IMPACT OF RE POLICY ON TECHNOLOGY COSTS – PV SYSTEM COSTS IN GERMANY

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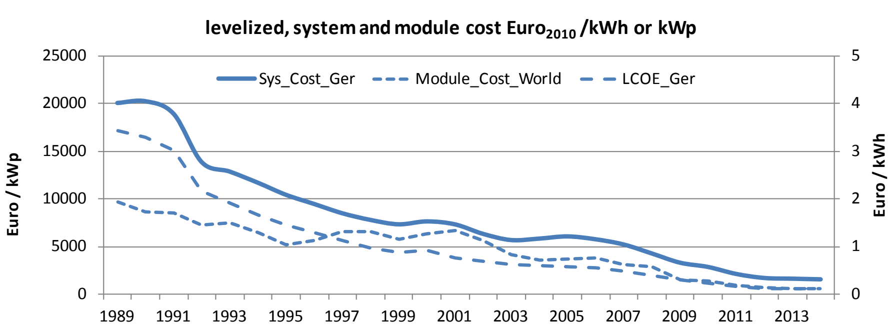
Abstract

The tremendous promotion of renewable energy technology (RET) deployment in Germany has entailed considerable costs and benefits. However, these costs and benefits accrue at different levels, are linked to different actors across time and making an assessment challenging. Especially, decreasing technology costs are considered as one major benefit of RET deployment and are used to argue for RET policy support. To capture these impacts, learning curves have been applied in many studies. Although learning curves include factors beyond demand, e.g. research and development, they ignore the interaction between demand and supply. This concept tends to include the impact of policies on demand and supply, and costs by applying a structural equation model. The results show that increased demand for PV modules increases prices while learning effects and large scale production decreases them.

1 Overview

Since the adoption of its Renewable Energy (RE) act in 2000 Germany has intensified its effort for renewable energy technology (RET) deployment. The main instrument has been feed-in tariffs, which have faced several adjustments in magnitude and specific designs. Nevertheless, promoting RET use entails increasing costs and benefits. While burdens for consumers have increased considerably from 4.7 bill Euro in 2008 to almost 19 bill Euro in 2014 (Monitoring Report 2015), benefits for consumers are difficult to capture and quantify. In addition, benefits and costs occur at three levels – system, micro- and macro-economic – and cannot be arbitrarily summed up (Breitschopf, B., Held, A. 2014). Especially, benefits arising from RE policies serve special attention as they accrue across al levels. Among them, the contribution to innovation and technology cost development is considered as one major positive aspect of RE policy support. To enrich and support the discussion on RET support and deployment targets, this paper strives to assess the impact of the German RE policy on RET costs in the case of PV in Germany. To evaluate the contribution of RE policies to market and technology development, especially in wind power and PV, 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.

Figure 1: Development of levelized costs (PV), system and module costs over time in Germany



Source: diverse sources, own compilation and calculation

Technology costs, especially PV system costs have shown a tremendous decline over time (see Figure 1). The paper aims to identify and assess the impact of the German RE policy on PV technology costs. In a first step, the “learning curve concept” is briefly discussed. Based on this discussion an approach is derived how to assess the impact of renewable energy policies (RE policies) that addresses demand for RET. It is intended to explain factors affecting technology costs and sketch a potential approach to assess the impact of RE policy on technology costs. The paper concentrates on PV and the demand focused policy (demand pull) in Germany. It includes further R&D policy (public R&D spending) but ignores supplier focused policies, although they are part of the RE policy bundle (IEA-RETD 2014).

2 Methods

2.1 Literature review on learning curve approach

Decreasing cost in 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 and the concept, Arrow (1962) sketched a model explaining technological changes as a function of learning (Nemet, 2006), whereas learning is referred to increasing productivity of labor due to growing experience within a manufacturing unit. Correspondingly, on company level learning curves are applied to project future costs and adjust corporate strategies. On policy level, the respective studies on learning curves in renewable energy technologies aim to deliver advices for the design of effec-tive policy instruments (Junginger, Faaij, & Turkenburg, 2005). Although learning curves are a widely accepted tool, the application of the concept bears some challenges.

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 by cumulative production or (in case of energy technologies) installed capacity. The derived One Factor Learning Curve (OFLC) only relates cost development to accumulated learning which is usually represented by cumulative capacity or installed capacity. The OFLC approach benefits particularly from easily accessible data (Wiesenthal et al., 2012) and stresses the basic concept of learning-by-doing (Ferioli et al., 2009). Nevertheless, econometric arguments require a thorough assessment of possible omitted variables. In particular, researchers have to make sure that all independent variables, whose regression coefficients are nonzero, are included. On the other hand regression coefficients will be biased unless the excluded variable is uncorrelated with other variables (Yu et al., 2011). Söderholm & Sundqvist (2007) remark, that this could be a serious problem in learning curve approaches since costs are obviously influenced by other factors than just cumulative capacities. On the contrary, multicollinearity may lead to discrepancies of regression coefficients. Multicollinearity increases the variance of the estimator (De La Tour et al., 2013) and is a common econometric issue.

As the high level of aggregation in One Factor Learning Curves 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). Thus, two factors are unraveled, namely learning-by-doing and learning-by-searching. Kobos et al. (2006) claim that the combination of learning-by-doing and learning-by-searching offers a complete framework to examine an underlying cost trajectory and advocate these advances. In addition, this approach allows to explore more thoroughly the impact of specific policy options (Wiesenthal et al.,

2012). Several studies expanded the OFLC approach by incorporating R&D through learning-by-searching estimates (see Table 2).
Klaassen et al. (2005) extended the idea by conceiving an advanced knowledge stock model, which regards depreciation of the cumulative knowledge stock and lagged addition of actual R&D expenditures to the knowledge stock. One major issue in TFLC models concerns low significances of estimated parameters as reported by Kobos et al. (2006) and Kouvaritakis et al. (2000). Kobos et al. (2006) particularly point out the effects of multicollinearity which are difficult to control while incorporating more factors into learning curve models. Although moving to TFLC approaches, which bear obvious conceptual benefits, they may not necessarily lead to significant results (Jamasb, 2007). Wiesenthal et al. (2012) underpin the objections by the fact that neither the support of R&D without supporting deployment nor the exclusive support of deployment have proven to be ideal policy strategies.

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. Referring to objections that learning curve predictions are actually lower than effective market development, Yu et al. (2011) suggest the incorporation of scale effects and input prices. In particular, they 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 relationship between productivity and output but should regard learning effects, scale effects, cost rationalization and technology improvement jointly (Henderson, 1972). To unravel particular influences of these aspects on photovoltaic learning curves, Yu et al. (2011) report first results of the incorporation of input prices and scale effects. Following their call for future research on additional factors, De La Tour et al. (2013) test the influence of different combinations of additional variables (among others, silicon and silver prices, R&D and scale effects). Following their results, not all additional variables necessarily improve the predictive power of the learning curve model. Finally, De La Tour et al. (2013) conclude that adding explanatory variables can be interpreted as a trade-off between the omitted variable bias and multicollinearity. Best predictions are achieved by incorporating experience and silicon price as additional explanatory variables. The omitted variable bias is being reduced and the effects of multicollinearity are limited as the correlation between silicon price and experience is low. While Yu et al. (2011) show significant results by incorporating scale effects, silicon price, silver price and a proxy for other-input prices deducing a learning rate of 13.5%, De La Tour et al. (2013) report a notably higher learning rate of 20.1% by just incorporating experience and silicon price. The results suggest that the predictions of advanced learning curve models still significantly depend on the set-up of the corresponding learning curve system. Although data consistency wasn’t verified, the completely different model specifications already illustrate unresolved challenges in learning curve modeling.

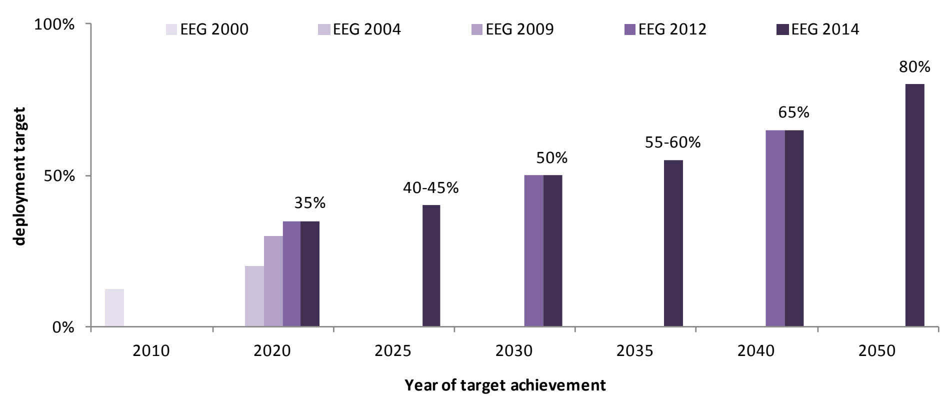
Nemet (2006) criticizes learning curves due to the uncertainties associated to the lack and treatment of data, as well as the aggregated approach to innovation. Based on these objections, Nemet (2006) develops a bottom-up cost model and compares the results to the assumptions behind the learning curve. Using the example of PV technology, the approach disaggregates historical cost reductions into observable technical factors. Indeed, Nemet (2006) suggests a set of observable technical factors whose impact on cost can be immediately calculated. For example, an explicit relationship between cost development and efficiency improvement is presented. Nevertheless, (Nemet, 2006) isn’t able to fully explain the cost development. Departing from the observation that 59% of the cost change remain unexplained, he suggests other factors, that may help to explain the residual but fails to quantify them explicitly.
In contrast, (Wiesenthal et al., 2012) refer to advances in cybernetic theory which imply that technology learning can be seen as a stable controlled property of a closed system in a competitive environment and complies with the observed learning rates around 20%.

Learning curves are seen as an important tool to endogenize technological changes in models and inform on future costs of RET use (Nemet 2006). The basic idea of learning curve is to draw conclusions from the quantitative relationship between costs and accumulated production or capacity by econometric analysis of empirical data (Ibenholt, 2002). Applying them is subject to certain limitations as their estimates are varying when using different time series or periods with the same data set, data sources, geographic coverage, explanatory variables, model specifications, or prices instead of costs. As Neij (1997) states properly, learning curves are not an established method or elaborated theory but just an empirical finding or statistical correlation that has been found for many different technologies. Subsequently, applying learning curves to assess the impact of demand promoting policies on technological changes requires an in-depth analysis of the underlying mechanism of demand-pull policies and technology costs.

2.2 Renewable energy policy in Germany

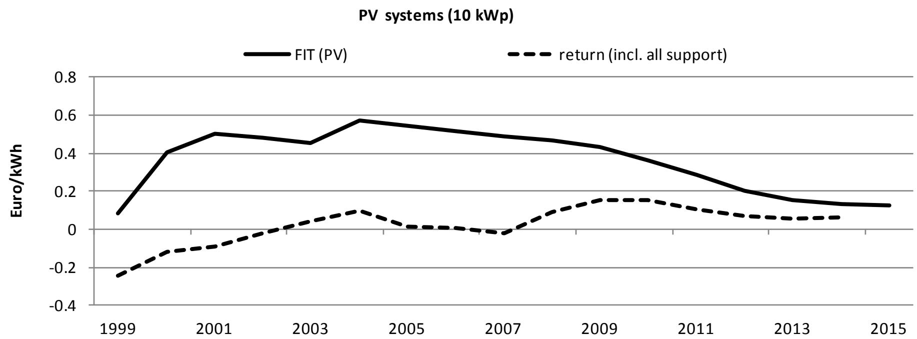
The German renewable energy policy has a long history. In 1991 the first renewable energy support policy has been approved, granting feed-in and a fixed tariff for RE power generation. However, this tariff was about 80-90% of the average revenue per kilowatt hours of energy suppliers in the retail sector. In addition, several specific private or public, regional support programs granting investment support for selected installations were offered in the 90s. In 2000 the so called RE act came into force granting a much higher feed-in tariff and access to the distribution network. In addition, an annual digression of the feed-in tariff and a deployment target of RE has been established. Till today, the RE act has undergone several adjustments, for example reductions of tariffs, differentiations of tariffs by type, location and size of RET, introduction differentiated deployment targets, deployment caps and feed-in premium. Figure 2 illustrated the targets set within the RE act (EEG) in Germany and Figure 3 the development of the feed-in tariff (FIT) for new installations over time.

Figure 2: Deployment targets of EEG (RE act) in Germany



Source: Breitschopf 2015a

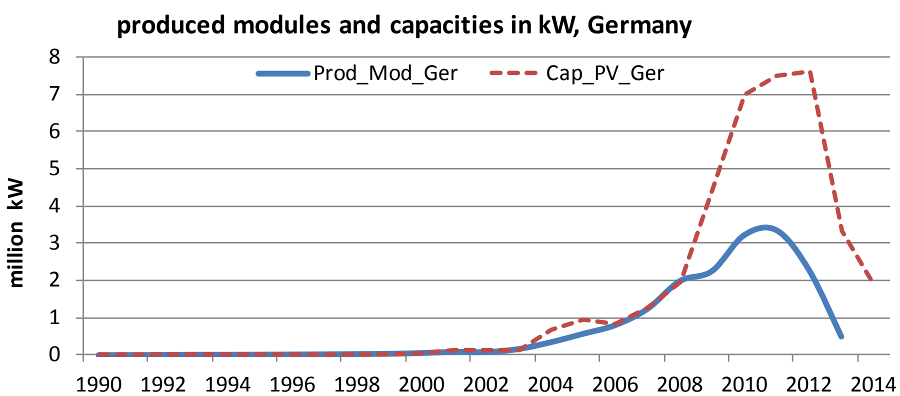
Figure 3: Feed-in tariff (FIT) and return (including all support instruments) of PV investment (10 kWp) in Germany



Source: Breitschopf 2015a,b

The impact of the policy can be described as follows: the demand-pull policy induces demand for PV installations measured by annually installed capacity. Growing demand leads to growth in production as depicted in Figure 4 , i.e. existing firms expand their production, new manufacturers enter the market, products or processes are improving or new ones arise. In Germany, demand for PV modules has exceeded production in Germany since 2008. Therefore PV module or cell imports have increased. A strong reduction of the demand pull effect (reduced feed-in tariffs) leads to stagnating or decreasing demand if return stagnates or decreases. This together with growing production (supply) intensifies competition, which in turn pushes firms to strengthen their competitiveness, either by decreasing production costs or improving product quality (efficiency). Subsequently, prices fall due to the increasing number of producers, stagnating or decreasing demand (surplus supply), increasing production and product efficiency. In turn, lower prices might increase profitability of PV investments and hence again push demand for further PV systems.

Figure 4: Annual production and installation of PV modules (capacities) in Germany



Source: Breitschopf 2015b

2.3 Approach for assessing impact of policies on technology costs

The total effect of these different interactions - demand, technology, firms – on technology costs has been captured by so called learning curves. One factor learning curves capture the market and production mechanisms in the factor “installed capacity”. Two factor learning curves include R&D support policies (see Figure x) to explain technological changes. Three factor learning curves apply further explaining variables such as prices of silicium or silver to reflect production costs.

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 system costs or levelized cost of electricity generation from PV installation. The starting point are learning curves, which are theoretically based on cost minimization (Yu, van Sark, Alsema, 2009; Berndt, 1991). The respective costs are a function of input prices, the amount produced and the functional parameters (return to scale). The learning cost approach has a flaw as the data used to depict "costs" of RET in learning curve are not costs but market prices determined by demand and supply. This calls for including a market pricing mechanism, which embeds implicitly utility or profit maximization at the demand side as well. In addition, market pricing mechanism is an interaction between demand and supply. Finally, the decision of suppliers to extend production (exploitation) or explore further technological potentials is a decision mechanism which depends on factors such as the maturity of the RET (Hoppmann 2013) or firm specific strategies. Subsequently, apart from "original" learning effects, interactions and economies of scale or, as Kahouli-Brahmi (2008) state, 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, technology cost 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 technology costs (prices), demand is depicted as a function of PV technology costs, expected returns on PV investments and other preferences (environmental). Finally, returns depend on technology costs and revenues that are triggered by RE support, i.e. demand-pull policies. The relations are depicted in Figure 3. Learing-by-using or interacting are not seperately adressed and might be captured by cumulated installations while economies of scale might be reflected by production. The impact of learing-by researching is represented by annual public R&D spending. Returns are measured as the difference between the specific generation cost of a small scale PV system adjusted by RE supports (further subsidies) and the specific revenues (feed-in tariffs). The pull effect of demand policy is understood as the difference between average specific revenues of energy suppliers (retail) and the feed-in tariff. Simultaneous structural equation modeling is applied to assess the impact of demand and policies on levelized generation costs of PV power and vice versa.

Figure 2: Structural model and dependent and explaining factors

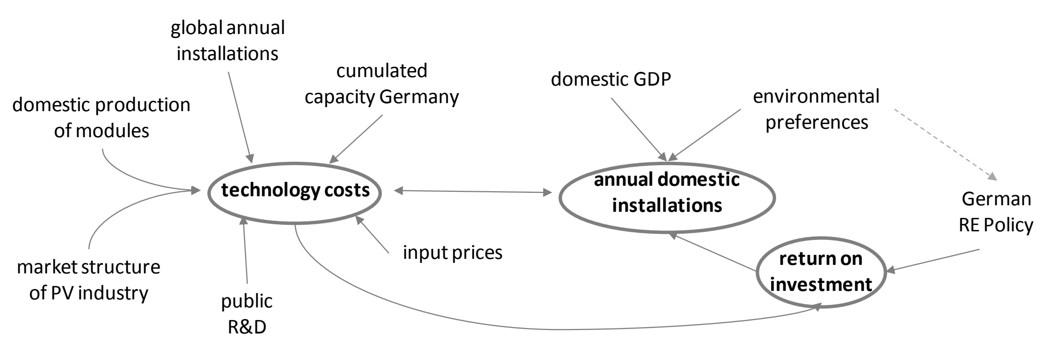


Figure 3 depicts the development of the feed-in tariff for a small PV system and the return on PV investment of a 10 kWp plant.

3 Results

To assess the impact of the German feed-in policy (RE act) on technology costs, the following model is applied: Input prices (P) e.g. Si, domestic demand (Q), market structure (MS) and size (Prod) of the domestic PV industry measured in annual production, learning effects measured by domestic cumulated capacities (Capc) as well as global growth in the PV market (GCap) determine technology costs (C). Global installed capacities are included because domestic demand has exceeded domestic production in Germany, and thus, domestic prices are not determined by German manufacturers solely. To account for technological changes R&D efforts (RD) are included. Moreover, to integrate policies, we assume that domestic demand depends on technology costs (C), profitability or return (R) and on environmental preferences (En) and control variable GDP. The profitability of a PV investment depends besides technology costs on policy support (Pull), i.e. the feed-in tariff.
Analogous to learning rate curves the functional form is:

Formula 1: $$lnC_t = \alpha_0 lnk + \alpha\, lnQ_t + \beta_i\, lnX_{it} + u_t$$

As demand is a function of the price and is determined by expected (marginal) returns as well as by preferences, it is modeled as a function of technology cost, return, preferences and control variable.

Formula 2: $$lnQ_t = \alpha_0 + \alpha_1 lnC_t + \alpha_2 lnR_t + \beta_i\, lnZ_{it} + u_t$$

Finally, return of PV power generators is triggered by technology costs and revenues, which are affected by the demand pull policy in Germany. Hence, the return is

Formula 3: $$lnR_t = \alpha_0 + \alpha_1 lnC_t + \alpha_2 lnPull_t + u_t$$

Xi includes MS, Prod, Capc, GCap, RD
Zi includes En and GDP

Technology system costs (C) are depicted as levelised cost of electricity generation per kilowatt hour for a 10 kWp in Germany. The levelized cost of electricity is applied because it incorporates changes in generation efficiency. To capture demand the annual PV installations in Germany in megawatts are applied. The cumulated installed capacity (Capc) in Germany is measured in megawatts and is supposed to reflect the learning effects in installation of PV systems. The German installed capacity is used for several reasons: (i) Germany has strongly dominated global capacity installations and is still leading 2014 in cumulated installed PV capacity (IEA PVPS 2015), (ii) the German demand-pull policy has pushed PV demand and hence domestic and global module production and (iii) the research questions centers on the impact of the German RE policy. Therefore, the pull-effect of the German demand policy in Germany is applied and changes due to other factors such as demand effects of other national policies should not be depicted in this variable. Nevertheless, foreign activities affect technology costs as well. For this reason, GCap as an external factor accounts for global growth in the PV sector. While market structure is measured by the average size of German and Chinese PV module manufacturers and account also for economies of scale, Prod stands for the domestic market size and competition.
R&D efforts are measured as the three year average of public R&D support for PV. Environmental preferences (En) are depicted by the votes for the environmental/green party in Germany. Profitability is the difference between the specific costs and revenues (Euro/kWh) from PV electricity generation, which takes all support policies such as feed-in tariffs or grants or subsidized loans into account. The Pull is supposed to show the strength of the demand pull effect by the difference between the feed-in tariff and the actual power reference price (average revenue without taxes of German power suppliers per kWh). All monetary values are indicated on price basis 2010.
Using the structural equation approach, the specified model are assessed by two simultaneous estimations (observed information matrix (OIM, variance; Table 1) and robust estimator variance (REV), Table 2) and two non simultaneous estimations (standard (ml) and general structural equation models (GSEM), Annex Table 1 and Annex Table 2). The observations cover the time period 1983(80) to 2015.

Table 1: Regression results OIM model

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 2: Regression results REV modell

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

Results suggest that demand as well as input prices significantly increase technology costs. In contrast, learning effects that also occur at construction sites lead to significant cost declines. In addition, global growth of PV installations is also significant, suggesting that a certain share of technology cost decreases is pushed by external (non-policy or non-German policies) factors. Demand for PV systems is significantly driven by costs (prices) as well as by expected returns while environmental attitudes (preferences) seem to correlate negatively with demand for PV systems. Returns of PV investments clearly depend on system costs and less on demand-pull policies. Overall, the impact of the demand pull policy (Feed-in tariff) on technology costs seems to push costs slightly upwards while domestic cumulated capacity, reflecting learning, and global market development reduce them significantly.

Applying the results in Table 1 and 2 show, that the direct impact of policies on return and hence on demand is insignificant while demand (annual capacity) affects costs by about 0.1% . The strongest impact on prices has the input price with 0.3% followed by learning-by-doing effect (cumulated capacities) with about -0.2% and the global deployment. Demand is strongly and significantly affected by costs (-4%) and green votes (-9%), of which the negative sign is difficult to explain (positive sign in the non-simulaneous approach Annex Table 1 and 2). Finally, the profitability depends on costs, but if these are skipped, then the pull effect explains to a small degree the profitability, and hence the impact on demand (Annex Table 1 and 2).
While the simultaneous approach reports significant values for all variables but production, market structureR&D and pull effect, the non simultaneous regression reports (R-square about 0.99) significant values for each variable except for demand, market structure and R&D.

4 Discussion and Conclusions

The results are based on a structural equation approach and accounts for a limited set of interdependencies. 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. Even so the simultaneous and non simultaneous regressions show different impacts, the consistenly report significant results except for production and market structure, signalling that these factors are either not well captured or insignificant. Inconsisten results are obtained regarding demand: the non-simultaneous approach does not report significant coefficients for demand.
Even so several different regressions are conducted, the approach has one major drawback: the data are time series, while the regression tool is based on the application of cross-sectional data. For example, autocorrelation and non-stationarity might cause problems, but it is still unclear how to adress them in structural equations. Therefore, further refinement of the model and assessment is needed. This aslo includes the design of the exogenous variable capturing demand pull policies. One problem can only be addressed over time: the analysis is limited by the number of observations, which is very small (n = 30).

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Annex

Annex Table 1: Non simultaneous regression results (ml)

Structural equation model Number of obs = 30
Estimation method = ml
Log likelihood = -66.669712

	Coef.	OIM Std. Err.	z	P>|z|	[95% Conf.	Interval]
Structural						
lnlcoe <-						
lncapann	.0272793	.0222878	1.22	0.221	-.0164039	.0709626
lnpricesi	.2846931	.0557472	5.11	0.000	.1754305	.3939557
lnmodul	.075882	.0368715	2.06	0.040	.0036151	.1481488
lnrd3yav						
L1.	.0184691	.109442	0.17	0.866	-.1960333	.2329716
lncapcum	-.1830121	.0367872	-4.97	0.000	-.2551137	-.1109105
lnglobannger	-.1831636	.0343301	-5.34	0.000	-.2504494	-.1158779
lncompet	-.0412568	.0377896	-1.09	0.275	-.1153229	.0328094
_cons	1.623125	.4819764	3.37	0.001	.678469	2.567782
lncapann <-						
lnmargincorr	-16.98595	15.06498	-1.13	0.260	-46.51277	12.54086
lngreenvotes	3.904563	2.327754	1.68	0.093	-.6577509	8.466877
lngdp_r	29.59588	6.622722	4.47	0.000	16.61558	42.57617
_cons	-168.2562	21.9057	-7.68	0.000	-211.1906	-125.3218
lnmargincorr <-						
lnpullcorr	.0379939	.0117325	3.24	0.001	.0149985	.0609892
_cons	3.257253	.0366832	88.79	0.000	3.185355	3.329151
var(e.lnlcoe)	.0106474	.0027492			.006419	.0176613
var(e.lncapann)	2.700743	.6973288			1.628186	4.47984
var(e.lnmargincorr)	.0022985	.0005935			.0013857	.0038126

LR test of model vs. saturated: chi2(19) = 155.83, Prob > chi2 = 0.0000

Annex Table 2: Non simultaneous regression results GSEM

Generalized structural equation model Number of obs = 35
Log likelihood = -47.597934

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnlcoe <-						
lncapann	.0272793	.0224176	1.22	0.224	-.0166583	.071217
lnpricesi	.2846931	.055755	5.11	0.000	.1754154	.3939709
lnmodul	.075882	.0369109	2.06	0.040	.003538	.148226
lnrd3yav						
L1.	.0184691	.109448	0.17	0.866	-.1960449	.2329832
lncapcum	-.1830121	.0368186	-4.97	0.000	-.2551753	-.110849
lnglobannger	-.1831636	.0343304	-5.34	0.000	-.25045	-.1158773
lncompet	-.0412568	.0378033	-1.09	0.275	-.1153498	.0328363
_cons	1.623125	.4820387	3.37	0.001	.6783468	2.567904
lncapann <-						
lnmargincorr	-2.76271	.3667062	-7.53	0.000	-3.481441	-2.043979
lngreenvotes	4.738192	1.82631	2.59	0.009	1.15869	8.317695
lngdp_r	25.03663	2.678022	9.35	0.000	19.7878	30.28545
_cons	-182.6911	17.77538	-10.28	0.000	-217.5302	-147.852
lnmargincorr <-						
lnpullcorr	.152416	.0670583	2.27	0.023	.0209841	.283848
_cons	2.823034	.2026966	13.93	0.000	2.425756	3.220312
var(e.lnlcoe)	.0106474	.0027492			.006419	.0176614
var(e.lncapann)	2.624448	.627363			1.642714	4.192895
var(e.lnmargincorr)	.0854614	.0205481			.0533469	.1369087