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Feed-in Tariffs for Photovoltaics: Learning by Doing in Germany?

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Abstract

This paper examines the potential effects of Germany’s feed-in tariff policy for small roof-top solar PV systems installed between 2009 and 2030. Employing a partial equilibrium approach, we evaluate the policy by weighing the benefits from induced learning and avoided environmental externalities against the social costs of promoting residential PV. We use a dynamic optimization model that maximizes social welfare by accounting for learning-by-doing, technology diffusion, and yield-dependent demand. We find a wide range of effects on welfare, from net social costs of 2,014 m€ under a “business as usual” scenario to 7,586 m€ of net benefits under the positive prospects of PV’s development. All scenarios reveal that the federal policy’s current remunerations are higher than the modeled feed-in tariffs.

Keywords: Photovoltaic, Learning by doing, Innovation, Renewable Energy Policy
JEL classifications: O33, Q42, Q48, Q55

1 Introduction

Solar irradiation provides the largest renewable energy potential on earth and solar photovoltaics (PV) are considered a promising technological solution to support the global transformation to a low-carbon economy and reduce dependence on fossil fuels. In recent years Germany has become the world’s largest market for installed PV. Although it remains one of the most expensive energy generation technologies, several studies expect PV to become competitive in the foreseeable future. Apart from progress in research, these presumptions are based on learning effects in production (learning-by-doing, LBD) as experience with PV technologies accumulates. However, PV’s missing competitiveness inhibits the realization of these learning effects and the associated capital cost reduction. Thus, the expected benefits on a macroeconomic level are suppressed by market failures and barriers from a microeconomic view.

Incentives in the form of properly-designed renewable policies can help to overcome the existing barriers. The German Renewable Energy Sources Act (Erneuerbare Energien Gesetz, EEG) with its feed-in tariffs has been especially successful for PV and other renewable energy technologies as measured by market growth. Nevertheless, this development has not solely found support in the political and scientific community. After the policy’s implementation, the high costs of promoting PV in a country with relatively low solar irradiation conditions, and the large profits returned to PV investors gave rise to a lively debate about the EEG’s economic efficiency and distribution effects for renewable energy technologies. An outcome of the subsequent re-negotiation of the EEG in 2008 is an amendment that adjusts feed-in tariff regulations for 2009-2012. At first glance, the re-negotiated EEG appears to be a flexible instrument with market-oriented tariff degression rates. However, an examination of the negotiation process suggests that the amendment is more political compromise than sound economic policy (Photon, 2008b).

This view could also be supported for EEG regulations in the past. Findings in innovation economics indicate that induced PV market growth in recent years has been too high to exploit learning effects optimally. Schaeffer et al. (2004) find that German PV module costs fell at a lower rate than the global average for each doubling in PV capacities. Neuhoff (2008a) also argues that growth rates should not be excessive for an optimal utilization of learning effects. For the last eight years, Germany’s exploding growth rates in the PV market have primarily resulted from the EEG’s feed-in tariffs. Studies of previous EEG regulations calculating the social costs and benefits for PV under existing feed-in tariff structures reach diverging conclusions (BMU, 2007; Frondel et al., 2008). Krewitt et al. (2005) predict PV’s global developments, but do not consider the German situation. Sandén (2005) develops a quantitative model to calculate PV’s future subsidy costs in OECD countries on an aggregated level. While Nitsch (2008) considers PV’s role in the future German electricity portfolio and the attributed social costs, he does not differentiate between types of PV installations. However, specific costs can vary considerably among small- and large-scale installations (BMU, 2007). A recent break-even analysis for German PV systems by Bhandari and Stadler (2008) focuses on PV’s grid parity using experience curves. They estimate learning costs, but do not determine an optimal subsidy policy. Partial analyses on avoided environmental externalities through PV power generation in Germany have also been undertaken (Krewitt and Schlomann, 2006; Klobasa et al., 2009). Nevertheless, these studies do not model consumer benefits from LBD, being a major argument in favor of PV technologies.

This paper determines an economically efficient policy of future feed-in tariffs for residential PV installations in Germany until 2030. Among the supported systems, residential roof-top installations show the highest specific investment costs and thus obtain the highest feed-in tariffs among the EEG-promoted technologies today. Therefore, this market segment is of particular interest for the subsequent cost-benefit analysis. Our inter-temporal model maximizes social welfare in a dynamic optimization approach, taking into account LBD and technology diffusion processes. For each year consumer benefits from learning processes and avoided environmental externalities are weighed against the feed-in tariffs’ social costs to determine an efficient remuneration scheme between 2009 and 2030. Assuming a business as usual case, we find that the support creates net social costs of about 2,014 m€ whereas in scenarios assuming different developments regarding economic growth and technological progress the net social benefits are 5,689 m€ or 7,586 m€ respectively.

The remainder of this paper is structured as follows. Section 2 reviews the concept of experience curves and empirical studies quantifying learning effects in PV industries. These findings are taken into account in the model introduced in Section 3. Section 4 presents the data and develops scenarios reflecting possible alternative developments in the residential PV market. Section 5 discusses the results and Section 6 concludes.

2 Learning by Doing

2.1 Theoretical Considerations

Learning or experience curves are a common concept to model technological progress in innovation economics. The concept is widely used to predict PV’s future costs as a function of experience with this technology. Although several functional forms have been proposed to represent LBD (Yelle, 1979), the most common approach is a power function:

$$C_x = C_1 x^{-\beta} \tag{1}$$

with C_x being the costs required to produce the xth unit, and x representing the cumulative production up to and including the xth unit of production. In the PV industry, cumulated production is generally measured in units of produced power capacity (e.g., Mega Watt peak, MWp). C_1 denotes the costs required for producing the first unit and β is the elasticity of unit costs with respect to cumulative production volume. The parameter β is also known as the learning or experience parameter.[1] In its

[1] According to Clarke et al. (2008), experience parameters additionally capture R&D, spillover effects, economies of scale, and other price-decreasing factors. Therefore, they are a generalization of learning parameters.

logarithmic form the relationship between costs and experience (represented as cumulated production) becomes more apparent:

$$\log C_x = \log C_1 - \beta \log x \tag{2}$$

Hence, double logarithmic graphs are often used to demonstrate learning effects, where the graph's slope is a measure of learning or experience. Owing to the described cost development for an increase in cumulative production, the learning parameter β is also used to calculate the progress ratio (PR):

$$PR = \frac{C_{x_2}}{C_{x_1}} = \frac{C_1 x_2^{-\beta}}{C_1 x_1^{-\beta}} = 2^{-\beta} \tag{3}$$

for $x_2=2x_1$. The PR measures the cost decrease per doubling of cumulated production. The learning rate (LR) is subsequently defined as:

$$LR = 1 - PR \tag{4}$$

and is usually expressed as a ratio or percentage. The LR indicates the savings in specific production costs after a cumulative doubling in production output. Due to learning curves' declining exponential form, production costs will tend to zero in the long run. Hence, Köhler et al. (2006) point out that floor costs are often specified for learning curves, which act as a lower bound on costs when technologies mature. Generally, cost predictions for PV do not apply floor costs because PV is still a young technology with specific production costs being far from zero in the foreseeable future.

As mentioned, a wide variety of learning or experience curves are applied in energy economics for policy and scenario studies. Gritsevskyi and Nakicenovic (2000) consider uncertainties in learning effects by a stochastic model of technological change. Harmon (2000) and Frankl et al. (2006) distinguish between regional and global learning to construct experience curves for PV. Different methodological approaches to determine learning curves also exist. Schaeffer et al. (2004) use weighted and unweighted linear regressions on lognormal cost and production data to infer learning curves. Staffhorst (2006) differentiates three types of learning curves concerning the measurement in costs and experience. Using learning curves in techno-economic models, the implementation of LBD also depends on the type of model, the production factors, and the number of goods under consideration (Göcke, 2000). Recent implementations of LBD to account for endogenous technological change in energy-environment-system models are further discussed in Löschel (2002), Grubb et al. (2002), Kypreos and Bahn (2003), Vollebergh and Kemfert (2005), Edenhofer et al. (2006), Pizer and Popp (2008), and Clarke et al. (2008).

2.2 Empirical Learning Effects in Photovoltaic Industries

The majority of studies focus on experiences in PV module production (Table 1) that are determined by global learning effects. However, a PV system also consists of wires, inverter, circuit breakers, safety switches, and other components needed for integrating PV in the grid. Often, different regional standards, technologies and network conditions make the attributed learning in *balance-of-system* (BOS) costs a local or regional phenomenon. Thus, a more comprehensive approach to evaluate PV system costs differentiates between specific costs for PV modules and all other system components, subsumed as BOS. This approach is commonly used to model PV cost predictions (Harmon, 2000; Frankl et al., 2006; Staffhorst, 2006; Benthem et al., 2008). Schaeffer et al. (2004) state that PV installations should be treated as compound systems between global (PV panels) and regional learning (BOS) because developments in production costs for the different components can vary considerably. They calculate separate LRs for inverters and remaining BOS components in Germany and the Netherlands.

Table 1: Empirical Studies on Learning Rates in PV Industries

Author	LR [%]	Time Period	Region	Component	Covered Cumulated Capacity [MW]	R^2
Harmon (2000)	20.2	1968-1998	global	modules	0.095-950	0.993
Parente et al. (2002)	22.8	1981-2000	global	modules	appr.[1] 10.5-1500	0.988
	20.2	1981-1990	global	modules	appr. 10.5-250	0.977
	22.6	1991-2000	global	modules	appr. 300-1500	0.978
Poponi (2003)	25	1976-2002	global	modules	4-2380	n.a.[2]
	19.5	1989-2002	global	modules	238-2380	n.a.
Strategies Unlimited (2003)	20 ± 0.4	1976-2001	global	modules	appr. 0.3-1800	n.a.
	23 ± 1.5	1987-2001	global	modules	appr. 100-1800	n.a.
Swanson (2006)	19	1979-2005	global	modules (cryst.[3] silicon)	appr. 3-4000	n.a.
Sark et al. (2008)	20.6±0.3	1976-2006	global	modules (cryst. silicon)	appr. 0.3-4000	0.992
	18.2±1.7	1987-2006	global	modules (cryst. silicon)	appr. 100-4000	n.a.
	29.6±1.4	1991-2006	global	modules (cryst. silicon)	n.a.	n.a.
	11.6±2.2	1997-2006	global	modules (cryst. silicon)	n.a.	n.a.
Maycock and Wakefield (1975)	22	1959-1974	USA	modules	n.a.	0.94
Williams and Terzian (1993)	18	1976-1992	USA	modules	n.a.	n.a.
Cody and Tiedje (1997)	22	1976-1988	USA	modules	n.a.	n.a.
Tsuchiya (1992)	21	1979-1988	Japan	modules (cryst. silicon)	n.a.	n.a.
IEA (2000)	16	1976-1996	EU	modules (cryst. silicon)	appr. 0.8-80	n.a.
	47	n.a.	EU	modules (cryst. silicon)	appr. 80-120	n.a.
	21	n.a.	EU	modules (cryst. silicon)	appr. 120-800	n.a.
Schaeffer et al. (2004)	26	1988-2001	EU	modules	appr. 170-1800	n.a.
	appr. 10	n.a.	Germany	modules	n.a.	n.a.
	appr. 10	n.a.	Netherlands	modules	n.a.	n.a.
	22 ± 1	1992-2001	Germany	BOS	appr. 3.9-162	0.878
	19	1992-2001	Netherlands	BOS	appr. 0.012-11	0.93
	9 ± 2	1995-2002	Germany	inverter	appr. 16-260	0.844
	7 ± 2	1995-2002	Netherlands	inverter	appr. 0.05-8.6	0.828

[1]appr. – approximately [2]n.a. – not announced [3]cryst. – crystalline

Source: Listed studies, Neij (2008), Staffhorst (2006).

The majority of global experience curves in Table 1 show LRs between 18% and 22%. In contrast, LRs for single countries or regions vary widely between 10% and 47%. According to Schaeffer et al. (2004), this can be explained by differences in national PV deployment programs and the associated installation numbers. Countries with growth rates in PV capacity above the global average will show less favorable LRs because module prices will decline at the same pace as in other countries, but the number of doublings in installation capacity will be higher than the international average. In the past this effect could be observed for countries with strong growth in PV installations, e.g., Germany and the Netherlands. Other discrepancies among experience curves for PV module costs can be attributed to differences in geographical conditions, technologies under consideration, and time periods. As discussed, experience and prices in BOS develop locally and thus, LRs for BOS will probably differ across countries (Neij, 2008).

3 The Model

Focusing on residential grid-tied PV installations, our calculations consider PV systems with a rated capacity up to 10 kWp.[2] Larger system capacities are considered as not applicable on residential roof areas for current efficiency factors of crystalline wafer-based solar panels. The same differentiation appears in other studies (BMU, 2007; Staiß, 2007).

3.1 Model Description

The model follows Benthem et al. (2008), who determine an efficient subsidy policy for residential PV installations within the California Solar Initiative policy. We modify Benthem et al. for application to Germany, but the modifications do not alter the model's basic properties, characterized by:

1. *Consumer choice*: reflected in the demand specification
2. *Learning-by-Doing*: represented through experience curves
3. *Environmental externalities*: directly incorporated in the objective function.

We wish to establish a time path of feed-in tariffs that maximizes the present value of net social benefits. However, this can also imply net social costs. Therefore, the EEG's benefits must be weighed against the feed-in tariffs' additional costs to evaluate the tariffs' impact on welfare versus a no-policy case. In our model welfare W accrues from costs and benefits in several years t.

The benefits from the feed-in tariffs' PV promotion are incorporated in the form of avoided external costs from fossil-fueled electricity generation (C^{ext}) and the consumer benefits from policy-induced LBD (CB_t). Owing to PV's prior electricity feed-in, C^{ext} is exogenously given, since it replaces a mix of gas- and coal-fired power plants. In contrast, consumer benefit CB_t is a function of the subsidy level s_t, the induced demand for residential PV installations q_t, and the average retail electricity price p_t^{el} in each period. The EEG's additional social costs are deducted from these benefits. They are determined by the difference between the paid feed-in tariffs FIT_t and the electricity prices p_t^{el}. This is represented in the model's objective function with the level of subsidies s_t being the decision variable.

[2] PV system capacities are rated in 'kilo Watt peak' (kWp), being defined as the power of a module under standard testing conditions (STC) of 1,000 Watt per meter square of irradiance, at 25 degree centigrade cell junction temperature on a solar reference spectrum of air mass 1.5.

$$\max_{s_t} W = \sum_t \frac{inst_t(s_t, p_t^{el}) \cdot \left\{ C^{ext} \cdot yield + CB_t(s_t, q_t, p_t^{el}) - \left[FIT_t(s_t) - p_t^{el} \right] \cdot yield \right\}}{(1+r)^t} \tag{5}$$

Being given as specific values, each of the benefits is multiplied by the installed capacity $inst_t$, which depends on the level of subsidies s_t and the electricity price p_t^{el}. To calculate total benefits from avoided external costs, additional multiplication by the average PV system’s annual electricity yield (*yield*) is necessary because specific external costs C^{ext} are given per kWh. The same holds true for the EEG’s social costs since feed-in tariffs are paid for the amount of electricity generated from PV. These costs and benefits are discounted at the social discount rate r to obtain the present value of welfare W.

A policy of s_t that maximizes W determines the optimal level of feed-in tariffs over time. Due to modeling reasons, we differentiate between feed-in tariffs (FIT_t) and the level of subsidies s_t. The latter is defined as the ratio between the feed-in tariff difference costs and the average retail electricity price p_t^{el} in each period t according to the following equation:

$$s_t = \frac{FIT_t - p_t^{el}}{p_t^{el}} \tag{6}$$

The ratio s_t is greater than zero, or becomes zero, when PV generation is competitive to average retail electricity prices p_t^{el} and therefore incurs no additional cost. Hence, the decision variable s_t is modeled as a positive ratio on the electricity price to determine the feed-in tariff in each period. This approach enables the model to account for varying p_t^{el} while decoupling the level of FIT_t from these fluctuations. Thus, combining equations (5) and (6) yields:

$$\max_{s_t} W = \sum_t \frac{q_t \cdot cap^{av} \left(\sum_{l=0}^{25} \frac{C^{ext} \cdot yield}{(1+r)^l} + CB_t - \left[\sum_{n=0}^{20} \frac{s_t \cdot p_t^{el} \cdot yield}{(1+r)^n} \right]_t \right)}{(1+r)^t} \tag{7}$$

with the additional denotations:

q_t	Demand for residential systems in number of installations
cap^{av}	Average capacity of residential PV installation
yield	Annual electricity yield per kWp installed PV capacity
l	The systems’ average lifetime period
n	Feed-in tariff remuneration period
r	Social discount rate

Apart from PV’s avoided external costs in electricity generation, the EEG’s second benefit accounts for cost reductions in PV equipment production through LBD from induced demand for the systems. Therefore, consumer benefit CB_t is calculated from actual costs for investment as well as operations and maintenance (O&M) for a PV system under the optimal feed-in tariff policy FIT_t in comparison to a no-policy case. Both investment costs C_t^{Invest} and O&M costs $C_t^{Operation}$ will be further specified later on. Again, O&M costs accrue over the system’s lifetime and need to be discounted.

$$CB_t = \left[C_t^{Invest}(0) - C_t^{Invest}(FIT_t)\right] + \sum_{l=0}^{25} \frac{C_t^{Operation}(0) - C_t^{Operation}(FIT_t)}{(1+r)^l} \tag{8}$$

The third summand in the objective function (7) deducts the EEG’s additional costs from the described benefits. Reforming equation (6) reveals that the product of s_t and p_t^{el} equals the cost differential between the current feed-in tariff FIT_t and the electricity price p_t^{el}. This difference constitutes the subsidies awarded due to PV’s missing competitiveness. Since feed-in tariffs are paid over a remuneration period of 20 years according to the EEG, the difference costs are discounted at the social discount rate r, transforming the series of payments to a discounted lump sum of subsidies at the point of investment.

Taxes are not considered in the objective function for three reasons. First, PV competes with centralized fossil-fueled generation in terms of generation and transport cost. For this purpose, household electricity prices must be considered net of taxes. Second, taxes obviously have allocative effects (“cash in transit”), but they influence welfare only marginally if price elasticity of demand is rather inelastic. This is obviously true of the electricity sector (Stoft, 2002). Third, rational investors will exploit the value added tax (VAT) exemption according to the German VAT Act.

3.1.1 Demand Specification and Calibration

Annual demand q_t is modeled according to Benthem et al. (2008). It consists of two terms, representing the price-quantity relation and PV’s diffusion ($diff_t$) into the market.

$$q_t = \frac{a_t q^{\max}}{a_t + (q^{\max} - a_t) \cdot e^{-b \cdot NPV_t}} + diff_t \tag{9}$$

The demand formulation above reflects price-quantity effects via the exponential term in the denominator. It accounts for investors’ aggregated microeconomic behavior, which is determined by the demand parameter b and the investment’s NPV. While b is derived from historical data and remains constant over time, NPV_t depends on the PV installation’s investment cost, the level of feed-in tariffs, and the electricity price. Calculating NPV_t is discussed below. Demand q_t is capped by the maximum annual market potential for residential PV systems $q^{\max}$. Moreover, the second demand function parameter a_t has a significant influence on q_t. As indicated by its index, a_t varies over time. It incorporates PV’s market diffusion $diff_t$ into the price-quantity term, accounting for higher acceptance and decreasing risk aversion to a fledgling technology when experience is accumulated.

$$a_t = a_{t-1} \cdot \left(\frac{q_{t-1} + diff_{t-1}}{q_{t-1}} \right) \tag{10}$$

The second term in equation (9), representing technology diffusion, follows a sigmoid curve and is formulated as a logistic growth function. It is based on the previous year’s demand level in the form:

$$diff_t = \gamma \cdot q_{t-1} \cdot \left(1 - \frac{q_{t-1}}{q^{\max}}\right) \quad \textbf{(11)}$$

Moreover, it depends on the diffusion parameter *γ*, which is determined from historical data and will be derived later in this section. Obviously, diffusion effects will asymptotically converge to zero as annual demand approaches its maximum $q^{\max}$.

Profitability determines an investment’s attractiveness. Consumer choice for residential PV is therefore reflected by its NPV in comparison to an alternative investment. This is taken into account by the investor’s discount rate *i*, which is determined by an alternative investment with equivalent risk-return conditions, assuming full information and rational behavior among investors. Hence, *i* mirrors the investor’s opportunity cost and must be distinguished from the social discount rate *r*. Depending on the year of commissioning, the NPV for a residential system, NPV_t, is calculated as:

$$NPV_t = -C_t^{Invest} + \sum_{n=0}^{20} \frac{(1+s_t)\cdot p_t^{el} \cdot yield - C_t^{Operation}}{(1+i)^n} + \sum_{m=21}^{25} \frac{p_{(t+m)}^{el} \cdot yield - C_t^{Operation}}{(1+i)^m} \quad \textbf{(12)}$$

With the additional denotations:

C_t^{Invest}	System’s specific investment cost [€/Wp]
$C_t^{Operation}$	Specific annual O&M cost [€/Wp]
i	Investor’s discount rate (opportunity cost of capital) [% per year]
m	Post feed-in tariff period [./.]

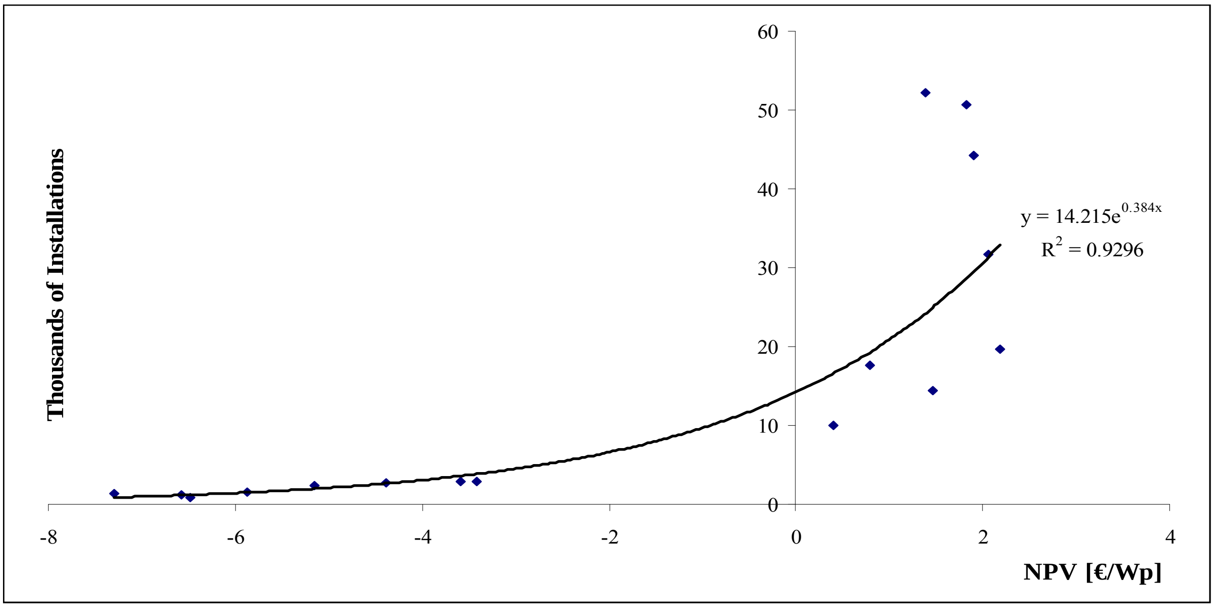
NPV_t is calculated from three summands as a specific value in €/Wp. The first summand represents the installation’s investment cost. The second reflects the earnings from fixed feed-in tariffs during the guaranteed remuneration period of 20 years less the installation’s expected O&M costs. These payments are discounted by the investor-specific discount rate *i*. The same calculation applies to the third summand, which reflects the investor’s avoided costs of external procurement. These benefits accrue after the period of guaranteed feed-in tariffs until the system’s expected end of life. Following the opportunity cost approach, the discount rate *i* acts as an internal hurdle rate for investments in PV. Any additional profits above the opportunity costs *i* will induce additional demand q_t, which is reflected in the above demand specification. In contrast, demand will drop to zero if the investor’s minimum profit expectations are not met. Consequently, NPV_t needs to be larger or equal to zero to incentivize installations. If NPV_t equals zero, investors are indifferent between an alternative investment and a PV investment. In this case we assume that the marjority of homeowners will usually decide in favor of their real estate’s appreciation in contrast to investing in government bonds with comparable risk-return profiles since the bonds are prone to inflation.

The above demand specification contains the parameters a_t and *b*, which are inferred from historical NPVs and the related number of installations. Owing to the technology diffusion term, demand follows a sigmoid curve according to a logistic growth function. We make use of the function’s characteristic that it approximates an exponential curve in its left-most interval. Hence, we follow the approach by Benthem et al. (2008) to calibrate the demand parameters a_0 and b as coefficients in the exponential regression function

$$f(x) = a_0 \cdot e^{bx} \tag{13}$$

where $f(x)$ is the number of installations (regressand) and x represents the NPV per rated Watt (regressor). Whereas b is constant over time, a_0 represents the starting value for a_t in the model’s demand specification. Using data between 1992 and 2007 to calculate historic NPVs and installations, the fitted demand curve is visualized in Figure 1. The resulting demand curve delivers parameter values of $a_0 = 14.215$ and $b = 0.384$. This fitted demand function has a coefficient of determination $R^2 = 0.93$, indicating that the regression parameters describe the historical data very well.

Figure 1: Annually Installed PV Systems versus NPV and the Fitted Demand Curve



Source: Own calculations, IEA (2006), Solarenergie-Förderverein (2009), RWE Transportnetz (2008), Vattenfall Europe Transmission (2008), e.on Netz (2009).

The diffusion parameter γ represents residential PV’s diffusion in percent of the prior year’s demand. It is therefore inferred from shifting the nonlinear regression curve from Figure 1 through the most recent data point (f(x) = 52,234 installations and x = 1.38 €/Wp in 2007), keeping b constant. The resulting adjusted coefficient a_0’ = 30.748 gives a new demand function that incorporates the diffusion effect over the last 16 years. Dividing both functions and the cumulated diffusion effect by 16 years we obtain the annual diffusion rate γ. It amounts to 0.135 per year. This falls in the same range as the findings for the California PV market by Benthem et al. (2008), who calculate an annual diffusion rate of 0.15.

3.1.2 Investment and Operation Cost Specification

We follow the approach to compose learning effects in PV system production from global learning in the PV panel industry and regional learning in BOS. This differentiation is common practice in recent studies on LBD in PV technologies (e.g. Schaeffer et al., 2004; Krewitt et al., 2005; Benthem et al., 2008). Thus, apart from PV panels, a system's cost positions are subsumed as BOS costs. BOS also includes inverter costs. Assuming that LBD exists in panel as well as BOS production, investment costs develop over time according to the following:

$$C_t^{Invest} = C_0^{Panel} \cdot \left(Q_{2007}^G \cdot \left[1 + g^{Panel}\right]^t\right)^{-\beta^{Panel}} + C_0^{BOS} \cdot \left(Q_{2007}^D + \sum_0^{t-1} q_t \cdot cap^{av}\right)^{-\beta^{BOS}} \qquad \textbf{(14)}$$

where the additional denotations are:

C_0^{Panel}	Starting value of specific investment cost for PV panels [€/Wp]
C_0^{BOS}	Starting value of specific investment cost for BOS devices [€/Wp]
Q_{2007}^G	Cumulative global PV capacity until 2007 [MWp]
Q_{2007}^D	Cumulative PV capacity for residential PV (<10 kWp) in Germany until 2007 [MWp]
g^{Panel}	Global market growth for PV panels [% per year]
β^{Panel}	Learning coefficient for PV panels [./.]
β^{BOS}	Learning coefficient for BOS devices [./.]

Because PV panels are traded on a global market, cost development in panel production is determined by an exogenous growth rate g^{Panel} assuming that German demand for small-scale PV does not effectively influence global PV module production numbers. In contrast, LBD for BOS components is driven by domestic demand. Hence, the second term of the compound experience curve in equation (14) reflects local experience in PV's integration into the existing grid.

Apart from the initial investment, O&M costs are distributed over the system's lifetime. Typically these costs comprise periodical payments (meter charge, safety checks, insurance), administration, cleaning and supervision, repairs, and component replacement. The largest cost position is caused by inverter replacement. In general, specific O&M costs decrease with growing system capacities. However, a recent empirical study of small-scale Swiss and German PV plants finds a strong heterogeneity in total O&M costs, which depend on the chosen concept of supervision and cleaning (BfE, 2008). Hence, we model O&M costs in the given formulation where ϑ is a parameter determining average annual O&M costs as a percentage of investment costs:

$$C_t^{Operation} = C_t^{Invest} \cdot \vartheta \qquad \textbf{(15)}$$

This is used by several other studies (WMBW, 2005; Staffhorst, 2006; Dürschner, 2009). This approach couples O&M to investment costs, also transferring learning effects in equipment production to O&M. It appears reasonable to connect the two terms, since learning also results in low-maintenance PV components.

4 Data and Scenarios

4.1 Data

Table 2 displays the input parameters and starting values in our model's base case. They refer to five categories: learning effects, market data, discounting, demand, and a group of remaining inputs. All nominal monetary values are in €$_{2008}$ to avoid inflationary distortions. If necessary, corrections using an inflation rate of 2% per year were made.

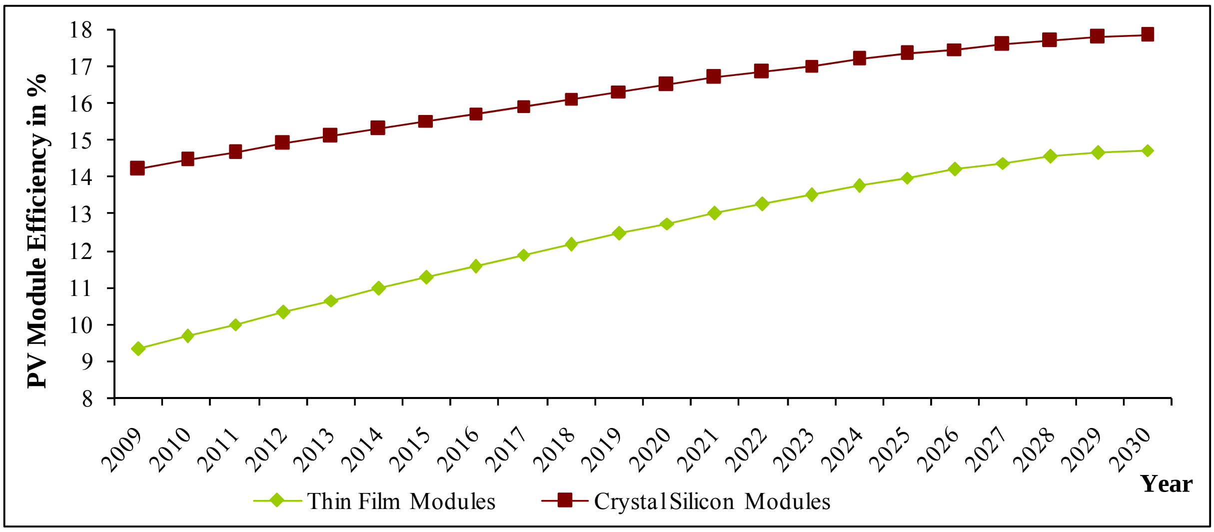
Table 2: Model Input Parameters and Starting Values

	Parameter	Denotation	Value	Unit	Data Source
Learning	Learning coefficient PV panels	β^{Panel}	0.322		Own calculations, using a LR of 0.2
	Learning coefficient BOS	β^{BOS}	0.234		Own calculations, using a LR of 0.15
	Investment cost for first production unit PV panels	C_0^{Panel}	57.2	€/Wp	Based on above LR and current module prices, PVXchange (2009b)
	Investment cost for first production unit BOS	C_0^{BOS}	7.9	€/Wp	Based on above LR, PVXchange (2009a), Photon (2008a)
Market Data	Cumulated residential PV capacity in Germany in 2007	Q_{2007}^{D}	1196	MWp	Own calculation, based on BSW Solar (2009) and Transmission System Operator data
	Cumulated global crystal silicon PV capacity in 2007	Q_{2007}^{G}	10500	MWp	IEA (2008), Staiß (2007)
	German demand in 2007	q_{2007}	52.234	Thousand	Own calculations, BSW Solar (2009)
	German demand in 2008	q_{2008}	71.2	Thousand	Own estimation, BSW Solar (2009)
	Maximum annual German market size	q^{max}	277	Thousand	Own calculations, Kaltschmitt et al. (2002), Kaltschmitt and Fischedick (1995)
	Retail electricity price in 2008 (net of taxes and charges)	p_{2008}^{el}	0.12	€/kWh	Nitsch (2008), price path B
	Average growth global PV panel production 2009-2030	g^{Panel}	15	% p.a.	EPIA and Greenpeace (2008), Roland Berger Strategy Consultants (2007), Frost & Sullivan (2006)
Discount Factors	Social discount rate	r	3	% p.a.	Evans and Sezer (2005)
	Investor-specific discount rate (opportunity cost)	i	4.8	% p.a.	Deutsche Bundesbank (2009)
Demand	Demand function parameter	a_0	14.215		Own calculations, cf. Section 3.1.1
	Demand function parameter	b	0.384		Own calculations, cf. Section 3.1.1
	Diffusion parameter	γ	0.135		Own calculations, cf. Section 3.1.1
Other Parameters	Specific external cost	C^{ext}	0.034	€/kWh	Krewitt and Schlomann (2006), Dones et al. (2005), Klobasa et al. (2009)
	Specific electricity yield	$yield$	0.95	MWh/kWp	Solarenergie-Förderverein Deutschland (2009), Staffhorst (2006)
	O&M cost coefficient	ϑ	0.015		Staffhorst (2006), Dürschner (2009)
	Average PV system capacity	cap_{2008}^{av}	5.46	kWp	Own calculation, based on Transmission System Operator data

Source: Listed references.

Increasing PV module efficiencies will affect future electricity yields. Therefore, progress in R&D will lower PV's electricity generation costs (learning-by-searching, LBS). LBS is not modeled separately since the experience parameter is supposed to capture R&D as well (see footnote 1). However, future PV module efficiencies have been inferred from historical efficiency developments according to NREL (2007). For future efficiency developments, a slowdown has been taken into account (see Figure 2) as the PV module industry matures. Apart from wafer-based crystalline silicon modules, thin film technologies are displayed because these technologies will be introduced in model scenarios. Assuming a constant available installation area, increasing module efficiencies are incorporated into the model via higher average PV system capacities over time.

Figure 2: Development of Future PV Module Efficiencies



Source: Own estimations, NREL (2007).

4.2 Scenarios

4.2.1 Scenario S1: “Business as Usual”

Currently, wafer-based solar cells dominate the market for residential systems. The model’s reference scenario refers to these technologies since they are expected to prevail in the future (EU COM, 2007). Hence, PRs of 0.8 (solar panels) and 0.85 (BOS) are used from the reviewed empirical studies in Section 2.2 to model future cost reductions for system components. Scenario S1 assumes a moderate increase in retail electricity prices according to generation costs by Nitsch (2008) and a constant level of electricity transportation and distribution fees. Empirically, PV-generated electricity replaces a mixture of gas- and coal-fired power plants in Germany owing to its preferential feed-in into the grid. Using data from Dones et al. (2005), estimated environmental externalities from coal- and gas-fired electricity generation have been weighed according to Klobasa et al. (2009) and then netted out against PV’s external costs to determine its benefits from avoided externalities. The starting values and parameters for this reference case are displayed in Table 2.

4.2.2 Scenario S2: “Economic Growth”

This scenario assumes a global economic upswing being mirrored in a strong increase in German retail electricity prices by an average rate of 3% per year. The increase is driven by soaring demand worldwide for energy fuels and increased domestic electricity consumption. These developments accompany an accelerated emission of greenhouse gases from fossil fuels. Therefore, avoidance costs for environmental externalities increase. However, PV's global capacity extension also profits from this positive economic environment, resulting in higher average market growth rates annually. At the same time, the average investor-specific interest rate also increases to 5.8% per year. Table 3 displays the changes in comparison to the base case.

Table 3: Input Parameters in Scenario S2 and Scenario S1

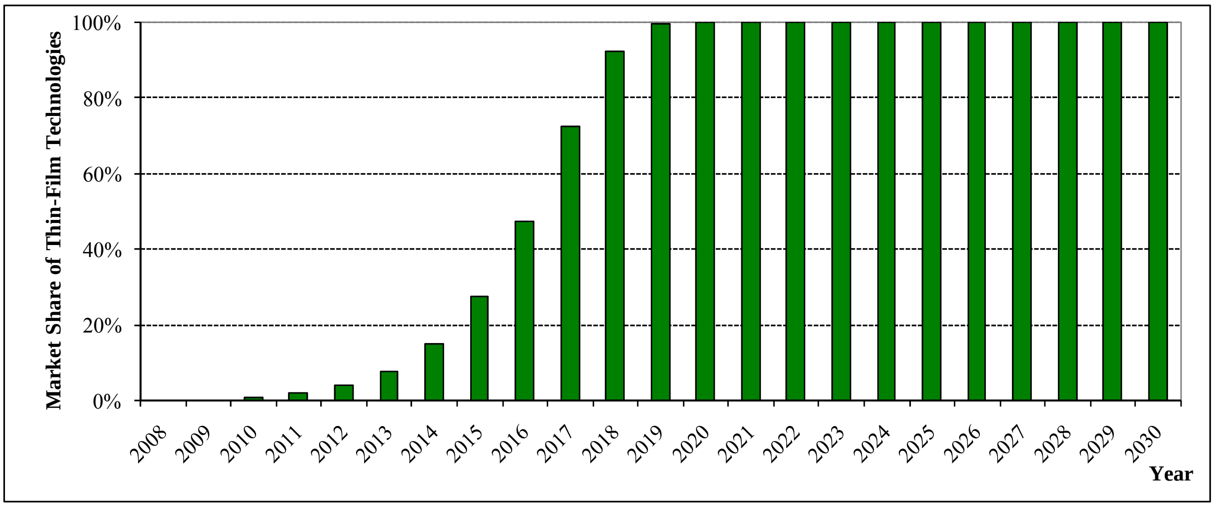
Input Parameter	Scenario S2	Scenario S1
Investor-specific discount rate i	5.8% p.a.	4.8% p.a.
Retail electricity price p_t^{el}	growth rate of 3% p.a.	Nitsch (2008), price path B
Annual market growth for crystalline PV panels g^{Panel}	20% p.a.	15% p.a.
Avoided external cost C^{ext}	0.05 €/kWh	0.034 €/kWh

Source: Own assumptions.

4.2.3 Scenario S3: "Sunny Future"

In contrast to S1, thin film technologies become financially more attractive for residential PV than crystalline silicon solar cells. Apart from their higher cost-savings potential, the slight convergence in efficiency factors closes the existing profitability gap to crystal silicon modules over time. Thus, thin film modules penetrate the market for residential PV until 2020. This process is modeled in Figure 3 as a sigmoid curve known from technology diffusion.

Figure 3: Thin Film Technologies' Market Share in Scenario S3



Source: Own assumptions.

Hence, several adjustments to the two previous scenarios are made. Thin films are considered as having a larger cost-reduction potential than crystalline solar cells in the coming years (BMWi, 2005). Therefore, the PR for thin film technologies, $PR^{'Panel}$, is set at 0.7 and a separate experience curve for thin film PV is introduced in accordance with Trancik and Zweibel (2006). However, this differentiation among modules does not affect PV's regional integration into the grid (BOS). This is taken into account by an adjusted experience curve with ms_t being thin film’s market share period t ($0 \le ms_t \le 1$) as shown in the following equation:

$$C_t^{Invest} = (1 - ms_t)\left\{ C_0^{Panel} \cdot \left(Q_{2007}^{G} \cdot \left[1 + g^{Panel}\right]^{t} \right)^{-\beta^{Panel}} \right\} + ms_t \left\{ C_0^{'Panel} \cdot \left(Q_{2007}^{'G} \cdot \left[1 + g^{'Panel}\right]^{t} \right)^{-\beta^{'Panel}} \right\} + C_0^{BOS} \cdot \left(Q_{2007}^{D} + \sum_{1}^{t-1} q_t \cdot cap^{av} \right)^{-\beta^{BOS}} \quad \textbf{(16)}$$

Moreover, the described technology transition affects average PV system capacity owing to thin films’ lower efficiency in comparison to crystalline modules. Thus, thin films’ average capacity $cap^{'av}$ amounts to 4 kWp, as inferred from specific installation areas per kWp for Cadmium Indium (Gallium) Selenide (CI(G)S) modules in comparison to crystalline modules. Although an emerging technology, it is assumed that thin film solar cell production grows faster than crystalline technologies, resulting in an average annual growth rate in global production $g^{'Panel}$ of 25% until 2030.

Apart from increased demand for fossil fuels, higher prices for CO_2 emissions under the EU’s Emission Trading Scheme (ETS) will also cause higher retail electricity prices in comparison to scenario S1. Moreover, increased external costs in comparison to current estimations for the German electricity generation mix occur. S3 applies the high electricity price scenario by Nitsch (2008) and specific external costs from scenario S2 to account for these trends. High abatement costs for CO_2 and the society’s increased preference for a low-carbon electricity sector affect homeowners’ attitude towards investments in renewables like residential PV. Owners still desire to maintain their investment’s real value, but partially abstain from the expected rate of return according to the opportunity costs. Thus, the investor-specific discount rate i reduces to 3% per year, which equals the social discount rate r. This is still above the long-term German inflation rate of 2% p.a. (DESTATIS, 2009).

5 Results

The model is solved with GAMS, using the CONOPT solver for nonlinear optimization problems. Due to discounting and normalizing inputs, all monetary results are given in €$_{2008}$. Table 4 shows the remarkable differences in the welfare effect; the results are discussed in the subsequent sections.

Table 4: Scenario Comparison of Optimal Policy’s Total Welfare Effect

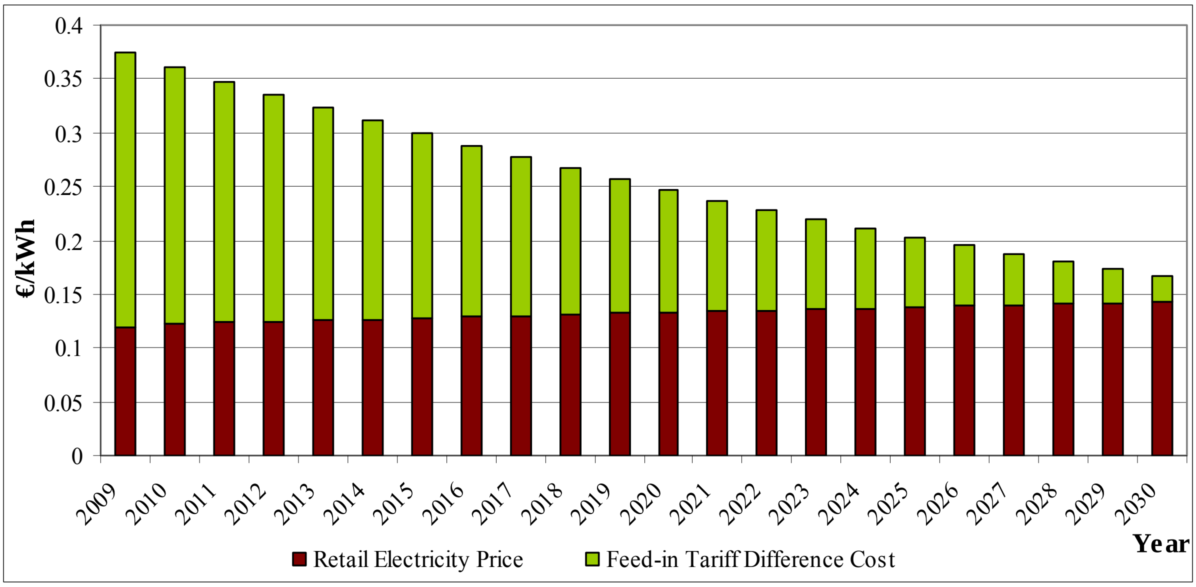
	S1 “Business as Usual”	S2 “Economic Growth”	S3 “Sunny Future”
Welfare Effect	-2,014 m€	5,689 m€	7,586 m€

Source: Own calculations.

5.1 Results S1 “Business as Usual”

The negative welfare effect of 2,014 m€ from the deployment of residential PV in Germany shows that the benefits will not outweigh the additional costs of PV’s promotion until 2030. Although feed-in tariffs (Figure 4) decrease steadily, residential PV does not reach competitiveness to average retail electricity prices within this period. However, the model reduces the level of feed-in tariffs significantly, from 0.4675 €/kWh to 0.3751 €/kWh, in comparison to 2008. This equals a 19.8% reduction that is 12.8% lower than the actual EEG remuneration level in 2009 (0.4301 €/kWh). Feed-in tariffs decrease at a rate between 3.7% and 3.8% per year after 2009 according to the learning effects in PV component production.

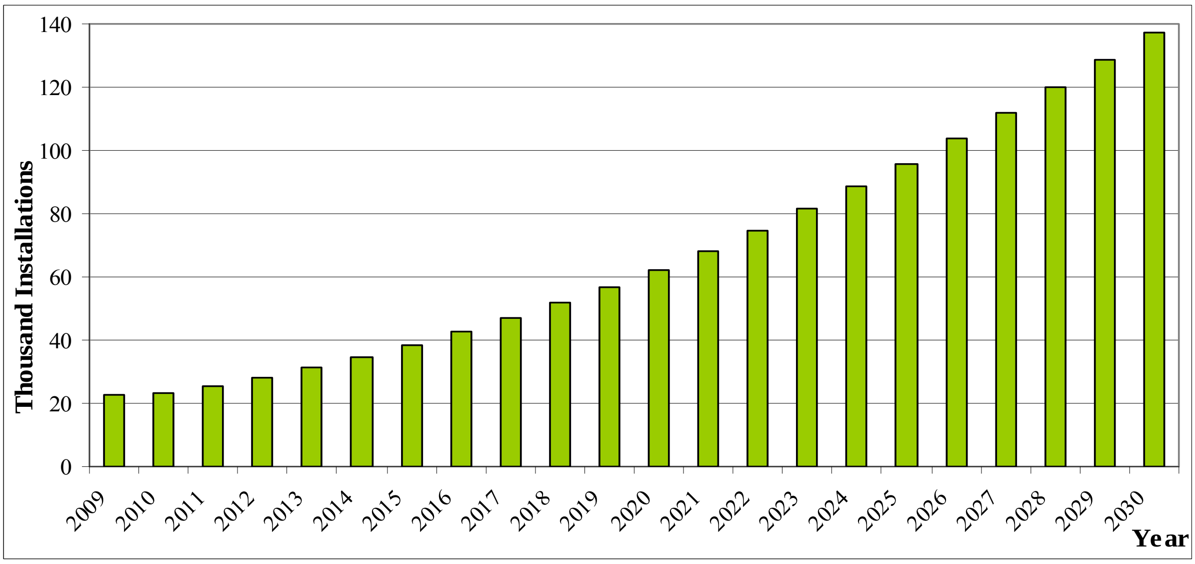
Figure 4: Feed-in Tariffs, Scenario S1



Source: Own calculations.

As a result of the cutback in feed-in tariffs, demand decreases from approximately 71,000 installations in 2008 to less than 23,000 in 2009 (Figure 5). Nevertheless, feed-in tariffs remain at a level that still induces demand for residential PV because the investor's minimum return expectations are fulfilled. Thus, demand rises throughout the modeled time period up to 137,000 installations in 2030. The rise is nonlinear, which is attributed to the modeled technology diffusion effect.

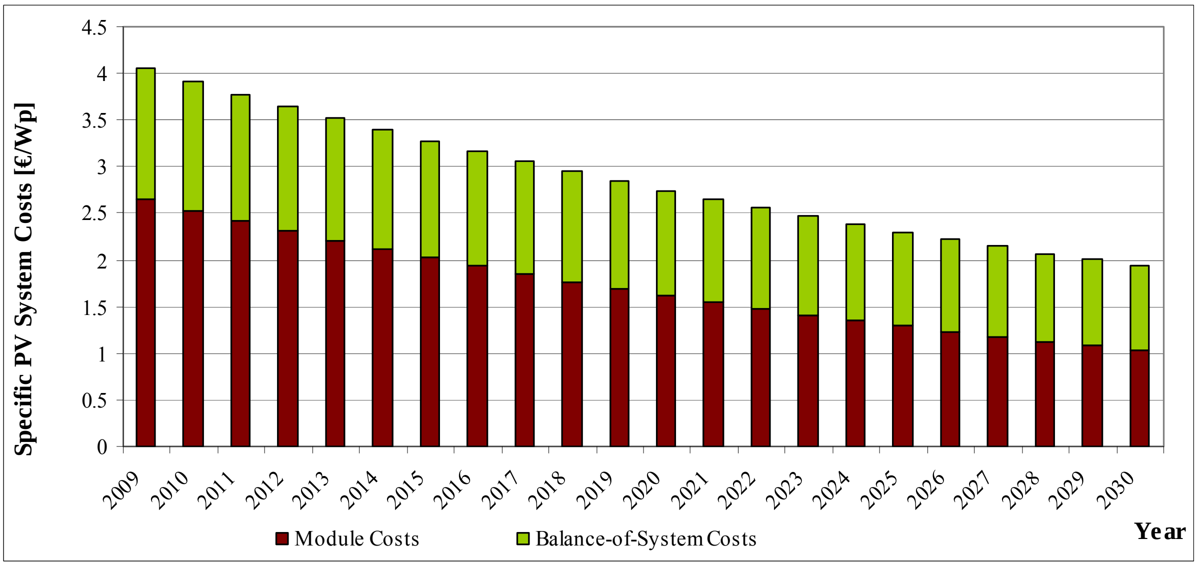
Figure 5: Demand for Residential PV Installations, Scenario S1



Source: Own calculations.

Under the given assumptions, major investment cost reductions for residential systems derive from LBD in PV module production. Between 2009 and 2030, specific production costs for crystalline silicon PV modules fall from 2.65 €/Wp to 1.03 €/Wp (Figure 6). BOS components show a significantly lower cost decrease from 1.40 €/Wp to 0.91 €/Wp during the same period. This development can be ascribed to the regional learning effects in BOS (PR_{BOS} = 0.85) that are a priori lower than expected learning effects in PV module production (PR_{Panel} = 0.8) and to the fact that domestic demand for residential systems increases at a lower rate than seen in international PV panel markets. Whereas global panel production grows by the exogenously given average rate of 15% annually, domestic demand increases in the range of 2.3% (in 2010) to 11% (in 2012).

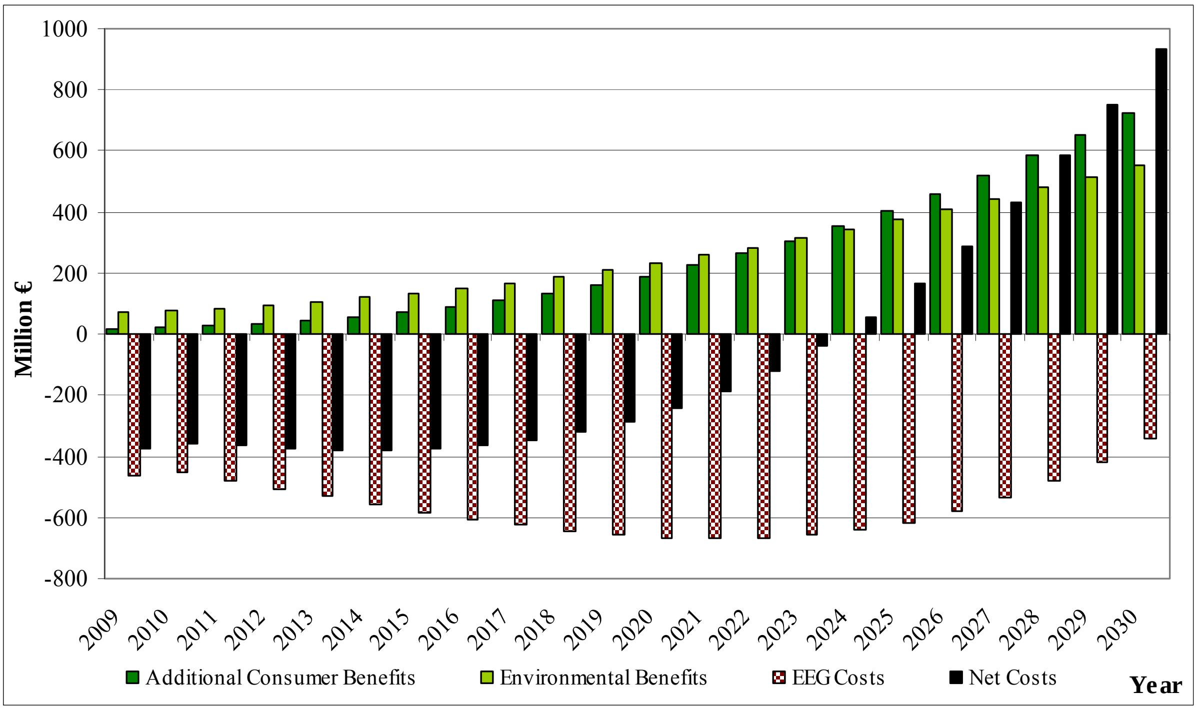
Figure 6: Specific PV System Costs, Scenario S1



Source: Own calculations.

Concerning the impacts on welfare, the model drastically reduces the EEG's costs in comparison to 2008 by the cut in feed-in tariffs and the associated plummeting demand. Thus, avoided environmental externalities as a benefit of new installed PV capacity also drop. This benefit grows at the same rate as demand for residential PV since – apart from demand for PV installations – environmental externalities are calculated from time-invariant parameters. Avoided environmental externalities amount to 72 m€ in 2009 and reach 552 m€ in 2030 (Figure 7). In contrast, consumer benefits are negligible in the model's first periods, but emerge subsequently as they result from additionally induced learning effects in comparison to a no-policy case. The growth is at a higher rate than environmental benefits and thus outweighs the latter in 2024 and beyond. Consumer benefits add up to 722 m€ (Figure 7) in 2030. Consumers will therefore profit from reduced investment costs in the long run. Turning from residential PV's environmental and consumer benefits to its social costs (EEG costs), the initial EEG costs of 464 m€ in 2009 grow until they culminate in 669 m€ in 2021, and then fall to 342 m€ in 2030.

Figure 7: Social Costs and Benefits, Scenario S1



Source: Own calculations.

Subtracting the social costs from the benefits, we obtain the optimal policy's net costs and benefits. After an initial increase between 2010 and 2014, net costs decrease from 2015 onwards. Hence, the benefits from residential PV's promotion grow at a faster rate than the EEG costs. In absolute numbers, net social costs under the cost-minimizing policy of feed-in tariffs add up to 376 m€ in the first model period and culminate in 379 m€ in 2014. Although net social costs turn into net benefits after 2023 and amount to 932 m€ in 2030, PV will not be competitive to average retail electricity prices by 2030. All in all, net costs overweigh until 2030 and lead to the accrued negative welfare effect as discussed above.

5.2 Results S2 "Economic Growth"

This scenario shows a highly positive welfare effect of 5,689 m€ and residential PV becomes competitive in 2023 (Figure 8 in the Appendix). Despite a slightly higher initial feed-in tariff of 0.3821 €/kWh in 2009 the tariffs decrease faster in subsequent years in comparison to S1. Starting at a degression of 4.9% in 2010, reduction rates grow continuously and amount to 5.5% in 2022 against the previous year before residential PV's subsidization expires in 2023. By then, retail electricity prices will have reached 0.2 €/kWh.

Demand develops similarly to scenario S1 until 2022, but it increases in the following years as PV becomes cost-competitive and therefore provides additional profits to the investor's minimum opportunity costs. Whereas the model minimizes net social costs by setting $NPV_t = 0$ as long as residential PV has not reached competitiveness, PV installations' profits increase steadily, up to 1.46 €/Wp in 2030, once the subsidies have been withdrawn. Thus, annual demand in 2030 adds up to 169,000 installations in comparison to 137,000 installations under S1. This additionally induced demand also influences learning in BOS equipment production. Whereas PV installations’ initial investment costs start from the same level as in scenario S1, they differ over time. Additional learning in PV module production is caused by higher global module production growth, whereas stronger domestic demand leads to slightly lower BOS costs until 2030 (0.89 €/Wp). Looking at Scenario S3’s social costs and benefits, it is clear that environmental and consumer benefits are considerably higher than in scenario S1. They balance out the feed-in tariff difference costs in 2018 and overweigh afterwards. As the EEG feed-in tariffs withdraw in 2023, the net social benefits steadily increase to 1,915 m€ in 2030.

5.3 Results S3 “Sunny Future”

Despite a lower increase in retail electricity prices in comparison to scenario S2, residential PV will already reach competitiveness in 2018 (Figure 8 in the Appendix). This is mainly attributed to thin films’ market penetration as a result of its considerably lower capital investment costs than crystalline modules. Although thin film technologies do not enter the market before 2010, the initial level of feed-in tariffs for residential PV is lower than in Scenarios S1 and S2. Additionally, thin film modules contribute to a stronger cutback in feed-in tariffs over time; the reduction rates are between 5% and 15.7% year to year. Looking at this feed-in tariff policy’s impact on demand, a static view shows approximately similar numbers of installations at the beginning and at the end of the modeling period in comparison to scenario S2. However, a closer look reveals that demand is higher between 2018 and 2029, which is primarily caused by supplementary profits for PV investors ($NPV_t > 0$) in addition to their minimum opportunity costs after PV has reached competitiveness. However, this does not have observable additional learning effects in BOS production. In contrast, the chief cost reductions for residential installations derive from thin film PV modules, resulting in a drop in capital investment costs (Figure 8 in the Appendix). PV module costs drop from 2.57 €/Wp in 2009 to 0.16 €/Wp in 2030, triggered by the introduction of new PV technologies. Looking at residential PV’s social costs and benefits, the accrued net welfare effect (7,586 m€) is higher than in the previous scenarios, because the early break-even between social costs and benefits is already reached in 2015. Apart from lower feed-in tariffs, positive assumptions on environmental and consumer benefits lead to the expected economic surplus after 2014. As in scenario S2, consumer benefits do not outweigh environmental benefits due to the assumed higher environmental external costs in comparison to scenario S1.

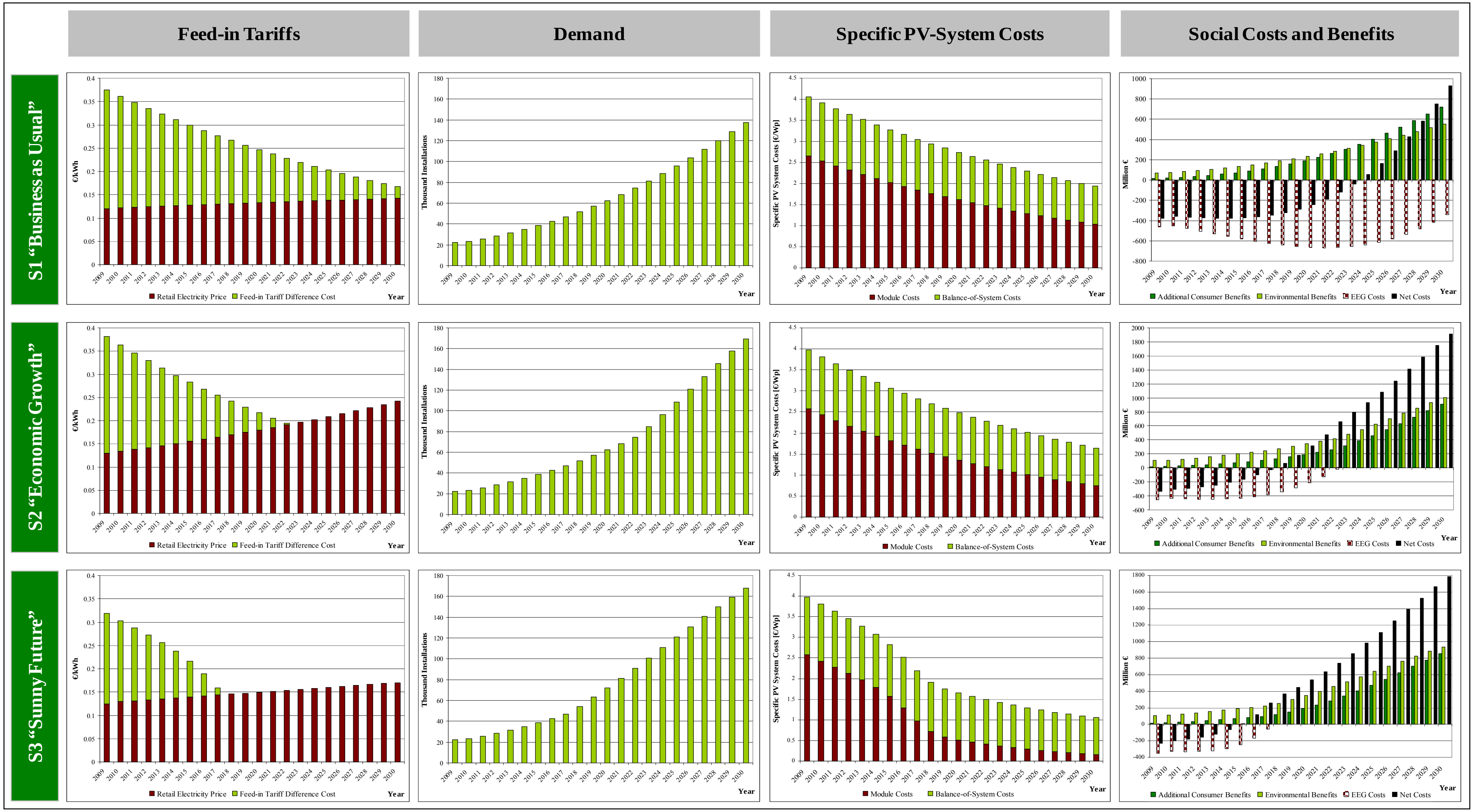
6 Conclusions

This paper determines an optimal policy of feed-in tariffs for residential PV systems in Germany. Using a simultaneous innovation-diffusion-approach, the presented model maximizes social welfare, taking into account avoided environmental externalities and consumer benefits from induced learning. A business as usual scenario shows that residential PV will not reach competitiveness to retail electricity prices in the medium term. Nevertheless, the optimal feed-in tariff policy as well as its welfare effect will vary considerably in the developed scenarios. The inclusion of optimistic economic growth rates and the switch to thin film solar cells for small-scale installations leads to considerable net social benefits and residential PV’s competitiveness until 2030.

The three scenarios modeled show that reductions in total system costs are primarily driven by global learning in PV module production. In contrast, cost reductions being influenced by domestic demand vary less among the scenarios. Assuming that investors for residential PV are price takers on the global PV module market, it appears that a national feed-in tariff policy does not generate considerable cost reductions from regional LBD. All three scenarios emphasize that the current feed-in tariff for small-scale PV according to the EEG is higher than for the economic efficient feed-in tariffs (12.8% above the optimal remuneration level in scenarios S1 and S2). Scenario S3 shows even lower initial tariffs (-26%). These results suggest that under the current political objective of promoting residential PV, the current level of feed-in tariffs should be lowered significantly. However, the model’s reductions in feed-in tariffs until 2012 (ranging between 3.7% and 5.3% against the previous year) are below the current EEG’s degression rates that are between 7% and 10%.

The findings above refer to a partial market equilibrium model. However, PV’s promotion is also a strategic investment, because it reduces Germany’s future dependence on fossil fuel imports. Hence, the negative welfare effect may be viewed quite differently when security of supply is additionally considered. Moreover, decentralized electricity generation from residential PV could reduce grid congestion.

Figure 8: Overview of Scenario Results



Source: Ow n calculations.

Appendix

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