}$$

If he chooses to not to invest, the utility function is:

$$U_{2t} = X_2, \tag{2}$$

which is normalized to zero.

The terms X_1 and X_2 are independent and identically extreme valued distributed according to the logit demand model. The function that describes the probability that a given consumer buys PV panels between t and $t+1$ is denoted by P_t. The logit demand model gives the probability function:

$$P_t = \frac{\exp(V_{1t})}{1 + \exp(V_{1t})}. \tag{3}$$

We embed into the standard logit demand model the following specification of the representative consumer's observed utility:

$$V_{1t} = NPV_t u_t + l_t, \tag{4}$$

where NPV_t is the *net unit present value* of an installation and l_t is the diffusion process.

The function $NPVu_t$ is defined as the sum of annual actualized cash flows over the life time less the initial investment cost, divided by the power of the installation:

$$NPVu_t = FIT_t.E.\sum_{k=1}^{N} \frac{1}{(1+\delta)^k} - p_t.(1 - r_t). \tag{5}$$

where:

FIT_t is the FITs level;

δ the rate of capital depreciation;

N is the life length of a facility;

E is the sunshine duration;

r_t is the investment tax credit (or ITC) level;

p_t is the unit price of the installation.

In the above equation (5), *system prices* p_t depend on the learning curve:

$$p_t = p_0 . \left(\frac{x_t}{x_0} \right)^{-b}, \tag{6}$$

where p_0 and x_0 are respectively the system price and installed capacity at date zero, and x_t the installed capacity at date t.

Finally, as for the *diffusion process*, we need to specify the demand function and the potential market. This latter, defined as the sum in terms of potential installed capacity of all individuals who are likely to invest in a project, will be denoted by M_t. Since the larger the amount of PV capacity, the larger the number of potential buyers (Lobel and Perakis, 2011), the l_t function is modelled as follows:

$$l_t = \log \left(\frac{x_t}{M_t} \right). \tag{7}$$

Finally, V_{1t} depends on three factors: the net present value at time t ($NPVu_t$) of the project, which in turn takes into account the system price evolution p_t according to the learning curve, as well as the technology diffusion process.

PV demand q_t depends on the dynamics of the installed capacity between t and $t+1$:

$$q_t = x_{t+1} - x_t, \tag{8}$$

or, by using equation (3):

$$q_t = M_t . P_t \tag{9}$$

The probability P_t is thus:

$$P_t = \frac{q_t}{M_t}. \tag{10}$$

Combining equations (3) and (10) gives:

$$\frac{q_t}{M_t} = \frac{\exp(V_{1t})}{1 + \exp(V_{1t})}, \tag{11}$$

or:

$$\frac{\frac{q_t}{M_t}}{1-\frac{q_t}{M_t}} = \exp(V_{1t}). \tag{12}$$

Assuming that the potential market size is very large[7] compared to demand over the period analyzed (i.e. $q_t/M_t < 1$) and that M_t changes little over the considered period (as in Guidolin and Mortarino, 2010),[8] we have:

$$\frac{\frac{q_t}{M}}{1-\frac{q_t}{M}} \approx \frac{q_t}{M} = \exp(V_{1t}). \tag{13}$$

Finally, recalling the demand equation (8) , we obtain:

$$x_{t+1} - x_t = \exp(V_{1t})M \tag{14}$$

For ease of reading, we rename the right hand side of function (14) as follows:

$$x_{t+1} - x_t = f(FIT_t, r_t, x_t). \tag{15}$$

The function $f(FIT_t, r_t, x_t)$ in equation (15) highlights the most important ingredients of the NPV and will enter the Government objective function to obtain optimal $FITs$, as we show in the following Section.

3 Optimal feed in tariffs

We now consider the cost minimization of a government whose objective is to reach a given target of installed capacity, by using $FITs$ as control.[9] For the PV capacity installed according to the discrete choice approach summarized by equation (15), the state has to pay the discounted cost of $FITs$, in proportion to the electricity produced over the lifetime of that

[7] This assumption is quite realistic if we compare 2020 and 2050 objectives. Indeed, worldwide photovoltaic will count for only 0.8% of renewable energy by 2020 against 22% in 2050 according to IEA forecasts.

[8] For a dynamic version of the Bass model, see Mahajan and Peterson (1978).

[9] The government could affect prices through the interest rate r_t which represents the investment tax credit. To solve the optimal control problem, for ease of calculation, we assume that the government uses only FITs and installed capacity targets as instruments, leaving aside the investment tax credit rate, which is used as a parameter.

installation. Thus, at a given time t, the cost for the state for installed PV, denoted by $c(FIT_t, r_t, x_t)$, will be:

$$c(FIT_t, r_t, x_t) = f(FIT_t, r_t, x_t).(p_t q_t r_t + \sum_{k=1}^{N} \frac{1}{(1+\delta^k)}.E.FIT_t). \qquad (16)$$

Summing the cost function in equation (16) over time up to T, the date at which total PV modules attain the deployment target gives the total PV cost:

$$C(T, FIT, r, x) = \sum_{t=1}^{T} c(FIT_t, r_t, x_t), \qquad (17)$$

where $x = (x_1, \ldots, x_T)$, $r = (r_1, \ldots, r_T)$ and $FIT = (FIT_1, \ldots, FIT_T)$.

Let us consider 0 as the starting year, with the installed capacity $x_0 = X_0$ and $x_T = X_T$. The objective of the government is to solve the following problem:

$$\min_{FIT,x} C(T, FIT, r, x) \qquad (18)$$

under the constraints:

$$\forall t \in [|0; T-1|] \; x_{t+1} - x_t = f(FIT_t, r_t, x_t), \qquad (19)$$

$$x_0 = X_0, \qquad (20)$$

$$x_T = X_T \qquad (21)$$

The optimal feed in tariffs balance two kind of drivers: direct subsidies that allow market growth, and the growth itself which reduces in the next period the cost of investments needed to maintain the adoption trajectory. This is actually a non-linear optimization problem that we solve numerically with MATLAB.

4 Empirical analysis: the German case

Since 2004, Germany is among the countries with the highest annual PV installations. In 2010 more than 50% of the worldwide PV installations were carried out in Germany with a capacity of around 17.2 GW connected to the grid and allowing a production of 12 TWh, roughly 2 % of the domestic consumption. All renewable energies together have a share of 16.8% of the domestic energy supply which, according to the German National Renewable

Energy Action Plan, will include a target of a 38.6 % for 2020. For PV, the scenario assumes around 7 % of the overall renewable production.[10]

The main driving force for the PV market in Germany is the Renewable Energy Sources Act (EEG) which determines the procedure of grid access for renewable energies and guarantees favorable FITs for them paid via the utilities.[11] For the PV sector, FITs depend on the system size and whether the system is ground mounted or attached to a building. Since 2009, there is also a tariff for self consumed power. The rates are guaranteed for an operation period of 20 years. Initially, a steady yearly reduction of the PV tariffs was foreseen. On the background of a constantly rising number of installations, a mechanism was introduced to adapt the EEG tariff to the market growth. Under this scheme, the reductions are increased or decreased if the marked deviates from a predefined corridor. For 2009 this corridor was framed between 1 and 1.5 MW, which was significantly exceeded as the market reached 3.8 MW. For 2010 to 2012, a new corridor between 2.5 and 3.5 MW was defined. Furthermore, for 2010 two additional reduction steps were agreed to adapt the tariff to the system price level. This resulted in an overall FITs reduction of roughly one third from 2009 to early 2011. However, with around 7 MW installed in 2010 the new corridor was surpassed again considerably. In July 2012, Germany's parliament has voted in favor of new photovoltaic cuts.[12]

Notwithstanding these changes, the overall FITs program helped make Germany the world's largest market for photovoltaic power generation. Our analysis is intended to shed lights on this fast growing market and the interaction between the development of PV capacity and energy subsidies.

4.1 Deployment Path

The model is calibrated on German data from IEA (2011), IEA-PVPS (2011) and IMF (2011), over the period 1998 to 2009. The long term interest rate which represents the capital depreciation rate is $\delta = 0.03$**,** according to

[10] For more details on the PV industry in Germany, see IEA-PVS (2011b), as well as Grau et al (2011).

[11] In addition to the EEG, PV receives support from other sources: local fiscal authorities provide tax credits for PV investments; the state owned bank KfW-Bankengruppe provides loans for individuals as well as for local authorities.

[12] The new building-integrated rates will receive the following support:small arrays up to 10 kilow atts: 19.5 cents per kilowatt-hour; 10 to 40 kilowatts: 18.5 cents; 40 kilowatts to one megawatt: 16.5 cents; 1 to 10 megawatts: 13.5 cents. All ground-mounted systems up to 10 megawatts now will be subject of a 13.5 cents incentive. As from 2013, the government will retain the 2.5 MW to 3.5 MW annual growth corridor.

OECD (2012). We calculate the coefficient of learning as the slope of the curve in equation (6): $b = 0.064$. Thus the learning rate is: $LR = 1 - 2^{-b} = 0.044$, meaning that for each doubling of cumulative installed capacity, the average price of PV has fallen by approximately 4%.[13]

We estimate the following diffusion model, which is the empirical counterpart of equation (14):

$$\log(q_t) = a_1.NPVu_t + a_2.\log(x_t) + a_3 + \varepsilon_t, \tag{22}$$

The following table shows results of the linear regression ($R^2 = 0.990$ with all the coefficients significative at 1% level).

a_1	$1.31.10^{-4}(0.315.10^{-4})$ ***
a_2	$0.848(0.051)$ ***
a_3	$-0.750(0.22)$ ***
R^2	0.990

Table 1. Coefficients for the objective function (standard error: in parenthesis)

We then simulate the optimal path between 2000 and 2020. In the base year, cumulative capacity was $x_0 = 76MW$, whereas the target for 2020 is $x_T = 70GW$. [14] We also consider the case for constrained $FITs$ to an upper limit of 6c€/kWh, as observed subsidies so far never exceeded this value. As for the other parameters, $E = 995\ kWh/m^2/year$.[15] We neglect maintenance costs (in general they account for 0.5% to 1.0% of total costs).

The optimal trajectory shows clearly three phases which we describe in turn.

[13] Notice that we prefer to estimate the learning rate specific to Germany as previous studies display very different figures. Studies such as Poponi (2003) or Bandhari and Stadler (2009) consider global learning rates of about 15-20%. Lobel and Perakis (2011) found a 8% learning rate in Germany for the period 1991-2007.

[14] At the time of writing this paper, this was the objective in force (http://heloim.sinclair.over-blog.com, BSW-German Solar Industry Association). Although the target capacity we choose is above the objective defined by the EEG in July 2012 (subsidies will be halted when a cumulative capacity of 52 GW is reached), our analysis remains valid as it has mainly a methodological intent.

[15] See http://www.sealite.com.au/technical/solar_chart.php.

4.1.1 Phase 1: priming and high growth

This first phase lasts until 2006 for the free case and until 2010 for the case in which the FITs are constrained. This phase is characterized by very high market growth which slows down during the transition to phase 2. It should be recalled here that we consider the annual installed capacity and not the cumulative installed capacity.

This first phase can be explained by the effect of the diffusion term $\log(x_t)$. Indeed, its marginal contribution is much more important when the cumulative installed capacity is still small, i.e. during the beginning of its development (Figure 1). This is a direct consequence of the shape of the logarithm which enters equation (22). Thus, we find that the optimal path corresponds to very high tariffs at the early development stage: FITs reach 1.4€/kWh in 2001. If we constrain the subsidies to the highest value observed so far, that is 0.6€/kWh, the trajectory slightly changes (Figure 2). Notice that optimal unconstrained FITs fall to zero in 2011, whereas they disappear in 2015 if the FITs policy is capped.

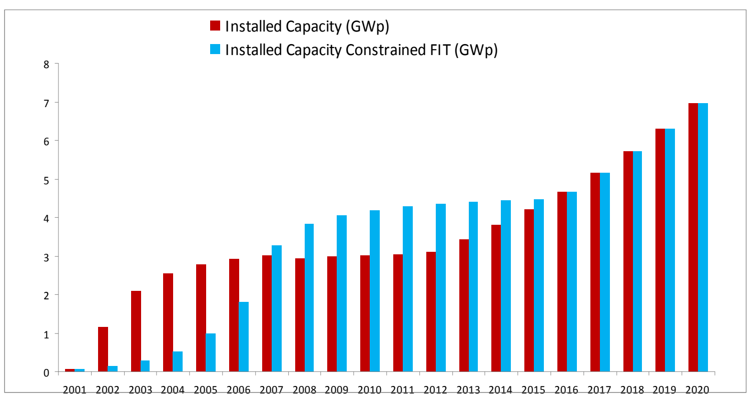

Figure 1: Optimal Trajectory: installed capacity.

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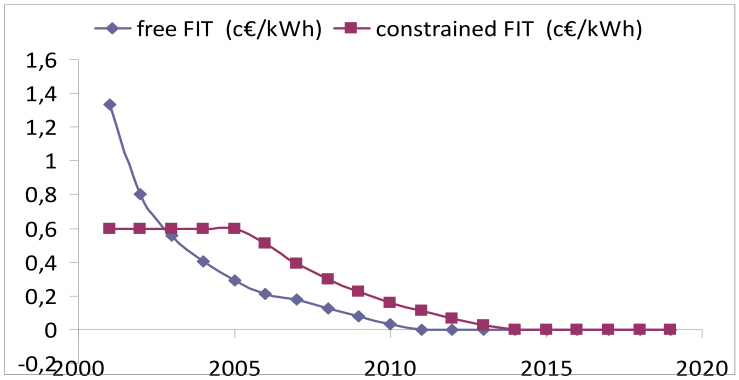

Figure 2: Optimal Trajectory: FITs free and constrained.

4.1.2 Phase 2: shift in business model and stable market

This second phase covers the 2007-2012 period for the free path and 2010-2016 for the constrained path. The market remains stable from year to year, contrary to phase 1. Explanation of the shape of the dynamic process can be found by observing the trajectory of NPV. Indeed, during the same period, the NPV decreases and becomes even negative (Figure 3). The market is no longer supported by feed-in tariffs but by the diffusion term only. Photovoltaic panels become a "standard" commodity.

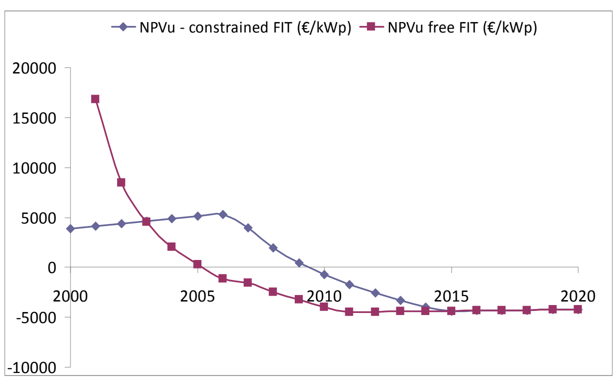

Figure 3: Net present value of PV investment.

This transition would mean that consumers invest only for green preferences or grid parity, two factors that are not explicitly taken into account here.

4.1.3 Phase 3: return to growth and economic maturity?

This third and final phase is the 2012-2020 period for the unconstrained model and 2017-2020 for the constraint model. It is characterized by a return to growth and the end of FITs. The return of growth is explained by the diffusion term, whose effect is dominant. Indeed, FITs no longer exist, but prices are still decreasing, providing a new driving force for growth. This phase could be interpreted as economic maturity given that the market develops without government intervention. System prices continue to fall providing sustainable driving forces to this new business model.

4.2 Forecasting with optimal path

We now compare simulations with real data. For the period between 2000 and 2009, prices and subsidies are observed data and as from 2009, and then simulated between 2010 and 2020. Similarly, installed capacity is simulated from 2001 to 2019. Investment tax credit rates are equal to zero from 2006. We forecast the electricity price through a simple linear interpolation based on data from 2000 to 2009. This part of the curve has an exponential shape both in the real and in the simulated case. As Figure 4 shows, the model adequately matches real data until 2009, stressing the reliability of our forecasts.

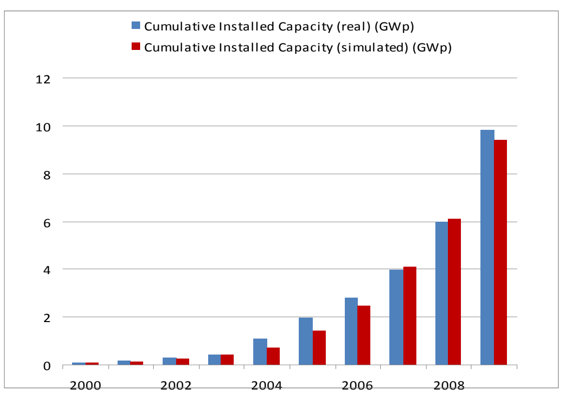

Figure 4: Path of installed capacity 2000-2009.

4.2.1 Installed capacity

After 2010 the curve displays a much more regular development. The second part looks like a simple linear trajectory but this observation is not entirely accurate as we can see on the annual installed capacity curve. This curve shows three different phases. The first corresponds to the 2000-2009 period. Annual installed capacity is small, but it increases quickly. This growth could be described as exponential. It then follows a more stable phase where the market is important but stable. This is indeed a linear growth for cumulative installed capacity and corresponds to the 2010-2017 period. The third period after 2017 is characterized by strong growth (Figure 5).

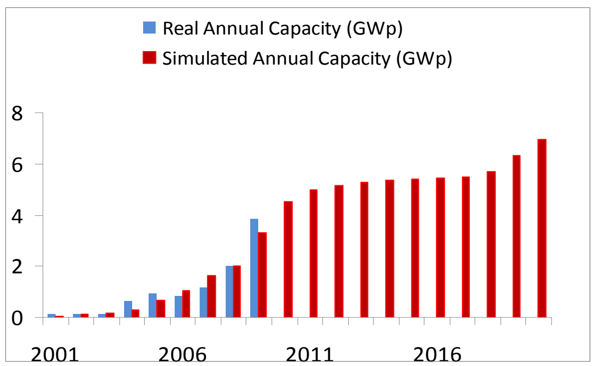

Figure 5: Annual installed capacity.

4.2.2 FITs trajectory

Tariffs level falls rapidly with the diffusion model (Figure 6). FITs reach the level of household electricity tariffs in 2012 and the level of industrial tariffs the year after. As a consequence, tariffs continue due to the commitment in the years prior to the grid parity, but are no longer needed from 2017.

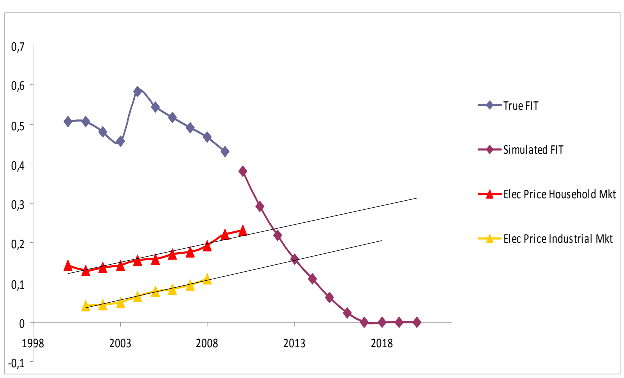

Figure 6: FITs forecast (euros/KWh).

4.3 Cost of the German policy

To complete our simulations, we calculate the cost of the German policy under three scenarios (optimal policy, constrained optimal policy and actual policy). Recall that each year, the Government commits to a FITs that will hold 20 years. Therefore, each year we take into account the forward looking cost in 20 years ahead.[16]

The *first scenario* corresponds to the optimal trajectory. Attaining 70GW of cumulative PV capacity costs $67 * 10^9$€, of which $25 * 10^9$€ at the very beginning of the simulated period (2000-2003) and the remaining $42 * 10^9$€ until 2012 when FITs fall to zero.

In the *second scenario* we take into account the cap on the FITs of 0.6€/kWh. Total costs amount to $104 * 10^9$€, an increase of nearly 55% compared to total costs obtained in the first scenario. During the period in which the cap applies, that is until 2006, constraining the FITs essentially smooths the cost to $26 * 10^9$€. As a consequence, the grid parity shifts to 2015, with a cumulative cost from 2007 of $78 * 10^9$€.

Finally, in the *third scenario*, we calculate the real costs up to 2009 and then we switch to the optimal trajectory as simulated according to our model calibration. Total costs amount to approximately the double of the costs we get in the first scenario, attaining $121 * 10^9$€. The cost of the German FITs policy implemented until 2009 is $50 * 10^9$€. Adopting the optimal policy from 2009 up to the grid parity, reached in 2017, would cost $71 * 10^9$€.

4.4 Comparison with the German roadmap

In this Section, we will compare the optimal path obtained by our simulations to the objectives of the German roadmap and in particular to Berger (2010). The main objectives described in the report are: to lower system prices by 50%; to install between 52 and 70GWp; and finally, to limit the additional cost of photovoltaics on the electricity tariffs to 2c€/kWh.

Assuming that the upper limit of installed capacity has to be reached, we focus on the evolution of system prices and FITs. In fact, the objective to reduce prices by 50% between 2010 and 2020 is very ambitious. According to the roadmap, two driving forces will help attaining this objective: low prices and 60% of self consumption. Figure 7 below compares the PV price

[16] In the Appendix, we report the detailed annual simulated data, FIT and installed capacity for each scenario.

forecasts of the report and those of our simulation. Regarding the latter, the price is estimated with learning curves, using the diffusion model for predicting installed capacities. We simulate our model by accounting for two learning rates, that is 4% , consistently with our estimates, and 19 % which corresponds to the global rate as in Shaffer et al (2004). Our model predicts a less pronounced price decrease than the two forecasts by Berger (2010), respectively in pink (less favorable scenario) and yellow (most favorable scenario). Both cases are in fact driven by a very high learning rate which does not specifically correspond to the German case.

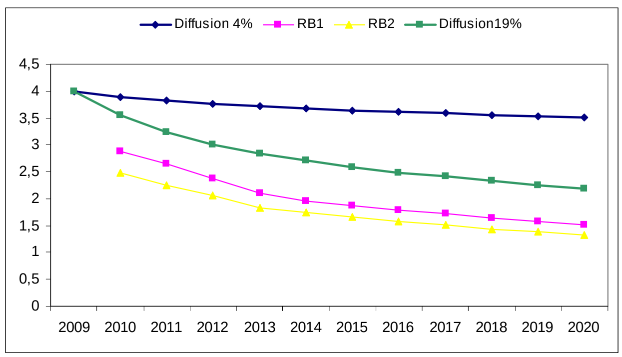

Figure 7: PV price forecasts (euro/Kwp).

Regarding the evolution of FITs, Berger's forecasts are made from the 2011 EEG law, assuming that PV capacity stays between the lower forecast (EEG1), corresponding to a situation where the objectives in terms of installed capacity are not reached, and the upper forecast (EEG2) that would apply if the installed capacity remains below the target. The shape of the FITs forecasted by our model decreases faster than the one provided by the report (Figure 8). Berger's results do not seem to take into account the evolution of electricity prices that would make PV competitive before 2020.

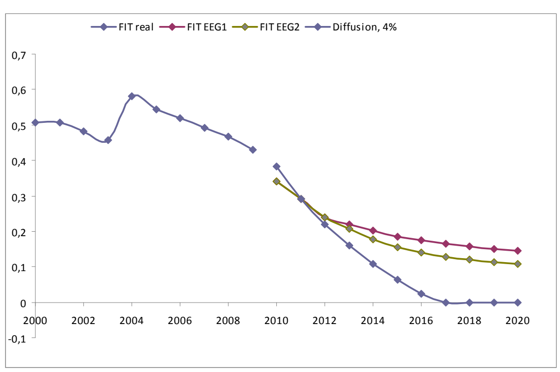

Figure 8: FITs forecast. Berger report and model simulations (euro/Kwh).

Different elements illustrate that simulations based on our diffusion model with a 4% learning rate describes the German PV deployment more adequately than the Berger's report, showing in particular grid parity for household in 2013 (2012 in simulations), with tariffs ending in in 2017, as in the model simulation.[17]

5 Conclusion

This paper develops a discrete choice approach which differs from the standard ones as we endogenise all the NPV drivers for PV investment: technology diffusion, learning rate and government subsidies. Based on that model, we numerically solve a non-linear optimal control model, consisting of the minimization of the total subsidies costs, for a given target of installed capacity. The model adequately describes the evolution of German PV market during the 2000-2009 period and allows to simulate its development until 2020. We identify three periods: a priming phase with strong growth, a transition with a stable market and a mature phase with a return to growth. Moreover, to minimize costs to the taxpayer and the State, we forecast that Germany FITs will reach the level of electricity prices for households at the and of 2012 and should disappear as from 2017.

The model would gain accuracy with a finer time step and the use of an explicit Euler scheme. Our approach could also be refined by adding financial terms in the discrete choice model to encompass gains from the price differential between conventional electricity and PV power. These extensions are left for further research.

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[17] Some further discrepancies with respect to the objectives of the roadmap remain because of a few differences in assumptions and data. In addition, the transition between phase 1 and phase 2 is irregular in reality since the EEG law changes were abrupt, while the simulation represents the optimal trajectory. Moreover, the roadmap studies specifically 30kWp facilities, whereas we take into account total installed capacity, thus all facilities.

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6 Annex

6.1 Detailed costs, FITs and cumulated capacity: first scenario, optimal policy.

Year	Cumulative Capacity MW	FITs Euros/KWh	Forward Looking Annual Cost
2001	61.10565394	1.33719	932,519,538.2
2002	1151.240813	0.804659	10,572,106,871
2003	2090.164893	0.557115	13,289,506,040
2004	2551.342982	0.40321	11,740,421,318
2005	2786.325298	0.293489	9,332,706,742
2006	2921.618557	0.208938	6,966,656,832
2007	3007.649705	0.180455	6,194,113,712
2008	2947.026329	0.124364	4,182,765,341
2009	2985.416758	0.075968	2,588,336,815
2010	3014.569524	0.033455	1,150,997,982
2011	3037.406223	3.30E-15	0.000114317
2012	3094.608816	3.85E-16	1.36053E-05
2013	3432.773382	1.48E-16	5.79562E-06
2014	3805.42991	9.34E-17	4.05557E-06
2015	4215.833155	1.19E-16	5.7401E-06
2016	4667.518911	1.76E-17	9.39474E-07
2017	5164.325913	2.45E-17	1.44433E-06
2018	5710.419236	1.46E-16	9.5089E-06
2019	6310.315312	0	0
2020	6968.609	0	0

Table A. Optimal Policy

6.2 Detailed costs, FITs and cumulated capacity: second scenario, constrained optimal policy.

Year	Cumulative Capacity MW	FITs Euros/KWh	Forward Looking Annual Cost
2001	61.10565	0.6	418,423,590.9
2002	139.9703	0.6	958,452,389.9
2003	272.7255	0.6	1,867,499,567
2004	521.4512	0.6	3,570,659,286
2005	978.5771	0.6	6,700,848,497
2006	1803.023	0.6	12,346,278,802
2007	3262.818	0.511372	19,042,014,965
2008	3832.256	0.388658	16,998,317,647
2009	4058.062	0.296152	13,715,682,493
2010	4197.52	0.222319	10,650,064,265
2011	4290.919	0.161076	7,887,962,289
2012	4357.34	0.108857	5,413,314,990
2013	4406.771	0.063404	3,188,750,079
2014	4444.879	0.0232	1,176,877,218
2015	4475.094	4.19E-18	0
2016	4667.519	1.07E-18	0
2017	5164.326	5.91E-19	0
2018	5710.419	3.96E-19	0
2019	6310.315	2.90E-19	0
2020	6968.909	9.30E-20	0

Table B. Constrained Optimal Policy

6.3 Detailed costs, FITs and cumulated capacity: third scenario, actual policy until 2009, optimal policy from 2010 to 2020.

Year	Cumulative Capacity MW	FITs Euros/KWh	Forward Looking Annual Cost
2001	61.10565394	0.5062	353,010,036.2
2002	1151.240813	0.481	579,708,157.7
2003	2090.164893	0.457	950,168,494.3
2004	2551.342982	0.582	1,998,560,175
2005	2786.325298	0.544	4,190,547,616
2006	2921.618557	0.518	6,200,879,702
2007	3007.649705	0.492	9,263,220,867
2008	2947.026329	0.4675	10,666,712,335
2009	2985.416758	0.4301	16,187,234,248
2010	3014.569524	0.38201	19,668,804,279
2011	3037.406223	0.291856	16,631,287,02
2012	3094.608816	0.21957	12,921,622,677
2013	3432.773382	0.159418	9,582,218,945
2014	3805.42991	0.108008	6,589,204,471
2015	4215.833155	0.063177	3,896,671,430
2016	4667.518911	0.023467	1,459,620,772
2017	5164.325913	8.26E-13	0.051729234
2018	5710.419236	1.58E-13	0.01026724
2019	6310.315312	9.47E-15	0.000681809
2020	6968.609	0	0

Table C. German Policy