CHAPTER 4

Application of experience curves and learning to other fields

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Abstract

The concept of experience curves is normally applied to analyze cost or price developments of technologies, but studies have shown that the concept can also be extended to other applications and fields. In this chapter, we show the application of experience curves to analyze energy use in industrial processes, energy demand of household appliances and discuss its application to describe and project developments in environmental impact of technologies. A second part of the chapter shows a case study of applying the concept of technological learning to the field of social behavior in what is called social learning (SL). This part of the chapter shows how the diffusion of electric vehicles is affected by different SL mechanisms.

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4.1 Introduction

Until now, we have discussed the main concepts: technological learning (TL) and a mathematical representation of its effects: the experience curve. In this context of TL, we consider *technological* improvements to production processes that result in a decline of the *cost* of technologies. In this chapter, we will discuss several ways to expand on this concept, by discussing learning processes related to social influence social learning (SL) rather than technological progress, and by including improvement due to technological progress in other metrics than cost (energy-efficiency and environmental learning), as well as application of the experience curve concept in environmental impact analysis.

4.2 Energy experience curves

4.2.1 Experience curves for energy efficiency in industrial processes

Given the value of experience curves to describe the cost reductions in technologies, and to project future costs of the studied technologies, several authors have attempted to apply this concept to analyze industrial processes.

Ramírez and Worrell (2006) analyzed the production of ammonia and urea in the United States, in order to determine experience curves for the cost of these products. During their analyses, the authors found that although there is clear evidence for technological improvements in the production processes of these fertilizers, the historical price developments of these products is affected by two major parameters: supply and demand relations, and the price of natural gas, which is used as a key input in the production of both ammonia and urea. The natural gas that is required was found to account for 70%−90% and 70%−75% of the total costs for ammonia and urea, respectively. Ramirez and Worrell argued that since these contributions are so high, technological progress would be likely to focus on reducing the amount of natural gas used and thus modified the experience curve concept to analyze not overall costs, but rather the specific energy consumption (SEC) of the production process. Furthermore, since this process is constrained by a physical minimum, they added this minimum to the experience curve:

$$\mathrm{SEC} = \mathrm{SEC}_{\min} + \mathrm{SEC}_0 \cdot \mathrm{Cum}^m$$

where SEC is the specific energy consumption of the production process, $\mathrm{SEC}_{\min}$ is the minimum specific energy consumption, Cum is the cumulative production, and m is the experience curve parameter. The parameter $\mathrm{SEC}_{\min}$ represents the theoretical physical minimum for this conversion process and serves as the asymptote of the experience curve function. Ramirez and Worrell found learning rates of SEC of 23% for ammonia, and 9% for urea production.

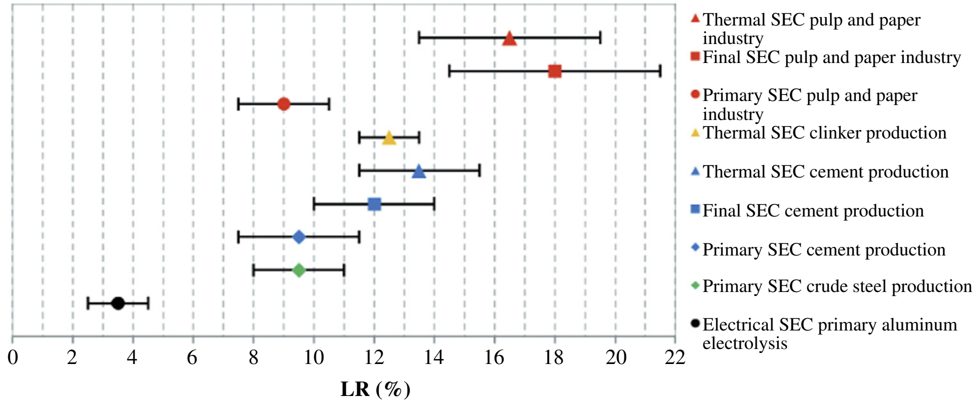

Figure 4.1
Overview of estimated learning rates for various industrial processes, as devised by Brucker et al. (2014). *Source: From Brucker et al. (2014).*

In similar work, Brucker et al. (2014) analyzed the specific energy consumption of several other industrial processes. The authors collected SEC data and built time series based on sector averages, or data on best-available-technology processes for paper and pulp industry, cement, clinker and crude steel production, and primary aluminum electrolysis. As shown in Fig. 4.1, a range of learning rates was found for these different products and industries, from 3.5% to 12.5% for primary energy SEC, while the coefficient of determination was 0.79 or higher, showing good agreement of the devised experience curve with the empirical data collected. The authors note that the learning rates were generally higher as the system boundary increased, seemingly confirming the notion that overall learning rates in industries are a combination of TL across a product's supply chain. The learning rates that were derived from the data for the different products were applied to analyze the development of SEC values up to 2035, based on bottom-up modeling results of the industrial sector (Fleiter et al., 2013), and note that although the results nicely agree with business-as-usual scenarios for developments of energy consumption, some results seemed too optimistic due to past leap improvements in SEC that would not be expected to occur again in the future.

4.2.2 Experience curves for energy efficiency in energy demand technologies

In a study of TL of energy demand technologies, Weiss et al. (2010) analyzed the learning rates of a variety of technologies, including dishwashers, washing machines, laundry dryers, refrigerators, and freezers. Table 4.1 gives an overview of the technologies analyzed, and the associated learning rates for different noncost parameters. Weiss et al. collected data from "The Consumentenbond," a Dutch nonprofit organization for consumer protection, over a time frame ranging from 1965 to 2008.

Table 4.1: Overview of results presented by Weiss et al. (2010) on the energy efficiency of large household appliances.

Technology	Learning rate	R^2	Learning rate parameter
Washing machines	35% ± 3%	0.92	Specific energy consumption in kWh_e/kg laundry
	28% ± 8%	0.57	Specific water consumption in L/kg laundry
Laundry dryers	20% ± 6%	0.84	Specific energy consumption in kWh_e/kg laundry
Dishwashers	18% ± 3%	0.89	Energy efficiency index
	31% ± 5%	0.84	Water consumption in liters
Refrigerators	17% ± 2%	0.87	Energy efficiency index
Freezers	13% ± 3%	0.79	Energy efficiency index

As shown in Table 4.1, especially the energy consumption of the household appliances reviewed show strong correlation with cumulative production of these appliances, and learning rates for energy consumption range from 13% to 35%. For water consumption of washing machines and dishwashers, strong learning rates are also observed, although especially for the former, the coefficient of determination is quite low, and the estimated error of the learning rate is quite large.

Weiss et al. list a variety of reasons that have led to the improvements of energy and water consumption in the household appliances. Improvements in refrigerators and freezers were the result of improved insulation and various optimizations to the cooling equipment (such as compressors, condensers, and heat exchangers). For dishwashers and laundry machines the reduction in energy consumption was stated to be for a large part of the result of decreased water consumption, as well as better heat recovery and progress in in other areas, such as improvements in detergent quality.

An interesting insight from the study by Weiss et al. was found when the authors analyzed the implementation of several energy efficiency policies in The Netherlands. By comparing the learning rate for energy efficiency before and after the implementation of these measures, the authors found that after the implementation, the learning rate increased significantly for dishwashers, refrigerators, and freezers. Especially for the freezers and refrigerators, the increase was large, going from 17% to 49% for refrigerators, and from 11% to 47% for freezers. These findings seem to indicate that learning rates can be influenced by policy makers, at least on the short term.

4.3 Experience curves for environmental impacts and life cycle assessment

As the previous section already made clear, the experience curve concept can be applied to several other metrics than just costs of technologies. The application of experience curves in energy modeling already has a long history, being applied to aid in the exploration of future energy systems that allow for a transition toward a low-carbon energy supply, in order to meet climate targets. Taking into account and quantifying the effects of technological progress is however also an important aim in studies of environmental impact of (energy) technologies, such as ex ante or prospective life cycle assessment (LCA).

Most of the examples of using experience curves for assessment of environmental impacts are related to photovoltaic (PV) technology. Louwen et al. (2016) collected LCA results of PV technology over a range of several decades. These LCA results were used to derive experience curves for the cumulative energy demand (CED) and greenhouse gas (GHG) emissions of mono- and polycrystalline–based PV systems. The study showed that these technologies exhibit learning rates of 12%–13% for CED and 17%–24% for GHG emissions. The derived experience curves were applied to calculate the total cumulative energy use and GHG emissions from the PV industry, in order to compare these environmental impacts with the environmental benefits gained as a result of electricity generation from the global installed PV system capacity. The authors found that in their most likely scenario, breakeven was achieved in terms of net environmental impact, and that after this breakeven point, the PV industry as a whole has had a net positive environmental impact, in terms of both GHG emissions avoided and energy output. Due to a decline in energy and GHG payback times of PV systems, strong growth (around 50% per year) of installed PV capacity is possible without creating an energy sink or increasing global GHG emissions on the short term.

Other authors have also applied experience curves in the domain of LCA. Sandén and Karlström (2007) applied experience curves to develop a method for consequential LCA to assess the environmental impacts of investing in alternative technologies. They argue that due to the concept of TL, marginal investments in alternative technologies help "drive technologies down" the experience curves; and hence, these contribute not only marginally to the current system but also make contributions to more radical system changes.

A more direct application of experience curves for prospective LCA would be to use them to generate foreground or life cycle inventory (LCI) data. As discussed by Arvidsson et al. (2018), experience curves could be used to generate this LCI data and could include technological parameters (such as those discussed in Section 4.2), or material inputs required to produce such technologies.

Bergesen and Suh (2016) used experience curves to generate these future material inputs for a prospective LCA on cadmium telluride (CdTe) PVs. By analyzing historical developments in the supply change of CdTe PV, they established learning rates for several of the foreground technology parameters, such as the amount of CdTe required, the efficiency of the PV modules, and the amount of electricity required in manufacturing. By combining these different learning rates, they were able to build a model that estimates the environmental impact of this technology as a function of increases in cumulative production.

Caduff et al. (2012) also applied experience curve concepts in order to assess the environmental effects of the increasing scale of wind turbines. The authors report that due to a combination of upscaling and TL the environmental footprint of electricity produced with wind turbines decreases as they are upscaled and improved.

4.4 Social learning

N.B. this section is a summary of Edelenbosch et al. (2018).

Besides technology costs, other behavioral factors, related to for example preferences, habits and values play a key role in technology choice (Mundaca et al., 2010; Gifford et al., 2011). Modeling behavioral influences on technology choice is however complex. There are a large number of factors that could be represented and are not easy to quantify (Stern et al., 2016). Behavioral factors also tend to be highly heterogeneous across different consumer groups (Laitner et al., 2000). In a technology transition, this is important because market heterogeneity itself can affect the choices of others through SL. We use "SL" in this context to indicate the change in individuals' understanding and preferences toward new technologies as a result of interactions within social networks (Rogers, 2003; Young, 2009; Reed et al., 2010). As an example, early adopters (EAs) moving to a new technology can impact others' preferences and decision-making processes by changing their perspectives on the status, reliability, and safety of a new vehicle (Axsen and Kurani, 2012; McShane et al., 2012). SL by users about the benefits and risks of new technologies is a key process in technology diffusion. In his seminal work on "diffusion of innovations," Rogers (2003) defines diffusion as the process by which an innovation is communicated over time among the members of a social system. These members are heterogeneous in their preferences, particularly toward risk and uncertainty. Earlier adopters are risk-tolerant or risk-seeking, preferring new and relatively untested technologies that offer novel attributes. Later adopters are risk-averse, preferring to wait until perceived technology risks are lowered by observing the experiences of EAs. Heterogeneous adopters are therefore interdependent, connected through social communication processes. Although the specific mechanisms of SL are diverse—ranging from word of mouth to visible "neighborhood effects" and compliance with social norms—the basic insight that heterogeneous consumers exchange information through social networks (Rogers, 2003) has been repeatedly confirmed both in general terms (e.g., Peres et al., 2010; McShane et al., 2012) and in studies specific to vehicle choice (e.g., Grinblatt et al., 2007; Axsen and Kurani, 2012).

A novel modeling approach developed by Pettifor et al. (2017) represents consumer heterogeneity in a global context and the dynamic nature of SL processes. Pettifor et al. (2017) compiled and synthesized empirical data on risk aversion to new vehicle technologies among different consumer groups. Following diffusion of innovations theory (Rogers, 2003), they then translated differing adoption propensities in to a single aggregated "risk premium (RP)," which declined as a result of social influence effects between the heterogeneous adopter groups.

That work was advanced by Edelenbosch et al. (2018) exploring how a dynamic representation of *both* SL *and* TL influences the long-term transition to battery electric vehicles (BEVs). The "SL" process has a clear analogy with TL as a process by which costs or barriers are reduced. Both types of learning effect impact how technologies diffuse, and both are processes that unfold over time. Both for TL as well as for SL it is not time per se that decreases perceived risks or costs but rather the experience of others (SL) and the experience of manufacturing and using technologies (TL).

4.4.1 Social learning in the transport sector

The transport sector represents one of the fastest growing sources of GHG emissions (Sims et al., 2014). Empirical studies show that in the transport sector behavioral factors such as esthetics, performance, attitude, lifestyle, and social norms have a strong effect on the choice of technology (Tran et al., 2012; Stephens, 2013; McCollum et al., 2017). The discussed recent modeling efforts have explored whether the behavioral realism of integrated assessment models can be improved, focusing on consumer choices for light duty vehicles (LDVs). LDVs are of particular interest as they account for approximately half of current energy consumption in the transport sector (Sims et al., 2014), and the sector is a very heterogeneous, with many users.

4.4.2 Modeling risk premiums and social and technological learning

Rogers (2003) distinguishes consumer segments along a normal distribution of adoption propensities. EAs have high initial adoption propensities and so high risk tolerance; early majority (EM), late majority (LM), and laggards (LG) are increasingly risk averse and have low initial adoption propensities. Based on this conceptualization, Pettifor et al. (2017) calculate initial RPs as a measure of adoption propensity for each of the four different adopter groups. Their RP estimates are based on discrete choice experiments that provide willingness-to-pay (WTP) estimates for new technologies, such as BEVs, for which limited market data is available. Pettifor et al. (2017) use a normal distribution of WTP point estimates from discrete choice studies to calculate a mean RP ($\bar{x}$RP) with associated standard deviation ($\bar{\sigma}$RP) for different adopter groups. Negative initial RPs indicate attraction to new technologies (risk-seeking), and high positive initial RPs indicate aversion to new technologies (risk-aversion). Following Rogers (2003), the EAs[1] occupy a 16% market share; both the EM and LM account for 34% of the market; and the LG the final 16%.

[1] Our Early Adopter (EA) group contains the both the early adopters and innovators described by Rogers, E.M., 2003. Elements of diffusion. Diffus. Innovations 5, 1−38.

Pettifor et al. (2017) also use a metaanalysis of 21 empirical studies to measure the effect of social influence on vehicle purchase propensities. They find that for every one standard deviation increase in market share, RPs decrease by 0.241 standard deviations, which increases vehicle adoption propensities [95% CI (0.157, 0.322), $Z = 5.505$, $|P| < .000$]. In other words, RPs decline as market share grows, using market share as a proxy for social influence. In the vehicle choice model of IMAGE the RPs (in $/passenger km) for each consumer group have been added to the travel cost. More details on the empirical analysis and the implementation in IMAGE are provided in "Supplementary Materials" of the study by Edelenbosch et al. (2018).

Besides SL dynamics, this study focuses on TL of the battery costs and distinguish between exogenous and endogenous learning scenarios. Battery costs in electric vehicles (EVs) have declined rapidly over recent years (Nykvist and Nilsson, 2015); therefore the battery costs start from a cost estimate of 300 US$/kWh in 2014 (Nykvist and Nilsson, 2015). In the exogenous cost scenario, we assume that battery costs could reach 125 $/kWh by 2025 (Faguy, 2015) and decline further to 100 US$/kWh over the course of the century. In the endogenous cost scenario, we use a learning rate of 7.5% (uncertainty range from 6% to 9%) in line with estimates from the literature (Nykvist and Nilsson, 2015). We also assume a floor price of 50 $/kWh, affecting the purchase cost of plug-in electric vehicles (PHEVs), BEVs, and fuel cell vehicles (FCVs). More widely used components of cars such as the car frame or engine are not assumed to be influenced by learning after many years of experience and so follow the same path as in the exogenous scenario.

4.4.2.1 Model setup

Consumer heterogeneity, TL, SL, and policy measures, can all influence vehicle choice. Fig. 4.2 demonstrates schematically how these processes are related in the model setup within the IMAGE transport vehicle choice module, a global integrated assessment model used for this analysis (Girod et al., 2012). Increased market share affects SL and TL for different adopter groups: EA, EM, LM, and LG.

4.4.2.2 Scenario framework

We use a set of four scenarios to explore the effects of SL and TL, and how they dynamically interact. In the reference scenario (labeled "Ref"), technology costs decline exogenously over time, and RPs are frozen for the four adopter groups. In the TL scenario (labeled "TL"), RPs are also frozen, but technology cost reductions occur endogenously based on a learning curve. In the reference + SL scenario (labeled "Ref + SL"), SL is included but with exogenous technology cost assumptions. Finally, in the technological and SL scenario (labeled "TL + SL"), both TL and SL occur endogenously.

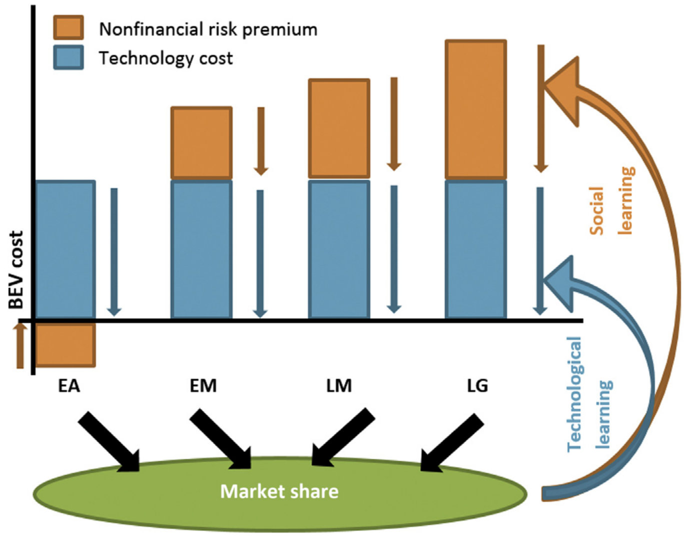

Figure 4.2
Schematic overview of the dynamic relationship between technological learning, social learning, and market deployment of new technologies. Four adopter groups are distinguished: EA, EM, LM, and LG. At a given time point, all four groups face the same technology cost but different monetized risk premiums. Net perceived costs therefore differ per group, with the lowest perceived cost vehicle selected by the cost-minimizing decision algorithm, resulting in changes to market share, which in turn stimulates further technological and social learning. *EAs*, Early adopters; *EM*, early majority; *LG*, laggards; *LM*, late majority. *Source: From Edelenbosch et al. (2018).*

4.4.3 Model results

4.4.3.1 Technological learning scenarios

Fig. 4.3 depicts market shares of the global vehicle fleet under endogenous and exogenous TL assumptions in the absence of SL. In the TL scenario the EA group shifts to PHEVs in the first half of the century given their preference for new technologies (represented by a negative RP that remains constant as there is no SL). Although EAs are also attracted to BEVs, this new technology remains too expensive through the first half of the century (Fig. 4.3 right panel). The deployment of PHEVs leads to reduction of both PHEV and BEV costs through TL in battery costs (Fig. 4.3 left panel). In the Ref (reference) scenario, BEV costs are projected to reduce rapidly in this period as well, based on exogenous assumptions. Once a certain BEV cost threshold has been passed, depending heavily on the learning rate (indicated by the TL range), EAs shift from PHEVs to BEVs. This shift leads to faster BEV cost reductions (Fig. 4.3 left panel). Under high learning rate assumptions, the EM group also adopts BEVs by the end of the century, by which point a small group of EAs move on to FCVs that have become more cost competitive.

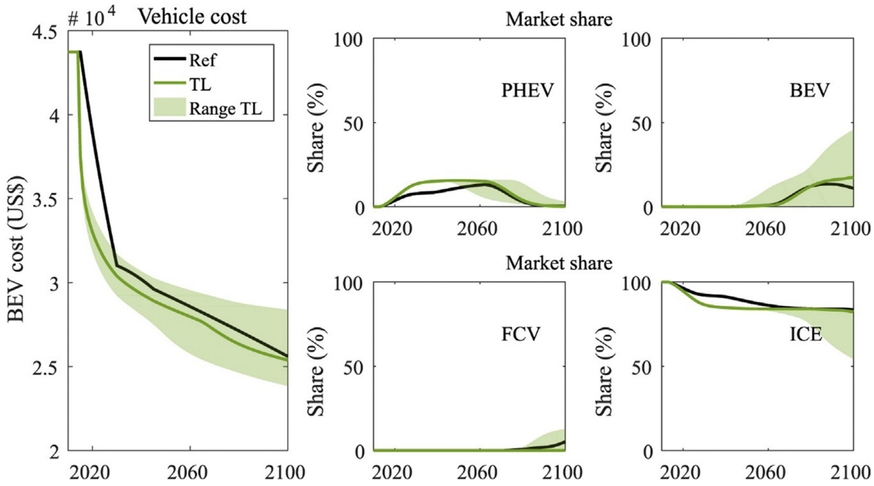

Figure 4.3

BEV cost over time in the Ref and TL scenarios (left panel), with resulting BEV, PHEV, FCV, and ICE market shares of the global vehicle fleet (middle and right panels). Shaded colors indicate the scenario range depending on assumed TL rates. *BEV*, Battery electric vehicle; *FCV*, fuel cell vehicle; *ICE*, internal combustion engine; *PHEV*, plug-in electric vehicle; *TL*, technological learning. *Source: From Edelenbosch et al. (2018).*

The EA group and TL play an important role in this initial phase of a technology transition. With slower learning rates, BEVs remain relatively expensive, and EV adoption might not take place at all. Even though the technology is competitive in terms of costs, if RPs remain at current levels purchasing a BEV is not an attractive option for the EM, LM, and LG.

4.4.3.2 Social learning and technological learning scenarios

In the SL scenarios the market deployment of BEVs drives down the RPs of the EM, LM, and LG, whereas for EAs the reduced novelty of BEVs makes them less attractive as RPs become less negative. Fig. 4.4 shows how the BEV RPs change over time for all four adopter groups in the Ref + SL and TL + SL scenarios.

The effect of SL can be seen in the diffusion of BEVs from EAs to the EM (Fig. 4.4 top right panel, compared to the reference scenario). The risk decline leads to higher BEV deployment that again leads to more risk decline (SL). As BEVs become mainstream, EAs become more attracted to distinctive alternatives, such as FCVs (seen previously in Fig. 4.3). Similarly, PHEVs become less attractive to EAs, which leads to an increase in the BEV share in the first half of the century compared to those scenarios where social influence is not represented. The Ref + SL scenario range shows that social influence effect size has little impact on the initial phase of the transition but significantly affects the speed of diffusion from EAs to other groups.

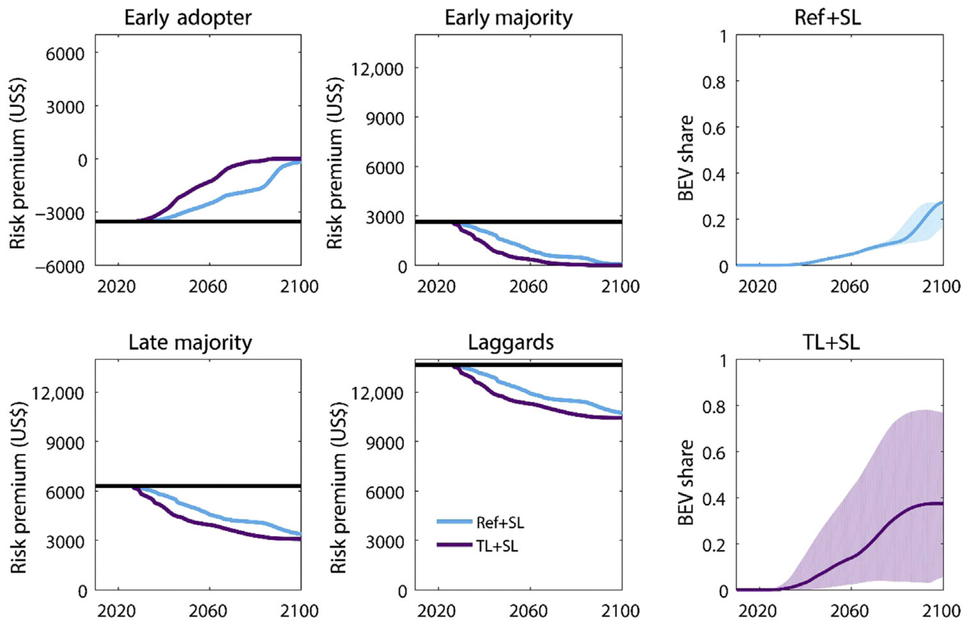

Figure 4.4
Risk premiums toward BEVs in scenarios with SL for the early adopter, early majority, late majority, and laggards (*left* and *middle panels*), and resulting market shares of the global vehicle fleet for BEVs (*right panels*). Shaded colors indicate the scenario range depending on technology learning rates and social influence effect size (*right panel*). *BEV*, Battery electric vehicle; *SL*, social learning. *Source: Figure adapted from Edelenbosch et al. (2018).*

The lower right panel of Fig. 4.4 shows how the combined effect of technological and SL leads to a faster technology transition and higher market penetration under assumptions of average learning rates and social influence effects. There are different phases during the technology transition in this scenario. First PHEV use by EAs leads to battery learning reducing BEV costs. The EAs then shift to BEVs, which results in increased TL and risk decline for the other adopter groups. The EM starts to adopt BEVs enlarging both types of learning effect. TL has occurred faster in the beginning and now starts to level off. RPs continue to decrease for the LM and LG. But additional policy is still needed to overcome the RP barrier for these groups. Clearly, these results are highly dependent on the social influence effect size and the learning rate, indicated by the colored area.

The importance of SL and TL during the different phases of the technology transition—with TL affecting the initial phase, and SL affecting further diffusion—can be traced back to their equational forms. The social influence effect equals the reduction in RP after an increase in market share, whereas the TL rate equals the cost reduction per doubling of cumulative battery production in EV application. Given the exponential form of the learning rate equation with its floor price to limit ever falling costs, the fastest learning happens in the initial deployment phase. In contrast, social influence has a linear relationship with deployment.[2]

While both processes impact vehicle choice in expected ways, their interaction is interesting and revealing. This new modeling approach demonstrates the different phases of a technology transition and its relevant dynamics. It shows how niche or EA groups can drive technology innovation by stimulating market demand.

BEVs can reach a larger market share if TL and SL processes work to mutually reinforce each other. Through SL and TL, new technologies can become more attractive to consumers. Generally speaking, TL affects the timing of adoption by EAs, whereas SL affects diffusion to other adopter groups. The two learning processes can stimulate each other in a positive feedback loop. Policy incentives stimulating EV deployment, such as a carbon tax, information campaigns, or dedicated transport sector policies, can spark positive learning feedbacks. However, the size of this effect depends strongly on the assumed TL rate and social influence effect size, which are key future uncertainties.

4.5 Conclusion

As we have shown earlier, the concept of the experience curve has many applications beyond its original aim to describe cost or price reductions of technologies in the global economy. Experience curves can be used to describe the effects of technological progress on the development of energy use of (industrial) production processes, energy demand of appliances, and environmental impact of technologies. Therefore experience curves have the potential to make valuable additions to for instance energy system modeling activities, broadening their application from "only" technology costs to a set of other metrics. Since only a limited number of studies have investigated these types of applications, further research should analyze whether they are as generally applicable as the original cost-based experience curves are regarded to be.

The second part of the chapter highlights the value of considering learning in other than technical domains. By taking into account SL processes, the modeling of behavior of consumers toward new technologies can be improved, allowing for a more realistic representation of this behavior in energy and integrated assessment models. Furthermore, it was discussed that while TL improves the competitiveness of new technologies, SL can increase the consumer acceptance of these technologies; hence, the market diffusion of such technologies benefits from both learning mechanisms, and both learning mechanisms can interact in a feedback loop.

[2] This linear relation has varying slope coefficients in specific periods of adoption due to the varying size of a market share corresponding to a standard deviation.

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