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Technological Change and Learning Curves in the Context of the TranSust.Scan Modelling Network

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Abstract

The paper deals with the concept of learning curves against a broader background of modelling technological change. Based on a literature survey the paper addresses four approaches (endogenous growth theory, learning curves, innovation theory and diffusion theory) and attempts to highlight the links between them. The second part of the paper tackles the empirical implementation of technological change in TranSust.Scan models. Learning curves are the predominantly used approach in empirical modelling as they show two main benefits: They allow inclusion of different technologies for which specific learning rates are estimated. Furthermore, evidence from ex-post observations and ex-ante estimation match closely.

1 Motivation

Within the last decade energy and climate change have gained in importance in political debate as well as in economics. It is a challenge to deal with these issues in economic theory on the one hand and in empirical assessment on the other hand. For both approaches the key role of technological change to reduce energy and carbon intensities of aggregate economic activity is widely recognised. New modelling approaches focus on endogenising technological change and shedding light on the factors that influence technological development as well as technology diffusion. This issue is a major challenge within the EU Framework Project TranSust.Scan[1]. The coverage of models included in TranSust.Scan illustrates the variety of ideas and modelling approaches in empirical energy and climate models based on different theoretical underpinnings. The objective of this paper is to relate the TranSust.Scan models with economic theory of endogenous technological change with a focus on the following approaches:

- New (endogenous) growth theory,
- Innovation theory,
- Technology diffusion, and
- Learning curves.

Endogenous growth theory as a top-down approach introduces a knowledge capital stock which determines productivity, while learning curves as a bottom-up approach relate reductions in unit cost to increases in cumulative production on the firm or sectoral level. Innovation and diffusion theory try to identify factors and processes of technological development emphasising the importance of uncertainty, path dependence and spillovers (see Köhler et al., 2006).

As most of the models of TranSust.Scan use learning curves to incorporate technological change, this paper uses this modelling approach as starting point. With respect to learning curves theoretical literature is rather scarce, whereas empirical observations provide support for the effects of learning. In the context of modelling endogenous technological change, learning curves are related to a wide range of different issues including technology diffusion as well as spillovers, lock-ins, the role of research and development (R&D) and the dichotomy of the knowledge capital stock.

[1] TranSust.Scan is a research project within the Sixth Framework Programme scanning a wide range of policy scenarios as to their relevance for the European Sustainable Development Strategy in view of Extended Impact Assessment. The project links and expands an extensive set of available models addressing strategic policy options.

2 Modelling technological change

The role of technological change for economic growth has been recognised in economic theory for a long time. Technological development was previously treated exogenously in top-down economic models like the Solow model up to the 1960s[2]. Romer (1986, 1990, 1995), Lucas (1988) and Aghion and Howitt (1992) pioneered a new strand of theory as 'technological change arises in a large part out of intentional actions taken by people who respond to market incentives' (Romer, 1990, p.S72).

Together with the new endogenous growth theory, innovation theory, diffusion theory and learning curves build the basis for modelling endogenous technological change in TranSust.Scan models.

New growth theory endogenises technological change by integrating a stock of knowledge into the traditional models. Knowledge is a non-rivalrous economic good in the sense that it can be used by different people at the same time without limiting individual use. Thus, knowledge in contrast to other inputs in the production process as labour or capital exhibits increasing returns to scale allowing for sustained economic growth (e.g. Romer, 1990).

In the new growth models, knowledge is a good produced in a separate sector with output depending on the amount of research – and hence researchers – in the production process. Total per capita output is an increasing function of total research determined by the number of researchers and thus the size of population. Empirical evidence does not always confirm the positive relationship between the growth rate of output and the growth rate of population (Jones, 1995b). This has brought about new approaches (e.g. Jones, 1995a; Kortum, 1997) that relate the increase in knowledge not to the growth rate of population but to the level of per capita income. Other extensions concentrate on research efforts in the product line: That is research activities can either enhance productivity for a given production process or increase the number of available products. Thus again growth is directly linked to research efforts (see Jones, 1999).

Innovation theory as formulated by Schumpeter defines innovation as the driving force in economic development. According to Schumpeter innovations are 'any "doing things differently" in the realm of economic life' (Schumpeter, 1939, p.84). This makes the concept applicable to a broad range of economic activities from the production of an entirely new good to introducing new organisation and business structures. As opposed to the concept of invention[3], innovation is not limited to targeted R&D activities, but captures a broad range of new economic activities.

Technically speaking, innovations can not only be regarded as a shift in existing production functions but as 'the setting up of a new production function' (Schumpeter, 1939, p.87).

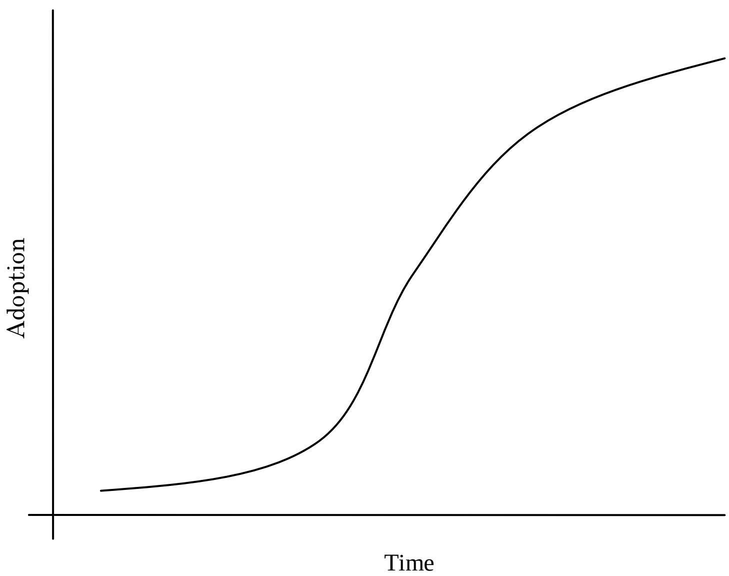
[2] Contrary to top-down models, Schumpeter addressed the process of innovation – and thus endogenous technological change - much earlier (Schumpeter, 1911).

[3] Theory distinguishes between 'invention' and 'innovation' as two supplementary concepts: "Invention is the first occurrence of an idea for a new product or process, while innovation is the first attempt to carry it out into practice" (Fagerberg, 2004).

Entrepreneurs are the driving force behind innovations in order to realise expected profits. Through the imitation of innovative activities, technological change and economic growth is induced. The growing number of imitators copying a successful innovation accelerates growth in the sector in which innovation takes place. Spillovers to related industries or technologies might occur as innovations tend to facilitate or induce other innovations. Innovations thus tend to “concentrate in certain sectors and their surroundings or clusters that may for a while grow faster than the economy as a whole” (Breschi et al., 2000). After a while growth in these industry clusters slows down yielding cyclical patterns of economic activity.

Schumpeter’s original concept of innovation was frequently taken up in economic theory. While, according to Schumpeter, the entrepreneurial spirit was the only source of innovation, other concepts took a mere change in relative prices as the driving force of innovation (Popp, 2002).

The theory of *technological diffusion* is closely related to innovation theory but focuses on the role of adoption of new technologies for technological progress. Karshenas and Stoneman (1995) present an overview of different theoretical approaches to technological diffusion. The underlying idea is that a broad adoption of new technologies is decisive for their economic impact. Over time technology diffusion is typically seen as an S-shaped curve. At the inter-firm level the number of firms adopting the new technology is considered: From the point in time that the first firm is using a new technology the number of other firms adopting this technology grows slowly but with an increasing rate until an inflexion point is reached after which the rate of growth of adopting firms decreases.



Graph 1: S-shaped diffusion curve (adapted from Karshenas and Stoneman, 1995)

The research questions on technological diffusion address the issue of time delay for broad adoption, differences across technologies and industries and the underlying reasons why some adopt earlier than others.

A general model of technological diffusion is the so-called epidemic theory of technology diffusion. The basic idea is that diffusion results from the spread of information about new technologies. In the beginning adoption is constrained by the number of firms who know about the new technology. Experience of early users spreads over time to non-users who then also become users. The epidemic model of technology diffusion is thus demand-side oriented. Extensions that address the interaction between demand and supply-side include cost functions for suppliers and their change over time, market structure and improvements in technology over time. Other extensions include uncertainty about new technologies stemming from poor information: Uncertainty contributes to the slow diffusion rate in the beginning as risk-averse firms will hesitate to use the new technology. The diffusion rate increases over time as uncertainty is reduced. Costs of adoption, and thus profitability, of new technologies are also of relevance. A change in costs over time again accelerates the spread of new technologies.

Learning or experience curves describe technological progress as a function of accumulating experience leading to cost reduction. According to the learning curve concept, productivity gains can stem from targeted processes as research or from quasi-automatic processes such as learning by doing. Learning curves allow for different degrees of productivity gains during the subsequent stages of technology development (S-shaped learning curves, see section 3.2). They can also incorporate induced technological change promoted by R&D policies or capacity-building policies. While learning curves originally could only represent one type of learning at the same time, the two-factor learning curves, recently developed, depict productivity gains from capacity building and R&D simultaneously.

A common feature of the four approaches addressed is the concept of a knowledge capital stock. It allows the combination of the four theories, providing a broader picture of the implementation of technological change: Innovation theory shows persistent market failure in technological change as a result of increasing returns due to increasing experience and implies that there will be imperfect competition in technological change (Boldrin and Levine, 2004). In addition it suggests that due to increasing returns path dependency - and thus possible lock-ins in (inefficient) technologies - might occur (Arthur, 1989). As knowledge can be regarded as a public good, spillovers might result in private R&D efforts below the social optimum; on a global scale this problem could be even intensified by limitations to technology diffusion due to trade barriers or barriers to foreign direct investment (Romer, 1989). Finally, the inherent uncertainty of returns to R&D may again result in investment below the social optimum, if private actors act less risk-friendly or have fewer possibilities to spread risk than society as a whole. The diffusion process is dependent on the spread of knowledge about new technologies, the cost of adoption and thus the profitability of the use of a new technology.

3 Relevance of learning curves for modelling technological change

The theoretical literature on learning curves is rather scarce, empirical observations provide support for the effects of learning with several examples of energy technologies (e.g. Grübler, 1998; Köhler et al., 2006). In the context of modelling endogenous technological change, learning curves are basically able to deal with technology diffusion as well as with spillovers, lock-ins, the role of R&D and the knowledge capital stock. Limitations exist with respect to dealing with more than one phenomenon at the same time. Some of the limitations can be overcome by the recently developed two-factor learning curves.

The concept of learning curves was introduced by the engineer Wright (1936). Since 1922 Wright had studied the change in costs per aircraft with increasing production at Patterson Air Force Base. In his seminal paper 'Factors Affecting the Cost of Airplanes' Wright developed the concept of a 'progress curve' which can be regarded as the basis for the concept of learning curves. He was able to demonstrate that man-hour inputs decreased by 20 percent for every doubling of cumulative output. In addition to these cost reductions, Wright also observed a decline in both raw material and purchased material input as a result of the improved skills of workers and managers.

Arrow (1962) was the first to integrate the concept of the learning curve in economic theory. His paper 'The Economic Impacts of Learning by Doing' can be regarded both as a milestone in modelling technological change and as one of the most important predecessors to new growth theory. Arrow designed an analytical framework to model technological change as a product of accumulating experience by explicitly stating the notion of 'learning by doing' for cost reductions resulting from increasing cumulative investment in a technology. Arrow thus developed an alternative formulation of Wright's progress curves by replacing cumulative output by cumulative investment as a measure of experience.

Since then the concept of learning curves has been incorporated into models of firm behaviour, industry dynamics and international specialisation. In these contributions the role of learning was extended to barriers to entry. Spillovers and R&D were introduced as possible determinants of cost reductions in production (Spence, 1981). Today learning curves do not only cover cost reductions stemming from increased output but also from increased investment in R&D or from improved communication between the producer and the user of a product. Latest developments of the learning curve concept also deal with two different types of learning at the same time ('two-factor learning curves'), see e.g. Kouvaritakis et al. (2000) or Miketa and Schrattenholzer (2004). Complementing innovation theory and the new endogenous growth theory in accounting for technological progress and knowledge capital, learning curves play a major role in empirical modelling of endogenous technological developments.

3.1 Different types of learning

The following types of learning are most commonly distinguished (see for example Malerba, 1992; Junginger et al., 2005):

Learning by doing occurs in the production process. By repetition working processes become more productive leading to cost reductions in production. There are several possible types of learning by doing: On the one hand workers gain experience over time and thus labour input (working hours) declines for a given level of output. On the other hand improvements in the management of production processes – e.g. a restructuring of working task assignments - can also lead to a decline in production costs. Another factor that might decrease production costs are improvements in technical processes due to optimised use.

Learning by using was added as a complement to learning by doing by Rosenberg (1982). In general, this concept captures aspects of learning due to final utilisation of a product. According to Rosenberg, learning by using applies especially to (consumer) capital goods as neither the performance characteristics of these goods nor the interaction of their individual components are known in advance.

Learning by interacting refers to productivity increases due to close contacts and intensive communication between the user and the producer of a technology. It can thus be regarded as a link between learning by doing and learning by using. Effectively, 'it transforms the outcomes of learning by doing and learning by using from being local to becoming non-local' (Lundvall, 2005, p.2). It thus captures the transformation process from tacit to codified knowledge which plays a crucial role in the generation of knowledge spillovers.

Learning from inter-industry spillovers (Epple et al., 1991) denotes productivity gains due to knowledge spillovers between different industries. As knowledge generated in the research process cannot be fully internalised by the firm, research and development activities in one industry or sector can affect production costs in other industries. In the theory of technological diffusion, inter-industry spillovers are crucial for a broader adoption of new technologies and thus positive overall economic effects. This is similar to the arguments brought up by Schumpeter shaping innovation and diffusion theory.

Learning by researching denotes cost decreases as a result of an organised search for new knowledge. It is a process at firm-level closely related to the production process and in most cases specific to the product. This type of learning is thus closely related to endogenous growth theory where the knowledge stock accumulated through R&D is the driving factor of economic growth.

Learning by exploring is similar to the concept of learning by researching. Major advances in science and technology resulting from basic research lead to cost reductions in various technologies. In contrast to learning by researching, learning by exploring is less profit-oriented with advances in research being applicable to a broader set of technologies. Learning by exploring is thus linked to endogenous growth theory via the idea of knowledge capital and to innovation and diffusion theory based on the concept of technology spillovers.

Lundvall (1985) defines increasing returns to scale as another type of learning, namely as *learning by producing.* Cost reductions in large-scale production result from high fixed costs and decreasing marginal costs.

All of these types of learning lead to productivity gains in a technology. While learning by researching and learning by exploring describe targeted processes aimed at the production of new knowledge, the other types of learning refer to quasi-automatic improvements accompanying the technological development.

3.2 Learning curve equations

Most common single-factor learning curves as depicted in Equation 1 are used to model technological development.

$C = C0\ X\text{-}\alpha$ Equation 1

C unit cost of technology

C_0 cost of the first unit of the technology

X measure of cumulative experience

α learning index

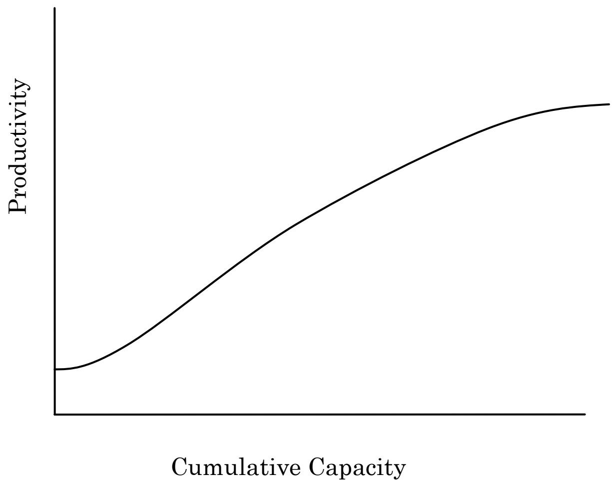
Equation 1 states that the unit cost of a technology (*C*) essentially depends on two parameters: the cost of the first unit of the technology installed (C_0) and some measure of experience (*X*) to which a learning index (α) is applied. The type of learning under consideration determines the measure of experience (see section 3.1) which may range from cumulative capacity to cumulative expenditures on research and development.

By taking the logarithm of Equation 1, a linear model is obtained which can be estimated econometrically, thus deriving α:

$\log C = \log C_0 - \alpha \log X$ Equation 2

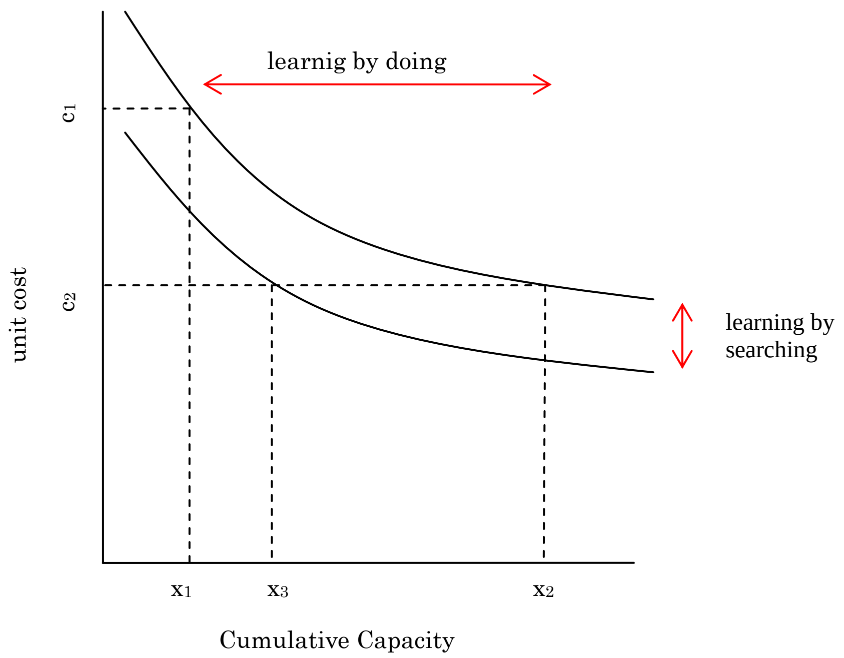
The progress ratio which gives the percentage change in costs for a doubling of capacity (output etc.) is calculated by $2^{-\alpha}$, implying a learning by doing rate of $1\text{-}2^{-\alpha}$. Estimated learning rates vary strongly with respect to technology, geographical scope and time frame chosen (Ibenholt, 2002; Harmsen and van Sambeek, 2003; Junginger et al., 2005).

The learning rate is not constant over the life-cycle of technologies. For most technologies only a slow productivity increase can be observed at the beginning (infancy phase of the technology), followed by a considerable increase during the growth phase of the technology. As the technology matures productivity growth is limited or even declines because, for example, individuals forget knowledge, or their motivation declines. This development process is depicted by so-called S-shaped learning curves (see Graph 2). The similar shape of the learning curve and diffusion curve highlight the stages in a life cycle of a technology from different perspectives.



Graph 2: The S-shaped learning curve

Recently the formulation of the single-factor learning curve to a two-factor learning curve was extended (see for example Kouvaritakis et al, 2000, or Miketa and Schrattenholzer, 2004). Two-factor learning curves simultaneously account for two types of learning with a focus on learning by doing effects, combined with learning by researching effects. Thus, to calculate capacity (or output) the stock of knowledge as measured by cumulative R&D expenditures or by the number of patents relating to a certain technology is added as another factor for productivity increases. The concept of the two-factor learning curve is illustrated in Graph 3.



Graph 3: The two-factor learning curve (adapted from Jamasb, 2006)

The learning by doing effect from increasing cumulative capacity is represented by the decreasing curve. The learning by searching effect (R&D) from technological improvements results in a new production technology which is represented in a downwards shift in the curve.

Thus a cost reduction for a given technology from c_1 to c_2 is either attainable by a mere increase in cumulative capacity from x_1 to x_2 (volume effect), or a capacity increase from x_1 to x_3, combined with a shift in the learning curve induced by increased R&D efforts.

The concept of the two-factor learning curve can be written as:

$$C = C_0 X^{-\alpha} K^{-\beta} \qquad \text{Equation 3}$$

K stock of knowledge (e.g. cumulated R&D expenditures or the number of patents)

β learning by searching index

Equation 3 states that the unit costs of the technology for the two-factor learning curve depend on the costs of the first unit installed and on two different measures of experience – the cumulative stock of knowledge and cumulative capacity. By taking the logarithm of Equation 3, a linear model is obtained which can be estimated econometrically, thus deriving the two learning indices α and β:

$$\log C = \log C_0 - \alpha \log X - \beta \log K \qquad \text{Equation 4}$$

The progress ratio, which gives the percentage change in costs for a doubling of capacity (output), is again calculated by $2^{-\alpha}$, implying a learning by doing rate of $1\text{-}2^{-\alpha}$. In addition to this learning by doing rate, the two-factor learning curve also gives a learning by researching rate ($1–2^{-\beta}$), which shows the impact on technology costs of a doubling in the R&D based variable. In empirical modelling, two-factor learning curves are not found very often, as the optimisation problem becomes non-convex and might lead to unstable results (Hedenus et al., 2006; Köhler et al., 2006). Nevertheless, compared to single-factor learning curves, Söderholm and Sundquist (2003) identify two major advantages of two-factor learning curves: Firstly, they are able to model policy-induced technological change. Secondly, through the introduction of R&D two-factor learning curves are subject to a smaller omitted variable bias as variations in costs that are due to R&D support are no longer attributed to the learning by doing effect.

3.3 Assumptions shaping the concept of learning curves

Learning curve theory has a relatively weak theoretical underpinning, sometimes referred to as a concept rather than a theory. The other three approaches discussed in this paper concentrate more on the theoretical underpinning of technological change. While this aspect seems advantageous compared to the learning curve concept at first sight, it might also be regarded as an obstacle for empirical modelling as these approaches require restrictive assumptions due to data limitations (e.g. Köhler et al., 2006).

Learning curves, however, also depend on a wide range of assumptions constraining their applicability: Firstly, learning rates depend, compared to other concepts, strongly on the selected time frame. Because of the small number of variables used, even very small shifts in the period chosen might result in major changes to the estimated progress ratios. Thus, the prediction of technological development might be particularly arbitrary and ambiguous.[4] Secondly, the boundaries of the learning system influence the resulting learning rates. Analysing experience curves of wind turbines, Junginger et al. (2005) e.g. show that an experience curve might either be based on the production of wind turbines (‘wind turbine learning system’) or on the installation costs of wind farms (‘wind farm learning system’). Depending on the learning systems different progress ratios are the result. Thus, the same technology but different system boundaries may yield different experience curves and progress ratios. Thirdly, the choice of the learning parameter is essential for the outcome. Depending on the type of learning examined, different parameters are chosen to measure experience. Junginger et al. (2005) find that with respect to wind turbines four different types of learning curves might be considered: Most experience curves found in literature (e.g. Seebregts et al., 1998; Neij et al., 2003) analyse the cost reduction of wind turbines per unit

[4] The choice of time period and variables included in the model of course is also decisive for other modelling approaches. Still, learning curves react especially sensitive to changes in the time period due to the small number of variables included.

of capacity vs. the cumulative capacity produced or installed. Other learning curves relate either the cost reduction per kWh to cumulative electricity production or cumulative capacity. Another type analyses the decline of electricity costs with the number of installed wind turbines, restricting direct comparability.

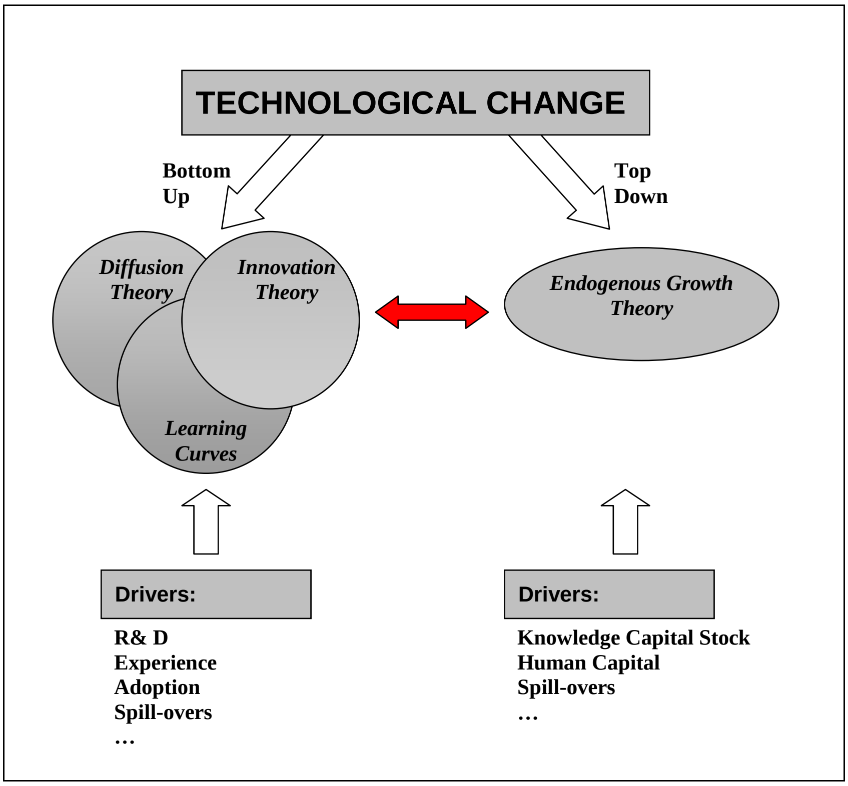
3.4 Linking the theoretical approaches

All four approaches discussed in this paper incorporate a broad range of important assumptions on the nature of technological change: Spillovers are recognised as a central source in the innovation and diffusion process. This understanding is not only limited to innovation and diffusion theory, but is also integrated into endogenous growth theory and learning curve theory. R&D is also implemented in all of the approaches: While it is closely related to diffusion and innovation theory as a decisive element of innovation, in learning curve theory R&D is regarded as a source of experience. In endogenous growth theory, R&D efforts result in an increase in the knowledge capital stock. The stock of knowledge is, again, an integral element of innovation and diffusion theory as it opens up the possibility for the development of new technologies and their spread across the economy.

In Graph 4 we summarise the links between the theoretical concepts of technological change addressed in this paper. We find that the described bottom-up models[5] show a pronounced overlapping with respect to the drivers of technological change. The focus on particular drivers then determines the specific categorisation. While the concept of learning curves builds primarily on experience, diffusion and innovation theory mainly address adoption and R&D respectively.

The drivers also establish a link to endogenous growth theory which addresses technological change from a top-down perspective. As in bottom-up models, spillovers are a main feature driving technological change in endogenous growth theory. R&D enters the model by contributing to the accumulation of the knowledge capital stock.

[5] Bottom-up models are based on a detailed representation of different technologies whereas top-down models are built on more aggregate economic structures. Bottom-up models focus on specific sectors and technologies in a partially analytical way, whereas top-down models consider all sectors simultaneously accounting for interdependencies between sectors.



Graph 4: Links between the selected theoretical approaches

4 Empirical evidence on learning in energy technologies

Since the beginning of industrialisation energy and carbon intensities of economic processes have generally been declining for the majority of countries (see Grübler and Nakicenovic, 1996). Technological change can be regarded as the key to this development: The replacement of old with new technologies is a gradual process occurring as the performance of new technologies improves and their costs decrease in a learning process. Typically, as technologies mature, their learning progress slows down so that new technologies can catch up with them in terms of cost-efficiency and productivity.

In the context of climate change and global warming, learning processes and potentials of new energy technologies are gaining in importance. Learning curves are widely used to model the expected development and potential of low carbon energy sources based on historical development. Harmsen and van Sambeek (2003) investigate the impacts of different future feed-in tariffs on windmills in the Netherlands using learning curves for both offshore and onshore windmills. The analysis builds on global prices for turbines (as data on the production cost was not available) and global cumulative capacity in order to assess potentials of windmills in the Netherlands accurately. From 1987 to 2002, five doublings of global installed windmill capacity could be observed, accompanied by learning rates of between 10% and 13%, equalling an annual reduction in production costs of 2.5% to 4.5%.

Hansen et al. (2001) examined the connection between green subsidies and efficiency gains due to learning by doing for the Danish windmill industry. A decrease in the cost disadvantage of wind power stations compared to traditional power stations was shown as a result of the strong learning by doing effect. Between 1983 and 1999 annual production of Danish windmills has increased from 40MW to 1900MW, over the same period production per windmill increased from 31kW to 698kW. Prices for windmills have sharply decreased making the industry more competitive and export-oriented, producing 50% of productive capacity installed worldwide.

Klaassen et al. (2005) analysed the impact of R&D policies on cost-reducing innovation for wind turbine farms in Denmark, Germany and the UK based on a literature survey and two-factor learning curves. Learning curves include cumulative capacity as the learning by doing variable and the stock of knowledge learning as the research variable. The latter is measured by (public) R&D expenditure. Depreciation of knowledge and the time-lag between R&D investment and observed cost reductions were taken into account. Klaassen et al. showed that the development of investment costs in the three countries supported the concept of the two-factor learning curve with statistically significant learning parameters. While initial investment costs of wind turbine farms differed in the three countries, learning parameters were comparable.

Jamasb (2007) conducted a comparative analysis of learning effects and technological change in the power sector. A two-factor learning curve was coupled with a diffusion model in order to assess both the effect of learning by doing and learning by researching on technological progress at four different stages of the development of a technology – mature technologies, reviving technologies, evolving technologies and emerging technologies. Jamasb shows that learning by searching (R&D) effects are higher than learning by doing effects at all stages of technological development and that there is only limited substitution potential between the two types of learning. Still, results differ significantly for the four different stages: Evolving technologies such as nuclear or wind power show both high learning by doing and learning by researching rates. Reviving technologies such as CCGT (Combined Cycle Gas Turbines) and small-scale hydropower instead exhibit high learning by researching rates without facing significant market constraints. Emerging (thermal solar power) and mature (coal) technologies show both low learning by researching and learning by doing rates. Simple learning by doing curves thus tend to 'overestimate the effect of learning by doing and in particular for emerging and new technologies' (Jamasb, 2007, p.69) where R&D is especially important for technological development.

McDonald and Schrattenholzer (2001) conduct a literature survey on learning rates in energy models. 26 data sets for different energy production technologies with cumulative capacity, cumulative production or cumulative sales as measure of experience are examined. Learning rates for the technologies range between 5.8% and 34%. McDonald and Schrattenholzer highlight that in many cases estimated learning curves have a limited explanatory value as expressed by a low R2. This holds especially true for learning rates based on prices rather than on costs. Learning rates vary for same technologies, especially for gas turbines and GTCC power plants: Learning rates based on later data generally tend to be lower. Based on this review of learning curves McDonald and Schrattenholzer (2002) examine possible biases of estimated learning rates for eight technologies. Estimated learning rates ranged between 10% for air conditioners in Japan and 37% for AC/DC converters in Eurasia (see Table 1).

Table 1: Overview of Learning Rates (adapted from McDonald and Schrattenholzer, 2002)

Technology	Country/ Region	Time Period	Learning Rate	Performance Measure	Experience Measure
Oil extraction	North Sea	-	25%	labour (man hours)	units (platforms)
AC/DC converters	World	1976-1994	37%	conversion losses	capacity
Gas turbines	World	1981-1991 1991-1997	-11% 26%	investment price	capacity
Wind energy	USA	1985-1994	32%	production cost	production
Solar photovoltaic modules	World	1968-1998	20%	investment price	capacity
Ethanol	Brazil	1979-1995	20%	sale price	production
Air conditioners	Japan	1972-1997	10%	sale price	sale
SONY laser diodes	-	1982-1994	23%	production cost	production

McDonald and Schrattenholzer show that learning rates tend to be biased due to differences in time range and data quality of performance and experience measures used. In addition, learning might not be the only source of efficiency improvement for the technologies. Additional factors such as R&D, market size, market structure or government regulation might be other influences.

Jamasb (2007) stresses the shortcomings of single-factor learning curves when modelling policy-induced technological change: Originally designed to model technological change in mature industries, single-factor learning curves are of limited use to infant industries as they cannot simultaneously account for push (R&D) and pull (demand) factors. In general, they focus on capacity building and neglect the importance of R&D measures to induce technological change. Two-factor learning curves overcome these shortcomings but show other limitations. Sijm (2004) points out that two-factor learning curves might result in biased learning rates due to restrictions in the empirical measurement of input variables. The learning by searching effect is based on estimations of the stock of knowledge for which no standardised method is available. Furthermore, consistent time series of the relevant data are rarely available so caution is needed when interpreting the estimated coefficient for R&D. On the one hand in the theoretical concept two-factor learning curves attempt to include other driving factors for technological development (e.g. knowledge stock) than output and capacity. On the other hand the concept finds its limits in empirical measurement of these variables.

5 Learning and technological change in TranSust.Scan models

Within the TranSust.Scan research project a number of modelling groups in Europe are trying to develop a new generation of models dealing with sustainability issues. Some of the models involved focus on the issue of endogenous technological change to analyse the transition to sustainable economic structures. In a first step, existing models are extended to reflect the multifunctionality aspect of sustainability policies and the trade-offs with other policies. In a second step the set of improved models are used for a comprehensive analysis of a wide range of policy scenarios.

The project team comprises twelve research groups from nine EU member states. Within the project twelve economic models are used with differing regional and methodological backgrounds. Out of the twelve models, seven deal explicitly with endogenous technological change. Table 2 summarises the main characteristics of the TranSust.Scan models based on a questionnaire and model documentation provided.

Table 2: Characterisation of TranSust.Scan models

Model	Institution	ETC	No ETC	Description
DART	IfW	x		Global multi-regional, multi-sectoral recursive dynamic model
DEMETER	IVM-VU	x		Long-term integrated assessment model
GAIN	WIFO	x		Extended energy model
IMACLIM-S	SMASH-CIRED	x		Multisectoral macroeconomic general equilibrium framework
IMACLIM-R	SMASH-CIRED		x	Energy systems model
IMPEC	LIFEA		x	Multisectoral macro model
KLUM	University of Hamburg		x	Global agricultural land allocation model
MARKAL	ECN	x		Bottom-up energy system optimisation model
PACE	ZEW		x	Comparative-static multi-region, multisectoral CGE model
POLES	SMASH-CIRED			
WITCH	FEEM	x		Regional integrated assessment hard-link hybrid model
W8D	LIFEA	x		Macroeconomic model of the Polish economy

TranSust.Scan models that explicitly model technological change use top-down as well as bottom-up approaches. Top-down models depict the economy on an aggregate macroeconomic or sectoral level, allowing for feedback effects between different sectors and markets. Instead of examining the special features of specific energy technologies, top-down models use production functions to represent the energy sector(s). Substitution elasticities thus drive changes in the energy sector. Bottom-up models, on the contrary, represent energy technologies in detail with less focus on macroeconomic modelling.

In the remainder of the chapter we concentrate on the models that explicitly tackle technological change (Table 3) and provide sufficient modelling documentation. The characterisation of the models attempts to relate the empirical implementation of endogenous technological change to the four theoretical concepts discussed above.

Table 3: Characterisation of TranSust.Scan models

Model[2]	LC[1]	EGT[2]	IT/DT[3]	Model Description
DART			x	top-down model
DEMETER	x			top-down model that is calibrated to fit bottom-up descriptions of certain energy technologies
GAIN	x		x	bottom-up
IMACLIM-S	x			top-down model harmonised with information from a bottom-up energy model
MARKAL	x			bottom-up
WITCH	x	x		top-down structure with a detailed description of the energy sector.

[1] Learning Curves
[2] Endogenous Growth Theory
[3] Innovation / Diffusion Theory

Learning curves are the prevailing concept in empirical modelling of endogenous technological development in literature, despite the weak theoretical background. The TranSust.Scan models with endogenised technological change also fit this pattern: Five models use the concept of learning curves. GAIN and WITCH use a hybrid approach combining learning curves with innovation theory and endogenous growth theory respectively (see Table 3).

The learning curve concept in the TranSust.Scan models

DEMETER (IVM-VU), IMACLIM-S (SMASH), and MARKAL (ECN) build on learning curves. DEMETER is a long-term integrated assessment model which incorporates learning by doing effects in the economic analysis of climate change. In the current version, learning by doing is limited to the energy sector. Endogenous technological change is explicitly modelled for fuel-based energy, carbon capture and sequestration (CCS) and non-carbon energy sources. Technological development occurs in the form of cost reductions of energy technologies dependent on the cumulative capacity of the technology installed. Thus, energy production costs decrease with the installation of new energy vintages: For energy production new capacity equals the energy output of the new vintage. For CCS new capacity is the amount of emissions prevented. Each new vintage in the energy sector requires investment which is proportional to previous investment and current maintenance costs. All other technological change is exogenous, determined by a benchmark (business as usual) growth path. Within the TranSust.Scan project model extensions cover the modelling of different leakage processes for CCS.

IMACLIM-S is a static general equilibrium model which integrates information from a bottom-up energy model (Ghersi, 2008 forthcoming). Investment initiates (Hicks-neutral) technical progress which is based on learning by doing and R&D.

MARKAL is a bottom-up energy system model. The model incorporates learning by doing effects in so-called “technology clusters” (see e.g. Seebregts et al., 1999; de Feber et al., 2002; Smekens et al., 2003; Smekens, 2005). These clusters are groups of technologies that have a common essential component. This can either be the technology as such (e.g. stand-alone gas turbine or CGET plant) or a part of it (e.g. gas turbine). Endogenous learning effects are defined for the learning components in different technologies and sectors as gas turbines or PV panels in the power sector, fuel cells in the transport sector or CO_2 injection in the downstream sector. Single technology components are used by different technologies, so that learning effects - and hence cost reductions - accrue to all the technologies which employ the same components. Thus, the MARKAL model does not only cover endogenous learning within a firm or sector but also technology spillovers. The close link between diffusion theory and learning curves is, therefore, again confirmed.

Innovation theory in the TranSust.Scan models

DART (IfW) is a global multi-regional, multi-sectoral recursive dynamic model. It is the only model within TranSust.Scan using innovation theory in the sense of Hicks as the basis for modelling technological progress. DART builds on the induced innovation hypothesis introduced by Hicks (1932) postulating that 'a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind - directed to economizing the use of a factor which has become relatively expensive' (pp.124-125). Rising energy prices provide incentives to invest in energy-saving technologies. Thus, for given technologies there is a substitution between energy and other inputs associated with innovation.

DART uses three data sources to relate technological development to changes in relative prices: The model follows Dowlatabadi and Oravetz (1997) in explaining energy intensity as a function of energy prices. To capture the impacts of energy prices and the stock of knowledge on energy-saving innovation the model builds on Popp (2002). The impact of new technologies on energy consumption in the model follows Popp (2001).

The approach uses sound empirical estimates on the relationship between energy prices and energy efficiency improvements. In the modelling approach, just as in the learning by doing approach, innovation comes at no cost.

Hybrid models within TranSust.Scan

GAIN (WIFO) and WITCH (FEEM) combine the insights from two sources: While GAIN uses the learning curve concept and innovation theory, WITCH incorporates learning curves and endogenous growth theory.

In the WITCH model (Bosetti et al. 2006 and 2007) technological change is modelled endogenously and can, for example, be induced by climate policy or international spillovers. The model incorporates endogenous technological change by both learning by doing effects (bottom-up approach) and by the accumulation of knowledge through R&D investment. Using learning effects, the observed empirical relationship between investment costs and cumulative installed capacity is integrated in the model for wind and solar technologies. The WITCH model uses world learning curves, which relate investment cost reductions to the capacity installed worldwide. This approach allows cross-country differences in learning rates.

Thus, the model assumes perfect technology spillovers and constant learning rates across all countries. As WITCH incorporates different electricity production technologies the model allows for changes in the power-production mix. The model can thus depict changes in investment in different technologies in response to policy measures.

In addition to learning effects, WITCH uses investment in energy R&D to model technological change. Through R&D investment, energy efficiency is enhanced as technological improvements are captured by the stock of knowledge in different regions. The creation of knowledge through R&D activities exhibits positive externalities, so that the social returns on R&D are higher than the private ones. WITCH integrates positive externalities from private R&D investment by assuming that returns on R&D investment in energy technologies are four times higher than returns on physical capital. At the same time, the opportunity cost of crowding out other forms of R&D is integrated by subtracting four dollars of private investment from the stock of physical capital for each dollar of R&D crowded out by energy R&D. Based on empirical observations by Popp (2004), WITCH assumes that R&D investment in new energy technologies crowds out 50% of other R&D. Technological change resulting from R&D expenditure is applied to power generation and advanced biofuels. For biofuels a time lag of ten years is assumed for innovation spillovers between regions.

6 Concluding remarks

This paper presents a review of the theoretical and empirical modelling of technological change. The focus is especially on the links between various theoretical approaches to technological change and their application in TranSust.Scan models. Concentrating on the concept of learning curves this approach is then enriched with aspects of other theories. The paper distinguishes between four approaches: Learning curves, endogenous growth theory, diffusion theory and innovation theory. A further distinction is made between bottom-up and top-down concepts. The bottom-up approaches (learning curves, diffusion and innovation theory) show a pronounced overlap with respect to the drivers of technological change. Spillovers as a main characteristic for driving technological change in endogenous growth theory (top-down) establish a link between bottom-up and top-down modelling.

In the assessment of empirical models the implementation of endogenous technological change in the context of energy and climate change modelling is emphasised. The paper especially concentrates on the models within the research network TranSust.Scan. These models address particularly the issue of sustainable development and climate change. Out of the twelve models in the research network, five explicitly deal with endogenous technological change. As in other empirical models outside TranSust.Scan learning curves are the predominant concept for modelling technological change. The prominence of this approach is based on a rather straightforward empirical implementation: It allows inclusion of different technologies for which specific learning rates are estimated. Furthermore, evidence from ex-post observations and ex-ante estimation match closely.

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