PV, wind and biogas plants: Learning curves as a tool to explain feed-in tariffs, market diffusion and grid parity in Germany

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OBJECTIVES The objective of this article is to investigate the relationship between learning curves, grid parity and feed-in tariffs in the diffusion of renewable energy technologies (RET) in Germany. We take a closer look at the intersection of cost reductions, grid integration and support strategy for solar photovoltaics (PV), wind turbines and biogas plants.

We make use of learning curves to monitor price developments and compare them to manufacturing costs as well as the level of feed-in tariffs granted. In addition, we estimate the difference between actual price and break-even price (the difference between the cost of the technology taken into consideration and the cost of electricity from conventional/non-subsidized energy technologies). These additional costs may be referred to as learning cost investments necessary to make the technology cost-efficient (Junginger et al., 2010).

METHODOLOGY We implement a multiple-factor learning curve model (MFLC) to account for the impact of changing input prices and manufacturing scale (Yu et al., 2011). We argue that the importance of input prices is most evident for the case of biogas. Investments in bioenergy technology are correlated with the cost of feedstock and with competing land-use decisions, rather than being uniquely dependent on the efficiency improvements in biogas technology (Reise et al., 2012). In addition, the importance of local learning is most important where investors (mainly farmers) and resource availability is locally bound.

On the contrary, both PV and wind turbines are generally the product of a global learning system (Nemet, 2009; van Sark, 2008; Junginger et al., 2005). Nevertheless, country-specific peculiarities play an important role in the diffusion process and have been evaluated, for the case of Germany, by Klaassen et al. (2005); Ibenholt (2002); Durstewitz and Hoppe-Kilpper (1999). Furthermore, national and sub-national global learning curves have been adopted to evaluate specific policy schemes and their impact on the local market (e.g. van Benthem et al., 2008).

In addition to the standard estimation procedure based on the cumulative installed capacity of RET, we draw on a data set that comprises all registered plants that benefit from feed-in payments in the German EEG support scheme (EEG, 2012; EnergyMap, 2012). The data set allows us to monitor the year of installation as well as the installed power capacity of each individual system, thereby providing sufficient information to account for scale and learning effects related to system size efficiency. Furthermore, detailed geographical information is also given, thus enabling the model to account for important regional variations that may help to better understand clustering effects for the diffusion of specific learning processes (especially with respect to skilled workforce).

EXPECTED RESULTS We expect the learning curves to roughly match the decrease in feed-in tariffs, but we would like to estimate the level of learning costs granted by the government to the different RET and assess their relative success in terms of installed capacity diffusion per Euro invested, the actual amount of electricity fed-in, and the expected additional support funds needed to obtain grid parity.

Based on an evaluation of the historical development of RET, we presume PV systems to have been awarded an over-proportionate level of funding in comparison to wind energy, while biogas is likely to be strongly dependent on specific local conditions and feedstock costs, which renders it very difficult to directly compare its level of support with the other RETs.

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