Impact of RE Policy on Technology Costs-PV System Costs in Germany

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OVERVIEW

Since the adoption of its Renewable Energy (RE) act in 2000, Germany has intensified its effort for renewable energy technology (RET) deployment. The primary instrument has been feed-in tariffs, which have faced several adjustments in magnitude and specific designs. While costs for consumers have increased considerably from 4.7 bill Euro in 2008 to almost 19 billion Euro in 2014 (Monitoring Report 2015), benefits for consumers are more difficult to capture and quantify. To do so, the approach relies on a const benefit concept, which looks at additional costs and benefits at system-, micro- and macroeconomic levels (Breitschopf, B., Held, A. 2014). While additional costs for final electricity consumers occur at the micro level, benefits serve special attention as they accrue across all levels and are difficult to allocate to individual actors. Among them, the contribution to innovation and technology cost development is considered as one major positive aspect of RE policy support. Technology costs, especially PV system costs have shown a tremendous decline over time. This paper strives to assess the impact of the German RE policy on RET costs in the case of PV in Germany. Increased attention has been paid to the learning curve concept (Ek & Söderholm, 2009). This concept will be extended by taking into account interdependencies between technology, demand, and supply.

LITERATURE REVIEW ON LEARNING CURVE APPROACH

Decreasing cost of production have been observed and first described by {Wright 1936}. He explained them by learning effects, i.e. workers became more efficient as they produced more units of the same product with the same technology. Based on these observations, Arrow (1962) sketched a model explaining technological changes as a function of learning (Nemet, 2006). Learning curves in their basic form are derived by regressing the price or cost (De La Tour et al., 2013) of the technology in question on cumulative production. The derived One-Factor-Learning-Curve (OFLC) relates cost development to accumulated learning, usually represented by cumulative capacity. As the high level of aggregation in OFLC considerably simplifies cost dynamics (Wiesenthal et al., 2012), researchers started to extend the OLFC approach to a Two-Factor-Learning-Curve (TFLC). In TFLC models, investments costs are not only explained by cumulative capacity but also by an R&D based knowledge stock (Klaassen, Miketa, Larsen, & Sundqvist, 2005). Although Wiesenthal et al. (2012) point out, that it is already questionable whether the effects of learning-by-doing and learning-by-searching should be disentangled since they are both parts (and not the only parts) of one integral learning process, steps towards a Multi-Factor-Learning-Curves (MFLC) have been proposed. In particular, researchers (e.g. De La Tour et al. (2013) , Yu (2012)) draw on details given by Henderson (1972) concerning the originating idea of the experience curve by the Boston Consulting Group. He recalled that the experience curve does not solely refer to the relationship between productivity and output but should regard learning effects, scale effects, cost rationalization and technology improvement jointly (Henderson, 1972). While Yu et al. (2011) show significant results by incorporating scale effects, silicon price, silver price and a proxy for other input prices, De La Tour et al. (2013) report a notably higher learning rate by just incorporating experience and silicon price. Nemet (2006) develops a bottom-up cost model using the example of PV technology. The approach disaggregates historical cost reductions into observable technical factors. He suggests a set of observable technical (e.g. efficiency improvements) factors whose impact on cost can be immediately calculated. Nevertheless, Nemet (2006) isn't able to fully explain the cost development.

APPROACH

This paper analyses how strongly the demand pull policy (FIT) in Germany has driven the technology costs of PV installations over time. The analysis relies on historical cost data, i.e. on levelized cost of electricity (LCOE) generation from PV installation. The starting point are learning curves. But this approach has a flaw as the data used to depict "costs" of RET in learning curves represent not costs but market prices determined by demand and supply. This calls for taking market pricing into account, which embeds implicitly utility or profit maximization at the demand side as well. In addition, market pricing is an interaction between demand and supply. Subsequently, apart from “original” learning effects, interactions and economies of scale and, as Kahouli-Brahmi (2008) states, learning-by-using, which reflects the user’s feedback, and learning-by-interacting, which takes place at a large diffusion stage, push costs. For this study, LCOE is modeled as a function of demand for PV (annual installations), input prices, PV market development (production and structure), R&D spending, learning (cumulated installations) and external factors. As there are interactions between demand and LCOE, demand is depicted as a function of LCOE, expected returns on PV investments, preferences (environmental) and external factors. Finally, returns depend on LCOE and revenues that are triggered by RE support, i.e. demand-pull policies. The approach is depicted in Figure 1. Learning-by-using or interacting are not separately addressed and might be captured by cumulated installations while economies of scale might be reflected by average production per firm. Using the structural equation approach (SEM in Stata), the specified model are assessed by simultaneous (observed information matrix and robust estimator variance, see Annex with standardized and non-standardised coefficients), and non-simultaneous estimations. The observations mainly cover the period 1983 to 2015.

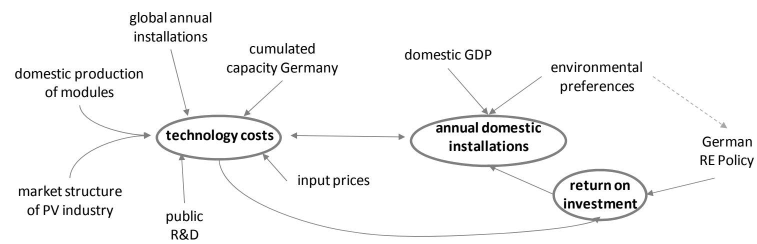

Figure 1: Structural model and dependent and explaining factors

RESULTS AND DISCUSSION

Demand (annual capacity) affects LCOE by about 0.1% in the short-run. The strongest impact on LCOE (price) has the input price with 0.3% followed by learning-by-doing effect (cumulated capacities), considered as long-term effects with about -0.2%, and the global deployment. Demand is strongly and significantly affected by costs (-4%). Finally, the return depends on LCOE, but if these are skipped, then the pull effect explains to a small degree returns, and hence the impact on demand.The primary impact of demand pushing policies augments prices through increased demand but as demand immediately is reflected in growing cumulated installations (learning), which significantly reduce costs, policy has, in a second step, a declining effect on technology costs. Simultaneous and nonsimultaneous regressions show different impacts, but they consistently report significant results for the LCOE regression for capacities, while other factors are either not well captured or insignificant. Inconsistent results are obtained regarding demand: the non-simultaneous approach does not report significant coefficients for demand. Even so this approach builds on learning curve approaches, there remains one major drawback: the estimator is based on cross-sectional data while time series data (mainly non-stationary) are applied. Applying time series based estimators requires an adjustment of the initial research question. This also includes the design of the exogenous variable capturing demand-pull policies. Finally, one problem can only be solved over time: the limited number of observations.

References

Breitschopf, B., Held, A., 2014; Guidelines for assessing costs and benefits of RET deployment, in the framework of DiaCore IEE Project (http://www.diacore.eu/images/files2/D4.1_FhISI_Cost_Benefit_Approach_DIACORE.pdf), April 2014

De La Tour, A., Glachant, M., & Ménière, Y. (2013). What cost for photovoltaic modules in 2020? Lessons from experience curve models. Working Paper 13-ME-03, CERNA, MINES ParisTech, (13-ME-03).

Ek, K., & Söderholm, P. (2009, September 07). Technology Learning and Research in Wind Power: Rethinking the Technology Development Process. Energy, Policies and Technologies for Sustainable Economies: executive summaries of the 10th IAEE European Conference 7-10 September 2009 in Vienna. Vienna, Austria.

Kahouli-Brahmi, S. (2008). Technological learning in energy-environment-economy modelling: A survey. Energy Policy, 2008(36), 138–162.

Klaassen, G., Miketa, A., Larsen, K., & Sundqvist, T. (2005). The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. Ecologi-cal Economics, (54), 227–240.

Monitoring Report 2015, Breitschopf, B; Klobasa, M; Sievers, L; Steinbach, J; Sensfuß, F; Diekmann, J; Lehr, U, Horst, J. (2015): Monitoring der Kosten- und Nutzenwirkungen des Ausbaus erneuerbarer Energien im Jahr 2014

Nemet, G. (2006). Beyond the learning curve: factors influencing cost reductions in photovoltaics.

Energy Policy, 2006(34), 3218–3232.

Wiesenthal, T., Dowling, P., Morbee, J., Thiel, C., Schade, B., Russ, P., et al. (2012). Technology Learning Curves for Energy Policy Support. JRC Scientific and Policy Reports,

Yu, C., van Sark, W., & Alsema, E. (2011). Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects. Renewable and Sustainable Energy Reviews, 2011(15), 324–337.

Annex

```
Structural equation model                       Number of obs      =         30
Estimation method  = ml
Log likelihood     = -49.063726
```

Standardized	Coef.	OIM Std. Err.	z	P>|z|	[95% Conf.	Interval]
Structural						
lnlcoe <-						
lncapann	.4301312	.1542895	2.79	0.005	.1277294	.7325331
lnpricesi	.132838	.0281547	4.72	0.000	.0776558	.1880202
lnmodul	.0775672	.1647408	0.47	0.638	-.2453189	.4004533
lnrd3yav						
L1.	-.0035988	.026749	-0.13	0.893	-.0560259	.0488284
lncapcum	-.9570727	.1919338	-4.99	0.000	-1.333256	-.5808893
lnglobannger	-.4311355	.0932107	-4.63	0.000	-.6138252	-.2484458
lncompet	-.0267843	.1345776	-0.20	0.842	-.2905515	.2369828
_cons	1.223865	.5088762	2.41	0.016	.2264859	2.221244
lncapann <-						
lnlcoe	-1.147056	.2580794	-4.44	0.000	-1.652883	-.64123
lnmargincorr	.4057717	.2257839	1.80	0.072	-.0367567	.8483001
lngreenvotes	-.4210799	.1709337	-2.46	0.014	-.7561038	-.086056
lngdp_r	-.1341459	.3361299	-0.40	0.690	-.7929484	.5246566
_cons	-12.01877	7.35805	-1.63	0.102	-26.44028	2.402747
lnmargincorr <-						
lnlcoe	-.6804165	.1300076	-5.23	0.000	-.9352266	-.4256063
lnpullcorr	.1455613	.1496193	0.97	0.331	-.1476871	.4388097
_cons	59.84182	6.407214	9.34	0.000	47.28391	72.39973
var(e.lnlcoe)	.0116485	.0043564			.0055966	.0242443
var(e.lncapann)	.1100997	.0339745			.0601344	.2015809
var(e.lnmargincorr)	.4777777	.1052915			.3101988	.7358877

```
LR test of model vs. saturated: chi2(17)  =     120.62, Prob > chi2 = 0.0000
```

Table 1: Regression results OIM model (standardised)

```
Structural equation model                       Number of obs      =         30
Estimation method  = ml
Log pseudolikelihood= -49.063726
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Structural						
lnlcoe <-						
lncapann	.1032998	.0396891	2.60	0.009	.0255106	.181089
lnpricesi	.3139851	.0712062	4.41	0.000	.1744234	.4535467
lnmodul	.0220912	.0368689	0.60	0.549	-.0501706	.094353
lnrd3yav						
L1.	-.0174183	.0853701	-0.20	0.838	-.1847406	.1499041
lncapcum	-.2309867	.040041	-5.77	0.000	-.3094656	-.1525078
lnglobannger	-.1877192	.0343511	-5.46	0.000	-.2550461	-.1203923
lncompet	-.0091076	.0353395	-0.26	0.797	-.0783718	.0601565
_cons	1.378429	.4996845	2.76	0.006	.3990652	2.357792
lncapann <-						
lnlcoe	-4.776242	.9585098	-4.98	0.000	-6.654887	-2.897597
lnmargincorr	34.14017	21.52887	1.59	0.113	-8.055633	76.33597
lngreenvotes	-9.300073	2.712377	-3.43	0.001	-14.61623	-3.983912
lngdp_r	-4.125356	12.81986	-0.32	0.748	-29.25181	21.0011
_cons	-56.36537	45.08654	-1.25	0.211	-144.7334	32.00263
lnmargincorr <-						
lnlcoe	-.0336738	.0094442	-3.57	0.000	-.0521842	-.0151634
lnpullcorr	.0108755	.0075234	1.45	0.148	-.00387	.025621
_cons	3.335596	.0276801	120.51	0.000	3.281344	3.389848
var(e.lnlcoe)	.0147765	.0068988			.0059178	.0368959
var(e.lncapann)	2.421537	1.20952			.909765	6.445445
var(e.lnmargincorr)	.0014844	.0005572			.0007113	.0030978

Table 2: Regression results REV modell