Applied Energy 88 (2011) 4387–4399

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Feed-in tariffs for photovoltaics: Learning by doing in Germany?

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ARTICLE INFO

Article history:
Received 30 May 2010
Received in revised form 8 May 2011
Accepted 11 May 2011
Available online 15 June 2011

Keywords:
Photovoltaic
Learning by doing
Innovation
Renewable energy policy

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 2014 million € under a "business as usual" scenario to 7586 million € of net benefits under the positive prospects of PV's development. Whereas the "business as usual" scenario underestimates actual price reductions, the positive scenario mirrors recent price developments and feed-in tariffs in the German residential PV market.

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 PV with approximately 17.3 GW of installed capacity at the end of the year 2010 [1]. 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. It guarantees a fixed price for PV-generated electricity over a period of 20 years.[1] 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 and 2010 is an amendment that adjusts feed-in tariff regulations for 2009–2012 according to Fig. 1. 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 [2].

This view could also be supported for EEG regulations in the past. Findings in innovation economics indicate that induced PV market growth has been too high to exploit learning effects optimally. Schaeffer et al. [3] find that German PV module costs fell at a lower rate than the global average for each doubling in PV capacities. Neuhoff [4] also argues that growth rates should not be excessive for an optimal utilization of learning effects. For the last 8 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 [5,6]. Krewitt et al. [7] predict PV's global developments, but do not consider the German situation. Sandén [8] develops a quantitative model to calculate PV's future subsidy costs in OECD countries on an aggregated level. While Nitsch [9] 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 [5]. A recent break-even analysis for German PV systems by Bhandari and Stadler [10] focuses on PV's

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[1] For a detailed discussion of feed-in tariff remuneration designs see Couture and Gagnon [69].

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doi:10.1016/j.apenergy.2011.05.015

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 [11,12]. 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 between 2009 and 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. Assuming a business as usual case, we find that the support creates net social costs of about 2014 million € (M€) whereas in scenarios assuming different developments regarding economic growth and technological progress the net social benefits are 5689 M€ or 7586 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 [13], 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.[2] In its 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. [14] 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 [15] consider uncertainties in learning effects by a stochastic model of technological change. Harmon [16] and Frankl et al. [17] distinguish between regional and global learning to construct experience curves for PV. Different methodological approaches to determine learning curves also exist. Schaeffer et al. [3] use weighted and unweighted linear regressions on lognormal cost and production data to infer learning curves. Staffhorst [18] 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 [19]. Recent implementations of LBD to account for endogenous technological change in energy-environment-system models are further discussed in Löschel [20], Grubb et al. [21], Kypreos and Bahn [22], Vollebergh and Kemfert [23], Edenhofer et al. [24], Pizer and Popp [25], and Clarke et al. [26].

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 [16–18,27]. Schaeffer et al. [3] 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.

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. [3], 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. It needs to be assessed if these findings apply to recent developments in Germany,

[2] According to Clarke et al. [26], experience parameters additionally capture R&D, spillover effects, economies of scale, and other price-decreasing factors. Therefore, they are a generalization of learning parameters.