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Learning-by-Doing in the Renewable Energy Equipment Industry or in Renewable Electricity Production – Why Does It Matter to Differentiate?

A Case Study of Germany

Berlin, May 2007

Opinions expressed in this paper are those of the author and do not necessarily reflect views of the institute.

IMPRESSUM

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Abstract

In economic models of energy and climate policy, endogenous technological change is generally introduced as the result of either investment in research-and-development or of learning-by-doing. In this paper, we analyze alternative ways of modeling learning-by-doing in the renewable energy sector in a top-down CGE model. Conventionally, learning-by-doing effects in the renewable energy sector are allocated to the production of renewable based electricity. We build on the observation that learning-by-doing also takes place in sectors that deliver capital goods to the renewable electricity sector, in particular in the production of machinery and equipment for renewable energy technologies. We therefore implement learning-by-doing alternatively in the renewable energy equipment industry and in renewable electricity production and show why it matters to differentiate between these two approaches. The main differences originate from effects on international trade, since the output of the machinery and equipment sector is intensively traded on international markets unlike renewable electricity.

Keywords: Learning-by-doing, wind energy, general equilibrium modeling, international trade

JEL classification: Q43, C68, O30, F10

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1 Introduction

In economic models of energy or climate policy, endogenous technological change is generally modeled as the result of investment in research and development (R&D) or of learning-by-doing (LbD). Both channels are based on the idea that there is a stock of "knowledge", which accumulates in reaction to an economic activity such as production or R&D. This knowledge influences production possibilities (or sometimes also consumption). In the first case (R&D), a stock of knowledge or human capital is generated through investment into research and development activities. Model parameters, such as price changes induced by policy measures, may lead to increased investment into the stock of knowledge capital with its subsequent effects on production possibilities and productivity. In the second case (LbD), knowledge accumulation is based on experience in producing or using a specific technology or process. The application of specific technologies, which may be encouraged by policy measures or other model parameters, then results in a decline of production costs as experience with this technology accumulates.

Given the model structure and sectoral and technology detail, macroeconomic (top-down) modelers tend to focus on the R&D approach while the majority of engineering (bottom-up) modelers focus on implementing the LbD approach taking advantage of the technological detail inherent to these models. For an overview of modeling approaches and results see, for example, Vollebergh and Kemfert (2005), Jaffe et al. (2003), Löschel (2002), Grübler et al. (2002), Edmonds et al. (2001).

Few studies so far have implemented learning effects into macroeconomic (top-down) models. They mainly differ with respect to the proxy/indicator for the activity which causes learning: i) cumulative installed capacity of a technology (Gerlagh and van der Zwaan, 2003), ii) sectoral output (Rasmussen, 2001; Carraro and Galeotti, 1997), iii) sectoral capital stock (van Bergeijk et al., 1997), iv) sectoral labor input (Kverndokk et al., 2004), v) technological know-how (learning-by-researching) (Goulder and Mathai, 2000), or vi) a combination of these indicators such as the two-factor learning curve that takes into account cumulative capacity as well as cumulative R&D expenditure (Kouvaritakis et al., 2000; Klaassen et al., 2005).

Most studies agree that learning effects are most pronounced for relatively new technologies, e.g. non-fossil energy technologies. Thus, they separate fossil energy from non-fossil energy and analyze the effects of learning-by-doing in non-fossil energy goods, such as renewable energy. When technological progress is induced via learning-by-doing rather than by autonomous efficiency improvement, this may have an influence on the optimal timing of environmental policies and of investment, which is the focus of most of those studies.

Conventionally, learning-by-doing effects in the renewable energy sector are allocated to the production of renewable based electricity. In this paper, we build on the observation that learning-by-doing also takes place in sectors that deliver capital (investment) goods to the renewable electricity sector, such as the production of machinery and equipment for renewable energy technologies. Machinery and equipment components have substantially improved over time leading to lower unit capital costs. Such improvements for wind power, for example, include increased hub height, larger rotor blades, innovative technologies such as new direct-drive (gearless) systems, better foundation and site preparation and more (Neij et al., 2004). Thus, substantial learning effects have been induced by both increasing experience in producing renewable energy technologies and using it to produce electricity. Naturally, there are additional learning effects on the electricity production side. They include an improvement in identifying and making use of most favorable locations, better information technology to respond to changing conditions.

In this paper, we introduce learning-by-doing on a sectoral basis in an energy-economy top-down general equilibrium model. LEAN_2000 is a two-region empirical general equilibrium model for Germany and the rest of the European Union with a particular emphasis on the representation of the energy markets and the simulation of policies to reduce CO_2 emissions (Welsch, 1996). We implement learning-by-doing in both the renewable energy equipment industry and in renewable electricity production and show why it matters to differentiate between these two approaches. The main differences originate from the impact on international trade. This is due to the fact that the output of the machinery and equipment sector is intensively traded on international markets unlike renewable electricity.

Learning is modeled as a function of the cumulative output in a sector and increases the efficiency of new technologies. This means that any given output can be produced at reduced costs because of increased efficiency in the use of, for example, capital and labor. We expect two main effects to take place by introducing learning-by-doing in the renewable energy equipment industry. Firstly, learning-by-doing leads to a reduction of the unit costs of equipment, which will via capital goods (investment) further translate into reduced renewable electricity costs and prices. The second effect relates to international trade. Renewable energy technologies are produced for either domestic demand or for exports. Exports in the sector are non-negligible (DEWI, 2006) and may even be more important in the future. In the case of wind power, for example, (on-shore) locations are getting scarce in Germany on the one hand, and on the other hand, world markets for wind are likely to be growing. Taking account of exports of renewable energy technologies may lead to a higher total demand for renewable energy equipment and result in higher learning effects with its subsequent effects on costs and prices. This increases the international competitiveness of renewable energy equipment and stimulates national and international demand for this technology, which then again would induce higher learning (first-mover advantage). An analysis of learning-by-doing effects in the production of renewable electricity alone is not able to take account of these international trade effects.

In addition to international trade of a specific good, such as renewable energy equipment, knowledge and technical know-how about this good, which is responsible for learning processes, can spill over from one country to another. Such knowledge spillovers and the induced innovation and diffusion of new technologies have been intensively discussed in the context of climate policy modelling (for an overview see Sijm, 2004 or Weyant and Olavson, 1999). A spillover can be defined as ‘any positive externality that results from purposeful investment in technological innovation or development’ (Weyant and Olavson, 1999). In view of German renewable energy equipment, spillover effects can take place in several ways. For one, Germany can profit from knowledge accumulated outside of Germany. Reversely, knowledge gained in Germany spills over to other countries. Moreover, several regions can simultaneously accumulate experience based on combined efforts to produce a technology. Depending on how such spillover effects are treated substantial effects on domestic production and exports patterns can be observed. Our analysis reveals positive effect of learning-by-doing on export opportunities and domestic production in Germany.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of the current status of the renewable energy industries in Germany. Section 3 discusses methodological issues related to the concept of learning-by-doing, while Section 4 describes the CGE model employed (LEAN_2000) and the implementation of learning-by-doing in the model. The scenario analysis and results including a sensitivity analysis of spillover effects are presented in Section 5. Section 6 summarizes the main findings and gives suggestions for future modeling strategies.

2 Renewable energy in Germany

Renewable based electricity generation has increased substantially in Germany over the last decade. Between 1994 and 2004, installed renewable electricity capacity quadrupled from about 6 GW to 24 GW (BMU, 2005). The increase can be attributed almost entirely to a soaring growth of wind power capacity (Figure 1).[1] In 2004, 9.4% of German electricity supply was generated by renewable energy sources (BMU, 2005). The German government aims to increase the share of renewable based electricity production by the year 2010 up to at least 12.5%. In the medium term, the goal is to produce at least 20% of electricity from renewable energy by 2020. In the long term, by 2050, the goal is to see the renewable share rise to at least 50% of total electricity production.

A renewable energy law was introduced to help reach these goals. The law was originally passed in 2000 and replaced the electric power feed-in-law of 1991. The law supports renewable energies (wind power, hydropower, solar energy, biomass) through two main features: a fixed compensation for renewable-based power fed into the grid, and a priority purchase requirement for renewable power imposed upon transmission system operators.

[1] Because wind power is the main driving factor of renewable electricity growth, the focus of this paper is on wind power production. Although the analysis refers to renewable electricity generation in general, many examples and explanations will relate to wind power production.

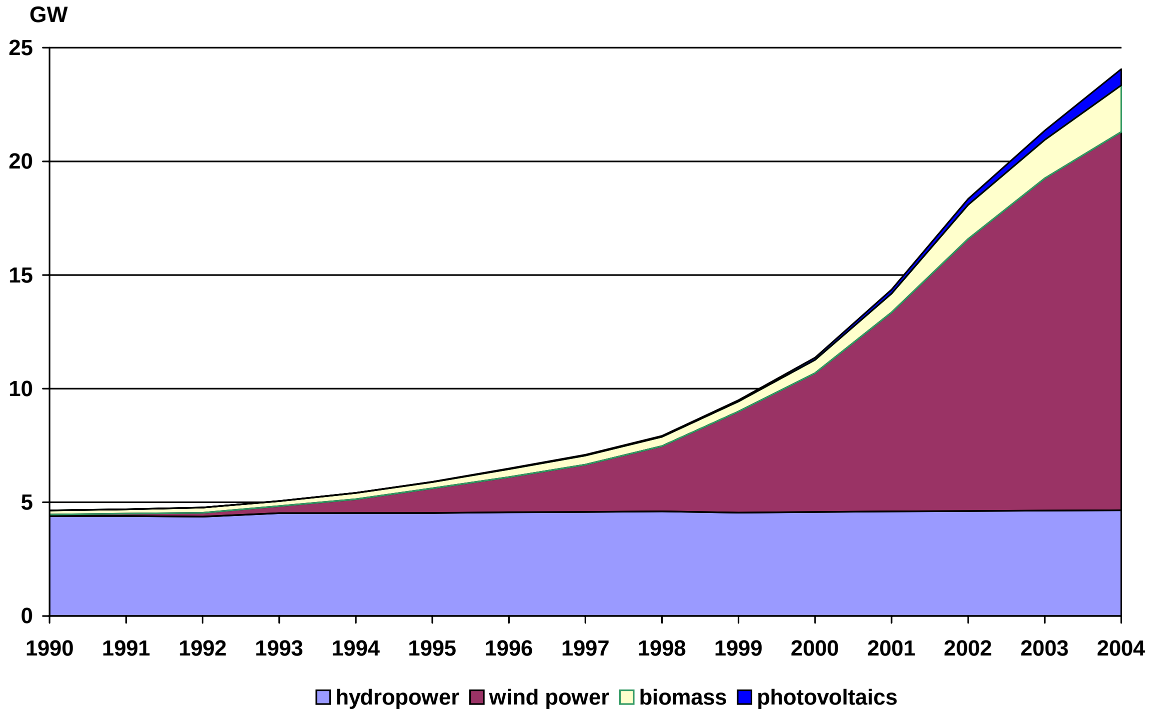

Figure 1 Installed renewable electricity capacity in Germany

Compared to other EU countries, Germany has by far the largest installed capacity of wind power, followed by Spain, Denmark and the Netherlands. While in 1997 Germany and Denmark had roughly the same total installed capacity of 2 GW, installed capacity in Germany had grown to more than 16 GW by 2004, whereas Denmark stagnated at about 3 GW (Figure 2).[2] In the early years of wind power generation (1995), most of the wind turbines were manufactured in Denmark and exported to Germany and other countries. The supply of wind turbines in Germany, however, is now mostly domestic (60%) (Neij et al., 2004). Moreover, exports of wind turbines from Germany have grown rapidly from a capacity of about 18 MW in 1994 to roughly 750 MW in 2003 (DEWI, various years). In 2004, Germany exported about 50% of its total domestic wind turbine production, mainly to Egypt, Japan, Austria, Australia and Slovakia (VDMA, 2005). This equals the average export share of the German manufacturing sector.

[2] Denmark, however, still possesses a higher share of wind power in total electricity generation. About 20% of electricity was supplied by wind energy in Denmark in 2004. In contrast, the share in Germany amounts to only about 6%.

With respect to costs of producing wind power, capital costs capture the highest share. The wind turbine itself accounts for about 80% of total costs. Additional costs relate to the installation of the wind turbine, such as costs of foundation, installation work, site preparation, roads, grid connection and also operation and maintenance work (Neij et al., 2004).

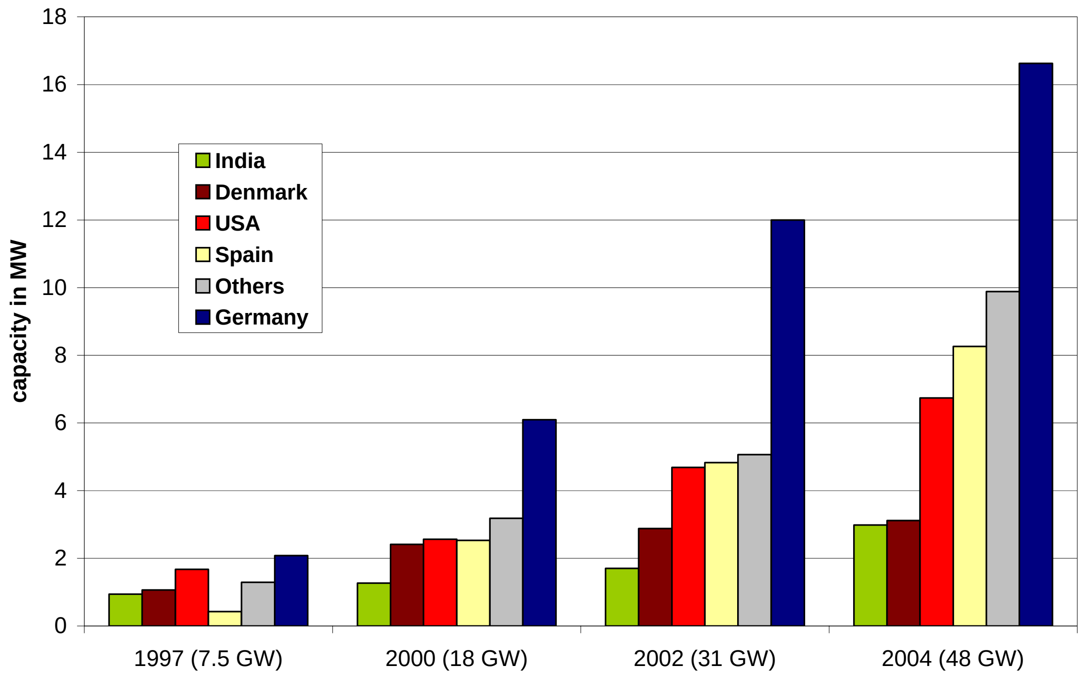

Figure 2 Total installed capacity of wind power, 1997-2004

3 Learning-by-doing and renewable energy

The concept of learning-by-doing is based on the observation that production costs or investment costs of a certain technology or product decrease with cumulated experience of producing it. Experience can be described in terms of cumulated production, output, sales or cumulative installed capacity. Often learning-by-doing is distinguished from learning-by-using or learning-by-researching. Whereas learning-by-doing refers to cost reductions that occur in connection with increasing experience in the production and installation of a specific technology, learning-by-using refers to cost reductions achieved by increased efficiency and experience in using a specific technology. Moreover, learning-by-researching refers to cost reductions that arise as a result of R&D activities (Löschel, 2002).

Hall and Howell (1985) distinguish learning curves from experience curves. According to their definition, the term learning curve indicates a relation between the costs of one of several, substitutable inputs (e.g. labor costs) and cumulative output (IEA, 2000), while the concept of experience curves is broader and refers to total costs, which allegedly occur over the total lifetime of a product (Boston Consulting Group, 1968). The experience curve, relating total cost (C) of a technology and cumulative quantity (X), can be described by the following equation:

$$C = \alpha \quad X^{-\beta} \tag{1}$$

where α reflects the base year cost, β is the learning elasticity (or learning index), which is used to calculate the relative cost reduction for each doubling of the cumulative production. With this definition, specific costs are reduced by a factor of $2^{-\beta}$ for every doubling of installed capacity. The amount $2^{-\beta}$ is defined as the progress ratio (PR) while $1\text{-}2^{-\beta}$ is called the learning rate (LR), e.g. a PR of 90% means that costs are reduced by 10% (LR) for each doubling of cumulative experience.

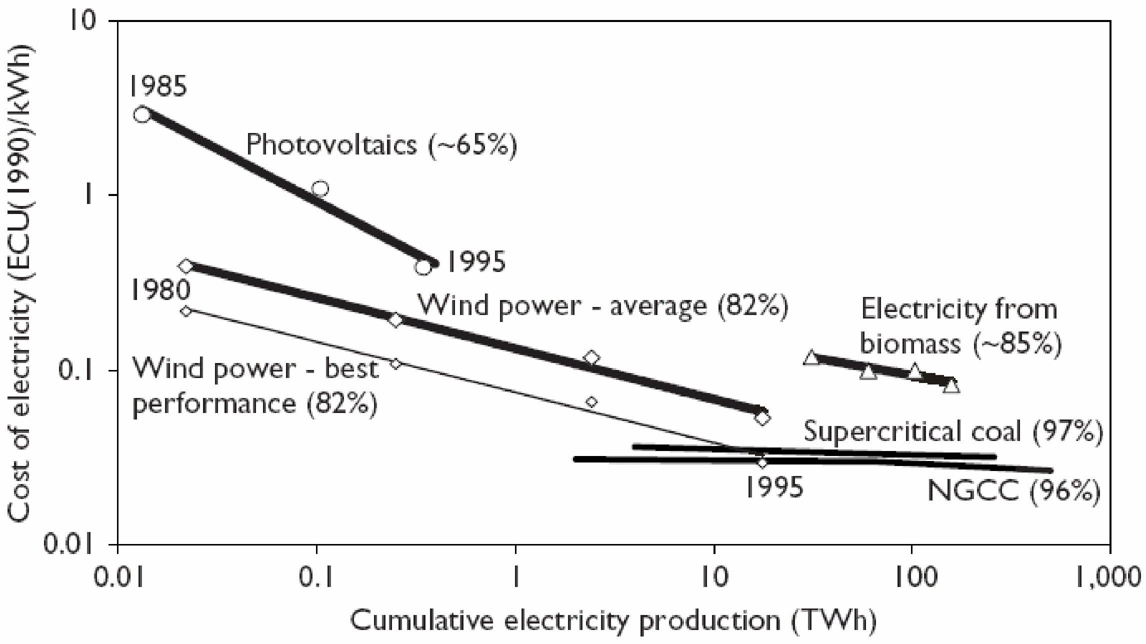

Figure 3 Learning effects for electricity technologies in the European Union, 1985-1990

Source: IEA (2000). Cost of electricity and electricity produced from selected electric technologies installed in the European Union 1980-1995. Numbers in parentheses indicate estimates of progress ratios. The two curves for wind power show the average production costs and the production costs of the most efficient plant.

Higher cost reductions and learning-by-doing can be observed for fast growing technologies that start out a low level of cumulative production, as a doubling of cumulative experience can be more easily achieved (McDonald and Schrattenholzer, 2001). Figure 3 illustrates learning in the European Union electricity sector between 1985 and 1990. Photovoltaic technologies show the highest learning rate, a cost reduction of 35% on average could be achieved for each doubling of cumulative electricity output. This is followed by wind power, which yielded an 18% cost reduction for each doubling of output between 1980 and 1995. New large-scale fossil fuel technologies, such as supercritical coal technologies or natural gas combined cycle plants, show substantially lower cost reductions in relation to changes in output with learning rates at 3 to 4%.

A wide range of learning rate estimates for renewable energy can be found in the literature (Neij et al., 2004; Papineau, 2006; Junginger et al., 2005; Ibenholt, 2002; IEA, 2000). They differ because of varying assumptions with respect to time periods, cost measures (investment cost, levelized cost of electricity production, electricity or turbine price), experience measures (cumulated installed capacity, cumulative produced capacity, electricity generated), geographical area, system boundaries, data availability and quality, and estimation methods.[3]

3.1 Learning-by-doing in renewable energy machinery and equipment

Machinery and equipment components have substantially improved over time leading to lower unit costs. Such improvements for wind plants have been brought about by increased hub height, larger rotor blades, innovative technologies such as new direct-drive (gearless) systems, better foundations and site preparation, better equipment to respond more immediately to changes in direction and speed of wind, increased efficiency of generators, improved grid connection etc. (Neij et al., 2004). All these improvements are based on increased experience in the production of renewable energy machinery and equipment and contribute via learning to cost reductions. A typical learning curve would thus relate the unit cost of renewable energy equipment to the current or cumulated output of the industry. As plant size (capacity) differs among units, costs are usually expressed as specific plant costs per unit of generation capacity (€ per kW) and experience is measured in units of generation capacity (kW).

3.2 Learning-by-doing in renewable electricity production

In addition to learning in the production of renewable energy equipment, efficiency gains can be observed in the use of this equipment, i.e. in the production of renewable electricity. They include an improvement in identifying and making use of most favorable locations, better information technology to respond to changing conditions, improved operation and maintenance, energy management, increased plant lifetime etc. Learning effects according to equation (1) can be estimated by relating levelized costs of renewable electricity production (€ per kWh) to cumulative experience measured in terms of electricity generated (kWh).

Most of these improvements reduce electricity costs but are not reflected in the capital cost. Some learning effects from the machinery and equipment sector, however, are carried over to the electricity sector in form of reduced investment costs. Thus, levelized costs of renewable electricity generation are lower not only because of learning in the production of electricity,

[3] Neij et al. (2004), for example, estimate experience curves for wind power in Denmark, Germany, Spain and

but also because of learning in the production of machinery and equipment components. This implies that an approach, which estimates the cost reduction for renewable electricity production, covers the sum of both effects, and the learning effects for electricity production alone cannot be singled out.

Often, data on levelized costs of electricity production is not readily available and electricity price data is used instead. Using price data as a substitute means that mark-ups on costs (and more importantly changes thereof), as they may be caused for example by policy support or market power, have an impact on the estimation of learning. Learning estimates based on prices may thus under- or overestimate real learning. Up to now, learning has been estimated for the costs of renewable energy without distinguishing the source (industry) from which it originates. Also, the modeling of learning-by-doing attributed all learning to the electricity-generating sector. In the following sections, we explore the consequences of a more differentiated attribution of learning effects.

4 LEAN_2000

4.1 The model

In this paper, the effects of learning-by-doing are examined using a modified version of LEAN_2000, a computable general equilibrium model. LEAN_2000 is a two-region empirical general equilibrium model for Germany and the rest of the European Union with a particular emphasis on the representation of the energy markets and the simulation of policies to reduce CO_2 emissions (Welsch and Hoster, 1995). Each region is represented in 15 sectors, seven of which are energy sectors (Table 1). LEAN_2000 is a recursive-dynamic model. Under the assumption of myopic expectations, it solves a sequence of static equilibria, which are connected via capital accumulation, technological change and exogenous assumptions on the development of some parameters. The model solves over a time horizon of 35 years from the base year 1995 to the year 2030. Crucial parameters, such as elasticities of substitution have been estimated (Welsch, 1996). The model is "calibrated", that means the remaining parameter values are determined in such a way as to reproduce the data of the base period.

Sweden and reveal progress ratios in the range of 83% to 117% depending on the assumptions made.

Table 1 Production sectors in LEAN_2000

Production sectors	
Energy sectors 1. Hard coal and hard coal products 2. Lignite and lignite products 3. Mineral oil and mineral oil products 4. Natural gas and produced gases 5. Electricity 6. Nuclear fuels 7. Renewable energy	Non-energy sectors 8. Agriculture 9. Metals, minerals and chemicals 10. Equipment, investment goods 11. Consumption goods 12. Construction 13. Transport services 14. Other services 15. Non-market services (government)

Production possibilities in each sector are represented by a nested constant-elasticity-of-substitution (CES) or fixed coefficient (Leontief) production function. Electricity production by different fuels is based on limited substitution possibilities because individual fuels are often used in different load sequences and thus cannot be easily substituted.

Private consumption is modeled by a representative household with a linear expenditure function. Consumption of each commodity consists of two components: a basic or subsistence consumption, which is consumed independent of income and prices and an additional consumption that depends on income and price level. **Public expenditure** is a linear function of GDP.

Aggregate **labor supply** is described by a dynamic wage equation, which explains wage formation by the dynamics of labor productivity in conjunction with a Philips curve mechanism. Labor is assumed to be mobile across the domestic sectors but immobile across borders. **Capital stocks** are fix within each time period and sector but change over time as capital depreciates and new investment is added. Sectoral investment is based on intertemporal cost minimization and depends on the interest rate, expected prices of variable input factors and expected demand.

Germany’s most important **trading partners**, the European Union (EU) countries, are aggregated and explicitly modeled as one region. Trade flows between Germany and the rest of the EU are endogenous and depend on the relative prices of goods. **Foreign trade** with the rest of the world is modeled by means of a world trade pool with exogenous import volumes and export prices of the rest of the world. Foreign trade follows the Armington approach, modeling domestic and foreign goods as imperfect substitutes.

The model incorporates factor-augmenting **technical progress** for all production factors. For capital, technical progress is embodied. The average efficiency of each sector's aggregate capital stock can only be increased by introducing new, more modern equipment (Solow, 1962). For the other factors of production, technical progress is disembodied, meaning that it affects the total amount employed in each time period.

Because there is capital-augmenting technical progress, it is useful to introduce the concept of average capital efficiency. The efficiency of the existing sectoral capital stock ($\tilde{K}_t$) is a weighted average of the efficiency of last period's capital stock ($\tilde{K}_{t-1}$) and the efficiency of the latest vintage now in operation ($\tilde{I}_{t-1}$). In the original version, the efficiency of the latest vintage is assumed to grow at an exogenous rate.

$$\tilde{K}_t = \frac{(1-\delta)K_{t-1}}{K_t}\tilde{K}_{t-1} + \frac{I_{t-1}}{K_t}\tilde{I}_{t-1} \qquad (2)$$

The following section describes how we modify this assumption to account for learning-by-doing.

4.2 Implementation of learning-by-doing in LEAN_2000

We introduce learning-by-doing on a sectoral basis in LEAN_2000. Learning is a function of the cumulative output in a sector. Due to learning, any given output can be produced at reduced costs because of increased efficiency in the use of factors of production. Learning-by-doing can apply to the efficiency of both capital and labor input, i.e. factor-neutral, or can apply to only one production factor (factor-augmenting). In the case of capital input, learning-by-doing increases the efficiency of new investment, i.e. the latest vintage, $\tilde{I}$.

$$\tilde{I} = \left(\frac{X_{cum,t}}{X_{cum,0}}\right)^{\beta} \qquad (3)$$

X_{cum} refers to sectoral cumulative output in period t and period 0 respectively, while β represents the learning index. As $\tilde{I}$ enters the efficiency of the total capital stock, this implies that we endogenize capital embodied technological change. Similarly, we make labor efficiency a function of cumulated output and the learning index.

Implementing learning-by-doing into a dynamic-recursive model that solves for a sequence of temporary equilibria under myopic expectations means that future development, in particular effects from learning-by-doing, cannot be taken into consideration by decision makers in each period. This approach is well suited to represent market behavior as each individual actor has only a limited influence on learning and, therefore, does not consider it in its decision making process.[4]

4.3 Renewable energy equipment in LEAN_2000

In our analysis, we assume that the production of wind turbines is part of the machinery and equipment sector. In order to account for material and equipment specifically used in the renewable energy equipment (such as the wind turbine) industry we introduce a new sector in LEAN_2000 called renewable energy equipment (EQIP), a sub-sector of the equipment sector. In 1995, the share of renewable based electricity was still at a rather small level (Figure 1). It is guesstimated that the value of output in renewable energy equipment accounted for only about 0.5% of the total value of output in the equipment sector in 1995 (VDMA, 2005a).

We assume that the inputs to the renewable energy equipment sector show the same pattern as the inputs to total equipment. On the use side (row IO table), we assume that products from the renewable energy equipment sector are used by one single sector, the electricity sector. In addition, renewable energy equipment is exported. We assume that initially 0.5% of total equipment exports are to be allocated to renewable energy equipment exports.

5 Analysis and results

In order to explore the effects of learning-by-doing in renewable energy equipment and in renewable electricity production, we conduct three scenarios: (1) a base case scenario where no learning takes place in either sector; (2) a counterfactual scenario lbd_elec where learning-by-doing takes place in renewable electricity production; and (3) a counterfactual scenario lbd_eqip where learning-by-doing takes place in production of renewable energy equipment.

The base case scenario assumes a climate policy targeted at those sectors covered by the EU emissions trading scheme. In particular, we introduce a 20 Euros per t CO_2 in 2005, linearly increase it to 40 Euros per t CO_2 by 2010, and keep it constant thereafter. The climate policy equally applies to the two learning scenarios. For all three scenarios, assumptions about the development of the energy sector are in accordance with projections for Germany by IEA (1997) and Enquete (2002). Output of renewable energy in LEAN_2000 is exogenously given in accordance with the government goal for renewable electricity production. We assume wind power to be the single most important driver of growth in renewable energy with high initial growth rates that taper off over time. For renewable energy other than wind, we assume hydro capacity stable over time, as resources are limited, and allow for an increase in biomass- and waste-based electricity production. Additional baseline assumptions relate to prices of imported fuels, nuclear phase-out, and a minimum use of coal (FEES, 2007).

An exogenous path for renewable energy affects the way learning-by-doing can be analyzed. In this framework, learning-by-doing leads to a reduction of the unit costs of production, but not to an increase of the output of renewable electricity. For renewable energy equipment no output constraint is given. Since exports play a substantial role in this sector, production may increase even if domestic output of renewable electricity is exogenous. Learning induced cost reductions enhance (international) competitiveness and stimulate demand, which may then induce further learning.[5]

A crucial parameter of the policy scenarios is the learning rate. Based on the literature review (section 3), we realize that learning rates for renewable electricity technologies have been in the range of up to 18% and more in the past, i.e. that the unit cost of renewable electricity production decreases by this rate for each doubling of cumulated output. In our analysis, we assume a more conservative learning rate of 10% for both learning scenarios (compare Table 2). In the learning scenario lbd_elec, we assume that the cost reduction is due to an efficiency increase in the use of capital induced by learning in renewable electricity generation only. In

[4] Learning may thus generate a positive external effect, which means market behavior may not lead to an optimal solution (market failure).

[5] It needs to be stated that an exogenous path for renewable energy may be considered a constraint that impedes some of the effects on output that could result from learning induced cost reductions. We chose this approach as a simple approximation of the government development goals for renewable electricity production in Germany supported by the renewable energy law. We do not investigate which regulation or incentives are put in place to induce the targeted increase of renewable energy, which implies that we do not model policy induced technology diffusion. In our approach, incentives for investment in renewable energy are based on export opportunities in addition to supplying the domestic market and crowding out imports.

the scenario lbd_eqip all cost reduction is attributed to learning-induced efficiency increases in the sector producing renewable energy equipment. Here we assume that the efficiency of the use of capital and labor is affected simultaneously. In the first scenario lbd_elec, learning reduces the costs of renewable electricity only, whereas in the second case lbd_eqip, it affects the costs of the relevant equipment as well and thus entails effects on international trade.

Table 2 Assumptions on learning rates in scenario analysis

Scenario / Sector	base case	scenario lbd_elec	scenario lbd_eqip
renewable electricity production	-	10%	-
renewable energy equipment	-	-	10%

5.1 Output, investment and price effects

This section presents the effects on output, investment and prices for the three scenarios (base, lbd_elec, lbd_eqip). We discuss the effects for each sector separately.

Effects on renewable energy equipment sector: In the base case, cumulated investment in renewable energy equipment as well as output of renewable energy equipment rise over time (see Figure 4 and Figure 5). This is to meet the capital demand of the renewable electricity sector with its exogenously given production goals.

In the scenario where learning occurs in the production of renewable energy technologies (lbd_eqip), pronounced effects on production costs and output prices of the sector can be observed (Figure 6). The decline in production costs increases export demand and thus spurs production, which then reinforces the learning effect. Therefore, cumulated output rises substantially (Figure 4) while cumulated investment in the renewable electricity sector in Germany (Figure 5) even declines slightly (compared to the base scenario) because capital efficiency increases while renewable electricity output is fixed.

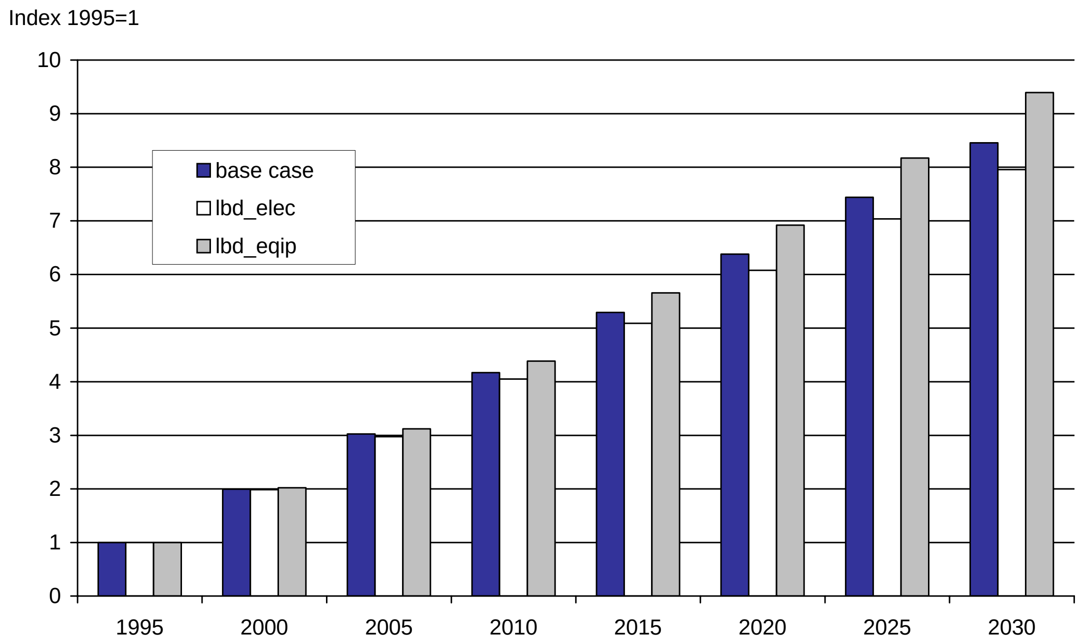

Figure 4 Cumulated output in the renewable energy equipment sector: base case and two counterfactual scenarios, indexed to 1995 thus reflecting quantity changes over time

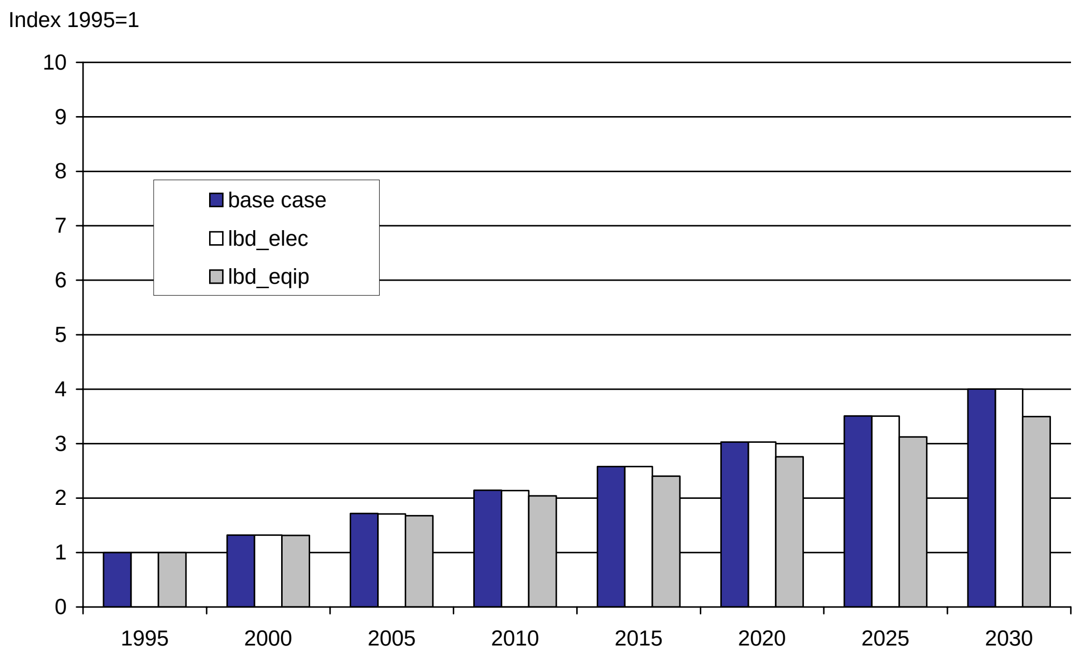

Figure 5 Cumulated investment in the renewable energy equipment sector: base case and two counterfactual scenarios, indexed to 1995 thus reflecting quantity changes over time

With learning-by-doing in renewable electricity production (scenario lbd_elec) rather than in the production of equipment, capital productivity of electricity production increases and thus less investment is needed in renewable electricity production to produce a given electricity output. Consequently, demand for renewable energy equipment decreases slightly and cumulated output of the renewable energy equipment sectors is lower than in the base case. Accordingly, a small decrease in investment in the renewable energy equipment sector can be seen. The effect on prices is small.

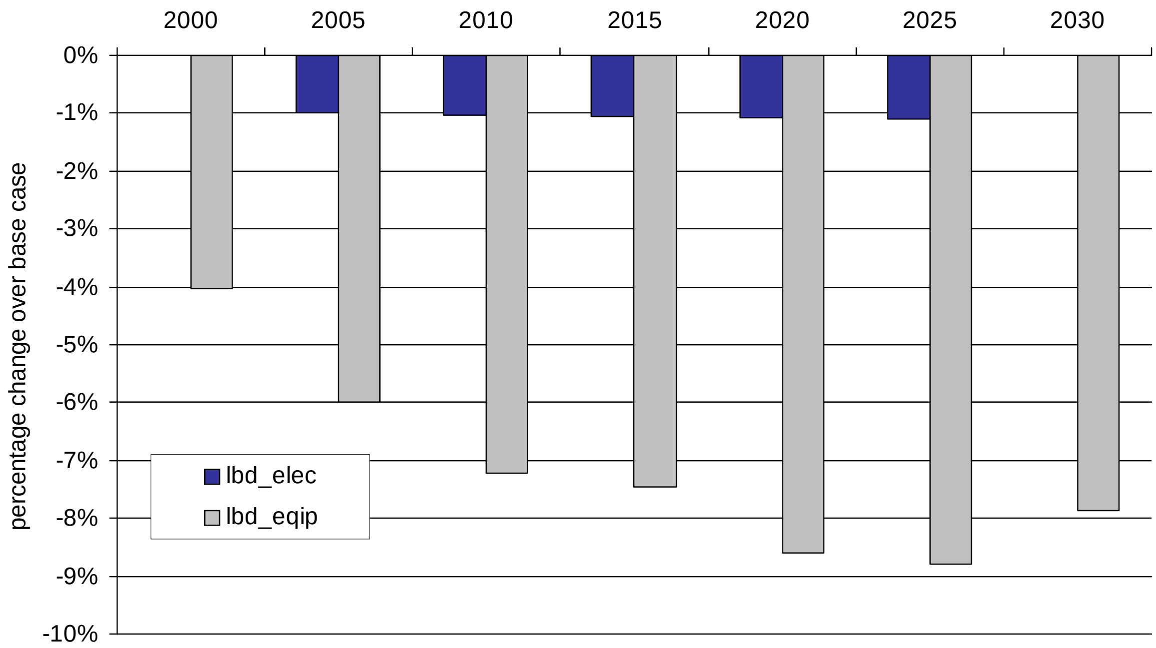

Figure 6 Output price renewable equipment sector, percentage change over base case

Effect on renewable electricity sector: In our model, output from renewable electricity production is exogenous and thus the same in all scenarios (as seen in Figure 7). Investment rises over time in the base case to meet the output goals of electricity produced by renewables.

With learning in the production of renewable energy equipment (scenario lbd_eqip), no change in cumulated electricity investment compared to the baseline can be seen. The same amount of capital as in the base case is needed to produce a given amount of electricity output (Figure 7). However, learning induces a reduction in the costs of renewable energy equipment (Figure 6) and thus leads to increasingly lower unit capital costs for the renewable electricity sector. Equipment serves as one of two main inputs to electricity production. Therefore, the reduction of equipment prices translates into a decline of the price of renewable electricity output (Figure 8). The decline is not as pronounced as the reduction of equipment prices (Figure 6) because prices for inputs other than equipment are not affected.

With learning-by-doing in renewable electricity production (scenario lbd_elec), less investment is needed to produce a given amount of electricity output (as seen in Figure 7). Thus, cumulated investment in electricity production is lower than in the base case. The increase of capital efficiency leads to reduction of electricity prices (Figure 8). The price of renewable electricity declines over time compared to the base case as cumulated output increases and higher learning effects are induced. The decline in electricity prices is higher in the scenario where learning occurs in the electricity sector than in the scenario where learning occurs exclusively in the production of renewable energy equipment because the capital efficiency gain immediately translates into cost reductions.

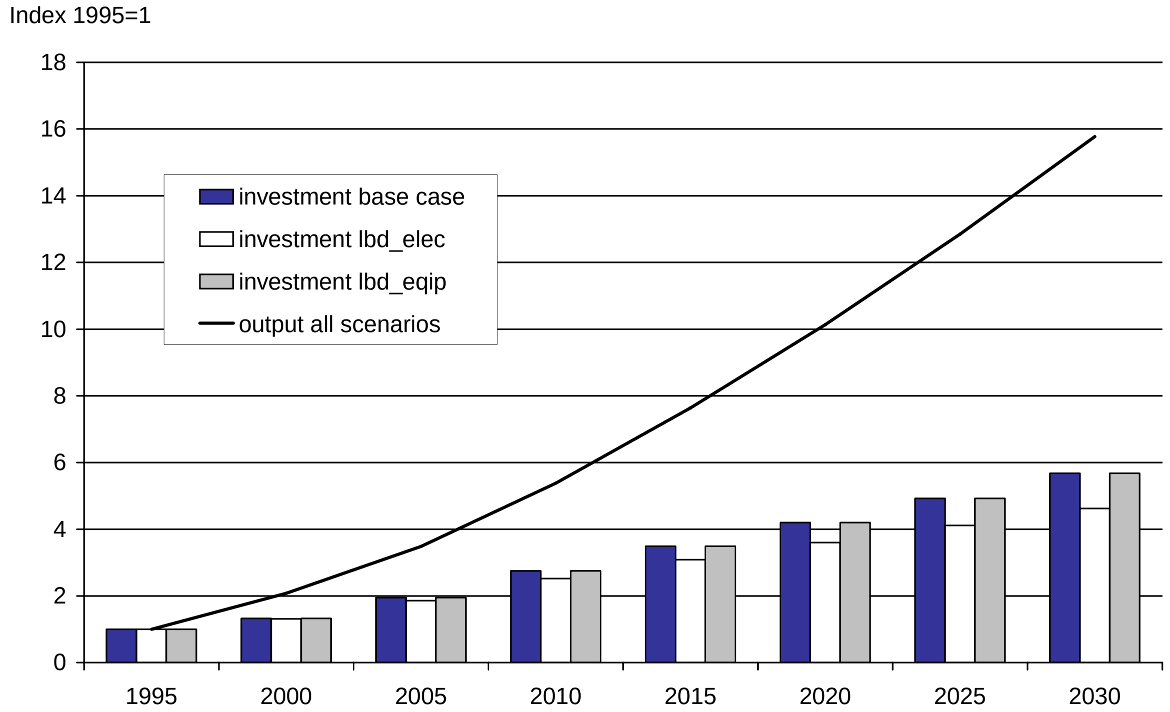

Figure 7 Cumulated output (line) and cumulated investment (bars) in the renewable electricity sector: base case and two counterfactual scenarios, indexed to 1995 thus reflecting quantity changes over time.

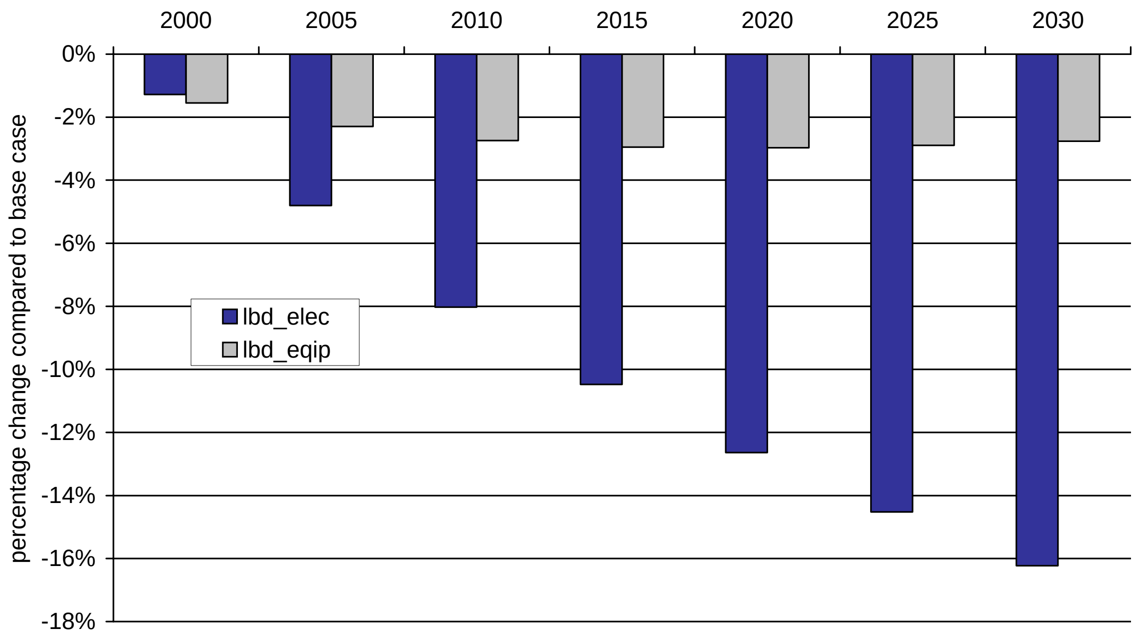

Figure 8 Output price renewable electricity, change over base case

To summarize, both counterfactual scenarios reveal effects on the price of renewable electricity. In scenario lbd_eqip the reduction in the price of renewable electricity production takes place through a reduction in the unit **cost** of capital investment (with capital efficiency in renewable electricity production constant) while in scenario lbd_elec the effect happens because of a reduced need for capital **input** per unit of output (with the costs of capital investment hardly affected). A learning rate of 10% in electricity production has a more direct and thus stronger effect than a 10% learning rate in the production of renewable energy equipment.

5.2 Macro-economic and international trade effects

As indicated above, the implementation of learning-by-doing in the renewable equipment sector (scenario lbd_eqip) stimulates an important effect on international trade. Exports in the sector are non-negligible (DEWI, 2006) and may even be more important in the future: On the one hand, (on-shore) locations are getting scarce and the expansion of wind energy generation may slow down in Germany, on the other hand, world markets for wind are likely to be growing. Exports of renewable energy technologies increase total demand for renewable energy equipment and result in higher learning effects with its subsequent effects on costs and prices. This increases the international competitiveness of renewable energy equipment and may set off a virtuous circle: it stimulates international demand for this technology, which then again would induce higher learning (first-mover advantage). An analysis, which attributes all learning to the production of renewable energy electricity alone, does not take account of these international trade effects.

Figure 9 shows the development of domestic production and exports of renewable energy equipment compared to the baseline for the two learning scenarios. The positive effect of learning-by-doing in the industry producing renewable energy equipment can clearly be seen. Over time domestic production and exports increase significantly compared to the base case. Exports from Germany level off over time. However, the rise in domestic production continues as imports of renewable machinery to Germany are substituted by domestic production, which continues to become more competitive.

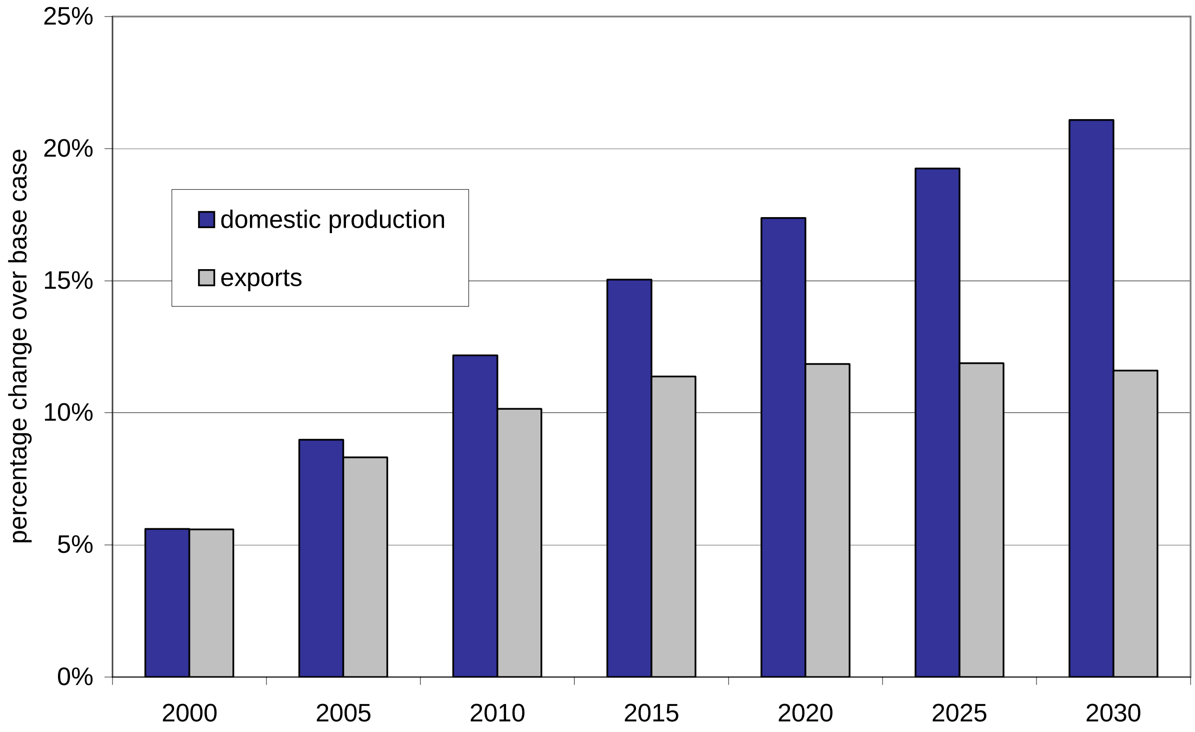

Figure 9 Domestic production and exports of renewable energy equipment: scenario learning-by-doing in renewable equipment, lbd_eqip (percentage change over base case)

The effects on GDP in Germany are shown in Figure 10. They are positive but small given the small share of the renewable equipment sector. Both learning scenarios lead to positive effects because more capital resources are available for productive use in other sectors.

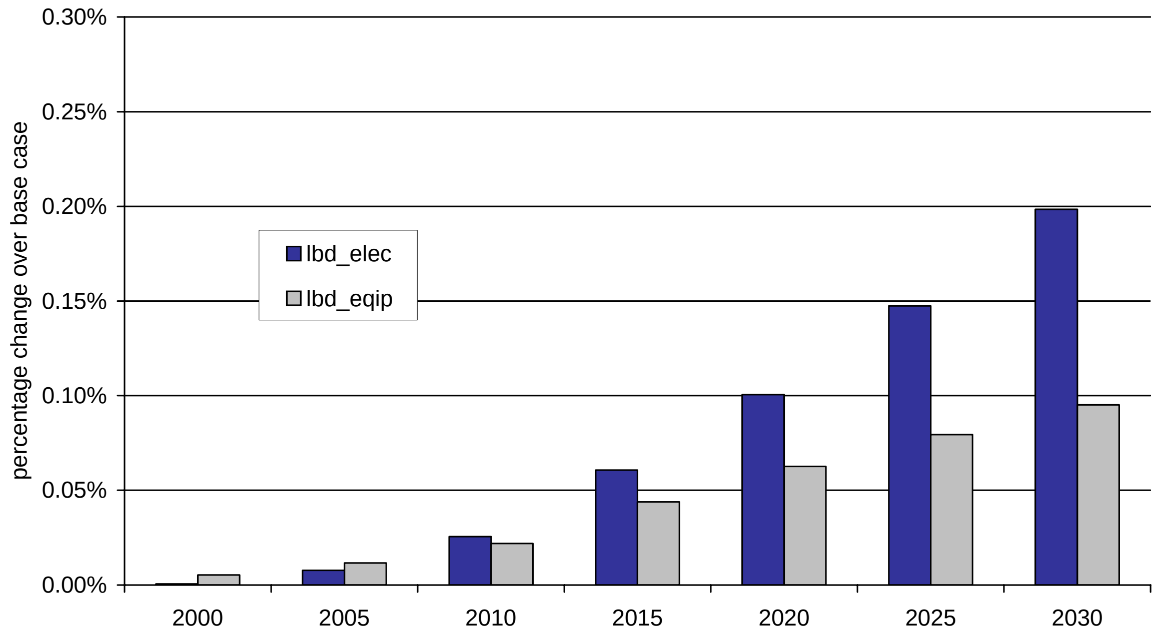

Figure 10 GDP real (percentage change compared to base case)

5.3 Relative speed of learning and spillovers

The previous analysis assumes that learning by doing depends on economic activity in Germany only, i.e. that there are no international spillover effects.[6] Moreover, we assume that learning by doing takes place in Germany only. In this section we explore the effect of these assumptions on our results.

In the literature, alternative views of learning and spillovers can be found. Learning systems can be considered regional or global. While in a regional learning system, as simulated above, learning is restricted to the production of a certain country or region, global learning depends on and affects production in several countries. Learning should be considered global if, for example, producers of wind turbines learn from producers or employees from other countries and knowledge and technical know-how is transferred from one country to another. Such

[6] On the other hand, it is implicitly assumed that learning provides an external effect, which spills over among domestic producers of either renewable energy equipment or renewable electricity in form of efficiency improvements in response to increase in total cumulated output of either industry.

knowledge spillovers and the induced innovation and diffusion of new technologies have been intensively discussed in the climate policy literature.[7]

In this section, we conduct a sensitivity analysis with respect to spillover effects. Our analysis so far is based on the assumption that there is no international knowledge spillover. We assume that Germany profits from learning-by-doing within its own borders based on domestic production of renewable energy technologies. Countries other than Germany experience no learning by doing or spillover effects. In light of the fact that Germany is now a major exporter of renewable energy technologies and its embodied know-how, but also that countries, such as Denmark in the case of wind turbines, provided much of the technology and know-how in the early stage of renewable energy development, several other cases can be distinguished (see also Table 3):

1) **Spillover Case 1** assumes that Germany cannot exclusively appropriate the benefits from technological learning within its own borders, because knowledge spillover takes place from Germany to other countries, i.e. learning-by-doing takes place in Germany and in the rest of Europe based on cumulated experience (output) in Germany. This means that countries other than Germany benefit from increased production experience in Germany and can apply the same technologies in their production processes or copy German products. As a consequence domestic production in, and exports from, Germany decline (compared to the scenario lbd_equip) as other countries appropriate state of the art development. This scenario would be most appropriate if Germany is seen as a technology leader and EU wide technology development solely depend on activities in Germany.

2) **Spillover Case 2** assumes that learning within both Germany and the rest of the European Union draws on cumulated experience gained not only within Germany but also within the rest of the European Union, i.e. on cumulated overall output in the EU. This means both Germany and the rest of the EU learn at the same rate. The effect is similar to the previous case. Domestic production and exports from Germany decline compared to the case without spillover effects as other countries benefit likewise from

[7] See for example Sijm (2004) for a thorough assessment of this issue. The concept of spillover effects has its origin in the literature on R&D and technological change. It refers to spillovers in the form of positive externalities such as R&D, knowledge, technology, and innovation transfer but also to negative externalities such as the transfer of emissions (carbon leakage) and environmental effects to other regions or countries (Weyant and Olavson,

learning effects in response to increased experience. In our base scenario, we assume that growth of cumulated output is slightly higher in the rest of the European Union compared to Germany, with other countries pursuing similar (EU) renewable energy policy targets and catching up with Germany. Therefore, the cumulated output growth for Europe as a whole is also slightly higher, as Europe improves its competitiveness vis-à-vis the rest of the world. This means that learning effects in Germany are a bit more pronounced than in the previous case. Nevertheless, the effects on the economy (output/exports) are substantially lower than in the case without knowledge spillover where learning takes place in Germany only.

3) **Spillover Case 3** assumes that learning in the rest of the European Union depends on cumulated output within the rest of EU and learning in Germany depends solely on cumulated output in Germany. No knowledge spillover takes place but both regions experience learning effects within their own regions. In this case, learning is lower in Germany than in the rest of EU because cumulated output in Germany grows at a lower rate. Thus exports from and domestic production in Germany are smaller than in Spillover Case 2.

Table 3 Assumptions for spillover analysis

	Learning takes place in…	based on experience accumulated in
No spillover	Germany	Germany
Spillover case 1	Germany and rest of EU	Germany
Spillover case 2	Germany and rest of EU	both regions
Spillover case 3	Germany and EU for each region separately i) Germany	i) Germany
	ii) rest of EU	ii) rest of EU

Note: In all cases, learning refers to a cost reduction of 10% for each doubling of cumulative output in renewable energy equipment as outlined above.

The three cases are similar in that they allow knowledge to be accumulated in both regions, either as a spillover from Germany to the rest of the EU or in the last case as separate learning in each region.

1999; Jaffe et al., 2003; Grubb et al., 2002). Weyant and Olavson (1999) define technological spillovers as ‘any positive externality that results from purposeful investment in technological innovation or development’.

We see that international knowledge spillovers dampen the benefit that Germany can draw from early investment in renewable energy technology. Figure 11 shows the results on domestic production and exports exemplified for spillover case 2 where learning takes place in each region based on total cumulated production of renewable energy technologies for all regions. Compared to the base case without any induced learning, all learning cases show a positive effect of learning-by-doing on export performance and domestic production in Germany, the effect, however, is more pronounced when there is no knowledge spillover between regions.

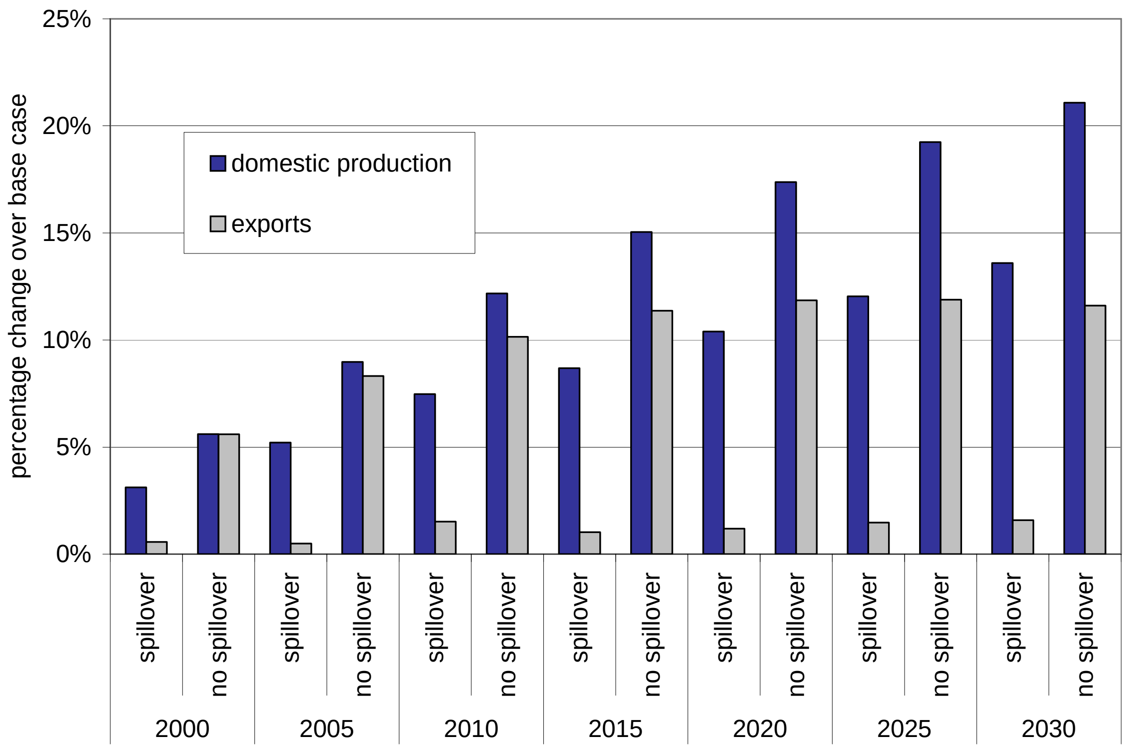

Figure 11 Domestic production and exports of Germany's renewable energy equipment industry with and without knowledge spillover of learning in renewable energy equipment. In the spillover case, both Germany and the rest of the European Union experience learning in response to increased cumulated total output of both regions (Spillover case 2). In the 'no spillover' case, only Germany experiences learning in response to increased cumulative output within its own borders.

6 Summary and conclusions

Technological progress reduces the costs of renewable energies. When technological progress is induced via learning-by-doing rather than by autonomous efficiency improvement, this may have an influence on the optimal timing of environmental policies and of investment.

In previous analyses, all learning is commonly attributed to the renewable electricity sector, whereas it is quite evident that part of the learning takes place in upstream sectors, in particular in the production of renewable energy equipment. Our analysis shows that it does matter to differentiate between learning-by-doing in the renewable energy equipment and in renewable electricity production.

Two main effects take place by introducing learning-by-doing in the renewable energy equipment industry. Firstly, learning-by-doing leads to a reduction of the unit costs of equipment, which will, via capital goods (investment), translate into reduced renewable electricity costs and prices. The second effect relates to international trade. Learning improves the international competitiveness of renewable energy equipment (first-mover advantage) and stimulates national and international demand for this technology, which then again may induce higher learning. Those effects and their stimulation of higher production activity and learning get commonly overseen when implementing endogenous technological change in the form of learning-by-doing in top-down energy-environment models. If learning-by-doing affects export sectors and improves international competitiveness this has consequences for the economic assessment of the costs and benefits of climate policy. Further analyses in this area may profit from the literature on international trade and its dynamics in the context of learning-by-doing (see for example Young, 1991).

The current empirical literature on learning by doing does not give any definite information in which sectors learning occurs or on spillover effects (Neij et al., 2004). The stylized modeling in this paper may guide future empirical work distinguishing between sectors and incorporating spillover effects.

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