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Summary

This paper explores the opportunities for integrating Initiative Based Learning (IBL) and Integrated Assessment Models (IAMs) in order to improve our understanding of learning in the context of societal transition pathways, and more specifically by focusing on solar PV as an energy transition technology. Our analysis shows that IAMs and IBL conceptualize learning in a very different way, and the two approaches have major structural differences with respect to the geographical as well as the temporal scale of analysis. This is also due to the different goals of the two methodologies. The aim of IAM is to develop long-term energy and technology scenarios for the next thirty to eighty years, and to describe learning processes mostly to account for future potential improvements in technologies, while IBL focuses on understanding the configuration of actors in specific institutional settings that legitimize and support specific technologies and ultimately lead to dynamics of social learning. Although ambitious forms of integration between IAMs and IBL are not feasible today, the two approaches can be used in parallel and lead to mutual enrichment via a process that we label a two-way recursive collaboration.

Keywords: Social Learning, Innovation Diffusion, Technology Adoption, Integrated Assessment, Case Study, Transition Research, Initiative-based Learning, Solar PV Learning Curves

JEL Classification: O31, O33, O35, Q42

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Knowledge Creation between Integrated Assessment Models and Initiative-Based Learning - An Interdisciplinary Approach

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Abstract

This paper explores the opportunities for integrating Initiative Based Learning (IBL) and Integrated Assessment Models (IAMs) in order to improve our understanding of learning in the context of societal transition pathways, and more specifically by focusing on solar PV as an energy transition technology. Our analysis shows that IAMs and IBL conceptualize learning in a very different way, and the two approaches have major structural differences with respect to the geographical as well as the temporal scale of analysis. This is also due to the different goals of the two methodologies. The aim of IAM is to develop long-term energy and technology scenarios for the next thirty to eighty years, and to describe learning processes mostly to account for future potential improvements in technologies, while IBL focuses on understanding the configuration of actors in specific institutional settings that legitimize and support specific technologies and ultimately lead to dynamics of social learning. Although ambitious forms of integration between IAMs and IBL are not feasible today, the two approaches can be used in parallel and lead to mutual enrichment via a process that we label a two-way recursive collaboration.

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1 Introduction

Addressing the global environmental and sustainability transitions poses analytical challenges that require integration across disciplines. Alternative integration strategies exist, ranging from more ambitious efforts to integrate insights from one discipline into another, to more modest forms of integration where multiple approaches are used in parallel, engage with each other, and enrich each other (Turnheim et al. 2015). An important dimension related to societal transition pathways is the process of learning entailed by the use of new technologies and innovations (Geels 2010, Geels et al. 2015, and Turnheim et al. 2015). Yet, different conceptualizations of learning across disciplines might delay insights that could arise from cross-disciplines fertilization. Clarifying these differences can facilitate the development of integrative approaches to sustainability.

Quantitative system modelling, such as Integrated Assessment Models (IAMs), and case study research on Initiative Based Learning (IBL) are two approaches used to analyze sustainability transition pathways. Traditionally, they have been utilized by separate communities, but recent research has begun to build bridges across very diverse methodologies[1]. Integrated Assessment Models inform us about the technological requirements to achieve future goals by providing a forward-looking perspective of transitions. They can project the changes over time required to achieve predefined goals under specific sets of economic and technological scenarios, but they do not outline the conditions that enable the governance and actor dynamics which would support certain pathways.

Case study research on Initiative Based Learning focuses on entangled social dynamics in local transition inititiatives, but pays less attention to the broader and long-term perspectives on transition dynamics. IBL is a qualitative approach that uses case study analysis to examine the mechanisms and dynamics in concrete projects and local initiatives involving a wide range of societal actors, such as citizens, businesses, civil society organizations and (local) government. It reveals the emerging properties in processes of system change ignored by approaches such as IAMs, and informs us of the configuration of actors and motives that lead to successful solutions that favor innovation (Turnheim et al. 2015).

Both, IAM and IBL researchers address different learning mechanisms or drivers, which contribute to improving and spreading technology. They make a broad distinction between learning mechanisms involving the interaction among agents and actors – which we refer to as social learning – and learning mechanisms related to the process of production and use of specific technologies – which we refer to as technical learning.

IAMs focus on replicating historical statistics on energy and mostly rely on learning curves to project future technology costs based on historically observed trends. They focus on technical learning, a reduced form of learning driven by technical drivers, such as cumulative capacity installed (Learning-By-Doing) and R&D expenditure (Learning-By-Research). IBL provides interesting insights into forms of learning that remain unobservable in IAM approaches. In the IBL approach, learning focuses on social learning, defined above as the processes and interaction among actors that determine the success or failure of a given initiative, and it includes technical, organizational, and cultural aspects.

IAMs and IBL conceptualize learning in a different but complementary way, indicating that more insights can be gained by combining different approaches. Indeed, each method provides only a partial understanding, and a more comprehensive assessment can be achieved by developing a joint analysis.

In this paper we explore the opportunities that exist for integrating IBL and IAMs as related to understanding learning in the context of transition towards cleaner energy technologies. We investigate whether the combination of these two methodologies can offer better insights into the role of learning in transition dynamics. Specifically, we examine the differences between IBL and IAM with respect to learning, and the extent to which they can complement each other in characterizing learning dynamics in energy transitions. We focus on solar photovoltaic (PV) technology both in IBL case studies and in IA modelling, since this technology will play a crucial role in future decarbonization pathways. Moreover, a wide empirical literature

[1] PATHWAYS project – http://www.pathways-project.eu/

has been dedicated to the historical development of PV technology, so that at present it is rather well understood.

The remainder of this paper is organized as follows. In Section 2 we begin our analysis by describing the frameworks used by IAMs and IBL to conceptualize learning. As an empirical context, studies on solar PV technologies are used. In Section 3 we review the empirical evidence in both fields of research. In Section 4 we investigate whether the evidence emerging from the case studies can inform IA modelling and whether the framework used in IAMs can open new perspectives in analyzing case studies by IBL. Section 5 concludes with some remarks on the opportunities for integrating IBL and IAMs.

2 Learning: conceptual frameworks

Different disciplines have formulated stylized representations of the learning process in relation to technological innovation and diffusion. Despite these different conceptualizations, S-shaped curves tend to appear in different fields of research. The diffusion of many innovations generally resembles an S-shaped or sigmoidal adoption distribution path, depending on the innovation (Roger, 2003). The literature on innovation research has introduced the "epidemic" diffusion model (Rogers, 2003, Geroski 2000, and Stoneman 2010), in which innovation spreads quite autonomously from a certain point in time, for example in an endogenous way through word of mouth. In "epidemic" diffusion models, the number of adopters increases over time as non-adopters get into contact with adopters. The process of technology diffusion relies very much on the model of the spread of diseases. In epidemic models, diffusion relies on the spread of information among potential adopters. Alternatively, "probit models" (Geroski 2000) consider adoption rather an individual choice (for example, adoption by firms), thus depending more on external, exogenous driving factors such as the relative price of competing innovations, or the technological improvements of the innovations and developments in competing or complementary technologies, respectively. For instance, if the price or the investment cost of the innovation falls over time, the adoption threshold lowers and more adopters appear, leading to a diffusion path.

Although often criticized because of its theoretically weak analogy of biological evolution and socio-technological change, Rogers's diffusion of innovation is still a staple in diffusion research (Sarkar 1998). Rogers demonstrates that S-shaped adopter distributions closely approach a normal distribution. By making use of the mean and the standard deviation as the defining parameters of a normal distribution, he suggests differentiating between five categories, which vary generally from innovators to the early majority on the left side of the adoption mean time, and then from the late majority to laggards on the right side (see Fig. 1a). The categorization is asymmetrical. There are three categories left of the mean, but only two categories right of the mean. Rogers (2003) explains that "innovators" and "early adopters" are not combined because of the very different characteristics of each. Innovators are more adventurous and open to taking risks, in contrast to early adopters, who are rather role models which the majority follow and whose approval they seek. Unfolding the distribution into a diffusion path over time reveals the S-shaped diffusion of innovation, assuming complete adoption (100 Percent of Adoption) (see Fig. 1b).

All models of epidemic, S-shaped diffusion curves suggest an exclusively positive learning experience, in a monotonic fashion. The adoption rate of innovation "accumulates" over time, sometimes faster at the beginning, sometimes slower at the end. People adopt an innovation sooner or later or never – but do not abandon it. On the contrary, Fenn and Raskino (2008) and Beers et al. (2014) stress the idea of a "learning cycle" in innovation research. Fenn and Raskino (2008) suggest a cycle to represent the adoption and social application of specific technologies as well as business strategies. The hype cycle introduced by Gartner Inc. in 1995 combines a more emotionally and irrationally-driven hype level curve with a technology S-curve adoption curve, resulting in a bell-shaped curve (see Figure 2). While the hype cycle received great attention in business consultancy, it still lacks academic recognition. According to Dedehayir and Steinert (2016), only eleven papers in the top twelve technology and innovation management (TIM) journals have dealt with the hype cycle in sufficient depth in order to test its validity. They conclude that hyped dynamics should be captured by existing life cycle models on the order of Rogers’s (2003).

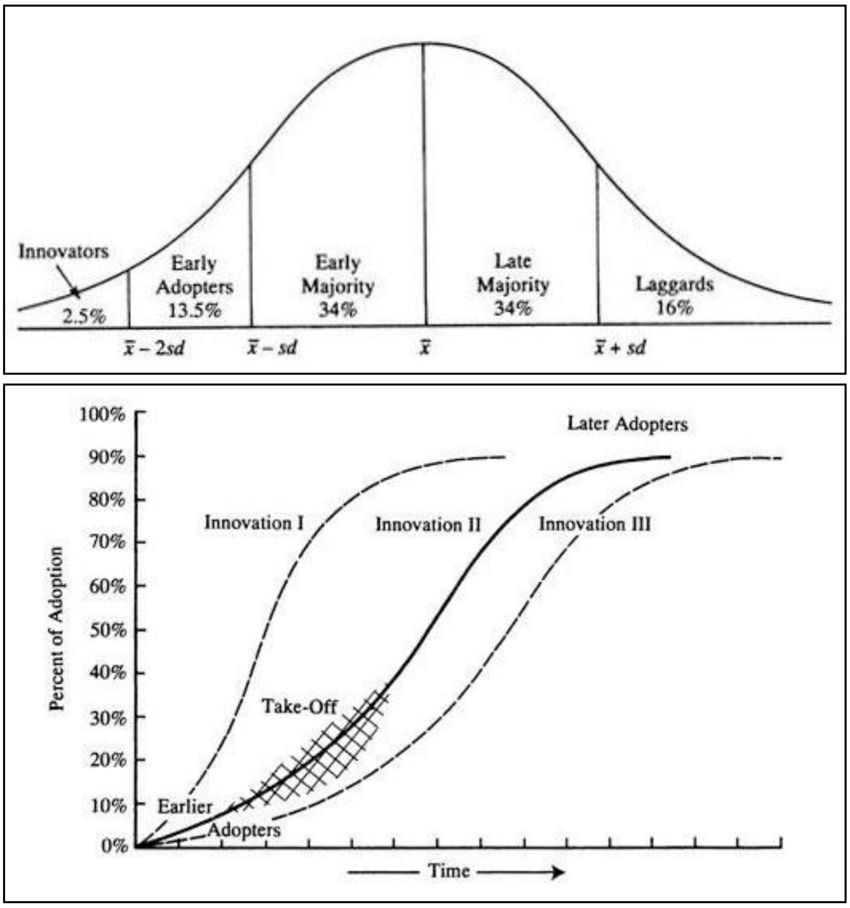

Figure 1: Rogers’s adopter categorization (a - above) and diffusion process (b - below).
Source: Rogers (2003), pp. 34 and 306.

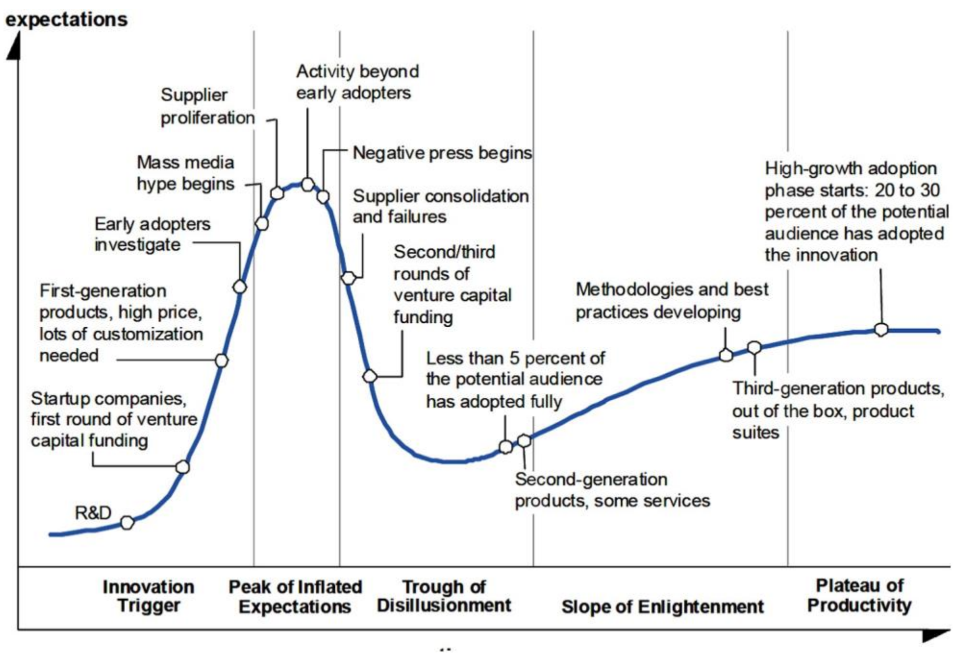

Figure 2: The Hyple Cycle and its Stage Indicators.
Source: Dedehayir and Steinert (2016, p. 30) based on Fenn and Raskino (2008).

Theoretically, the hype cycle highlights and accentuates an understanding in cycles that may be helpful for a better understanding of case studies in transition research: a technology triggers publicity until inflated expectations peak, following an S-shaped learning curve (see Figure 2 for stage indicators). However, in a "trough of disillusionment", also described as a "valley of death" in related theories, and related to the idea of a creative destruction by Schumpeter (1939), implementation fails and interest wanes. People seem to adopt new ideas and abandon them after some time, and this gives rise to a cyclical pattern. If technology providers survive and improve their products to the satisfaction of early adopters, second and third product generations may appear where the technology is improved and more widely adopted. More funding opportunities emerge, the mainstream also adopts the innovation, and the diffusion takes off to broad level of market applicability, reaching a plateau of productivity again in a new S-shaped curve of learning, to resemble more an asymmetrical, slower Gompertz growth function.

Schilling and Esmundo (2009) suggest that S-shaped curves can also be observed if instead of examining adoption over time we analyze performance improvements in a given technology over the effort allocated to that specific technology. S-shaped curves have been empirically observed for a large number of energy technologies. When performance is plotted against the amount of effort measured as cumulative R&D expenditure, several technologies show a slow improvement at the beginning, followed by accelerated and diminished improvement, as characterized in Rogers's diffusion model (Figure 1). Generally, the initial phase of technology diffusion is associated with the innovation phase, during which greater effort might be made, especially in terms of R&D. Experience curves used in Integrated Assessment Models, which generally measure effort in terms of cumulative installed capacity, tend to capture the second phase of the diffusion process, after take-off, where the logarithmic shape prevails.

Different learning mechanisms or drivers contribute to improving and spreading technology during the different stages of the innovation and diffusion phase (Kahouli-Brahmi 2008). Some learning mechanisms highlight the social learning processes as depicted above: *Learning-By-Using* (Rosenberg 1982, Lee, 2012) refers to the positive feedback that can be transmitted by user experience to the producer, who can then build on consumer reaction to improve his product. *Learning-By-Interacting* (Lundvall, 1988, Habermeier 1990, Lee, 2012) refers to the interaction among various actors, such as laboratories, industries, end-users, political decision-makers, etc., which can enhance diffusion and ultimately facilitate cost reduction. In this context, network relationships play a crucial role. The *Learning-By-Doing* (LBD) mechanism describes the improvement in the production process associated with experience, or the repetition of tasks, which can also involve changes in labour efficiency and administrative structure (Wright, 1936 in the aircraft industry, Arrow 1962 in the context of growth models). The Learning-By-Doing mechanism itself can be broken down further into different kinds of improvement, such as learning-by-manufacturing (e.g. in the process of manufacturing PV modules), learning-by-copying (e.g. by imitating competitors such as in PV cell development), learning-by-operating (e.g. the tacit skills gained by workers), and learning-by-implementing (e.g. learning about integrating PV modules into an efficient, well-functioning unit: see Sagar and van der Zwaan 2006 for a review). *Learning-By-Researching* (LBR) describes the learning effects stemming from R&D and the innovation processes (Cohen and Levinthal 1989). Other studies (see Baker et al. 2013 for a review) highlight the role of other factors, such as economies of scale, knowledge spillovers, organizational forgetting, and employee turnover (Argote and Epple 1990). *Economies of scale* are associated with a decline in average production cost in large-scale production activities characterized by high initial costs. Nemet (2006) finds that plant size accounted for 43% of the cost reduction in solar cells. Economies of scales are different from Learning-By-Doing effects because the former is driven by demand whereas the latter by cumulative capacity installed. Economies of scale are linked to the production process of typically capital-intensive industries, such as those in the energy sector. *Knowledge or experience spillovers* can occur across sectors, technologies, regions and countries, reinforcing the cost reduction stemming from the other forms of learning (Kahouli-Brahmi 2008). An example of cross-sectoral spillovers is the cost reduction in solar cells driven by events in the semiconductor market (e.g. decline in silicon costs, Nemet 2006). There is also a broader societal and institutional transformation necessary for supporting the spread of a new

technology, including systemic improvements and broader reductions in the cost of energy services (Sagar and van der Zwaan 2006).
The above-mentioned learning mechanisms can be broadly grouped into drivers involving the interaction among actors – which we refer to as social learning mechanisms – and drivers related to the process of production and technology deployment – which we refer to as technology drivers or technical learning (Table 1).

Social learning	**Technical learning**
Learning-By-Using (interaction between producer and end-users)	Learning-By-Doing - LBD (cumulative production or cumulative capacity installed)
Learning-By-Interacting (interaction between laboratories, industries, end-users, political decision-makers)	Learning-By-Researching - LBR (R&D expenditure, knowledge stock)
Spillovers (interaction between sectors, countries, producers)	Economies of scales (Production)

Table 1: Learning mechanisms. A summary.

The remainder of this paper focuses on the two specific forms of learning that have become prominent in the two analytical approaches examined, namely social learning in IBL and technical learning in IAMs. Section 2.1 presents the conceptual framework used by IBL, whereas Section 2.2 briefly summarizes the conceptual framework used in IAMs. The objective is to illustrate common and/or contrasting concepts in order to first establish a commoorganizn ground.

2.1 Social learning in Initiative Based Learning (IBL)

Initiative-Based Learning (IBL) focuses "*on agency and interactions at the level of individual initiatives and projects. Legitimation of novelty and public participation are seen as crucial for radically novel socio-technical configurations. These initiatives may be viewed as microcosms of future reconfigured systems. [...] Learning from initiatives on the ground is hence critical to the governance of transitions in the making, particularly effective forms of shaping and fostering transition efforts from the ground up"* (Turnheim et al. 2015, p. 244).
Assuming that IBL consists of "*microcosms of future reconfigured* systems", we focus on the first level of social learning that takes place between actors, and will not deal with structural changes that guide learning on a larger scale.
IBL literature in transition research defines and addresses social learning in numerous different ways and from various perspectives. In this paper we focus on social learning as "*learning that occurs when people engage with one another, sharing diverse perspectives and experiences to develop a common framework of understanding and basis for joint action*" (Schusler et al., 2003). The literature consistently describes individuals interacting in social groups, forming a "community" that mediates individual interests that face a changing institutional and organizational setting in favour of a shared interest. Social learning is *"a learning process in which actors meet, discuss, and start to develop a shared meaning"* (Nykvist, 2014; also Wenger, 2009). It is "*an aspect of the adaptive management approach"* (Albert et al. 2012), in which skills are needed to adapt to changing planning and implementation strategies on the basis of emerging knowledge. Axelsson et al. (2013) see stakeholders learning "*how to steer the development towards sustainability"* within a multi-level setting in social-ecological systems or landscapes. In addition to Albert et al. (2012), Axelsson et al. (2013) take note of issues such as trust and norms, which refer to an institutional setting rather than the learning capacities of individuals and groups. Though IBL puts social learning into perspective "*from the ground*", it is acknowledged that social learning takes place in an institutional rather than an individual or single organizational setting, thus emphasising the multi-level notion of learning. We

understand research on IBL to be an integral part of multi-level transition analysis (see Turnheim et al. 2015, and Liedtke et al. 2015 for IBL as real experiments or Living Labs in transition research).

Sol et al. (2013) have observed that learning is a "dynamic process," in which knowledge is created in an ongoing fashion. The term "dynamic" incorporates the possibility that changing internal interaction between actors may affect the quality and effectiveness of learning. In addition to internal dynamics, external dynamics such as trends, hierarchy or money also play a crucial role and influence internal learning dynamics between actors. Internally and externally driven dynamics may cause learning patterns which face struggles that hinder, stop or even destroy learning efforts.

On the one hand, social learning can be understood as part of our daily lives, occurring through social interactions and processes within a closer social network. On the other hand, social learning can become deeper learning in the sense of transformative learning, i.e. in the form of double-and triple loop learning. Learning in loops has the capacity to transform the frame of reference, call into question guiding assumptions (Nykvist, 2014), and, if successful, effectively neutralize commonplace notions. Whereas single-loop learning refers to the simple adaptation of new knowledge, double-loop (or deutero-) learning hence considers the ability to learn itself (Albert et al., 2012). In this respect Kemp et al. (1998) evaluate learning processes as most effective when they contribute not only to everyday knowledge but also to "second-order learning" where people question the assumptions and constraints of regime systems. Second-order learning emerges when basic assumptions and values are challenged and become the very subject of learning. More recently, van Mierlo (2012) takes up Kemp's and colleagues' different orders of learning where first-order learning includes gaining experience about how to do things better within the framework of pre-existing goals and assumptions. In this view, first-order learning alone would not contribute to regime change, while second order learning is assumed to be essential for regime change (van Mierlo 2012).

Moreover, van Mierlo (2012) further differentiates between the concept of convergent and divergent learning. Convergent learning occurs when "*diverse actors develop visions on solutions and problems that complement one another, and change their roles and goals in close association with each other*" (p.5). It highlights the "*complementarity among the fundamentally different assumptions and values of the various project participants. They do not necessarily come to share a completely common view during the learning process; it suffices if their perspectives overlap partially or are mutually supportive*" (p.7). Convergent learning takes place when visions and actions align as a result of experiences in the pilot project. Challenging a regime may require this type of learning. In contrast, divergent learning occurs in the individual participants' thinking, such that it is purely actor bound. Individual learning experiences may deviate and contradict each other, though divergence can nonetheless be seen as a learning process (van Mierlo, 2012).

2.2 Technical learning and experience curves in Integrated Assessment Models (IAMs)

Technical learning in quantitiative system models has been conceptualized mostly through experience curves, which, by focusing on *Learning-by-Doing* (LBD) and *Learning-by-Researching* (LBR), are used by IAMs and energy system models to describe the observed reduction of technology costs occurring with the increased experience documented for several energy technologies. In contrast to the literature that has examined social learning, which is much more oriented toward understanding the underlying processes and the role of governance and institutional factors, the approaches using experience curves focus on the drivers that are 1) easy to quantify (e.g. LBD and LBR) and 2) simple to represent in the models by reduced-form equations to project future technology costs.

The purpose of learning curves in models is not to explain the complexity of the underlying processes (e.g. what are the drivers), as in IBL, but rather to project long-term technology costs by considering historically observed patterns (Wiesenthal et a. 2012). The simplicity of reduced-form approaches offers tractability within the context of complex IAMs. Simplicity, however, comes at the cost of not addressing what the "actual" drivers are that explain the observed reduction in future technology costs, and thus potentially omitting some important variables (Nemet, 2006; Nordhaus, 2009).

The Learning-By-Doing hypothesis describes the improvement in a technology performance occurring with the growing effort dedicated to that technology. Performance is generally measured by using indicators such as the reciprocal of capital costs or unitary investment costs. Effort is generally measured in terms of cumulative installed capacity. Specifically, a power function is used to describe a negative relationship between the cumulative capacity $K_{t,i}$, installed at time *t* in country *i*, and installation capital costs, $CC_{t,i}$, where $K_{0,i}$ and $CC_{0,i}$ respectively represent the cumulative installed capacity and the installation capital cost at the beginning of the period:

$$CC_{t,i} = CC_{0,i} \left(\frac{K_{t,i}}{K_{0,i}}\right)^{-b} \qquad \text{Eq. [1]}$$

The parameter *b* measures the strength of the learning effect. It relates to the learning rate, *LR*, which measures the rate at which unit costs decrease for each doubling of the cumulative capacity, through the following relationship, $LR = 1 - 2^{-b}$. For instance, a 20% learning rate corresponds to a 20% cost reduction for each doubling in the cumulative installed capacity compared to the initial level. Some models include a floor cost (FC) to set a minimum price below which investment costs cannot fall:

$$CC_{t,i} = max\left\{FC, CC_{0,i} \left(\frac{K_{t,i}}{K_{0,i}}\right)^{-b}\right\} \qquad \text{Eq. [2]}$$

Learning-By-Researching describes the improvement in technology performance occurring with an increased effort dedicated to R&D, measured in terms of either R&D expenditure or R&D knowledge stock. The models representing both LBD and LBR adopt two-factor learning curves, which separate the effect of experience from that of R&D:

$$CC_{t,i} = CC_0 \left(\frac{K_{t,i}}{K_{0,i}}\right)^{-b} \left(\frac{R\&D_{t,i}}{R\&D_{0,i}}\right)^{-c} \qquad \text{Eq. [3]}$$

The power function form is the one most commonly used because it is generally a good fit for the data (Baker et al. 2013). When plotting an indicator of performance, such as the reciprocal of unitary investment costs, versus cumulative capacity installed as an indicator of effort, this functional form results in a logarithmic relationship, which can be seen as the second part of an S-shaped curve after technology take-off (see Figure 1). This is a good approximation when the focus is on Learning-By-Doing. In the case of Learning-By-Researching, where R&D investments are used as an indicator of effort, an S-shaped relationship seems to be a better fit for the data (Schilling and Esmundo 2009). Several models (e.g. WITCH, Bosetti et al. 2016 and Emmerling et al. 2016 IMAGE, Stehfest et al. 2014) do account for knowledge and experience spillovers, and assume that the cumulative capacity installed in any world region reduces technology costs everywhere. In regard to knowledge spillovers, models (e.g. WITCH) often assume only a limited degree of international spillovers.

Models generally rely on history-based empirical evidence for calibrating the learning rate parameters. Understanding how the observed trends can be used in models for future scenarios is important because assumptions about the functional form, the learning rates, and the floor cost crucially affect the results of models and influence the future energy mix, as discussed in Section 4.

3 Empirical evidence on Learning from Initiative Based Learning cases and Integrated Assessment Modelling

Theoretical approaches from different disciplines seem to converge on a vision of the learning process associated with technology diffusion as having a sigmoidal, S-shaped form, or as a sequence of S-shaped alternating processes. This section summarizes the empirical evidence on learning that emerges from the case studies examined by the IBL approach and from Integrated Assessment Models.

3.1 Social learning – Evidence from case studies

In searching for "social learning", "sustainability transition" as well as "sustainability learning", "grassroots initiative learning" and "sustainable niches" in Google Scholar, we identified 208 studies addressing social learning. The whole study sample consisted of case studies as well as studies providing more conceptual and theoretical insights. In a subsequent step, we selected a sub-sample of studies that: 1) deal with social learning, 2) address one of the domains at stake in the underlying research project - mobility, energy (consisting of electricity and heating), or agri-food/land use, 3) focus on either the UK, Germany, Sweden or the Netherlands[2]. This process led to a final set of 17 IBL cases that systematically review the role of main actors involved and mechanics and dynamics of the learning process (e.g. how they learn and in what forms and dynamics, what drivers and barriers they encounter throughout their learning process.)

Convergent learning is typically prevalent throughout the studies analyzed: a common idea/vision of the project seems to be central to social learning processes. Some studies stress the importance of the multi-actor framework and stakeholder involvement in learning processes. In all cases, multi-actors and stakeholders engage in a collaborative learning process. In this respect, hierarchical internal social networks as well as external hierarchies determined by power, money and time affect the individual's behaviour and the social learning progress as a whole. Social learning involves the management of differing interests, understanding and skills in order to anticipate and adapt to possible actions and consequences resulting from internal and external hierarchies. The cases commonly stress that learning is highly affected by trust among the members within the learning network. As such, the social capital accumulated by the members of the network very much predicts the learning outcome. Equally important are more tangible characteristics of the members of the social network, such as expertise and skills that members can contribute in order to solve the issues at stake, and leaders can provide in order to organize the learning process and foster learning ties among members. In addition, a beneficial management of learning depends on a leadership of change-oriented agents with convincing visions and the capacity to come up with and communicate innovative solutions. A successful learning management needs to spread of consciousness-raising information and requires the involvement of group members in order to motivate them to participate in the learning processes. In this regard, small learning networks are more likely to show social cohesion and group affinity in personal contacts, which seems beneficial for social learning. Although small in size, a heterogeneous composition of the learning network, including actors across sectors and levels, seems to be helpful for social learning. In a nutshell, social learning in heterogeneous groups depends on the power structure of the network and trust-relationships.

In order to foster inter-group learning between small but effective learning networks, personal contacts need to be forged across the network's boundaries. It follows that in turn, a beneficial internal and external communication within and between social networks depends on the communication skills of the learning leaders. Typically, the key dimensions and variables that determine social learning in IBL studies interrelate with each other. The management of trust, social capital, expertise and skills among the members of the learning network depends on the size and composition of the network, and vice versa. The most frequent networks are heterogeneous ones, characterized by intimacy, smallness and social cohesion, managed by skilled leadership and consolidated by social capital.

[2] The research was conducted within the PATHWAYS project, which focuses on those selected European countries.

Case studies also inform us of how social learning proceeds. Some of the cases deal with forms and levels of learning occurring in initiatives and projects. We find that social learning takes time and is a dynamic process in which past learning experiences shape future learning processes (intertemporal dynamics). Within these dynamic forms, learning faces drawbacks, setbacks, radical processes and peaks, and may end on learning plateaus and thus show diverse, non-linear forms of learning. Also, destructive learning and conflicts are described in some cases, as discussed in Section 4. External and contextual factors, such as changes in financial schemes or legislation, may trigger a learning crisis and thus intervene in social learning processes.

The importance of the local context (i.e. actors and networks from varying cultural, institutional, geographical and even climatic conditions) clearly emerges in the cases analysed, which show that a great diversity in nature and initiatives within the same domain or pursuing the same or similar goals can yield different learning results because of the different contexts (involving also different potentially unexpected events or external factors of influence) in which they are carried out. Indeed, projects might be understood as local reinterpretations and reinventions of a more generic, mobile concept of an emerging niche trajectory (Raven et al., 2008). The results of a learning processes depend on the kind of knowledge involved and on the way in which social relations and communication are carried out, which, in turn, depends on the kinds of social relations and knowledge people have (Lahtinen, 2013).

It is possible to translate a generic concept into a local project, as well as transfer local lessons into general rules, but these processes are difficult and require careful analysis (Raven et al., 2008)[3]. Indeed, as the practical experiences are so variable and diverse, it might be very difficult to draw general conclusions beyond a certain level of abstraction. According to Axelsson et al. (2013), *"a key challenge in social learning for sustainable landscapes is to move from local experiences and results to local tacit knowledge, and from tacit to explicit knowledge"* (p. 242). Niche innovation occurs in relation to a particular local context; consequently, socio-technical innovation and the particular context within which it takes place mutually shape each other (Hodson and Marvin, 2007; Raven et al., 2008). Raven et al. (2008) found e.g. that the sensitivity to local context and the local nature of the project were key factors determining the success of the project. Local communication and participation are particularly significant, and *"ready-made solutions cannot be dropped into a context without local negotiations"* (Raven et al., 2008, p. 16).

The analysis of the IBL cases points to a number of characteristics with respect to four main dimensions of social learning, summarized in Table 2, namely management, size and composition of networks, length and timing of learning, and local context. The management of learning depends on trust, social capital, expertise and skills among members of the network and its leaders. The size and composition of successful learning networks is typically small, heterogeneous, but socially cohesive and characterized by personal contacts. Typically, the length of learning extends only through the duration of the initiative or project (short time scale). This means that social learning takes place throughout the whole project time (within the project), but not between projects (e.g. follow-up projects on a medium to long-term time scale). Learning between projects is typically not observed. The timing of learning is dynamic and non-linear. Social learning typically passes through different phases and speeds of learning. Apart from typical variables and identified key dimensions of social learning, the cases emphasize the role of the local context. Depending on the context of the initiative, network members bring in and formulate a consensus on respective tacit knowledge. The cases are embedded in specific regional or national institutional contexts (politics and policies). Thus, external factors may cause intra-project crises and conflicts, depending on changing contextual circumstances.

[3] For further reading on generalising case study research, we refer to Flyvberg (2006) and Yin (2013).

Management of Learning	Size and composition of network	Length and timing of learning	Local context
Trust Social Capital Leadership Expertise Skills	Small Heterogeneous Personal Socially cohesive	Extensive (within project, short-term) Dynamic Non-linear (drawbacks, setbacks, conflicts radical, peaks, plateaus)	Tacit knowledge Local reinterpretation Institutional embedment External factors (crisis)

Table 2: Summary of key dimensions of social learning in Initiative Based Learning (IBL).

Of the 17 IBL case studies, van Mierlo (2012) focuses on photovoltaic energy projects in the Netherlands. She analyzed multiple stakeholders (companies, Dutch government and private households) in four different photovoltaic energy pilot projects in the Netherlands, and identified very diverse learning experiences. Compared to the other 16 cases, van Mierlo's (2012) case combines the diversity of learning experiences by using the example of solar PV.

The observed diversity stems from different levels of ambition of the projects, different negotiating processes, and different kinds of network management of different heterogeneous networks. Both convergent and divergent learning were observed in the case studies. Van Mierlo´s (2012) inquiries on four cases on PV are the most elaborate and extensive ones found in the literature. However, her results are still inconclusive. The author found convergent learning in three cases, whereas in one other no shared vision was observed. At the same time, divergent learning revealed non-contradictory learning experiences in one case to several contradictory learning experiences in another. When it comes to learning beyond the projects analyzed, in three cases almost all the participants were involved in new projects in the same market segment, whereas in only one case the architect was involved in a new project. When it came to exploring new market segments, again, in three cases new potential was explored, in one case no repeated use has been observed. In the end, the author calls for further inquiry into relationships between divergent, convergent and second-order learning.

The evidence from the case studies highlights the importance of internal and external factors that shape and influence the learning process, such as the role of network size and composition and the importance of local context. Yet, the thin empirical evidence on social learning in the PV cases does not allow us to draw general conclusions on social learning in PV. Rather it highlights the diversity of learning experiences encountered in all of the cases. Learning occurs convergently and divergently, opening up to the possibility of "contradictory" (van Mierlo 2012) or "iterative" (Turnheim 2015) and potentially non-linear learning experiences.

3.2 Technical learning – Evidence from the existing literature

Continuity in learning is an assumption that characterizes the modelling of technical learning in IA models as well, and which is supported by historical data when statistics over longer time periods (e.g. annual time series) are considered.

IA models rely on empirical evidence for the calibration of learning rate parameters. Several reviews have been done of the existing empirical literature on historical LBD and LBR learning rates for power generation technologies. Focusing on solar PV, Table 3 summarizes the estimates reported in the most recent reviews (Rubin et al., 2015, Baker et al. 2013, La Tour et al. 2013, Junginger et al. 2008, Kahouli-Brahmi 2008, Neij, 2008) together with some new econometric analyses (Witajewski-Baltvilks et al. 2015, Lee 2012).

LBD estimates a cluster around 20% of cost reduction for each doubling in the cumulative installed capacity, with a range from 9 to 47%. The broad range in estimates is due to the temporal and geographical characteristics of the data set used in the estimation (Soderholm and Sundqvist 2007), the empirical specification, and the extent to which endogeneity issues are addressed (Soderholm and Sundqvist 2007, Nordhaus, 2009, Witajewski-Baltvilks et al. 2015). Witajewski-Baltvilks et al. (2015) show how LBD rates can vary when statistical uncertainty is considered and when some of the variables that are generally omitted from experience curves, such as policies and energy prices, are included. Soderholm and Sundqvist (2007) show that explicitly accounting for economies of scales reduces LBD rates, suggesting that if this driver is not modelled, LBD rates are upward biased. Soderholm and Sundqvist (2007) show that including a time trend so as to capture any underlying change in trend other than R&D knowledge stock or installed capacity absorbs all variation otherwise captured by the R&D stock, whereas LBD rates are quite stable, especially when endogeneity issues are taken into account.

Source	**# Factors**	**Rate**	**LR (%)**			**Timeframe**	**Method**
			min	**max**	**mean**		
Baker et al. (2013)	1	LBD	17	35	20	na	Review
Junginger et al. (2008)	1	LBD	10	47	22	1957-2006	Review
Kahouli-Brahmi (2008)	1	LBD	18	35	23	1959-1998	Review
La Tour et al. (2013)	1	LBD	10	30	21	1965-2005	Review
Lee, conference proceeding (2012)	2	LBR	9	15	11	2001-2010	Regression analysis
Lee, conference proceeding (2012)	2	LBD	10	10	10	2001-2010	Regression analysis
Neij (2008)	1	LBD	10	47	20	1976-2001	Review
Rubin et al. (2015)	1	LBD	10	47	23	1959-2011	Review
Rubin et al. (2015)	2	LBR	10	14	12	1971-2001	Review
Rubin et al. (2015)	2	LBD	14	32	18	1971-2000	Review
Witajewski-Baltvilks et al. 2015, Mod 1	1	LBD	9	33	20	1990-2012	Regression analysis
Witajewski-Baltvilks et al. 2015, Mod 2	1	LBD	10	46	27	1990-2012	Regression analysis
Witajewski-Baltvilks et al. 2015, Mod 3	1	LBD	10	29	19	1990-2012	Regression analysis
Witajewski-Baltvilks et al. 2015, OLS	1	LBD	10	14	12	1990-2012	Regression analysis

Table 3: Learning rate estimates based on the empirical evidence.

Most IA models use an approach based on endogenous technological change modelled through a one-factor learning curve (LBD) as described in Eq. [1]. This is the case for E3MG, IMACLIM, IMAGE-TIMER, REMIND and WITCH. A few models (MERGE-ETL, POLES) use a two-factor learning curve for endogenous technological change, considering both the effects of learning-by-doing and learning-by-researching, whereas some other models (e.g. MESSAGE and GCAM) use an exogenous technical change by defining different investment costs for future periods (which vary according to reference/policy scenarios). Table 4 summarizes the learning rates and the floor costs used by the IA models with endogenous technological change. Since models rely on empirical literature, it is not surprising that the range of LBD rates in terms of minimum, maximum and mean values is similar to the range emerging from the empirical literature in Table 3. What has not been fully explored is how different learning rates interact with floor cost used by some models (Eq. [2]) to determine technology penetration.

Source	# Factors	Type	LR (%)			Timeframe	Floor cost
			min	max	mean		(2005$/kW)
E3MG (Edenhofer et al. 2010)	1	LBD	na	na	30	Constant	1250
IMACLIM (Bibas et al. 2012)							
central station PV	1	LBD	15	25	na	Constant	982
rooftop PV	1	LBD	15	25	na	Constant	1715
IMAGE-TIMER (Baker et al. 2013)	1	LBD	na	na	35	2000	0
	1	LBD	na	na	9	2100	0
MERGE-ETL (Magné et al. 2010)	2	LBD	na	na	10	Constant	0
	2	LBR	na	na	10	Constant	0
POLES (Criqui et al. 2015)	2	LBD	na	na	20	2010	1100
	2	LBR	na	na	45	2010	1100
REMIND (Luderer et al. 2015)	1	LBD	na	na	20	Constant	500
WITCH (Emmerling et al., 2016)	1	LBD	na	na	16.5	Constant	500

Table 4: Learning rates and floor costs in IAMs. Miminum, maximum, and mean values for LR result from the survey of existing models with endogenous technological change. "Constant" means that the LR is constant over time, whereas in the other cases LR is varying over time and values for 2000/2010/2100 are provided.

As discussed in Sagar and van der Zwaan (2006), it is not clear how learning rates should be extrapolated when moving into the future. Soderholm and Sundqvist (2007) find that learning rate estimates over more recent periods are larger than those calculated on the full sample because of the market power that characterizes the initial diffusion of the technology, whereas the increased competition that emerged during the diffusion stage led to a faster decline in technology costs. However, bias could also go in the other direction because of diminishing returns and the difficulty of further reducing costs beyond certain levels.

Only a few estimates are available in the literature for future periods. OECD/IEA (2014) and Neij (2008) provide an estimate for LBD rates up to 2035 and 2050 respectively, whereas Bosetti et al. (2016) present a review on recent expert elicitation exercises about future cost reduction stemming from different levels of R&D expenditures, see Table 5. While LBR estimates tend to be lower than the few estimates reported in the empirical literature, LBD rates are not very different from the ones estimated from historical data.

Source	# Factors	Rate	R&D	LR (%)			Timeframe	Method
			Level	min	max	mean		
Bosetti et al. (2016) CMU	1	LBR	High	-1	13	6	Future: 2030	Expert elicitation
Bosetti et al. (2016) FEEM	1	LBR	High	4	12	7	Future: 2030	Expert elicitation
Bosetti et al. (2016) Harvard	1	LBR	High	-3	11	3	Future: 2030	Expert elicitation
Bosetti et al. (2016) CMU	1	LBR	Low	-2	13	5	Future: 2030	Expert elicitation
Bosetti et al. (2016) FEEM	1	LBR	Low	1	10	6	Future: 2030	Expert elicitation
Bosetti et al. (2016) Harvard	1	LBR	Low	-2	8	2	Future: 2030	Expert elicitation
Bosetti et al. (2016) UMass	1	LBR	Low	-1	7	4	Future: 2030	Expert elicitation
Bosetti et al. (2016) FEEM	1	LBR	Mid	2	11	6	Future: 2030	Expert elicitation
Bosetti et al. (2016) Harvard	1	LBR	Mid	-1	10	3	Future: 2030	Expert elicitation
Bosetti et al. (2016) UMass	1	LBR	Mid	-1	7	5	Future: 2030	Expert elicitation
Neij (2008)	1	LBD	-	15	25	20	Future: 2050	Expert elicitation / Extrapolation from historical values
OECD/IEA (2014)	1	LBD	-	20	20	20	Future: 2035	Extrapolation from historical values

Table 5: Learning rate estimates based on expert elicitation.

4 Exploring integration opportunities between IBL and IAM approaches: Results and Discussion

Having laid out the different concepts of learning at the core of IBL and IAM approaches, in this section we explore whether forms of integration between IBL and IAMs exist, and whether they could lead to an improved characterization of learning dynamics in energy transition scenarios.

Structural differences between IBL and IAM approaches make ambitious forms of integration between IBL and IAMs unfeasible. IAMs have been developed with the goal of integrating global climate, energy, and socioeconomic dynamics in a consistent framework and in a quantitative way. IAMs have so far adopted parsimonious representations of the human system and have not described societal dynamics and interactions because human behaviour such as power, agency, and social learning are difficult to capture in mathematical equations (van Vuuren and Kok 2012). However, the combination of IA models and multi-scale stakeholder processes seems a promising approach for improving the representation of complex human-technology-environment systems (Pahl-Wostl 2005) and the incorporation of human behaviour and social influence effects into IA modelling is becoming increasingly attractive (e.g., for the introduction of consumer vehicle choices in the personal transport sector, see McCollum et al. 2016). IAMs are outcome-oriented and focus on the consequences of exogenously specified policies, with very limited attention to the processes leading to those outcomes. IBL, on the contrary, engages in concrete projects, where it is examined how actors with different views and motivations align themselves with technological opportunities, consumer preferences, infrastructure requirements, and policy frameworks into working configurations. IBL studies reveal the complexity and uncertainty of transitions in the making, but cannot capture the broader understanding of macroeconomic, systemic consequences as provided by IAMs.

A more feasible method of integration is probably a "*two-way recursive collaboration*" (Turnheim et al. 2015, p. 248), with which two methodologically distinct approaches are used to mutually inform each other. The in-depth analysis of social learning carried out by IBL through case studies highlights the role of important drivers commonly unrepresented in IAMs, which can address those drivers of social learning in the interpretation of their quantitative results and assumptions.

Section 4.1 gives an example of how the two-way recursive collaboration between IAMs and IBL could work in practice. A thought experiment is carried out in which IBL practitioners make an effort to draw stylized shapes of learning from the theoretical frameworks and empirical evidence that could be translated into functional forms in IAMs. IBL results are first generalized by means of a conceptual framework common to IAMs. IAMs use IBL results to interpret sensitivity analysis on learning curves. Note that this form of integration differs from *"one-off methodological enrichment"* (Turnheim et al. 2015, p. 247) because both research communities have actively engaged in the process.

In IAMs learning is driven by physical variables, such as capacity installed, and the learning rates are used to describe the relationship between capacity and costs. As discussed in Section 3, the actual value of learning rates is the result of interaction between observed measurable trends (e.g. the relationship between costs and capacity) and non-observable factors, which are not explicitly included in the analysis because not measurable. Issues such as trust, network structure, values, and norms are unobservable (from a quantitative point of view) but they do influence the empirical value of learning rates.

In the collaborative effort described below, we have tried to conceptualize learning in a similar way between the two approaches by looking at the relationship between a performance indicator (the reciprocal of the investment cost, i.e. how many watts can be generated for each dollar invested) and effort or time[4].

[4] It must be said that with time effort accumulates, so that having effort or time on the horizontal axis can lead to different shapes in learning. As discussed in Schilling and Esmundo (2009), if effort is relatively constant over time, plotting performance against time or effort would not make too much difference.

4.1 *Stylizing learning dynamics from IBL case studies*

One of the results emerging from the IBL case studies reviewed in Section 3.1 is the existence of non-linear social learning in the form of either rapid learning or destructive learning. Rapid social learning can be operationalized through three alternative functional forms:

1) An exponential function describing rapid learning processes at a late stage of the project or initiative, following an initial phase of limited learning. This may be the case when members join the social learning network, and the more members learn from one another, the faster learning accumulates. Indeed, the learning process is stimulated by the increasing skill and competence of its participants, and by an effective implementation of social learning management;

2) A logarithmic function describing radical learning progress at the beginning of the initiative or project, followed by a flatter, still positive, learning experience that at some point only reveals marginal learning progress and approximates a learning plateau;

3) An S-shaped function as proposed by Rogers (2005) and as also found by the empirical literature on learning curves (Section 3.2). Here, learning progresses slowly at the beginning and accelerates half way, to reach a learning plateau. This curve can be interpreted as the combination of the exponential (early stage) and the logarithmic (late stage) functions.

Learning may proceed rapidly, destructively, with peaks, plateaus or loops that may cause rapid performance gains with peaks and plateaus (stagnation), which in turn may slip into loss of learning caused by destructive learning or regain learning in loop learning. Based on the evidence from the case studies, a linear pattern is less likely, as it implies constant learning over time (Figure 3). As time goes by, effort accumulates to realize the target of the projects, and also across projects, as described by van Mierlo (2012), giving rise to monotonic learning. As the learning gained with respect to time may peak, plateau or reduce, the accumulated learning is always positive with respect to the duration of the projects.

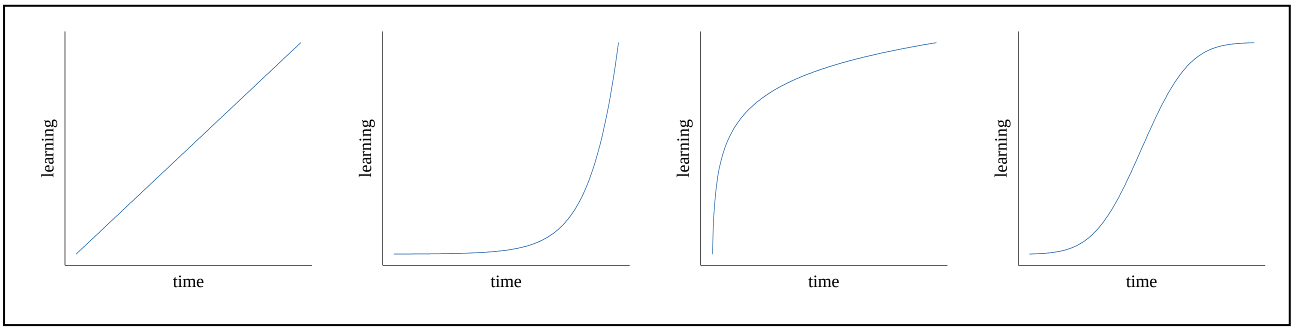

Figure 3: Constant and "rapid" learning – linear, exponential, logarithmic and logistic learning.

Destructive learning occurs when there is a loss of learning performance during the project and initiative (see Figure 4). This learning curve suggests steep learning at the beginning, leading to a peak from which learning may decrease (destructive learning), e.g. because of conflicts, crises or external shocks. Falling slopes eventually indicate a loss of learning, a loss of knowledge or, eventually, of performance. This may be the case when initiatives end and no inter-project learning is observed afterwards. That is, the project failed to implement a management that ensures that learning survives or even continues after the end of the project. This is neither implausible nor very likely in the short run (Albert et al. 2012).

Still, it is more likely to observe some sort of "creative destruction", when destructive learning paves the way for new learning and social learning occurs in learning cycles in which peaks, valleys and retreats take turns. Conflicts may be solved and external shocks may be adapted to (Feola and Nunes 2014). This stylized form of social learning is probably the most likely path to be observed in local initiatives. However, this applies to local initiatives with a short time horizon, which typically lasts between five and seven years, whereas in the long-run the local initiatives may last multiple generations or spread onto inter-project learning lasting for more than ten years. The longest period covered in the case studies analysed was 13 years (see Ornetzedera and Rohracher 2006 on Sustainable Buildings in Vauban, Freiburg, Germany). Analytically, at some point, IBL research is unlikely to grasp inter-project learning or learning in cycles in multi-generation projects, since those would require extensive qualitative historical research.

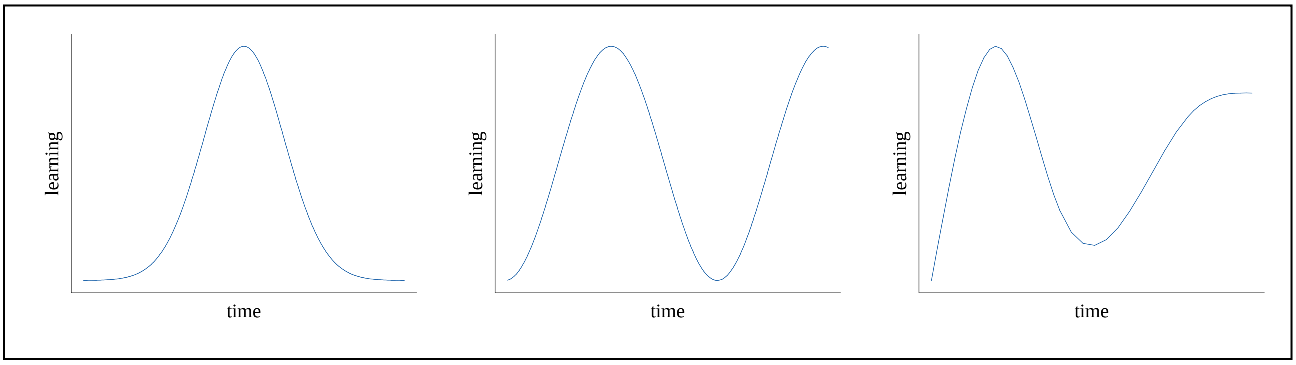

Figure 4: "Destructive" learning – normal, sinus and "hype" learning (learning cycles).

Van Mierlo (2012) characterizes learning outcomes in her case studies on PV in terms of number of houses equipped with PV technology, and total power in terms of kilowatt peak (kWp) generated. A major issue highlighted in the case study at the time of initiating the project was the high costs per kWh for PV. As a consequence large subsidies were paid to foster learning about the technical and social bottlenecks and possibilities of PV. Based on the van Mierlo's (2012) PV case studies, we decided to use performance measured in watt-peak per dollar (Wp/$) as a bridging device to operationalize learning in terms of the learning outcome in the following Integrated Assessment of PV. The use of this concept makes it possible to integrate the more qualitative findings from case studies into dynamics and forms of learning used by IAMs, so that a more direct operationalization through learning curves can be pursued.[5]

4.2 Exploring learning dynamics in IAMs. Evidence from the WITCH model

IAMs represent learning by means of S-shaped or logarithmic functions, therefore assuming positive and monotone learning. Destructive learning, which has emerged as a possible pattern from the case studies, especially in the short run, can hardly be applied in IA models as they have much longer time scales with time steps of at least one year. As previously discussed, while destructive learning is possible over the time horizon of individual initiatives, it becomes more unlikely over a longer time horizon and at broader geographical scales.

We use the IAM WITCH (Emmerling et al. 2016)[6] to illustrate learning dynamics of solar PV and perform a sensitivity analysis on the model's assumptions on PV penetration and technology costs. The WITCH model uses a one-factor learning curve with a floor cost, as described in Eq. [2]. The default values adopted in this work for the learning rate and the floor cost are 16.5% and 500$/kW. Consistently with Table 4, throughout this section monetary values are expressed in US 2005 dollars.

From the reciprocal of the investment cost as performance indicator (y-axis) and cumulative capacity as effort indicator (x-axis), the resulting learning curve for a baseline case is a logarithmic relationship between capacity and performance (see Figure 5, which compares the Business-as-Usual scenario to a climate policy

[5] However, it is crucial to note that none of the case studies operationalize or quantify any "amount" of social learning over time, but focus on how social learning may proceed over time and why. The graph depictions on forms of learning thus are to some extent hypothetical and stylized, only serving to illustrate social learning as described in the cases and to translate them into potential functional forms of social learning. This is partly due to the fact that different forms of social learning may occur on different levels of analysis, for example in terms of joint problem-solving, acquired knowledge, etc. An overview on this can be fond in Rodela (2011) as well as Schol et al. (2013).

[6] http://doc.witchmodel.org/

case)[7]. The time horizon is 2005 to 2100 and the model represents the massive deployment in solar PV observed over the last decade. Learning is very fast at the beginning but it slows down over time, finally approximating a learning plateau. As discussed in Section 2, an S-shaped relationship tends to prevail when the role of R&D during the early stages of innovation are considered. Since the time horizon of the analysis here starts in 2005, we are already in the deployment stage of the technology, or in the late stage of the S-shaped curve, which is why a logarithmic behavior appears. When a climate policy is introduced, the installation of solar capacity is stimulated, which drives investment costs further down to achieve the floor cost.

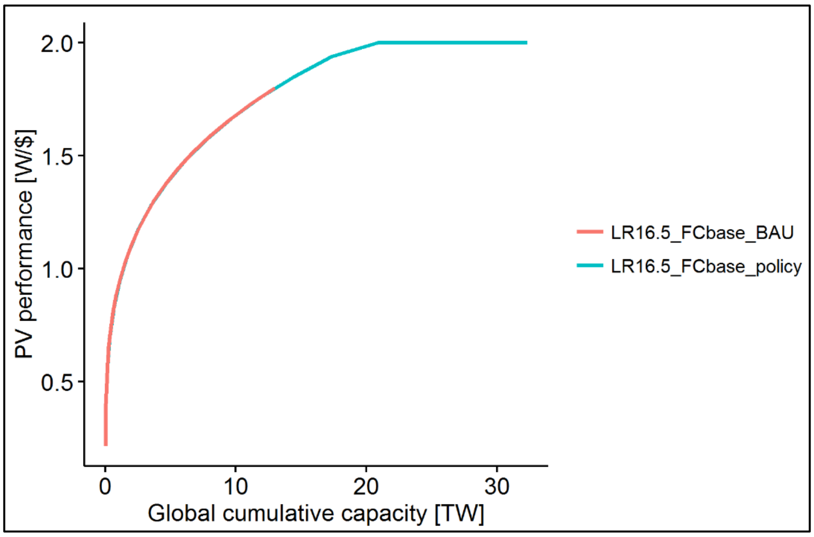

Figure 5: Performance of solar PV as a function of global cumulative capacity to 2100, Business-as-Usual and policy scenarios, LR=16.5%, floor cost = 500 $/kW (hence 2 W/$).

The default learning value (16.5%) is close to the mean value estimates found across studies (see Tables 3-5), and it has also been chosen to largely reproduce the actual cost path that took place over the decade from 2005 to 2015. However, as discussed in Section 3, a broad range of values (9 to 47%) results from the review of the existing empirical literature. One of the arguments behind these different values is the presence of omitted variables, which could include forms of social learning. As discussed in Section 2, other forms of learning, more difficult to quantify, could accelerate and reinforce the impact of cumulative capacity installed on cost reduction. In the language of the model this would translate into different learning rates. Social learning, therefore, can be addressed in IAMs by varying the exogenous value assigned to learning rates. Furthermore, the floor cost is another important parameter that affects the extent and the speed of technology penetration.

Here we examine the sensitivity of the model's results to the range of learning rate values identified by the empirical literature and examine twelve combinations of learning rates (9, 20, 35, 47%) and floor cost (0, 587, 1349 $/kW) values for the solar PV technology. The values chosen for the learning rates correspond to the minimum, mean and maximum values from literature (9, 20 and 47 respectively, see Tables 3, 4, and 5), whereas 35% was selected as an intermediate value to cover the broad segment from the medium and the

[7] In the Pathways project two alternative decarbonization scenarios, Pathway A and Pathway B, have been considered. The two scenarios share the same mitigation policy targets: an 80% reduction in GHG emissions in 2050 compared to 1990 levels in the European Union and an increase in global temperature in 2100 of less than 2°C relative to pre-industrial levels with a likely chance. Pathway A focuses on technological substitution in the form of efficiency improvement and fuel switching as the main mitigation strategy, while Pathway B considers a reconfiguration of the social and economic regime, with behavioural and preference changes and the involvement of new actors. Pathway A is the considered policy case. A Business-as-Usual (BAU) scenario, where no policies or specific technological assumptions are implemented, has also been taken into account.

maximum learning rates. Values for floor cost correspond to the minimum, mean and maximum values from the ones used in the IA models (see Table 4). The minimum value actually implies the absence of a floor cost. The analysis reveals that at increasing levels of learning rates, the curvature tends to progressively decrease, and the shape of the curve tends to converge to a linear learning (Figure 6, where two additional cases have been considered, i.e. learning rate equal to 25% and 30%, in order to show the progressive behaviour more clearly).

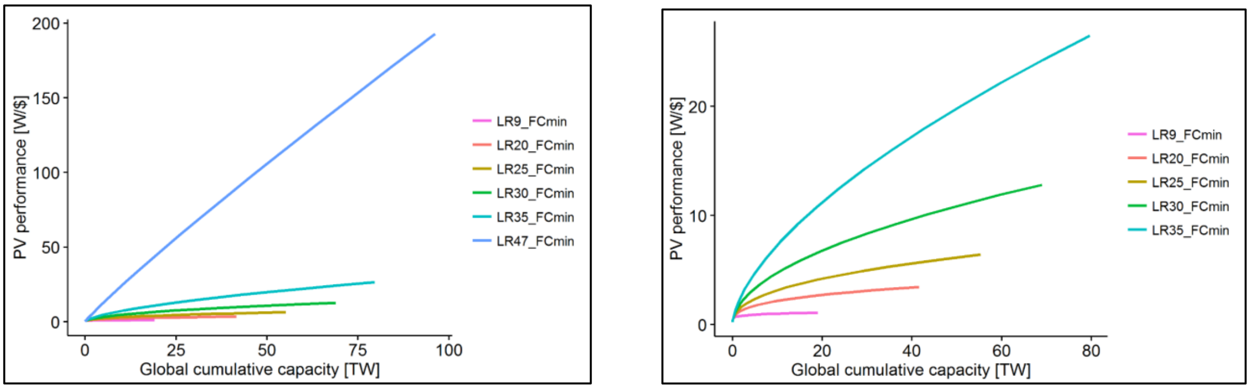

Figure 6: Performance of solar PV as a function of global cumulative capacity to 2100, policy scenario, detail on minimum floor cost scenarios.

Note: The right panel excludes the maximum LR scenario.

Low values of learning rates correspond to a slow reduction in technology costs, so that the floor cost threshold is hardly reached by 2050 and different floor cost values have barely any impact on PV penetration (see LR9 cases in Figures 7 and 8). On the other hand, when learning rates are high (see LR35 and LR47 cases in Figures 7 and 8) the cost decrease is fast and the floor cost threshold is soon reached: the floor cost represents the actual investment cost for a considerable part of the century and different floor cost values significantly influence PV penetration.

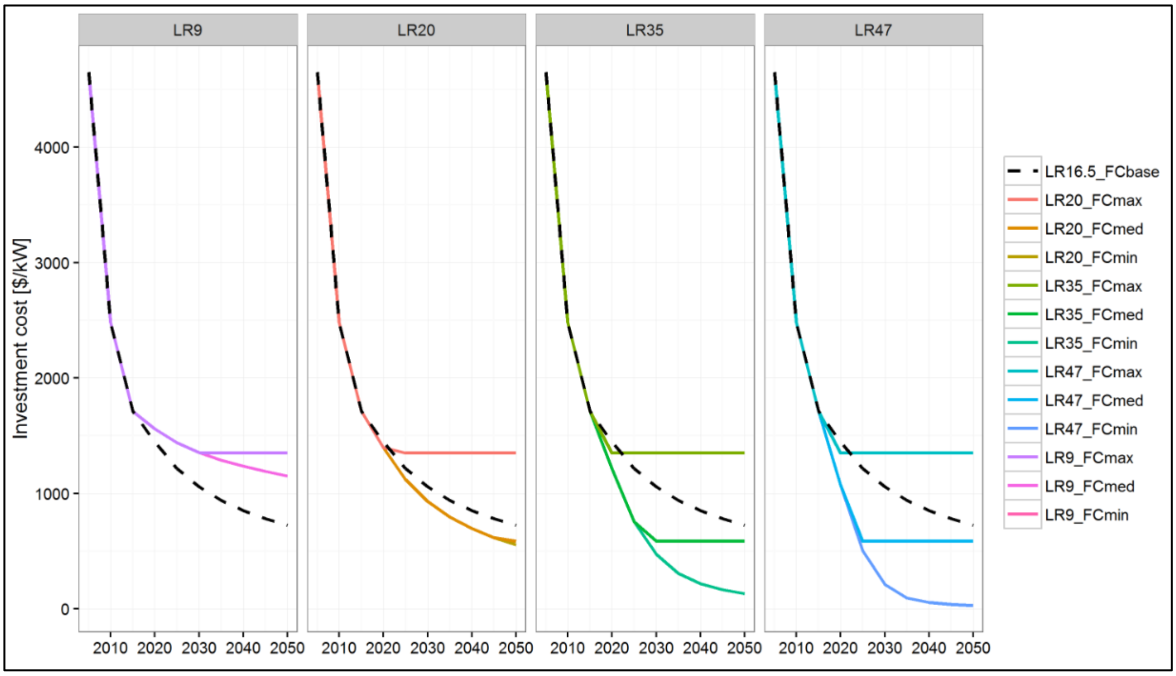

Figure 7: Global average PV investment cost to 2050, policy scenario, for different sets of learning rates and floor costs. The global average value has been computed as a regional average weighted over the regional PV capacity.

More in detail, the high floor cost is reached in 2020 under all values of learning rates except for LR9, where it is reached in 2030. In all these scenarios, world PV penetration tends to stabilize at about 3% of the electricity mix (Figure 8). The average floor cost is reached in the three highest learning rate scenarios (in 2025 for LR47, in 2030 for LR35, in 2050 for LR20). When such a value is reached, PV penetration sets at about 8% and remains stable over time. The minimum floor cost hypothesis is relevant for the two high learning rate scenarios, where PV penetration can increase beyond the afore-mentioned 8% threshold. However, an analysis of the results after 2050 would show that, in any case, PV penetration would not exceed 25% even with investment costs close to zero. This is due essentially to two main factors. The first is related to the equations which model the system integration constraints of wind and PV in the electricity mix and which do not allow an indefinite penetration of those technologies. The second and main factor is related to the WITCH modeling structure, which is based on a Constant Elasticity of Substitution (CES) framework. According to the CES structure, the competition between technologies is not based on pure economic considerations only. It is complemented with additional constraints (such as the system integration equations) and follows a strict hierarchical sequence: PV competes with wind and CSP, then the renewable technologies compete with fossil fuel-based generation, and so on. Since this competition is not fully flexible (i.e. the substitutability across technologies is not infinite for modelling what in reality is experienced as a preference for heterogeneity), there is ultimately an implicit threshold to the penetration of each technology, even if it is installed free of charge, as would happen in the cases considered (see Carrara and Marangoni, 2016 for more details).

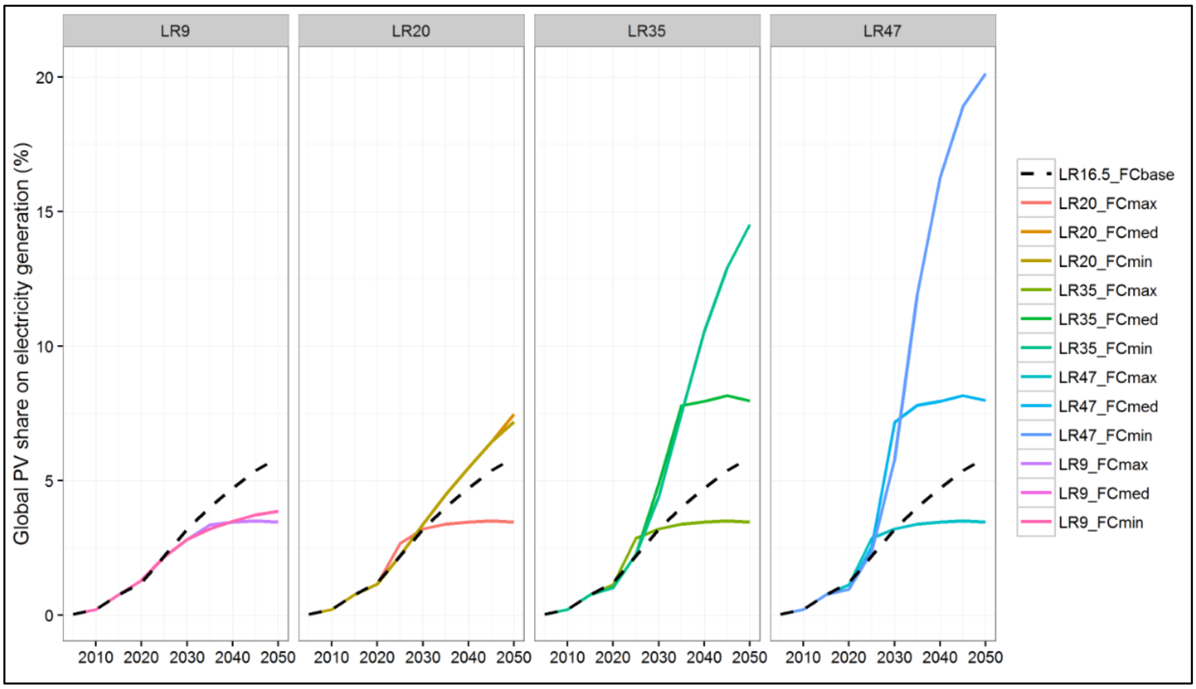

Figure 8: Global PV penetration rate in the electricity mix to 2050, policy scenario, for different sets of learning rates and floor costs.

5 Conclusions

In this paper we have explored opportunities of integrating two different analytical approaches used in the analysis of learning within the context of sustainable transition pathways, integrated assessment models (IAMs) and Initiative Based Learning (IBL). IAMs are quantitative systems modelling tools that provide a forward-looking perspective. They project the changes over time that are required to achieve predefined goals under specific sets of economic and technological assumptions. IBL is a qualitative approach in which

transition pathways emerge as the upscaling of successful solutions on a local scale. They reveal the emerging properties in system changes.
IAMs focus on technical learning, namely a reduced-form of learning driven by cumulative capacity installed (Learning-By-Doing) and R&D expenditure (Learning-By-Research). The empirical values used to parameterize learning in models varies substantially. This broad range reflects omitted variables and the impossibility of observing and measuring less tangible forms of learning, such as social learning. Learning rates are generally estimated by fitting the observed data of investment costs and cumulative installed capacity or R&D expenditure. Factors such as spillovers or contextual factors such as policies, institutional frameworks, governance structure, etc., are generally not included. The omission of variables that reinforce or undermine learning lead to biased estimates.
IBL refer to the learning that results when people engage with one another and consider the adoption and diffusion of a technology to be a function of social learning. Moreover, whereas IBL cases focus on how the dynamics of social interaction (e.g. social learning) influence the spread of technology, IAMs focus on the implications of the adoption/use of technology on technology performance measured in terms of reciprocal of unitary investment costs. IAMs refer to the learning that occurs when more technology capacity is installed, regardless of the underlying reason (e.g. imitation, cost competitiveness). Therefore IBL tend to see technology adoption as a function of social learning over time, while IAMs relate improvements in technology costs to cumulative deployment. While IAMs tend to view learning as a monotonic process because that pattern fits well with the empirical data on a national scale over a time horizon of a few decades, IBL's case studies point to a richer description of the possible learning dynamics. S-shaped or logarithmic learning is one possible outcome, though less linear dynamics can also be observed, especially in the short term. The very different time scale of IAMs and IBL explain why such differences can be observed.
IBL provides interesting insights into learning what remains unobservable in other approaches. Learning goes beyond the notion of the Learning-By-Doing used in IAMs, to include technical, organizational, and cultural aspects.
This paper examines the potential for integration with respect to the characterization of learning in the context of energy transition for solar PV technology, which plays an important role in the future decarbonization strategies and has received wide consideration in the empirical literature, and whether the IBL-based empirical evidence highlights the diversity of learning experiences and the importance of key factors such as network composition and size, timing, and non-linearity in more local and short-run learning experiences. The case studies on initiatives suggest that a small, heterogoneous but cohesive social network, in which expertise is gathered and trust is built, fosters social learning. A skilful project management that organizes and maintains engagement of its network members is crucial to successful learning. However, social learning remains highly dynamic and non-linear. Learning may be progressive at some point of the initiative; at the same time, it may face retreats and setbacks that may even "destroy" learning when external effects, such as changing financing schemes, intervene and lead to intra-project crisis or to "lost" learning when inter-project learning or follow-ups are missing. An interesting result that emerged only in the specific case of learning in solar PV is the presence of learning across projects (e.g. spillovers), which might suggest a longer term and more stable prospect for learning in PV. Indeed, it should be kept in mind that the analysis of cases on PV covers a project period of up to seven years.
Differences with respect to the scale of analysis, the time-horizon, the treatment of complexity, as well as the representation of innovation, make ambitious forms of integration between these two approaches non-viable. Moreover, the number and geographical coverage of the case studies examined in this paper are probably too limited to allow us to derive more general patterns. For this reason, a soft form of integration between IBL and IAMs has been explored. We consider the resulting form of integration an example of "two-way recursive collaboration". First, IBL practitioners draw stylized shapes of learning from the theoretical frameworks of the literature and empirical evidence from the case studies that could be compared to the functional forms used in IAMs. Second, IAMs, and in this specific example the WITCH model, are used to compare the learning dynamics resulting from the IA modelling approach with the stylized shaped proposed

by IBL. The logarithmic learning assumed by WITCH is one of the likely learning dynamics identified by IBL. At the same time, the IBL cases stress the fact that learning may get lost and learning may continue non-linearly, leading to learning cycles between preceding and subsequent projects. However, this pattern might hold true only for the short time horizons covered by the IBL cases, up to 13 years. In the long-run, the ups and downs of learning cycles may be straightened into an S-shaped learning. This idea is underpinned by theoretical models of diffusion research.

The sensitivity analysis using the WITCH Integrated Assessment Model illustrates that different parameterization of learning within the range of what was observed in the empirical and modelling literature has significant implications for the model projections of technology penetration and costs. The resulting learning dynamics always fall within the stylized patterns identified by IBL. Elements of social learning are implicit in the choice of the parameter values used in models, and therefore insights from IBL can be used to interpret the different learning dynamics, mostly in terms of speed, that result from different parameter choices.

We conclude that a two-way collaboration between IAMs and IBL can lead to mutual enrichment. On the one hand, IAMs show the relevance the modelling of learning can have for future energy and technology pathways. On the other hand, IBL points out the importance of less tangible forms of learning, such as social learning, which can accelerate the speed of technical learning. In terms of future research directions, more research on inter-initiative learning cycles to grasp implications for long-term learning is needed within the IBL field of research. To be more relevant for future-oriented analyses, IBL could also be used to frame the analysis of case studies such as those provided in IAMs, which need to assess the sensitivity that learning dynamics have on energy and technology scenarios and interpret the results in light of the insights provided by other disciplines, such as IBL.

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