EPRG WORKING PAPER

UNIVERSITY OF CAMBRIDGE

Electricity Policy Research Group

Learning by Doing with Constrained Growth Rates and Application to Energy Technology Policy

EPRG Working Paper 0809

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Abstract Learning by doing attributes cost reductions of a technology to cumulative investment and thus experience. This paper argues that the additional dimension of investment volume growth rate has to be considered. This growth rate has historically been limited in most sectors, thus allowing for feedback in the learning process. When market growth is below the 'optimal' rate, the marginal value of additional investment could be a multiple of the direct learning benefit. Analytic and numeric models quantify the impact — emphasising the need for tailored technology policy in addition to carbon pricing. Implications for the modelling of endogenous technological change are discussed.

Keywords Learning-by-doing, growth rate, technology policy, welfare analysis

JEL Classification H23, L94, O31

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Publication January 2008
Financial Support Supergen

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

1. Introduction

Many of the cost reductions for new technologies are expected to come from learning by doing (Arrow, 1962). Producers will explore new ideas to reduce production costs when they build a new production line – and repeat successful approaches in future investments. This suggests that learning by doing requires some market growth in order to allow for the construction of new production lines. However, the more production lines are built in parallel with the same technology, the fewer the number of additional insights from an extra line. This suggests that growth rates should not be excessive. Reviewing studies across various technologies we observe growth rates rarely exceeding 35% per year, while new technologies exhibit high learning by doing rates up to these growth rates.

The learning by doing methodology has been frequently applied to assess whether public support for new technologies is justified by the future benefits derived from renewable technologies. This paper expands previous work and analyses the marginal benefit of an additional unit of subsidised new technology – with a puzzling result: even where the overall scheme is profitable, the extra subsidy is larger than the discounted future cost reductions that result from it.

The puzzle's solution is the growth constraint for the new technology. Production volume of new technologies can only grow gradually, due to of constraints on production capacity and qualified labour. Also, industry takes time to gather experience from production at a new installation. If too many new installations are built in parallel this will reduce the learning benefit.

Now assume today's investment in the new technology is reduced by one unit, the implication is that all future investments will also have to be reduced by one unit if the future growth constraint is not to be violated. This will delay the time when the new technology becomes profitable and reduces the future market size of the new technology. The marginal value of capturing the full growth potential can be a multiple of the direct value from the cost reductions associated with the new technology.

This is not too surprising. If it is profitable to use a strategic deployment program for a technology, then the discounted future benefits outweigh the additional costs that are born earlier on. If the deployment can be accelerated without compromising the learning by doing rate, then future benefits are delivered earlier and do not need to be as heavily discounted, thus increasing the overall profitability. If costs are too high and output too similar to conventional technologies, feed-in tariffs, traded certificate schemes, and tender auctions are used to create markets for new technologies in order to create sufficient private demand for low-carbon options.

Some analysts argue instead that governments should rely on the carbon price to internalise the environmental externality and incentivise the development of technologies (Manne and Richels 2004). This assumes that investors anticipate high future carbon prices and shoulder the early costs of deploying a new technology, by selling a technology below cost so as to develop the market and gain learning experience. Given the difficulties of appropriate innovation in the energy sector (Stokey 1996), and the sharing of the benefits among many players that may be involved in the development of the technology, this is an unlikely scenario (Neuhoff 2005). It is more likely that technology companies and investors will wait until the carbon price sufficiently increases the costs of competing conventional technologies in order to make the new technology competitive. This will result in a peaky CO_2 price. In the model carbon prices will not only peak, but remain at far higher prices for many years until technology costs are reduced via learning by doing.

Due to technology spill over the market outcome will no longer coincide with the social optimal investment pattern. This has also implications for modelling approaches. While the representation of endogenous technological change has become standard for large scale modelling approaches (Koehler et al 2006), the precise formulation of the optimisation function and its implementation can influence the outcomes. This paper suggests a framework to classify different simplifications used to represent endogenous technological change (Sijm 2004). This helps to understand the implications of different model formulations and solution algorithms.

This paper first reviews the empirical evidence for learning by doing and discusses approaches to represent and quantify the effect. Using the learning-curve approach, Section 3 analyses the marginal value of additional learning investment, and Section 4 illustrates the result with a numerical example. Section 5 discusses the implication for public policy analysis and Section 6 concludes.

[1] I would like to thank Sarah Lester and Amalia Kavali for the survey on learning rates and Richard Green, Jake Jacoby, Sarah Lester, Andreas Löschel, David Newbery, Michael Pollitt and Ian Sue Wing for comments on earlier versions of the paper. Research support from Project SuperGen Flexnet is gratefully acknowledged. University of Cambridge, Faculty of Economics, Sidgwick Avenue, Cambridge CB3 9DE, UK, karsten.neuhoff@econ.cam.ac.uk.

2. Empirical evidence - improvements through market experience

The cost of new technologies falls with increasing deployment, both for energy technologies and other industry sectors. The IEA (2003) concludes that "there is overwhelming empirical evidence that deploying new technologies in competitive markets leads to technology learning, in which the cost of using a new technology falls and its technical performance improves as sales and operational experience accumulate." Isoard and Soria (2001) identify Grainger causality between installed capacity and capital costs both for wind and PV. McDonald and Schrattenholzer (2001) also show that for emerging technology, the price reduction typically falls between 5-25% with each doubling of cumulative industry output, with most reductions clustered between 15-20%.

However, careful assessments have also illustrated that extremely high improvement rates calculated by some initial studies can be partially attributed to factors such as capital availability or changing product quality (Thompson 2001, Nemet 2006). A survey of several industries indicates that learning effects usually dominate scale economies (Isoard and Soria 1997), for example Watanabe (1999) shows that 70% of price reductions in the Japanese PV industry can be attributed to learning effects.

One fundamental assumption of the improvement through market experience (learning curve) methodology is that the pattern of cost reductions caused by global installed capacity will not undergo fundamental future change. This result requires thorough examination as it has significant implications for government technology policy. Lieberman (1984) shows that in the chemical processing industry time becomes statistically insignificant if log cumulative production is used as an explanatory variable, and Jensen (2004) critically discusses different modelling approaches. In contrast, Papineau (2006) identifies time as a significant explanatory variable for price reductions in a regression of PV module prices. One possible interpretation of this finding is that if we merely wait for a sufficient period of time, the technology cost will fall. However, the estimation did not include the log of global cumulative installed capacity as an explanatory variable. In the observation period, global PV penetration increased exponentially (with constant growth rates). Therefore, the log of global cumulative capacity is almost perfectly correlated with time. In the sample it is impossible to identify whether time or global cumulative installed capacity drives the cost reduction.

Various extensions of the learning curve model are currently being developed to capture the interaction of cumulative production and R&D (Research and Development) expenditure. All the models try to explicitly model the impact of R&D expenditure, which is implicit in the traditional learning curve model. The learning rate is estimated on historical data, and historical cost reductions are explained by cumulative production and of R&D expenditure. Gruebler and Gritsevskyi (1997) introduce a model that assesses learning as a function of aggregate expenditure on R&D and market expenditure. Kouvartiakis et al (2000) apply the two-factor learning curve (see also Jamasb 2007). This is a Cobb-Douglas type production function, with both factors acting as substitutes according to their so-called learning-by-doing (cumulative installed capacity) and learning-by-searching (R&D) elasticities. Barreto and Kypreos (2003) suggest that the two-factor learning curve approach is limited by "unsolved estimation and data issues, but constitutes an important step towards understanding the role of R&D".

One disadvantage of the traditional learning curve is that costs approach zero with increasing deployment, which is not realistic. To address this concern, some authors suggest a learning curve with a floor cost level (e.g. Tsuchiya and Kobayashi, 2003).

A factor that has not been analysed explicitly in previous papers on learning by doing is the market growth rate. Surveying the literature it is notable that the growth rate for the new technology is frequently not even reported, even though the necessary data must have been available wherever a learning rate was calculated for a technology. Figure 1 illustrates that in most of the studies that reported both growth rates (or allowed for deduction of the growth rate from reported market volumes), the rate is in the range 0-30% per year, with only a few studies exhibiting growth up to 40% per year.

This empirical observation is also reflected in many macroscopic model formulations. Barreto and Kypreos (2002) apply maximum growth and decline rates (15%, 10%) for R&D budgets in their model for endogenous technological change. Rasmussen (2001) includes learning by doing in a macroscopic model, but fixes the rate of subsidy for renewable technologies. This effectively allows the author to set growth rates for renewable technologies. MERGE at Stanford assumes that a new technology can enter at maximum 1% of total production in the initial year with an increase by the factor of three in each subsequent decade. Time steps of MERGE are ten years. (Manne and Richels 2004)

We were also interested to see whether a relationship between growth rates and learning rates can be established for the surveyed technologies. Figure 1 does not reveal such a trend, perhaps because the number of observations is still too low, or because other factors – like industry sector, have to be considered. But it might well be that different effects cancel each other out. With higher growth rates less time is available for industry to learn from previous experiences and learning rates should decline. At the same time, successful technologies should receive more market demand or public support and thus correlate with higher growth rates.

In the energy technology sector, manufacturing and installation costs are the biggest cost share, with reductions in these components being the focus of technology policy. Therefore, this paper is based on installed capacity rather than produced output. Estimations of learning curves typically use price rather than production costs as input, but in competitive industries such as PV, long-term learning rates are either not affected by market power mark-ups or average out over time (Duke 2002). In contrast, in the short-term excess demand or production shortages can result in scarcity prices above production costs, as currently observed for wind turbines and PV panels.

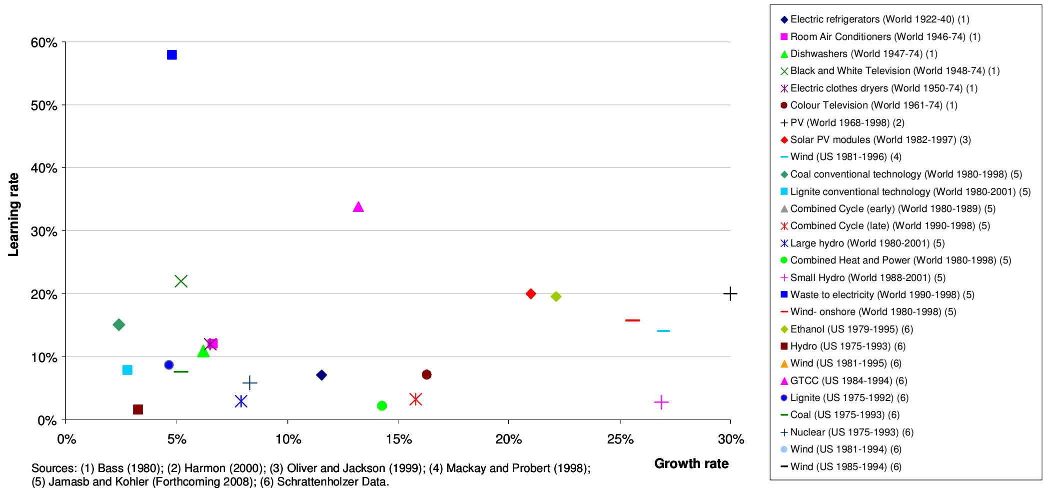

Figure 1 Market growth rate and learning rate across a set of technologies

3. Marginal analysis

We define the social welfare function and then calculate the optimal level of investment in a new technology over time in the presence of learning by doing. Thus the marginal learning benefit with and without technology growth constraints can be calculated.

We assume production $P(K_t,L_t)$ is a function of capital input K_t and labour input L_t. The output can be consumed X_t or invested in new production facilities I_t.

$$P(K_t, L_t) = X_t + C(E_t) I_t \qquad (0)$$

The function $C(E_t)$ captures the idea that the productivity of capital can change over time with experience E_t. For the purpose of this model it is assumed that knowledge is not lost and thus experience does not depreciate over time, but grows with all new investment.

$$E_t = E_0 + \sum_{l=1\ldots t-1} I_l \, \forall_t \qquad (1)$$

In contrast, physical capital grows with new investment, but a fraction δ of existing physical capital depreciates each period:

$$K_t = (1-\delta)^t K_0 + \sum_{l=1\ldots t-1} (1-\delta)^{t-l} I_l \forall_t , \qquad (2)$$

We use the global welfare function that discounts annual welfare $U(X,L)$ with the factor β and substitute from (0).

$$W = \sum_{t \geq 1} \beta^t U(X_t, L_t) = \sum_{t \geq 1} \beta^t U(P_t - C(E_t) I_t, L_t). \qquad (3)$$

Substituting E_t and K_t from (1) and (2) and differentiating with respect to the investment in any one year (3) gives the marginal value of additional investment:

$$\frac{dW}{dI_t} = -\beta^l \frac{\partial U_l}{\partial X} C(E_l)$$

$$+\sum_{t>l} \beta^l \left(\frac{\partial U_t}{\partial X}\frac{\partial P_t}{\partial K}(1-\delta)^{t-l} - \frac{\partial U_t}{\partial X}\frac{\partial C_t}{\partial E_t} I_t \right)$$

$$+\sum_{t>l} \frac{\partial W}{\partial I_t}\frac{\partial I_t}{\partial I_l} \qquad (4)$$

Please note that to simplify (4), the term $\beta^l \left(\frac{\partial U_l}{\partial X}\frac{\partial P_l}{\partial L_l} + \frac{\partial U_l}{\partial L_l} \right)\frac{\partial L_l}{\partial I_l}$ has been omitted. The labour choice in period l is assumed to be optimal in equilibrium and therefore $\frac{\partial U_l}{\partial X}\frac{\partial P_l}{\partial L_l} + \frac{\partial U_l}{\partial L_l} = 0.$ Likewise the terms $\sum_{t>l} \frac{\partial W}{\partial L_t}\frac{\partial L_t}{\partial I_l}$ have been omitted, as future labour choices are assumed to be optimal and therefore $\frac{\partial W}{\partial L_t} = 0.$

On the equilibrium path, the investment decision is optimal in each period. For a positive investment quantity I_l in period l, a marginal change should have no impact on global welfare. A marginal change in investment I_l reduces the consumption in period l by $C(E_l)$. This disutility is compensated for by additional consumption in future periods. Future consumption increases for two reasons. First, because the capital stock is increased (in (4) part one of line 2) and second, because future investment is cheaper by $\partial C_t / \partial E_t$ (in (4) part two of line 2). Line three gives the impact of a change of investment in period l on future investment decisions. We can now differentiate between two cases. If investment decisions are unconstrained, then they are chosen such that $\partial W / \partial I_t = 0$. Alternative growth rates for investment in a technology can be constrained if production capacity cannot be expanded too fast without loss of learning experience. This can be represented by:

$$I_t + 1 \le (1+g) I_t. \qquad (5)$$

If the constraint is binding, then $dW / dI_t > 0.$ at the equilibrium I_t. Substituting the constraint $\partial I_t / \partial I_m = (1+g)^{t-m}$ in (4) gives:

$$\frac{dW}{dI_l} = \frac{\partial W}{\partial I_l} + \sum_{t>l} (1+g)^{t-l} \frac{\partial W}{\partial I_t}. \qquad (6)$$

Increased investment in one period allows for additional investment in future periods which can offer additional benefits.

For the case where the growth constraint (5) is not binding, an analytic solution for (4) can be determined. We assume constant growth rates g for the new technology and therefore

$$E_t = (1+g)^t E_0,\ I_t = g(1+g)^t E_0, \qquad (7)$$

and the standard learning by doing function for investment costs:

$$C(E_t) = C_0 E_t^{-\lambda}. \qquad (8)$$

In addition constant marginal utility $\partial U_t / \partial X_t = 1$ is assumed and returns to scale are constant $\partial P_t / \partial K = const$. Substituting (8) and (7) in (4) gives:

$$\frac{\partial W}{\partial I_l} = \beta^l C_0 (1+g)^{-\lambda l} E_0^{-\lambda} + \sum_{t>l} \beta^t \left(\frac{\partial P_t}{\partial K}(1-\delta)^{t-l} + C_0 E_0^{-\lambda}(1+g)^{-\lambda t} \lambda g \right),$$

and after rewriting the investment sums gives:

$$\frac{\partial W}{\partial I_l} = -\beta^l C_0 E_0^{-\lambda}(1+g)^{-\lambda l} + \beta^l \frac{\beta(1-\delta)\partial P_t}{1-\beta(1-\delta)\partial K}$$

$$+\beta^{l} C_0 E_0^{-\lambda}(1+g)^{-\lambda l}\lambda g \frac{\beta(1+g)^{-\lambda}}{1-\beta(1+g)^{-\lambda}}. \qquad (9)$$

Equation (9) shows the three influences on welfare from an additional unit of investment in the new technology in period l. (i) Costs for investment are incurred and are falling over time due to experience in the growing market. (ii) The produced electricity has a net present value, which in our subsequent calibration will be related to the levelised costs of the conventional generation technology. (iii) The extra investment creates additional experience that reduces all future investment costs. If the growth constraint is binding, then an additional term appears, but could not be presented in a closed form analytic solution. Therefore we proceed to a numeric example.

4. Numeric example

We proceed to a numeric example, based on the example of photovoltaics for electric power generation within the European Union. This is currently a very high cost technology with a low installed capacity base. To quantify the value of the individual components, the following assumptions are made:

Parameter	**Value**	**Implication**
Discount rate	r =7.5%	β=0.93
Depreciation	δ =7%	
Levelised cost new tech, $t=0$	$C_0 E^{-\lambda} = 250 Euro/MWh$	
Levelised cost old tech,	62.50 Euro/MWh	$\frac{\partial P_t}{\partial K} = 9.74$
Max growth rate new tech	$g = 0.3$	
Learning rate	20%	$\lambda = 0.322$

Inserting the parameter values into (9) gives:

$$\frac{\partial W}{\partial I_0} = -250 + 62.50 + 153 + [Euro/MWh] = -34.50[Euro/MWh]. \quad (10)$$

The initially striking result is that the sum of the value of future energy (62.50 Euro/MWh) plus the value of future cost reductions (153 Euro/MWh) is below the cost of the investment into the new energy source (250 Euro/MWh). Does this suggest that welfare is not improved by supporting photovoltaic deployment?

Now we assume that a growth constraint is binding at a growth rate of 30% (equation 5). Thus a change (e.g. decrease below 30%) of the investment volume in one period can also change the investment volume in all subsequent periods. The sum of the full derivative (10) does not converge. This is because the future benefits grow faster with market growth than their contribution to the net present value. In reality markets will eventually be saturated with the new technology, and thus the growth constraint will no longer be binding. If the growth constraint is binding for 23 periods, then the numerical calculation gives $dW/dI_0 = 13135 Euro/MWh$.

The marginal benefit of additional investment by far exceeds the values in (6). This shows that if the growth constraint is not yet binding, it is valuable to increase the investment volume to the level at which the growth constraint is binding, and hence the value of marginal investment has to be calculated for the case of binding growth constraint.

So far the analysis focused on one year and assumed the growth constraint would be binding for the subsequent 23 years. To illustrate the role of the different learning benefits over time we assume an existing power system with generation capacity of 350 GW, annual demand growth of 2% and initial share of the new technology in energy provision of 0.1%. Levelised investment costs for the coal power stations are 15 Euro/MWh (6000 full load hours), fuel costs are 15 Euro/MWh increasing at 1% real per year. Carbon constraints create additional costs for CO_2 certificates of 20 Euro/MWh in 2008 that are increasing at 3% per year. Figure 2 shows that because of the larger learning stock and a smaller investment rate of the traditional technology costs fall more slowly than the costs of the new technology. In 2030, as the new technology captures the whole market of new investment, growth declines in line with demand growth and replacement of depreciated capacity.

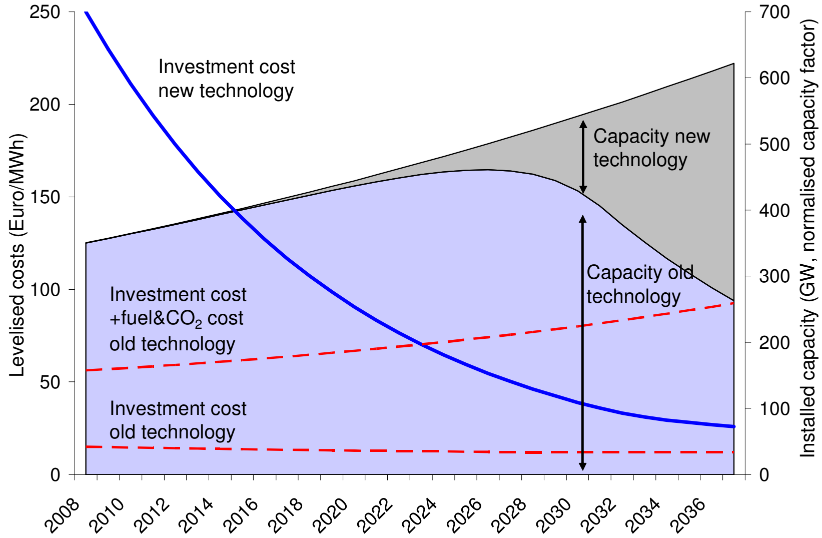

Figure 2 Evolution of generation share and levelised costs of coal and photovoltaic

To allow for a comparison between a capacity with high fixed costs (photovoltaic) and a technology with high variable costs (coal), the levelised generation costs over an assumed 20 year operation period are depicted and used for the subsequent cost calculations. In the initial years investment costs for the new technology exceed the costs of investment and fuel using the conventional technology.

Figure 3 illustrates that it is nevertheless socially beneficial to invest. The benefit from future cost reductions compensates for a large share of the additional investment costs. The benefits from accelerated deployment more than make up for the remaining contribution. Private investors would only start buying the technology at production costs in the year 2023 when it breaks even with the levelised costs of coal power stations.

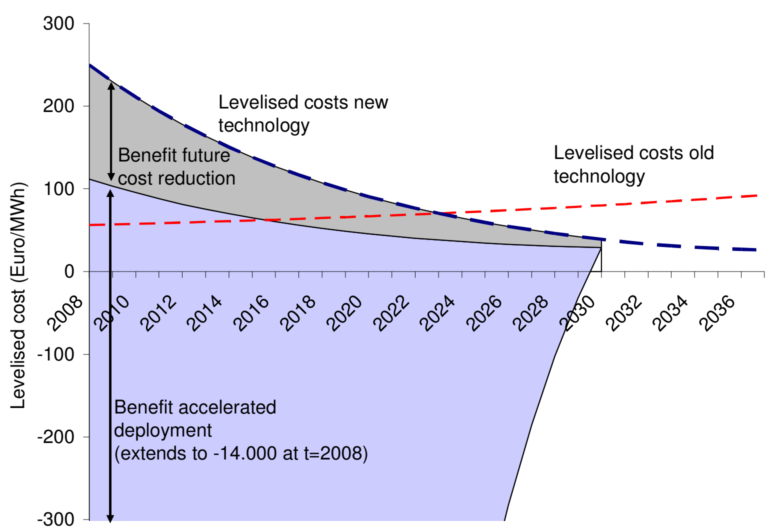

Figure 3 Evolution of marginal benefit of last unit of investment into photovoltaics.

In Figure 4 the discounted costs for the investment and operation of all new plants over their life time is calculated. If higher discounting factors are assumed, then this obviously reduces net present costs. If the growth rate of photovoltaics is very low, then any activities on photovoltaics are small relative to the total market, and thus do not significantly influence overall costs.

As the growth rate increases towards 10% per year, the overall costs increase. This is because the investment volume and thus initial costs increase. However, improvement through market experience is slow, and it takes too long for the new technology to become cost competitive. Therefore, it becomes preferable not to use the technology at all (see Manne and Barreto, 2004)

The benefits of the new technology available at low cost and scale can, in this model, only be captured where growth rates exceed 15% per year. With increasing growth rates, the benefit increases as the cost improvement of the technology accelerates and a low cost technology is available earlier. In reality it should be expected that learning rates decline if growth rates are too high, i.e.; if companies replicate new production facilities rather than explore new production opportunities and therefore do not capture additional learning benefits.

Figure 4 also illustrates how learning by doing creates multiple local optima, with one local optimal growth rate of 0. If the use of the technology is profitable then a second, global optimal growth rate is at the maximum possible market growth that supports effective learning by doing. Analysis that focuses on local optimisation runs the risk of ignoring the global optima once the local optima has been identified. This non-convexity is created by the non-convex learning function.

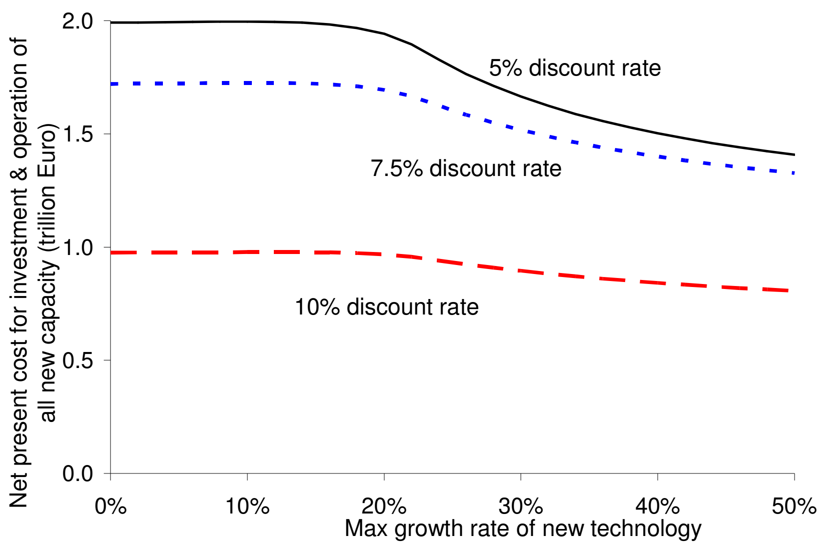

Figure 4 Net present value of levelised costs calculated over operation time of all new plant

5. Implications for public policy analysis

Sometimes it is argued that carbon pricing, whether pursued via carbon taxes or cap and trade schemes, suffices to incentivise the development and deployment of new technologies. If a new energy technology is worthwhile, then it will become competitive as soon as the CO_2 price rises sufficiently.

The following simulation illustrates the implications of such an approach. Again 350 GW installed conventional generation capacity and demand growth of 2% per year is assumed. It is assumed that the carbon constraint is tightened by 1% of initial emissions per year and that the carbon market allows for a linear supply of allowances. The slope is calibrated to equal an initial supply elasticity of 1%.

Off-shore wind is this time considered as the new technology with cost estimates of 120 Euro/MWh (German feed as July 2008 with tariff levelised over 20 years). The effect that will be demonstrated would be even more extreme with photovoltaics. Initial installed off-shore wind capacity is assumed to be 2 GW and again learning rates of 10% and maximum growth rates of 30% are assumed.

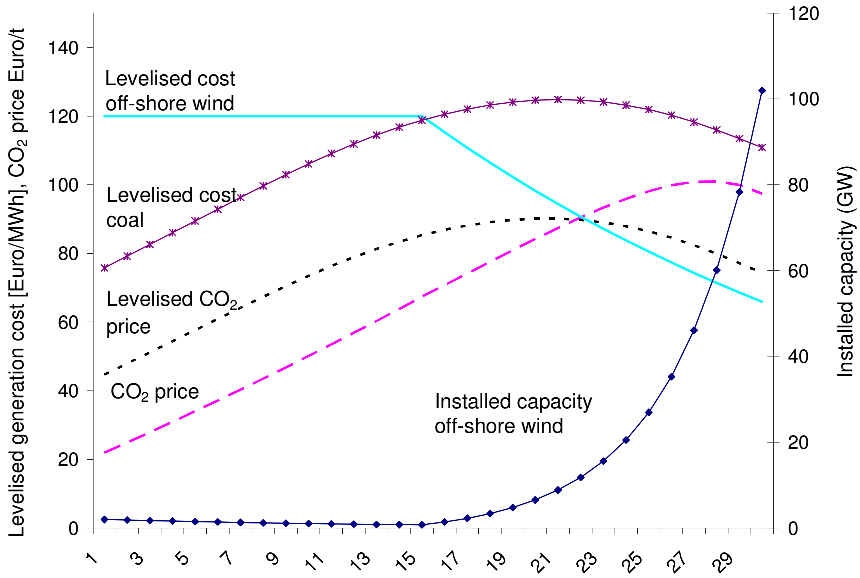

Figure 5 Technology and carbon prices - without dedicated renewable support scheme

Figure 5 illustrates that the CO_2 price will rise together with the 20 year average CO_2 price, until it is profitable for investors to use the new technology in year 16. In the subsequent years investment costs are significantly below the 20 year average CO_2 price and it would therefore be profitable to expand investment in any of these years. However, the maximum growth of new installations is limited to 30% per year. As a result the CO_2 price continues to rise, and peaks in year 26. In anticipation of the future decline of the CO_2 price, the levelised CO_2 price starts falling after year 20. Numeric models (see e.g. Riahi et al 2004, Figure 12) produce similar peaky prices when growth constraints are implemented for new low emission technologies.

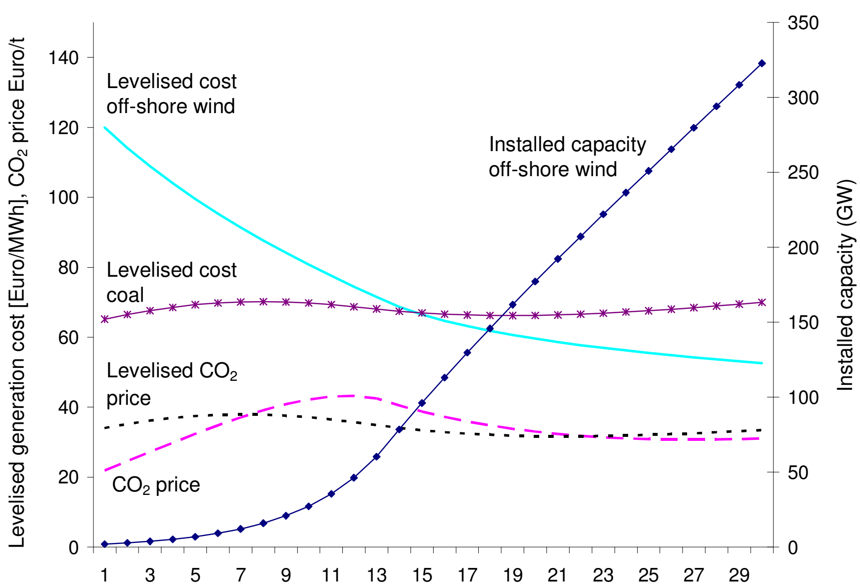

Figure 6 Technology and carbon prices - with strategic deployment program

In Figure 6 this result is compared with a scenario in which the government pursues active technology policy and starts deploying the renewable technology in year 1 with a growth rate of 30%. The difference between the levelised cost of off-shore wind and the levelised cost for coal presents the learning investment that has to be provided as subsidy per MWh electricity produced over the live time (20 years) of the turbine. If policy analysts wish to ignore the idea and benefits of strategic deployment, then they can translate the premium of around 50 Euro/MWh paid in the initial years in additional carbon prices of 55 Euro/t CO_2 for deep water off-shore parks (assuming coal with emission factors 0.9 tCO_2/MWh is replaced). However, with the last edits of this article, coal and gas prices have more than doubled and pushed base load power prices to 100 Euro/MWh, with carbon costs adding further 20 Euro/MWh. Should fossil fuel prices remain at these price levels, then support with feed-in tariffs only offers price guarantees but does not create extra subsidy requirements.

By year 9, the improvements arising from market experience have reduced costs to a level that is sufficient for strategic deployment to be abandoned. The most important effect is that the early deployment creates the capacity to provide carbon free energy and therefore reduces the high scarcity value of CO_2 that was previously observed. Future energy technologies are a crucial input in models that determine the benefits and costs of different climate policy options. Koehler et al (2006) provide a comprehensive survey of such modelling approaches with endogenous modelling of learning by doing or R&D.

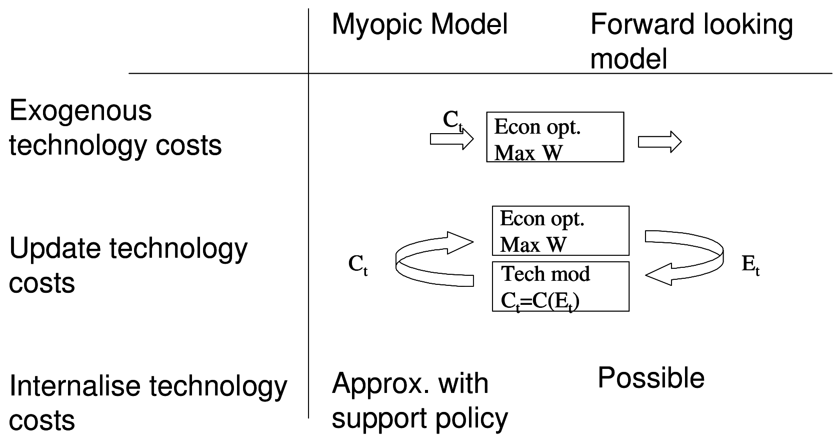

Figure 7 Technology representation in numeric economic models

Figure 7 offers a system to classify macroeconomic models. Models differ in whether they optimize over the entire horizon and are therefore forward looking, or whether they are myopic and assume that investment and labour decisions are made on the assumption that current prices will prevail in the future. Three basic approaches can be used to represent technology costs in models.

First, the model can take technology costs as exogenously given and will therefore ignore all the learning benefits. If analysts 'believe' that learning by doing does not exist, then they will only evaluate investment projects based on their direct benefits in terms of (for example) energy delivered.

Second, a technology model can be added to update technology costs. In this case an initial set of technology costs are fed into the economic model. The economic model determines the equilibrium investment quantities in different technologies. Based on the experience with these different technologies, the technology model is run to update the technology costs. Then the economic model is run again with the updated set of technology costs. This procedure is iterated until the technology prices and investment quantities converge. While this second set of models calculates technology costs over time, it does not internalize the improvements through market experience. At each iteration of the economic optimization the technology costs are fixed and therefore benefits of using the technology for future cost reductions and future growth potential are not considered. This has strong implications. Without initial investment improvements through market experience will not materialize and therefore costs will stay high - in the absence CO_2 pricing the new technology would never be deployed. In the second example with CO_2 pricing, the models would predict the high CO_2 peak prices of Figure 5. The impact of a full internalisation can be approximated, if an economic model with technology updating is either 'forced' to apply a new technology by setting quantity obligations, or tempted to apply the new technology by modelling financial incentives. Comparing the total discounted costs of models run with and without forced deployment helps to illustrate whether the strategic deployment of a technology is beneficial.

Third, assume a model solves the full optimization problem and therefore determines the equilibrium specified in (4). Such a complete optimisation can determine the socially optimal investment and consumption path, but faces the challenge that $\partial C(E_t)/\partial E_t$ is not a linear function of E_t and therefore the maximization problem is no longer linear. This complicates the numerical solution of large economic models..

6. Conclusion

Countries implement strategic deployment programs to subsidize investment in renewable technologies. They do not aim only for the direct carbon and energy benefits of the projects, but also expect that increased experience will reduce technology costs and allow for large scale application in the future (Grubb, 1997). This is expected to be a major contribution to low cost mitigation strategies (Edenhofer et al 2006, Stern 2006, IPCC 2007).

If a new technology competes with existing technologies in providing a homogeneous product, then the social value of investing in the technology might exceed the private value of the investment. This is because the investment creates market experience that reduces future investment costs. The investment also results in usage and expansion of production and installation capacity for the technology. If expansion rate of a technology is constrained, early expansion of capacity can create future benefits in the form of higher production capacity. Depending on the sector and the technology, private investors can capture some of these benefits. To the extent that they are not able to capture the benefits, and where they are not in a position to invest in a new technology without these benefits, public support for strategic deployment may be warranted.

To inform the decision whether the provision of public support is warranted, the paper suggests an approach to quantify the marginal social benefit of additional investment in new technologies. It points to the importance of growth constraints for new technologies. If these growth constraints are not considered, then evaluations of technology policy can provide misleading results that underestimate the value of the strategic deployment program.

The growth rate at which a new technology is deployed is an important policy variable. Typically, social benefits increase with a higher growth rate of deployment. This suggests that the optimal technology policy will deploy the technology at maximum growth rate.

This paper assumes a fixed maximum growth rate for a technology of 30%. Implementing public policy that is close to the optimal growth rate for a technology is important to maximize social benefits. Therefore it will be important to further investigate the optimal growth rates for different technologies, sectors and levels of experience gathered with a technology.

The focus of this paper was on equilibrium growth rates that are expected by market participants. Neuhoff et al (2007) illustrates that unexpected growth can result in scarcity prices and thus higher costs. This shifts the corporate focus on production expansion rather than leveraging learning benefits, and can thus reduce the cost reductions from learning by doing.

Some countries are reluctant to invest in strategic deployment programs, and discuss the option to free ride on the investment of other countries. The large marginal value of additional investment in strategic deployment programs that was identified in this paper has a promising implication. Even if only a fraction of the benefit is captured domestically, it is worthwhile pursing the program. Obviously this is subject to the assumption that the growth rate for the technology does not exceed the rate at which additional growth contributes to additional learning.

Rather than using strategic deployment programs, it is sometimes argued governments should pursue direct R&D programs. In the technology sector, however, much of the research capacity and experience has moved to private companies, and it is difficult to see how such research could be incentivised without the existence of profitable market opportunities. In addition, where much of the cost reductions are expected from improvements of the production process, ongoing production is required. Thus it seems that technology policy should combine support for public and private sector R&D with strategic deployment programs. Analysis to support such strategic deployment programs needs to reflect uncertainties associated with cost and learning estimates (Neuhoff 2005), for example by considering the merits of supporting a portfolio of different renewable technologies.

A numerical example was used to illustrate the benefit to society of implementing a technology policy to internalize the learning benefit, in addition to implementing an environmental policy to internalize the negative environmental externalities of CO_2 emissions. In particular, if emissions constraints are binding, early development of emissions free technologies can avoid high scarcity prices.

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