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To cite this article: Roberto Pasqualino *et al* 2024 *Environ. Res. Lett.* **19** 073004

ENVIRONMENTAL RESEARCH
LETTERS

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RECEIVED
3 October 2023

REVISED
12 March 2024

ACCEPTED FOR PUBLICATION
16 May 2024

PUBLISHED
21 June 2024

TOPICAL REVIEW

Modelling induced innovation for the low-carbon energy transition: a menu of options

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Keywords: induced innovation, energy transition, low-carbon, integrated assessment models, modelling

Supplementary material for this article is available online

Abstract

Induced innovation is a multi-faceted process characterized by interaction between demand-pull forces, path-dependent self-reinforcing change, and the cost reduction of technology that occurs with cumulative deployment. By endogenously including induced innovation in energy models, policy analysts and modellers could enable a mission-oriented approach to policymaking that envisions the opportunities of accelerating the low-carbon energy transition while avoiding the risks of inaction. While the integrated assessment models used in the intergovernmental panel on climate change (IPCC-IAMs) account for induced innovation, their assumptions of general equilibrium and optimality may reveal weaknesses that produce unsatisfactory results for policymakers. In this paper, we develop a menu of options for modelling induced innovation in the energy transition with non-equilibrium, non-optimal models by a three step methodology: a modelling survey questionnaire, a review of the literature, and an analysis of case studies from modelling applications within the economics of energy innovation and system transition (EEIST) programme. The survey questionnaire allows us to compare 24 models from EEIST partner institutions developed to inform energy and decarbonisation policy decisions. We find that only six models, future technological transformations, green investment barriers mode, stochastic **e**xperience **c**urves, economy-energy-environment macro-econometric, M3E3 and Dystopian Schumpeter meeting Keynes, represent endogenous innovation—in the form of learning curves, R&D, and spillover effects. The review of the literature and analysis of case studies allow us to form a typology of different models of induced innovation alongside the IPCC-IAMs and develop a decision tree to guide policy analysts and modellers in the choice of the most appropriate models to answer specific policy questions. The paper provides evidence for integrating narrow and systemic approaches to modelling-induced innovation in the context of low-carbon energy transition, and promotes cooperation instead of competition between different but complementary approaches. These findings are consistent with the implementation of risk-opportunity analysis as a policy appraisal method to evaluate low-carbon transition pathways.

1. Introduction

The current basis for decision-making associated with the transition to decarbonised economies may be biased against correctly estimating the opportunities and economic benefits from decarbonisation policies due to the underrepresentation of innovation and technological change processes [1–3]. Already by 2007, the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment acknowledged in its Summary for Policymakers that 'Remarkable progress has been achieved in applying approaches based on induced technological change to stabilisation studies; however, conceptual issues remain. In the models that adopt these approaches, projected costs for a given stabilization level are reduced; the reductions are greater at lower stabilisation levels.' ([4], p 8). The relevance of this has been underlined by the remarkable progress in many low-carbon technologies since then, particularly where governments have taken strong action to foster emerging technologies at scale. Yet, some influential climate models still pay little attention to the matter of induced innovation, often treating technological change as exogenous [5, 6] instead of endogenous [7].

Induced innovation is a multi-faceted process characterized by interaction between demand-pull forces, path-dependent self-reinforcing change, and the cost reduction of technology that occurs with cumulative deployment [8]. From the perspective of climate policy, this requires to highlight the fundamental difference between endogenous technological change (EnTC) and exogenous technological change (ExTC) in models that support decision making to decarbonize the global economy [9, 10]. If the process of technological change is endogenised in the structure of a model, then the conclusions tend to indicate an action-driven approach by the government to support innovation towards a lower-cost sustainable economy [11, 12]. This is due to the fact, that in an EnTC model, a policy can induce innovation via the endogenous mechanisms it contains [7]. In this way, it can help support government action transitioning away from the current state to other (hopefully desirable) ones. If the self-reinforcing loop of learning-by-doing (more capacity, lower cost, higher appeal for investments) is activated and supported, it can trigger lower costs over time and accelerate the transition [11]. This may stimulate demand even further, and initiate path dependent processes which self-sustain a technology transition due to policy [8]. In an ExTC model, technology changes as a function of time only. In doing so, the government is given a passive role, waiting for technology costs to decrease before taking action. This leads to technology stagnation, and lock in of old incumbent technology [13]. In the context of the decarbonisation of our economies, the inclusion of innovation and self-reinforcing change is fundamental to achieving successful policy impacts in countries across the world [14–18].

The field of informing climate policy using models is currently dominated by integrated assessment models (IAMs) (see [19]). The formal definition of IAMs is that of models that integrate climate and land systems with different scientific domains (e.g. energy or economics) by accounting for feedbacks among those [15]. According to the IPCC Sixth Assessment Report, IAMs can be divided between those that have a more detailed representation of the land, energy and economic sectors and a reduced representation of the climate system—used to assess the linkages between sectors and how they relate to the climate system—and those that focus on costs associated with climate change impacts, with reduced representation of the economic system—used for assessing climate impact and mitigation in a cost-benefit analysis (CBA) framework, and to evaluate the social cost of carbon [20]. Previous literature has pointed out some of the limitations of such models, including their limited representation of innovation processes (often exogenous) and increasing marginal returns [6, 9, 11], their inability to capture environmental tipping points [18, 21], limited representation of financial and economic aspects (e.g. prices) [22], and their assumption of rational homogeneous agents driven by perfect foresight [23, 24]. As most of the IAMs used for the analysis of the IPCC share these characteristics, for the purpose of this paper we refer to those as IPCC-IAMs (see Annex III in [20] for details).

While the IPCC-IAMs are currently most prevalent in informing climate policy decisions [24, 25], an emergent field of new economic models is developing [26]. These 'new' models do not necessarily build on the assumption of equilibrium or optimization. They are proposed as a complement and as an alternative to the IPCC-IAMs in informing climate policy by relying on the features mentioned above, such as self-reinforcing change, innovation and technology diffusion, non-linearity and analysis of tipping points [26]. Due to their characteristics, these models can be seen as 'disequilibrium' models and accept uncertainty at their core[11]. The question remains as to whether these new models and techniques can provide a valuable alternative to IPCC-IAMs in a meaningful way to answer to policy needs linked with modelling innovation, and whether they can demonstrate their value in complementarity, seeking collaboration instead of competition based on the policy questions that they are designed to answer.

This paper provides a menu of options for endogenously modelling induced innovation alongside IPCC-IAMs, using models from the Economics of

[11] For these reasons they can be used for the Risk-Opportunity Analysis (ROA) instead of the Cost Benefit Analysis (CBA) as conceptualized in [46, 81].

Energy Innovation and System Transition (EEIST) programme (see appendix A for further details on EEIST). This is done by forming a typology of models adapted from [26] which focuses on the modelling of induced innovation, and supporting it with a decision tree that guides modellers and policy analysts in choosing the most appropriate model depending on their research needs. The typology is informed by (i) the empirical evidence demonstrated through a survey questionnaire applied to 24 models in use as part of the EEIST programme, which shows how the models account for innovation in energy and transport systems, and (ii) a literature review of published work based on the collection of case studies from [26] and the related state of the art. The decision tree is formed starting from the perspective of a modelling analyst that is required to analyse policies for a low-carbon transition linked with induced innovation. It is then deduced by analysing different case studies consisting of the application of different models to answer the policy questions they are designed to address.

The aim of this research is to support a better integration of induced innovation modelling in the climate policy debate and modelling tools. It aims at being instrumental in navigating the choice of models that integrate induced innovation between first, those that rely on the analysis of static data; and second, those that explore more dynamic uncertain scenarios based on a systemic approach and analysis of tipping points. This typology is further illustrated by a review of modelling case studies that reflect general principles embedded in those models.

Among the static models, we find (1) the use of system mapping to provide a systems understanding of the impact of innovation on policies for decarbonizing the economy [2, 27] historical data analysis based on learning curves to generate probabilistic forecasts (e.g. [28]) and (3) wider system perspectives with econometric analysis which we discuss with the example of economy-energy-environment macro-econometric (E3ME) as a case study [29, 30]. In the dynamic category of models, we find those that apply a system dynamic perspective (4) to the analysis of mixed policies that aim to trigger positive tipping points, with future technological transformations (FTT) as an example [31–33], and (5) those that rely on heterogenous ABM and value the flexibility in generating behaviours, rather than providing precise forecasts at the micro- and macro-economic levels, and we discuss DSK as an example from our survey (e.g. [34, 35]). The models used as cases in this paper are explained in detail in each of the relevant sections. This paper proposes the use of the aforementioned models alongside the WITCH IAM [36] that represents a best-in-class approach for modelling induced innovation in the IPCC community, and the IAM E3ME-FTT-Grid ENabled Integrated Earth (GENIE) which is formed of a combination of models from EEIST [22].

The rest of the paper is organised as follows. The next section provides the background of the research by summarizing the key literature around models of induced innovation. The third section covers the methodology adopted in this paper and provides the list of the 24 models included in the survey. Fourth, we present how the models in the survey represent innovation and select those to be analysed via case studies. Fifth, starting from the modelling typology proposed in [26] and extending it via a review of relevant published modelling work, we propose a typology of models. Sixth, we propose a decision tree linked with the typology to support the modelling audience in their choice of the most appropriate models of induced innovation alongside IPCC-IAMs. Finally, section seven discusses the main outcomes of the paper and section eight concludes.

2. Research background

2.1. Systemic and narrow approaches to innovation in energy systems

In the context of environmental innovation, the theory of induced innovation suggests that environmental policies and regulations can stimulate the development and adoption of new technologies and practices that reduce environmental impacts [2, 37]. It is possible to differentiate approaches to innovation between those that prioritize a systemic approach capturing the system at large (see [38, 39]) (defined as ‘systemic’ in this paper) and those using narrow applications focused on specific aspects of the energy transition (e.g. learning curves—defined as ‘narrow’ in this paper) [40–42].

On the one hand, the systemic approach recognizes that technological change does not occur in isolation but is deeply intertwined with various social, economic, and institutional factors [39, 43] and that policies for decarbonizing the economy have impacts on a range of societal goals [44]. Considering these complex interactions, the systemic approach aims to create an enabling environment that fosters innovation and accelerates the deployment of new technologies passing through, often bidirectionally, the various stages of invention, development, demonstration, market formation, deployment and diffusion [8]. It considers the broader context and interconnections between different elements of the energy system, including technology, finance, infrastructure, markets, policies, knowledge creation and user behaviour [45]. This perspective allows for a comprehensive understanding of the barriers and opportunities for technological change, enables the identification of systemic bottlenecks that may hinder innovation, and more importantly, it encourages the iterative and reciprocal processes of learning and adaptation [46]. By integrating feedback loops between technological advancements and system performance, it facilitates the identification of lessons learned and promotes continuous improvement. This reiterative learning process is crucial for refining technologies, scaling up successful innovations, and avoiding costly mistakes. Indeed, the systemic approach recognizes that technological change does not occur in isolation but through synergistic interactions between different sectors and technologies. By exploring and leveraging these synergies, the systemic approach can unlock new opportunities and accelerate the development and diffusion of innovative technologies [14, 39, 46, 47].

On the other hand, the narrow approach builds empirical evidence from historical analysis to minimise the uncertainty that is typical of the systemic approach. For example [10, 40], use historical data to analyse learning curves that help explain the transition between dominant technologies in the past two centuries, and claim that there is enough evidence to develop simple dynamic models of systems transition. While the narrow approach minimizes the need for substantial system-level changes and incremental improvements are often easier to achieve in terms of technical feasibility, one of the primary criticisms is its reliance on existing technologies, which may have inherent limitations in terms of environmental sustainability and long-term viability [5]. Additionally, a narrow focus on incremental improvements may overlook potential breakthrough innovations that could radically reshape energy systems [48, 49]. As a result, we believe that a combination of the two approaches is key for supporting meaningful policy making in the context of low-carbon transition, and the ability to model both aspects is an important factor that needs clarifying.

2.2. Induced innovation in models

Grubb *et al* [9] describe the differences between autonomous and induced technical change, and what implications these might have for modelling results and policy advice. Autonomous innovation models are categorized as having an 'exogenous' approach to modelling innovation, whereas models of induced innovation have closed loop feedbacks that can prompt innovation. It is by including those causal effects in models that a change in policy can develop non-linear change by inducing innovation.

Grubb *et al* [9] based their analysis on a literature review to compare 22 energy, environment and economic models[12]. By revisiting the model outputs under uncertainty of costs and emissions, they also found that in the context of the energy transition, induced innovation could trigger a self-reinforcing mechanism prompted by policy action. This could lead to a drastic change in the application of climate policy for decarbonisation, and support a mission-oriented approach to policy making. A clear recent example of this can be found in the development of zero electric vehicles in China since early 2000 [14]. A few years later [11, 12], expanded these findings in the innovation modelling comparison project. Edenhofer *et al* [11] selects ten energy models that represent induced innovation, and classify them by type and overarching assumptions[13]. The ten models account for induced technical change either related to energy intensity i.e. by decreasing energy use per unit of productive assets; or carbon intensity i.e. reducing carbon per unit of energy produced. Their assessment consists in testing every model both (i) for the implication of ignoring EnTC (endogenous innovation parameters such as learning rates or R&D accumulation as not influential, or behaving as if innovation was modelled as exogenous or only dependent on time), against (ii) considering it at different levels of magnitude (endogenous innovation parameters having influence on the outcome of the simulation). The results confirmed the finding of [9], suggesting that further analysis of innovation can have extreme effects on the ability of policy makers to decarbonize the economy, and most importantly, do this at a lower cost than what models that do not consider endogenous innovation could do.

Different ways for representing induced innovation endogenously in models are proposed below.

References [13, 50–52] distinguish induced innovation modelling approaches in four general categories: [1] R&D-induced, where investments in research and development shape the direction of technological change (see [15, 53–56]), [2] 'learning-induced' where the unit cost of a technology decreases as the cumulative deployment of that technology increases (see [10, 57, 58]), [3] 'spillovers' (or 'crowding out' effects) highlighting that both learning curves and R&D can provide positive externalities to the system via imitation without incurring in additional costs [35, 59, 60], and [4] changes in the form of the production functions that allow analysts to test how innovation can trigger changes in the demand

[12] The authors compared 22 models that were characterized by the modellers using or developing them as belonging to the following types: Integrated Assessment Modelling (9 models), Computable General Equilibrium (7 models), Macro-Econometric (2 models) and Energy Sector Models (4 models). The models that included some representations of induced innovation were: POLES, ICAM3, IMAGE, WARM, IIASA models, e.g. MESSAGE, RICE, Goulder & Matthei, EGEM, E3ME. The models considered not to include any representation of induced innovation at the time of the publication were: IEA models, FUND, DICE, G-cubed, GEM-E3, GREEN Pizer, MIT, Markal, MACRO and GLOBAL 2100, PAGE95.

[13] The IMCP compared the ten models by dividing them in a typology of four categories: bottom-up Energy System Cost minimization models (MESSAGE-MACRO, GET-LFL, DNE21+) and top-down models including five optimal growth models for welfare maximization (ENTICE-BR, FEEM-RICE, DEMETER-ICCS, AIM/Dynamic-Global, MIND 1.1), one simulation macro-econometric model (E3MG), and one computational general equilibrium model (IMACLIM-R).

for production factors or productivity gains [52]. The approaches to modelling those effects are reviewed below.

2.2.1. R&D-induced innovation

A review of different approaches to support public energy R&D decision making under uncertainty in decision frameworks, expert elicitations, and IAMs, is available in [15]. Anadón *et al* [15] demonstrates how IAMs should represent R&D energy investments as affected by non-linearities such as costs, competition and complementarity among technologies in the market and irreversible tipping points linked with environmental damages. They also analyse how decision-makers make decisions under such uncertainty. Analytically, the models presented in [13], refer to R&D as an accumulation of investments in a stock of knowledge. Such accumulations can affect the factors of demand and supply via the use of elasticities that quantify the impact of R&D accumulation on efficiency [61, 62], reduction of carbon intensity [55], or abatement costs of technology [63]. Both [63] and the updated paper [64] explore model uncertainties by testing changes in elasticities that link the accumulation of knowledge and experience in relation to a reduction in the technology cost. The literature on modelling energy R&D is often linked with modelling spillover effects [15, 35, 60] and multi factor learning curves [41, 65] as follows.

2.2.2. Learning or experience curves

The most basic version of a model of learning-induced innovation captures an exponential decay of cost based on the cumulative output. Such a relationship is captured by raising the accumulated output stock to the power of a negative learning elasticity parameter, and a parameter used to normalize the shape of the curve at the initial unit cost [13]. The use of learning curves for forecasting costs has to be on a case by case basis but addressing their limitations (e.g. the presence of omitted variable bias and simultaneity of factors influencing learning, as well as the treatment of the associated use of data) [5, 42]. For the specific case of green technology expansion, probabilistic forecasts are a response to criticisms and provide reliable estimates of future costs within uncertain ranges [15, 28].

The logic of learning by doing can be extended by assuming that technology diffusion happens in at least two phases: (i) an R&D phase where cost reduction can decrease due to research and development with limited application of technology, and (ii) gradual deployment of technology, characterized by output generation and driven by learning by doing [41, 65]. Account for both phases by using a two-factor learning curve, where the decrease in cost is dominated by R&D investment at the start, and from learning by doing during technology diffusion. Such an approach is helpful to find inflection points between the two phases as theorized by [10].

2.2.3. Spillover effects

The innovation literature includes the modelling of spillover effects from the knowledge of capital stock in different ways [62] consider spillovers in two ways: (i) every firm creates new knowledge by relying on the accumulation of knowledge from all other firms in the sector, and (ii) the share of returns on innovation is higher with the amount of firms that innovate in the same sector [61] consider spillovers across regions by creating an international knowledge stock, and assuming that the innovation in every region contributes to the accumulation of that international knowledge, allowing for the same stock to spillover towards every other region. Both papers imply that the inclusion of spillover can have a higher rate of innovation diffusion in comparison to not including spillovers. Other work considers the role of spillovers at the technology level [66, 67].

2.2.4. Changes in elasticities of substitution

The literature also suggests ways to model efficiency as the impact of a model on a production function [52]. The logic behind these consists of a variation in elasticities starting from a constant elasticity of substitution (CES) production function. The standard CES function implies that full production at a given capacity can be achieved only when input factors to production remain at a fixed proportion among each other [52]. Assumes that these elasticities can change due to innovation, thus shifting the demand for input factors towards a low (or high) carbon economy. For example, electricity generation from green technology can be expanded against fossil fuels, leading to a change in demand towards the renewables sector, and pushing the system towards a new energy mix.

2.3. Induced innovation in low-carbon technologies

The literature on induced innovation for a low-carbon economy recognizes that EnTC can be applied to both high-carbon and low-carbon technologies. For example [55], shows that a technology choice towards green energy remains a more important factor for decarbonizing the US economy than innovating fossil fuel energy sources. In fact [55], 'R&DICE' extend the standard DICE model by integrating the treatment of R&D accumulation for high carbon industries (i.e. decreasing carbon intensity of fossil fuel sector, rather than increasing productivity of the low-carbon energy sectors) [68]. The study shows that the application of induced innovation with the aim of decarbonizing high carbon industries would remain ineffective in comparison with the substitution of high carbon with low carbon technology. As a further extension to that [6, 56, 69], combine the two approaches: they demonstrate that induced innovation for green sectors can support substitution of high carbon with low carbon technologies by increasing cost competitiveness and technology productivity of the green technology.

All the models analysed for this paper give a stronger emphasis on the second approach to modelling energy transition, that is to apply the modelling of induced innovation in the green energy sector, and aim to support system transition via testing policies that make green technology more competitive and help unlocking the economy from the high carbon sector.

2.4. Complexity features and uncertainty require risk-opportunity analysis (ROA)

Meckling *et al* [70] show the extent to which different countries are investing by funding and adapting their institutions to support their energy innovation efforts for decarbonisation. Such a transformation brings uncertainties, that models of induced innovation explore by means of introducing complexity features in their models. Koomey *et al* [71] refers to complexity features in models of induced innovation as increasing returns to scale [72–74], learning curves [10, 40, 58], the results of wider non-linear effects that are dependent on innovation spillovers and network effects [28, 75, 76]. All of these complex features in models generate path dependency, so that past decisions impact the future of a system, locking it in into specific (often undesirable) paths [6, 8, 74]. This indicates that the understanding of dynamic effectiveness of climate policies should be given priority to static efficiency [77].

Mercure *et al* [46] argues that the economy is in a state of non-equilibrium and should be modelled with complex systems tools appropriate for those dynamics. This includes a key role for inertia. Models should have these fundamentals to be useful for policy. They develop the ROA as a policy appraisal approach that relies on the understanding of such complex modelling features, while embracing fundamental uncertainty at its core [78, 79]. ROA relies on the principle that policy analysis of transformative change (such as those of energy and climate transition) should use systems mapping (see [80]) and dynamic non-equilibrium models (examples available in [26]) to assess future risks and opportunities instead of costs and benefits [46, 81]. Often rely on innovation as a core component of models that can trigger positive tipping points for the transformation of the economy. As tipping points are driven by self-reinforcing loops that cause non-linear change [18, 21, 48], these can lead to either risks or opportunities, with both positive and negative results [77]. It is by modelling these self-reinforcing feedbacks that models of energy transition show acceleration in the pace of low-carbon transition, i.e. when these feedbacks reach a certain level of strength, tipping points appear in the system in the form of non-linear change that trigger system transformation. For these reasons, dynamic models should rely on systems mapping as a powerful instrument to navigate complex systems and uncover powerful feedback dynamics that can trigger tipping points (either positive or negative) [46, 81].

3. Methodology

The literature review in the previous section was performed to set up the context and theory for modelling induced innovation. The review covers three aspects of induced innovation: (i) the distinction between 'narrow' and 'systemic' approaches to modelling innovation, (ii) defining what variables drive induced innovation in models, and (iii) an exploration of the complexity features of models required for modelling innovation. Based on that, this paper uses a methodology with three steps.

First, a survey questionnaire was developed by three authors of this paper (Dr Cristina Peñasco, Dr Sarah Hafner, Prof Laura Díaz Anadón) to develop an understanding of how models can be used to inform policy making. To address this, every model (or analytical tool) developed (or used) by the partner institutions in the EEIST programme was considered as input to the model assessment with the survey questionnaire. The final sample of analytical tools included 24 policy-oriented models (including economic, energy and agricultural models) that were used in the EEIST programme to provide evidence on how different models account for innovation in their structures. The survey questionnaire was designed to explore the representation of technological change, innovation, competitiveness and decarbonisation policies in modelling tools. The questionnaire was composed of five sections. The first section collected descriptive information of the models, while the following four sections delved into the details of the models. The second section (which defines the content of this paper) focused on the mechanisms adopted to capture technological aspects. The other sections focused on the description of the coverage of the most commonly implemented innovation, climate and decarbonisation policy instruments (see [44]), how these impact key competitiveness and innovation indicators, and how complexity features of models are represented in relation to the energy transition.

The survey was distributed to the participating modelling teams as an electronic questionnaire via email and followed up with clarifying questions with the lead modellers when needed. The collected information was compared with the available literature linked to these models for assessing the consistency of the information received. A total of 16 questionnaires were returned to the analysis team between October 2020 and April 2021, i.e. Agrilove, Balmorel, C-GEM China, DSK, E3ME-FTT, EPS

Table 1. List of EEIST programme's models from partners and their modelling approach.

Model name	Method	Key references
AgriLOVE	Agent based model	[82]
Balmorel	Partial equilibrium	[83]
C-GEM China, C-REM	General equilibrium model (closed economy)	[84, 85]
CPT-ABM	Agent based model	[27]
DCIM	Microsimulation	[86, 87]
DSK	Agent based model	[34, 35, 88–91]
E3ME	Macro-econometrics	[29, 60]
FTT	System dynamics	[59]
EPS India 2.1.2	System dynamics; input output	[92]
ERRE	System dynamics	[93, 94]
GCI, GAP, GCP	Data driven network model	[95]
GEM	System dynamics	[96]
GIBM	System dynamics	[97–99]
Stochastic experience curves (SEC)	Probabilistic data driven	[28, 100]
IPAC/Tech China	Programming least cost	[101]
Real exit option analysis (REOA)	Data driven	[102, 103]
M3-E3	Agent based model	[104, 105]
OccMob	Agent-based model, input output model	[106]
SDG-ETN	Network model	[107, 108]
SD-IOM	Input-output model	[109]
TeFE ABM	Agent based model	[110]
TERI CGE	General equilibrium model	[111]
TERI MARKAL	Partial equilibrium	[112]
TFR disaggr	Partial equilibrium	[113]

India, ERRE, GEM, green investment barriers mode (GIBM), stochastic **e**xperience **c**urves (SEC), IPAC, REOA, Tefe, Teri Markal, Teri CGE, TFR. As new modelling tools were developed during the EEIST programme, the lead modellers of seven additional models i.e. CPT-agent-based model (ABM), DCIM, GCI-GAP-GCP, micro-macro-model of economy-energy-environment (M3-E3), OccMob, SDG-ETN, SD-IOM; were asked to fill in questionnaires between August and October 2022. The analysis included in this paper relies on information from the first two sections of the survey, i.e. the general description of the models and the representation of technological change. This paper focuses on the question '*Does your model or analysis tool account for technological change in each sector or in general?*'. Table 1 shows the list of models by the model's name, the modelling approach, and the key references (see appendix B for the content of the questionnaire used in this paper). Other two papers that focus on the policy implications of models on innovation and competitiveness (led by Dr Sergey Kolesnikov) and implication of represented complexity features in these models (led by Dr Roberto Pasqualino) are under development.

Third, adapted from [26] and enriched with further literature on peer-reviewed published work, we propose a typology to differentiate classes of models in representing induced innovation. The survey allowed us to identify the models that consider induced innovation in their structures in conjunction with the modelling case study application as proposed in [26]. These models are analysed in detail to explain how induced innovation can be modelled with different methods.

The results from the literature and the insights from the modelling case studies are used to construct a decision tree linked to the typology of models with the goal of providing a guide for users in the modelling of induced innovation alongside IPCC-IAMs.

4. Survey of models results

Table 2 shows the information collected from the modelling survey in relation to how the different models of the EEIST programme account for technological change in their structure. Among the 24 models considered, 3 models do not consider technological change (neither ExTC nor EnTC) as part of the industrial, energy generation and transport sectors. This may be due to either the modelling choices around system boundaries—e.g. the Agrilove model is applied to the agriculture sector only [82]—, or simply due to a different focus in the method that does not require to model innovation—e.g. GCI is a static representation of green complexity based on historical data, and does not need to capture the dynamic representation of innovation by construction [95].[14]

[14] It is worth noting that the models of GCI [95] and SDG-ETN [108] are quantitative modelling approaches that can be considered under the umbrella of systems mapping methods. Other qualitative systems mapping work performed in the EEIST program used as a mean for developing participatory engagement work and that could not be included in the survey, as not linked to a numerical model, can be found in [27].

Table 2. Modelling induced innovation in the energy and transport sectors from the EEIST programme survey. Only 6 models out of 24 include induced innovation in their formulations.

Model	Energy end-use in transport, industry and buildings	Energy generation, including power, heat, and fuels
AgriLOVE	Not represented.	Not represented.
Balmorel	Exogenously (introducing cost declines over time)	Exogenously (introducing cost declines over time)
C-GEM China, C-REM	Changes in the elasticity of substitution[15]	Not represented.
CPT-ABM	Exogenously (introducing cost declines over time) e.g. by forecasted cost declines over time	Exogenously (introducing cost declines over time) e.g. by forecasted cost declines over time
DCIM	Exogenously (introducing cost declines over time or by changing the lifetime of existing coal plants)	Exogenously (introducing cost declines over time or by changing the lifetime of existing coal plants)
DSK	Spillover effects from other industries on (technology) costs Direct modelling of R&D processes.	Direct modelling of R&D processes.
E3ME	R&D processes Spillovers between technologies are considered	R&D processes. Spillovers between technologies are considered
FTT	Learning curves for technology/service cost. Spillovers within sectors are considered.	Learning curves for technology/service cost. Spillovers within sectors are considered.
EPS India 2.1.2	Exogenously (introducing cost declines over time)	Exogenously (introducing cost declines over time)
ERRE	Exogenously (introducing cost declines over time) Changes in the elasticity of substitution[15]	Exogenously (introducing cost declines over time Changes in the elasticity of substitution[15]
GCI, GAP, GCP	Not represented.	Not represented.
GEM	Exogenously (introducing cost declines over time) Changes in the elasticity of substitution[15]	Not represented.
GIBM	Not represented.	Exogenously (introducing cost declines over time) Learning curves in the electricity sector
Stochastic experience curves (SEC)	Learning curves for technology/service cost	Learning curves for technology/service cost
IPAC China	Learning curves for technology/service cost[15] Spillover effects from other industries on (technology) costs[15]	Learning curves for technology/service cost[15] Spillover effects from other industries on (technology) costs[15]
Real Exit Option Analysis model	Not represented.	Not represented.
M3-E3	Spillover effects via firm-to-firm imitation Direct R&D processes.	Spillover effects via firm-to-firm imitation Direct R&D processes.
OccMob model	Not represented.	Exogenously (introducing cost declines over time)
SDG-ETN	Exogenously (introducing cost declines over time)	Exogenously (introducing cost declines over time)
SD-IOM	Exogenously (changes in mix of energy production and use)	Exogenously (changes in mix of energy production and use)
TeFE ABM	Not represented	Learning curves for technology/service cost[15] Changes in the elasticity of substitution[15]
TERI CGE	Changes in the elasticity of substitution[15]	Changes in the elasticity of substitution[15]
TERI MARKAL	Exogenously (introducing cost declines over time)	Exogenously (introducing cost declines over time)
TFR disaggr	Exogenously (introducing cost declines over time)	Exogenously (introducing cost declines over time)

Note: Own elaboration with information collected in the survey questionnaire.

[15] The authors performed a validation of the information obtained through the survey by searching the literature linked with these models to confirm that the information collected from the survey were correct. When references could not be found, we assumed here that the model does not account for EnTC but only for an exogenous representation linked to the term indicated in the survey. The mismatch of information may be due either to early-stage work performed by the modellers that is not yet published, or by a misinterpretation of the terms used in the survey by the modellers filling the questionnaire. The subsequent analysis considers only the models which information provided could be confirmed via the literature check.

Out of 21 models that consider technological change, 12 models include ExTC, three of them in combination with EnTC representations. For the 12 models that account for EnTC from the supplied information in the survey—either in the form of change in elasticity of substitution (5 models), learning curves (5 models), R&D (3 models) or spillover effects (5 models) or combinations of representations—, a review of the published work was performed to explore how they include induced innovation. For the case study analysis, we only selected models for which a description of induced innovation was found in published literature. Only 6 models of the starting sample of 24 models were found to account for EnTC in published work either in the form of learning curves, R&D or spillover effects. This section provides a summary of the results obtained as represented in table 2.

4.1. ExTC

The 12 models that consider ExTC are: Balmorel, CPT-ABM, DCIM, EPS India, ERRE, GEM, GIBM, OCC-Mob, SDG-ETN, SD-IOM, TERI Markal, and TFR Disaggr. ERRE consider ExTC in combination with changes in elasticities of substitution [94], and GIBM in combination with learning curves for the electricity sector [97]. In these models, the rationale for modelling technological change as exogenous is that their stated goal is to test specific policies without obscuring findings with variables that have high uncertainty (see [114]). For example, the GEM model keeps technological change as a strategically important variable that must be kept exogenous to better appreciate the differences of technological variations [115]. A number of these models use the output of other models that capture dynamics of innovation as input. As a result, they take technological change as exogenous to their work. For example, the models CPT-ABM [27], OCC-Mob [106], SDG-ETN [108] use the output of the stochastic experience curve (SEC) model [28] as an input. Static models based on input-output analysis (i.e. TFR Disaggr and SD-IOM), consider technological change as implicit in the data they use, leading to excluding an explicit representation of induced innovation formulation from their models [109].

The TERI Markal model works on cost-optimum principles and is used for the study of least-cost energy mixes in specific countries [116]. Balmorel is a partial equilibrium model of electricity and heat consumers' marginal utilities and producers' marginal costs and is applied to different geographies [117]. Both models rely on ExTC due to the inherent assumption embedded in their models that would make optimization and recursive equilibrium not possible based on their formulation. Dynamic models such as EPS, ERRE, GIBM, simply focus on the dynamics of wider system behaviour (country-level in India, global, and country-level in UK respectively) answering policy questions that do not require to delve into the details of EnTC [92, 94, 97]. For most of these cases, the reasoning behind keeping technology as exogenous is the simplicity of communicating results against highly uncertain conditions that could break their argument, or simply not being the key focus of the model.

4.2. Modelling learning curves

Five models use learning curves and endogenous technology change. These are SEC [28], FTT [59], GIBM [97], IPAC and TEFE (no reference available to support these latter models). SEC extrapolates carefully verified learning rates and assesses stochastic probability distributions for more than 50 green technologies, and relies on the high quality of its input data to model expectations about technology costs into the future [28]. Technology cost forecasting research shows that, to date, model-based approaches for generating probabilistic forecasts surpass and differ from expert-based approaches [118]. FTT includes learning curves dynamically by closing the feedback loop between capacity accumulation and cost reduction. As a result, FTT provides a simplified model for endogenous technology modelling and uses this as a main driver dominating the behaviour of the model [59]. GIBM accounts for endogenous global representation of learning curves and their domestic representation with impact on the UK economy. The model implies learning rates are not central to addressing the financial gap of the green economy in the available publications [97]. No available publications on the modelling of learning curves in Tefe and IPAC support this evidence to date.

4.3. R&D processes

The direct modelling of R&D processes is captured in the E3ME [29, 60], ME-E3 [104, 119] and DSK [35] models. On the one hand, E3ME models R&D by an accumulation of investments which can influence the energy demand (country specific, e.g. the public investments in a country generate R&D accumulation) by means of elasticities [29, 60]. On the other hand, ME-E3 and DSK follow a common method, as both rely on the methodology proposed in [120]. They represent R&D investments as generating new products with their own markets. The aggregation of those products can give rise to emergent behaviours, such as learning curves and general technology cost decline over time [35, 119].

4.4. Spillover effects

The very same models that include the modelling of R&D are also the models that consider spillover effects in their dynamics. Differently from the other approaches to modelling technology change, spillovers require a source for technology development (either learning curves, R&D processes, or even exogenous), and use that to model knowledge transfer behaviour across companies or entire sectors. For example, DSK and ME-E3 assume that one company can imitate another company that has invested in R&D, thus imitating their product and increasing their competitiveness [35, 104, 119]. E3ME assumes that knowledge from R&D investments can spill over between sectors and countries [60]. This is similar to DSK, implicitly assuming they benefitted from an investment from another sector. FTT assumes similar technologies within a sector contribute to learning in their formulation of learning curves. No published evidence could be found to confirm how spillover effects are considered in the IPAC model.

4.5. Change in elasticities

Five models state they include change in the elasticities of substitution. However, none of them provide existing publications that show how this is done based on the inputs to the production functions as in the formulation described in [52]. The models of C-GEM China [121], GEM [96], TERI CGE [111], ERRE [94] use a CES production function, but there is no published evidence of these models testing the efficiency of innovation via changes in the elasticities of substitution. No publication on the TEFE model is available to date to assess the information provided.

4.6. Selection of models to inform the typology

Due to the description above, only six models are found to provide documented and realistic representations of induced innovation in peer-reviewed research among the EEIST models. These are SEC [28]—a model based on Wright's and Moore's law to assess the probabilistic outcomes of experience curves on different models; the GIBM [97]—a system dynamics model of the UK electricity sector integrated with public, households and financial sectors with partial representation of global learning curves created to support the UK energy transition; the FTT [59]—a sector specific system dynamics model which focuses on modelling the effects of learning curves and spillover effects between technologies as well as testing multiple policies to support technological transitions; the model E3ME [29, 60]—an econometric model built on input-output databases to give historical data validity to future scenarios and test policies including R&D investments and spillover effects across countries and economic sectors; the M3-E3 [119]—an ABM which focuses on the process of technology diffusion via R&D Investments and imitation (spillovers) among micro-founded heterogeneous agents to assess policies for energy efficiency and the effects on demand; and DSK [35]—an ABMs which extends the dynamics of innovation in M3-E3 to include private R&D investments and spillovers via imitation, but also accounting for a well-developed representation of the government, financial sector and a climate module with feedback on the economy.

Considering that the GIBM model provides a simplified representation of learning curves in comparison to FTT, and that the ME-E3 provides a simplified representation in comparison to DSK, the next section describes FTT and DSK as representative of the relative category of models. These four models form the base of the typology in line with the starting framework proposed by [26] and a review of published academic work as proposed in the following section.

5. A typology for models of induced innovation

A generic classification of modelling approaches for energy and climate policy is proposed in [26] by reporting the results of 15 modelling case studies applications as part of the EEIST programme. This section revisits such a classification in the context of modelling induced innovation. As the report by [26] is targeted to an audience of modelling practitioners and policy analysts (not necessarily academic), this review enriches the classification with additional literature as well as framing the terminology for an academic audience. All the models selected via the modelling questionnaire are described here in detail with regards to how they model induced innovation.

Figure 1 distinguishes models that give emphasis to the static analysis of data (data and static models) and models that formulate mathematical relationships around the dynamics of the system and analyse scenarios with simulations (simulation and dynamic models). The two-dimensional chart indicates the generic positive relationship existing between (i) the greater inclusion of dynamic assumptions in models against static data, and (ii) the greater flexibility that models can provide in exploring scenarios. This indicates that even those models that are categorized as static models, can gradually include dynamic assumptions in them (e.g. learning curves are based on dynamic theory of decreasing cost at increasing capacity) (see [28, 40, 65]) and the models that are categorized as dynamic embed data in their structure and must follow a meaningful validation procedures to compare model behaviours to data [34, 122]. When a modeller uses data and static models, the collection and analysis of data would be prioritized to the formulation of structural relationships. When a modeller uses simulation and dynamic models the logic would be reversed, thus prioritizing the formulation of causal interpretations of how systems work, and secondly compare (or calibrate) the resulting models' behaviours with data [26].

This section describes the selected categories in the context of modelling induced innovation. Appendix C in the supplementary material provides a detailed description of the selected case studies from

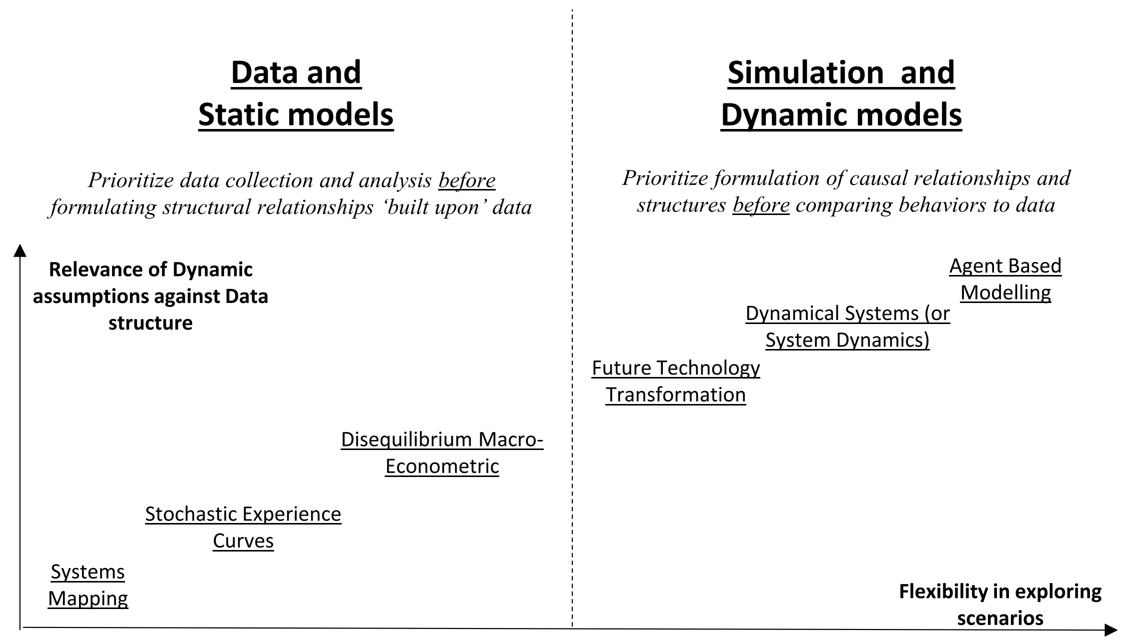

Figure 1. Generic representation of new economic modelling approaches by highlighting the balance between static and dynamic assumptions and the flexibility available to explore scenarios. Adapted from [26].

[26] around modelling of induced innovation and relative policy conclusions. These are system mapping [27], SECs [100], disequilibrium macro-econometric and FTT [30, 33], and ABM [123].

5.1. System mapping

System mapping is a powerful approach to complexity because it lowers the barrier of analytical thinking and helps decision makers frame problems around the key factors that matter in influencing behaviour of a system [46, 80]. Systems mapping is a broad term, used to describe many different things (e.g. see quantitative network approaches in [95, 108] or building systems mapping from interview with experts [124]). In this section we refer to systems mapping as the use of diagrams which describe the causal relations between factors, or variables, in a system of interest. This takes the shape of relational data connected among each other in the form of diagrams, or exists only as individuals' unexpressed mental models [80, 125, 126].

Specifically we focus on system mapping as used in the case study proposed in [27]. The case study exploits using system mapping as a means for building group understanding by combining analysis of literature review and participatory modelling for assessing differences between carbon tax and emission trading schemes policies and how they influence the dynamics of innovation in China. The case study aims to achieve two objectives. On the one hand, it lays out the dynamics of relevance for modelling of induced innovation plainly while making these factors tangible for policymakers and promotes carbon tax as a more suitable policy than emissions trading schemes (ETS) for exploiting the benefits of innovation and accelerating the energy transition in China. On the other hand, it informs the structure of and further analysis by an (CPT-ABM).

The approach belongs to 'data and static models' as the dynamic assumption the map contains is conceptual, while representing the state of the system in each point in time.

5.2. SECs

Learning rates are a key component of broader system behaviour, and reflect many of the dynamics which are found across models of induced innovation [15, 40, 57, 127, 128]. They rely on the relationship which states that costs reduce as cumulative production increases, reflecting the basic idea that expending greater effort induces greater effects. From the policy perspective, the cost of technology represents one of the key sensitive intervention points that can be triggered to shape the energy transition [77].

The model in the case study [100] uses SECs, a method initially proposed in [28], and relying on the vast literature on learning-by-doing curves. The effects of learning on cost are based on Wright's and Moore's law [57, 127], and apply probabilistic methods to generate confidence intervals in the forecast by using statistically validated data on more than 50 technologies that are key to the green energy transition. While the general criticisms on the learning curves literature include being over optimistic on forecasting cost reduction [5], SEC analysis in [28, 100] demonstrates that many forecasts on technology cost that were given as exogenous input to IAMs and published in policy reports over the past decades had rather been too pessimistic, even by the highest cost range of the probabilistic curves proposed in SEC analysis. As a result, the authors argue that the forecasts of the model can serve as a basis for improving more complex models such as IAMs [100]. Despite being categorized in the static models in [26] (see figure 1), it relies on the dynamic theory of learning curves, and provides limited flexibility in generating scenarios by informing the forecast with parameters that show ranges within the stochastic distribution.

5.3. Disequilibrium macro-econometric

Disequilibrium macro-econometrics consists of the use of large datasets of time series about macroeconomic variables that are tied up among each other with econometric relationships, which means that econometric equations are used to link the objects that are modelled. These models are in disequilibrium by construction in the sense that the regression between variables must be informed and follow the historical trend. The choice and linkages between variables determine the theory they belong to. For example, the E3ME [22] and E3MG [29] rely on the post-Keynesian theory.

The way in which modelling of induced innovation is performed in E3ME was proposed by Barker *et al* [29] in the preceding model E3MG in line with R&D-induced innovation literature [13, 54, 56]. As a demand-driven model, it accounts for R&D investments that accumulate in a knowledge stock, which impacts energy demand and consumption [29]. In line with the post-Keynesian theory, E3ME and E3MG use a systems wide perspective based on input-output data at multi-country, multi sector scales. The wealth of scenarios that can be generated by E3ME is significant, including non-linear dynamics emerging from the interaction between variables, but the approach still remains anchored to data to generate forecasts, and is categorized as a static approach in [26].

5.4. FTT

The FTT suite of models was designed to improve the dynamic representation of innovation of E3ME for specific sectors [59], and often simulate in conjunction with E3ME for policy analysis (see [22, 129]). The sectors considered include power [59, 130], transport [129, 131], steel [31], household heating [132] and agriculture [133]. The case study proposed in [30] is one example of the use of the integrated E3ME-FTT model to analyse the power sector in different countries.

The E3ME-FTT case studies present the ability to test policy options (e.g. different levels of a subsidy to a particular technology) in comparison to the methods of Systems Mapping and SEC, while they require the formal use of mathematical equations to represent the dynamics of energy systems. FTT formally embeds the reinforcing feedback loops considered in the previous two case studies (i.e. the feedback between capacity installations and reduced costs), to explore dynamics of emergence and diffusion of technology in line with the systemic transition frameworks [39, 47]. With FTT, the policies can be targeted towards specific thresholds (e.g. cost parity between technologies) where the reinforcing loop of green technology development passes positive tipping points that lead to the exploration of transformative scenarios while remaining anchored to empirical data econometrics with E3ME [30–33, 134]. E3ME-FTT is at the threshold between static models (E3ME) and dynamic models (FTT), and these are therefore suggested at the centre of the framework proposed in [26].

5.5. Dynamical systems (or system dynamics)

Dynamical system models (DSM) are intended as time dependent differential equations models, where 'positive' (amplifying the dynamics of change) and 'negative' (offsetting the dynamics of change) feedback loops influence the behaviour of the system [135]. Depending on the internal dynamic assumptions included in a model, DSMs can be suitable for addressing non-linear change and the outcomes of passing thresholds and tipping points [16, 17, 136]. In [26], DSMs are represented as higher feedback order system models in comparison to the FTT suite of models, in the sense that the dynamics of interest can be influenced by both feedback loops that drive innovation (e.g. learning-by-doing) and others (e.g. ecological, climatic). In this sense, DSMs can be seen as a broader term including simpler models such as the FTT as well as many IPCC-IAMs. Although [26] includes one case study that uses the GIBM model (see [97, 137]), which is categorized as a DSM linked with induced innovation via the modelling survey explored in the previous section, the case does not focus on induced innovation as determinant for the output of the study. As a result, this section briefly describes the modelling of induced innovation in modern IPCC-IAMs using the WITCH model [36, 138] and the published modelling work relative to EEIST models with the E3ME-FTT-GENIE [22].

5.5.1. Dynamical systems in IPCC-IAMs

A recent review of the modelling of induced innovation is available in [6] which compares 27 IAMs based on the way in which they model induced innovation. The findings show that these IAMs include EnTC in different forms of learning curves and R&D investments, with the World Induced Technical Change Hybrid (WITCH) model emerging as a best in class in this area. The WITCH integrates bottom up technology learning-by-doing with top-down R&D investments [139], accounts for international R&D spillover effects [140], provides a distinction between the invention phase and technology diffusion [141], and integrates these with variable renewable energy technologies and storage [142]. The model uses a neo-classical structure with the Ramsey-type optimal growth model based on nested CES production function. It disaggregates the world in 13 regions and can be used to play non-cooperative Nash games based on key decision variables [36, 138–142]. As a result, the model is often used to explore optimal growth pathways within climate policy objectives, but lacks the exploration of environmental tipping points [21], and the heterogeneous representation of agents to explore wider feedback systems behaviour (e.g. interaction with the financial sector). Despite accounting for the dynamics of induced innovation, the fundamental assumptions of optimality (as intertemporal-growth model with optimal resource allocation) of the WITCH model significantly influence the overall output that the model can generate [138].

5.5.2. Dynamical systems for non-equilibrium IAM

An alternative was proposed by combining E3ME, FTT and the GENIE system model in disequilibrium and non-optimal setting. In particular GENIE consists of a millennial carbon cycle model [143], first built to account for feedbacks between an ocean-atmosphere-sea ice climate model, and energy moisture balance atmosphere and a dynamic and thermodynamic sea-ice model [144]. Additional modules were added including, a land surface physics and terrestrial carbon model [145], ocean biogeochemistry and marine sediments model [146, 147], and a land use change module to explore a scenario of CO_2 fertilization to plant-based systems [148]. When integrated into FTT and E3ME, these feedback loops (often positive and non-linear) can generate an impact on land productivity, and influence the agricultural sector of FTT, leading to change in energy demand, prices, and ultimately support (or oppose) innovation in the model. Examples can be found both in exploring policy mixes that can support a transition within climate targets [22], and the link between macroeconomy and stranded assets [149]. Mercure *et al* [149] also includes a comparison of model behaviour with WITCH and other IPCC-IAMs.

5.6. Agent based modelling (ABM)

Figure 1 represents ABMs at the extreme of the spectrum of complexity, in the sense that the core dynamics is no more determined by the deterministic structure of the differential equations that form the system (such as in DSMs), but by individual behaviours of heterogeneous agents, thus increasing the degrees of freedom that allows for a deeper exploration of system complexity at the cost of computational complexity. The agents are modelled to interact with each other and with their environment without the need for a fixed pre-determined structure [150]. Because of this, complex behaviours, such as clustering effects between agents, can emerge from the interactions, leading to the study of induced innovation from new perspectives in comparison to the previous studies classified as FTT or DSMs.

Despite the flexibility of the approach, only two studies that directly investigate induced innovation with ABMs are available in the literature. Hötte [151] extends the EURACE ABM to explore path dependency in the dynamics of different diffusion curves based on learning by doing and R&D investments while testing policies (change in value added tax, subsidies on consumption and green technology) that act as barriers that can foster or hinder the diffusion of green technologies. Wei *et al* [152] use ABM to explore different ETS settings in China, and how these can promote the uptake of green technologies via diffusing innovation. Other ABMs also include induced innovation in their structures, even if these have not been directly mentioned in existing publications. Among those we find the DSK model [35, 89] that is used in the case study considered in this section [123]. Despite the advantages in terms of flexibility, ABMs present the drawback of often requiring significantly more computational power and data in comparison to the other approaches proposed in figure 1. As a result they might be difficult and time consuming to develop [26].

The DSK case study focuses on the interaction between an innovation-led private sector and public policies that can trigger to financial instability at the macro-economic level [123]. The DSK is considered by the authors as the first integrated assessment ABM [89]. It is a hybrid DSM-ABM model due to the inclusion of (i) the climate module (in line with DSM principles) initially conceived in [153], and (ii) the technological diffusion processes modelled with heterogeneous agents as described in [120, 154, 155]. These models are well known for the modelling of creative destruction theories based on [156] while embedding uncertainty in decision making of economic agents based on [157]. The technology diffusion focuses on the modelling of R&D investments that accumulates and increases competitiveness of firms, as well as imitation (or spillovers) of technologies between firms. In so doing, the model can reproduce a number of stylized facts triggered by overpassing both positive (expansion) and negative (market collapse) tipping points that emerge from the interaction between agents. Policies (mainly subsidies and carbon taxes) are demonstrated to break lock-ins in high carbon technology by acting in innovation clusters, and support green technology from niche to regime [38], as well as acting at different levels in the innovation process [39]. The model shows that by doing so, the economic stability can be preserved at lower economic cost [35]. For a detailed description of how innovation is modelled in the DSK see Appendix C. Several techniques used to validate and test the DSK model with data are proposed in Appendix D of the supplementary material.

5.7. Summary

Table 3 summarizes the insights from the models used in the case studies.

6. A menu of options for modelling induced innovation

IPCC-IAMs can model induced innovation in different ways [6, 36, 142], but still present limitations in terms of their assumptions around equilibrium and optimality which might hinder the results obtained [20, 138]. This section builds on the modelling typology to provide a set of different options in complement to IPCC-IAMs to help capturing the dynamics of innovation, potentially leading to different policy results in contrast to the former. This is represented as a flow-chart that helps guiding modellers and policy analysis in the choice of models depending on their policy question. Figure 2 shows the typology and decision tree proposed in this paper. For simplicity, we start this process by taking the perspective of an analyst who discovers that the system they aim at understanding presents out-of-sample non-linear behaviours, and they believe that the explanation for these effects lies in the dynamics of innovation.

6.1. Question 1: do you analyse the system by means of static models to build upon data, or dynamic models to compare with data?

The first question imposes a methodological choice between models that can be categorized as 'Data and Static models' and those that are 'Simulation and Dynamic' models.

In the 'static models' category, the approach gives priority to the deep analysis of existing data (both numerical and relational), including choices of what data to use, how to use it, and how to relate them to each other. In this group we include Systems Mapping (using qualitative understanding of systems), SECs (narrow approach to learning curves and probabilistic forecasts), and disequilibrium macro-econometrics (seeking the cascade of impact of R&D and spillovers across sectors and countries, e.g. E3ME) (see questions 2.1 and 2.2 for further details).

In the 'dynamic models' category, the focus starts from the formulation of causal interpretations and theories that form the model. These involve that the understanding of relationships in the system backed up by empirical data analysis support the modelling these relationships in dynamic terms. In fact, modellers in this group can validate these relationships either by using data analysis, or a number of qualitative techniques, including interviews, surveys and exploit academic theories. This category includes 'FTT' (using dynamic learning curves and spillovers to transform the economy, e.g. FTT), dynamical systems (extended framework that includes IAMs), and ABMs (modelling innovation both via public spending and firm-to-firm imitation, e.g. DSK) (see Questions 3.1 and 3.2 for further details).

6.2. Data models and analysis

6.2.1. Question 2.1: is there enough confidence in systems understanding to guide the static analysis of numerical data?

Either in explicit (causal loop diagrams or networks) or implicit (mental models) form, systems mapping is the core component for guiding every modelling effort, both in informing static data analysis and dynamic simulations. If high confidence in the understanding of a system is not achieved, neither dynamic or static data analysis can be performed, leading to starting exploring a system using systems mapping.

A good example of this can be found in [40] for the study of learning curves. By providing a deep analysis of learning curve based on historical data on costs, they infer conclusions spanning across several systemic aspects of the energy transition, including implications on the stages of development of technologies, required investments in R&D, transition dynamics and technology substitution among others. As a result, the insights gathered from the analysis of learning curves can go way beyond the parts that compose the model (mainly costs and capacity) thanks to keeping a system perspective on the analysis of learning curves [39]. In this case system mapping can be seen as a tool to explore the system on its whole to inform deeper analysis with existing numerical data.

System mapping can also follow quantitative techniques, as those used to form the basic structure of the E3ME model. The mapping of relationships composing E3ME is formed with a mix between theoretical (post-Keynesian theory), and data driven co-integration techniques [158]. This allows to link variables among each other and compute the econometric estimate of future forecasts [60].

From the perspective of dynamic and ABMs, they can be seen as 'living system maps'. In fact, every model of this kind starts being formed from a map of relationships across variables, and is formalized via equations and behavioural rules, ultimately generating insights via simulation. For details of how system mapping can be used to form basics of dynamic and ABMs see [80].

The case study on systems mapping proposed in [27] described in section 5 shows how the approach can also work as a stand-alone application in the context of informing policy for understanding the dynamics of induced innovation linked with ETS schemes and carbon taxes. In the same way, the system mapping method can be seen as the first step stone for sharing understanding between multiple-stakeholders, learn from them, and channel those insights for developing every other quantitative model, either static or dynamic.

Table 3. Summary of model case studies and literature and contribution to the typology. Source: adapted from [26].

Broad category	Category as in [26]	Considered case study in [26]	Considered case from the literature	Key features in relation to innovation in the case study	Properties of models in capturing tipping points via innovation	Policy or research question	Main findings
Data and static models	Systems mapping	[27]	—	Understanding the causal interpretation of learning by doing.	Only conceptually.	What is the most cost-effective form of carbon pricing in China?	Carbon tax can provide better performance than ETS as supports the reinforcing feedback of learning by doing
	Stochastic experience curves—SEC	[100]	[28]	Static learning curves based on wright's law and data.	Captures potential exponential drops in technology costs	How much will energy transition cost?	The energy transition is likely to save the global economy trillions of US dollars and the savings are greater if the transition happens quickly.
	Disequilibrium macro-econometric—E3ME and E3MG	—	[29]	R&D and spillovers to influence demand and supply of resources governed via input-output and econometric relationships.	Innovation network effects transferred in international trade via input-output database leading to technology substitution.	What is the impact of policies that induce R&D accumulation on atmospheric concentration of CO2 in the long term?	Technological progress can partially explain long-run growth in global GDP. Selected average permit prices and tax rates can support stabilizing atmospheric concentrations at 450 ppm C02 after 2100, while stimulating economic growth.

(Continued.)

Table 3. (Continued.)

Broad category	Category as in [26]	Considered case study in [26]	Considered case from the literature	Key features in relation to innovation in the case study	Properties of models in capturing tipping points via innovation	Policy or research question	Main findings
Simulation and dynamic models	Future technology transformation—FTT	[33]	[32]	Dynamic learning curves based on Lotka-Volterra replicator function applied to the road transport sector	Positive tipping points driven by innovation near the threshold of cost-parity between different technologies.	Which policies, individually and in combination, are most effective in driving the transition to electric vehicles?	Combination between EV subsidies and regulations can support EVs to achieve the tipping point cost-parity with ICEVs and accelerate the transition in the transport sector.
		[30]	[59]	Dynamic learning curves based on Lotka-Volterra replicator function applied to the power sector	Positive tipping points driven by innovation near the threshold of cost-parity between different technologies.	How can barriers to variable renewable energy uptake markets affect electricity prices in future power systems?	Overcoming barriers to variable renewable energy (VRE) uptake likely leads to further electricity price reductions regardless of pricing mechanisms.
	Dynamics systems modelling—E3ME-FTT-GENIE	—	[149]	Dynamic learning curves (FTT) R&D and spillovers (E3ME)	Combined effects of E3ME and FTT (see above) linked with climate ecological tipping points with GENIE.	What are the expectations for stranded fossil fuel assets in the near future and consequences for policy makers and global economy?	Stranded fossil fuel assets (i) are to occur as a result of the ongoing energy transition, (ii) can expand due to climate policies (iii) with inequal distributional consequences among countries, and (iv) limited impact on economic growth while expanding low-carbon sector assets.
	Agent-dased modelling DSK	[123]	[35]	R&D and spillovers diffused across firms via imitation between agents and creative destruction via new products that disrupt markets.	Both positive and negative tipping points emerging form the agent-to-agent interaction including clustering properties and non-linear technological diffusion.	Which climate policy packages can sustain the energy transition without destabilising the economic system and the public budget?	A mix of fossil fuel ban, public construction subsidies and electrification standards policies can reduce environmental impact while maintaining macro-financial stability and support economic growth.

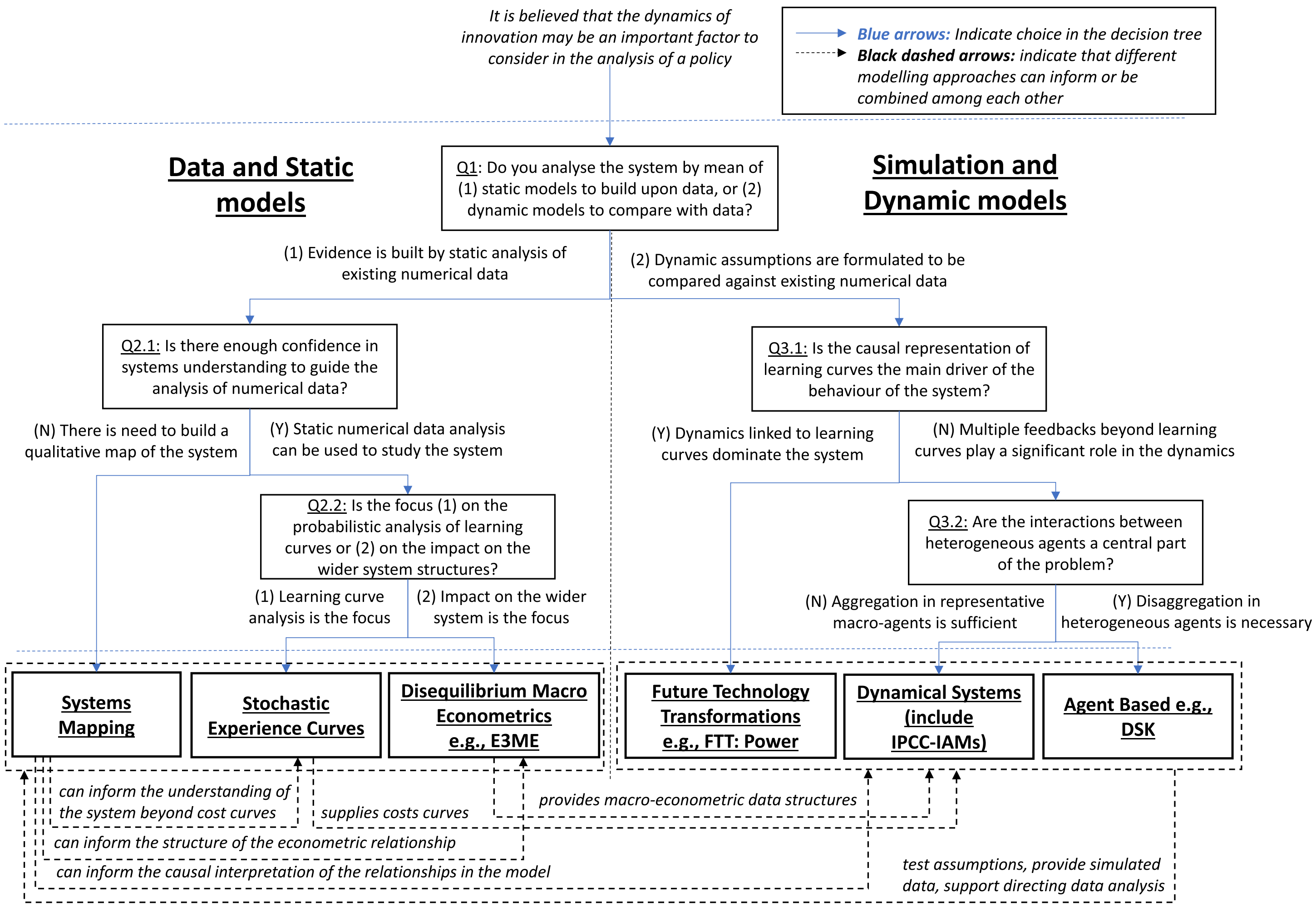

Figure 2. Typology and decision tree for informing climate policy analysis with models of induced innovation. Blue arrows indicate the choice between modelling approaches, and black dashed arrows indicate that different modelling types can be used to inform each other or even be combined.

6.2.2. Question 2.2: is the focus of the analysis the probabilistic analysis of learning curves or the impact on wider system structures?

In the context of static models linked with the modelling of induced innovation, the set of models considered divides between the narrow approach of learning curves, and the systemic approach of exploring distributional effects linked with R&D and spillover effects across the global economy.

The case study proposed in [100] and documented in [28] contributes to the literature on learning curves both (i) by focusing the study on specific technologies that are key for the green transition from 1979 to 2021, and (ii) by forming probabilistic distributions on the future of those data. The general conclusion is powerful by using a simple concept (cost decreases with capacity development) to infer implications for speeding up investments in green transition. The model is 'clean' of unnecessary complex feedback loops that could impede a clear communication of the main message, and can help informing any type of dynamic models that keep costs as exogenous with reliable forecasts on technology costs, including IPCC-IAMs or other dynamic models.

Looking at the system level, the disequilibrium macro-econometric approach (represented here by the E3ME and E3MG models) includes both R&D and spillover effects and distributes its effects thanks for the system network captured by the econometric relationships and data that form the model [29]. In comparison to IPCC-IAMs the model provides a reliable and validated data structure to help testing policies that link with the macro-economy and increase its strengths when integrated with other models, such as the FTT and GENIE.

6.3. Dynamic and simulation models

6.3.1. Question 3.1: is the causal interpretation of the dynamics of learning curves the main driver of the behaviour of the system?

The dynamic interpretation of the dynamics of learning curves is crucial in the FTT suite of models. FTT is driven by the understanding that the self-reinforcing mechanisms describing innovation via learning curves can stimulate investment decisions toward a low-carbon energy supply and products. By mimicking the characteristics of a socio-technical transition framework, the model can be calibrated between niche and regime level of technology diffusion [38, 47, 159]. Starting in proximity to cost-parity between technologies (e.g. same cost between solar and gas, or electric vehicles and internal combustion), it supports the testing a number of policies (e.g. subsidies, feed in tariffs) to push green technology below cost-parity and let the market pull the technological transition at lower costs for policy. When integrated with E3ME, the FTT can support understanding the analysis of energy transition and its influence on economic variables (e.g. employment, GDP, inflation) that are calibrated across countries and sectors in the global economy. In a similar way it can be integrated with the GENIE model, thus forming a fully functioning IAM that works on principles of disequilibrium and path dependency instead of optimization and equilibrium [22, 149].

6.3.2. Question 3.2: are the interactions between heterogenous agents a central part of the problem?

The distinction between ABMs, as formed by heterogenous agents interacting from a bottom-up perspective to the macro-economy, and DSMs, which adopts a macro-level perspective on structurally deterministic variables, is well established in the literature [160, 161][16]. As a result, if the heterogeneous characteristics of agents would not be important to model a system, the use of dynamic IAMs (e.g. E3ME-FTT-GENIE [149]) could be the choice. However, if the heterogeneity becomes essential, it would be necessary to use ABMs.

The DSK is an attempt to model induced innovation with R&D processes (product creation out of nothing due to investments and diffusion via market formation) and spillover effects (via technology imitation between firms), giving emphasis on the systemic approach [39], and by paying lower attention to the ability to generate precise forecasts on the behaviour of specific variables. Because of the heterogeneity linked with innovation that is captured in the model, DSK is suitable to explore both positive and negative tipping points in market formation as emerging form the dynamics of interaction between agents, including the effects of innovation clusters and competition in a free market economy [35]. As a result, this type of ABM represents the most comprehensive description of innovation processes among the models considered, at the cost of requiring sophisticated methodologies to compare the model with data (see appendix D).

7. Discussion

This paper provides a menu of options for modelling endogenous induced innovations alongside IAMs used in the IPCC (IPCC-IAMs) with models from the EEIST programme. This is done by forming a typology of models of induced innovation and supporting it with a decision tree that guides modellers and policy analysts in choosing the most appropriate model depending on the research questions that they need to address.

Induced innovation can be seen as a property of economic systems which emerges from the complex interactions of demand-pull forces, path-dependent and self-reinforcing processes, and

[16] The DSK belongs to the category of hybrid models, by including a SD representation of climate change based on [162] and a Schumpeterian induced innovation approach based on [88, 154].

general technology cost decline driven by the growth in cumulative output [8]. Literature on IPCC-IAMs demonstrates that modern climate models consider induced innovation endogenously and in different ways, including learning curves, R&D accumulation and spillover effects [6, 139, 142]. However, the reliance on the assumption of equilibrium in market clearing price mechanisms and optimization make them vulnerable to criticisms to address complex policy questions meaningfully [20, 24]. Alternative models of innovation that rely on assumptions of complex systems in out-of-equilibrium state, such as increasing marginal returns [91, 119], representation of innovation with learning curves [28, 59], R&D effects and spillovers [29, 35, 60], representation of financial and economic aspects [149] and heterogeneous boundedly rational agents [34] can provide insights to answer to the standard criticisms to IPCC-IAMs. The finding of this research can be summarized as follows.

First, only 25% of the models surveyed include some representation of EnTC (documented in academically published work) that is fundamental to test policies that induce innovation for a low-carbon energy transition. This may be due to a bias in modelling that implies that the modellers that keep innovation as exogenous (or do not account for innovation in modelling scenarios), do so for practical reasons, such as avoiding non-necessary complexity in their models that could make calibrations no more feasible, or a way more complicated and costly task [115, 116]. On the other hand, this may be due to the broader spectrum of models employed in a global project involving China, India and Brazil. In fact, most of the models of induced innovation assessed in IPCC are representative of European institutions [6, 20].

Second, system mapping emerges as a key approach to modelling and engagement that can be used both as means to influence policy on its own [27] (on the qualitative comparison between ETS and carbon tax scenarios linked with the dynamics of innovation) and as a channel to develop models from scratches [80]. As a result, if a model does not account for induced innovation in their structure, system mapping can be the point to start from to update that model.

Third, the different ways of modelling induced innovation seen in the literature (e.g. learning curves, R&D, or spillovers [13]) may imply a choice of methods that focus on narrow or systemic approaches to modelling innovation. For example, the modelling of learning curves can be represented in both static one factor (e.g. [40]), multi-factor (inclusive of R&D) [41, 65], probabilistic [28], and dynamic [59] approaches. In so doing, the models that rely on experience curves, also give a strong emphasis on the historical data, and use this as an anchor to develop deeper insights for the dynamics of the energy transition. On the other hand, and for the cases considered in this study, the modelling of spillovers requires the presence of multiple agents connected among each other in networks. This is the case for the E3ME by using econometric equations in an input-output economic database [60, 149], and in the DKS and M3 $\times$ 10^3 models using a system of imitation between firms that imitate the performance of technologies from each other [35, 119]. Among the models considered, R&D was applied only to the models that include a government and an economy explicitly, resulting in being a strong link with spillovers [35, 60]. This result seems to indicate that the type of innovation one wants to analyse might require a clear choice of solution method to employ.

Fourth, from the perspective of use for policy change, the models proposed in this review can be considered complementary to each other. All the models considered are designed to address different policy questions linked with innovation and how innovation impacts the energy transition. In general, these models tend to agree that the proper inclusion of innovation in models can generate better results in terms of smooth transition to the green economy, such as lower cost [28, 59, 131], improved financial stability and economic growth [91, 149]. In addition, by extending the IPCC-IAM with more detailed representations of economic system, these models can be used both alongside the other IPCC-IAM models or as IAMs of their own kind [22, 89].

Fifth, static and dynamic models can be integrated among each other meaningfully. This can be the case by the using of validated forecasts with [28] which may be given as input to IPCC-IAMs and other dynamic models, or by opting for a full system integration between the dynamic FTT model which focuses on learning curves, and the systemic econometric E3ME model that relies on the wider picture [149]. It is worth noting that while the models move from static to dynamic (left to right in the typology), also the uncertainty approached with these models increases. For example, the DSK can be used to test highly uncertain scenarios that link to how policies (e.g. subsidies or carbon taxes) can impact economic instability and cycles, and these dynamics can be further used to infer further analysis using static approaches to historical data [91].

Sixth, all of the findings above are consistent with the implementation of the ROA as a policy appraisal method [46, 81] instead of the CBA, which is more common to IPCC-IAMs [20]. ROA is a broader concept that relies on dynamic modelling and system mapping to uncover the complexity of a system and provide meaningful policy advice. As a result, the static models can be more suitable for mapping a system or uncovering the dynamics of specific aspects of the transition (e.g. the experience curves) while giving empirical evidence coming from numerical data.

These can be used as a means to inform the analysis with dynamic models that can address wider uncertainties in future scenarios based on policy inputs.

The results from the survey unveil a concerning result about the modelling of induced innovation in the EEIST programme partner countries (China, India and Brazil) that are meant to play a significant role in the global energy transition. The modelling community in those countries currently possesses limited capabilities in embedding the dynamics of innovation in their models. Of the six models that include technological change endogenously, only one considers the dynamics of endogenous innovation (M3-E3 model from Brazil) [119]. If the dynamics of induced innovation truly matters in the acceleration of energy transition across the world, more work on embedding its dynamics is necessary in these countries to speed up the progress towards a greener economy. Learning how to update models to include dynamics of induced innovation should be accelerated as well. For example, the E3ME-FTT is regularly applied to the modelling of the energy transition in these economies [30, 32, 33, 149]. System mapping can be seen as a starting point for kicking off learning across the modellers operating in these economies, to extract the relevant structure from existing models of induced innovation and embed them in the models that still do not account for it.

This research presents a number of limitations, mainly linked to the analysis of only the models that were included in the EEIST programme. This may generate a statistical bias from the results of the survey and subsequent results of the modelling case studies considered. To offset this limitation, the typology and the flowchart was informed by the existing literature when necessary, and all of the case studies proposed from [26] were also represented by using academically grounded peer review studies linked with these case studies. Despite the limited set of models used to inform the typology (only four models of innovation) we feel that the results are robust to demonstrate the value of such a menu of options to support informing climate policy in the context of induced innovation alongside the IPCC-IAMs.

Because of these limitations, we suggest that future work should focus on increasing the number of case studies and relevant modelling literature that conform with the innovation typology proposed in this paper. The aim is to support a broader dissemination of applied systems thinking methodologies. In addition to this, we believe that the approach adopted to generate the typology and guide in the choice of the most relevant methods for addressing induced innovation in models can also be generalized into other domains. Static and dynamic models can be used to address problems in several domains of science, and we would invite other researchers to apply this approach to other fields beyond the study of innovation and policy for low-carbon energy transition. Finally, we would suggest to explore future work in methodological innovation and transparency of modelling results. By engaging in complexity science, there is demand for investing in improving calibration and validation of models, improve the quality of data, and invest in communication and visualization of model insights. Appendix D of this paper shows only the tip of the iceberg in relation to how the ABMs follow procedures for validations of their output.

The performed research demonstrates how a set of models of induced innovation for low-carbon energy transition included in the EEIST programme can be used to answer policy questions that extend the scope of typical IPCC-IAMs. This is proposed alongside the decision tree to help guiding modellers and policy analysis in the choice of the most relevant models to fulfil their needs for policy. This guide shows these models as complementary to IPCC-IAM in addressing wider scope policy questions. A new generation of IAMs is already developing as pioneered by some of the models included in this review (the FTT-E3ME-GENIE and DSK ABM IAMs).

8. Conclusion

This paper provides a menu of options for modellers and policy analysts to model induced innovation for the low-carbon energy transition alongside IAMs used by the IPCC (IPCC-IAMs) and using models from the EEIST programme. Despite the fact that modern IPCC-IAMs also account for modelling innovation endogenously, the inherent assumptions of equilibrium and optimality may generate non satisfactory results in the context of the low-carbon energy transition [20].

After a comprehensive literature review that captures the overarching theories and methods to model induced innovation, we provide empirical evidence on how the EEIST models consider induced innovation via a modelling survey questionnaire for 24 modelling applications. The analysis of the information collected in the survey highlights that only six models out of 24 (25%) include techniques for endogenously modelling induced innovation as documented in published academic work. The endogenous innovation modelling exercise in these models is performed via learning curves (see [28, 59, 97]), R&D investments (see [60, 119, 123]) and spillover effects (see [59, 60, 119, 123]).

The empirical evidence from the survey is subsequently combined with a review of published modelling work, providing theoretical underpinning to the typology framework that was initially proposed in [26]. The survey shows that there is still a strong bias in modelling due to the geographical dispersion of institutions that build the models, as well as a tendency in the modelling community for keeping technology as exogenous to avoid complexity that could generate technical challenges. The typology includes the Dynamical models, which represent an extended definition of the most traditional IAMs used in the IPCC. Finally, the paper uses the information and policy questions answered by those case studies alongside IPCC-IAMs to develop a decision tree to support modellers and policy analysts in the choice of the most appropriate models to analyse specific aspects of the energy transition. The key insights from the paper can be summarised as follows.

System mapping emerges as a key approach to modelling and engagement, that can be used both as a standalone application as well as a means to develop and update quantitative models.

The different ways of modelling induced innovation seen in the literature (e.g. learning curves, R&D, or spillovers) imply a choice of methods that focuses on narrow or systemic approaches to modelling innovation. These span from static to dynamic modelling, including ABMs at their extremes (see appendix D for validation methods in ABMs).

From the perspective of policy change, the models proposed in this review can be considered as complementary to each other, and agree that the inclusion of endogenous innovation would bring benefits to the low carbon energy transition in terms of lower cost, improved financial stability and economic growth.

Static and dynamic models can be integrated meaningfully, thus reinforcing the complementarity between models and methods to lower barriers between them and promote collaboration. We suggest that modellers should spend effort in defining the boundaries between the different models that seek a similar purpose (e.g. accelerating the energy transition), so as to make clear to a decision maker where a model's usefulness ends and another model's usefulness begins. All of the findings above are consistent with the implementation of ROA as a policy appraisal method [46, 81] instead of the CBA, which is more common to IPCC-IAMs [20]. As a result, the use of these models in a new generation of IAMs will also require a change in the ways in which analysis and policy appraisal occur across countries.

This paper shows that energy models that agree with the terminology of ROA and use non-equilibrium non-optimising approaches can provide different results as well as extend the results obtained by IPCC-IAMs in the context of low carbon energy transitions. In fact, the ROA approach values the possibility of comparing model results when this is possible. This can create an opportunity to identify what the differences between the models are, and to better inform policy making, considering the dynamics of critical change more deeply [46, 81]. However, our results demonstrate a low uptake of innovation modelling in the countries that are meant to play a significant role in the global energy transition (e.g. China, India, and Brazil).

These results are limited by using only models that were developed or used as part of the EEIST programme. Because of these limitations, we suggest that future work should focus on increasing the number of case studies that conform to the innovation typology proposed in this paper, with the aim to support a broader dissemination of applied systems thinking methodologies. In addition to this, we believe that the approach adopted to generate the typology and guide in the choice of the most relevant methods for addressing induced innovation in models can also be generalized into other domains of complexity beyond low-carbon energy transition. Finally, we would suggest to explore future work in methodological innovation and transparency of modelling results. By engaging in emerging computational technology to invest in validation of models, as well as improve the quality of data, and invest in communication and visualization of model insights.

The speed of the energy transition might be dependent on the choice of energy systems models and how they implement induced innovation in their structures because they provide the foundation for policy decisions. The choice to exogenously consider technology change implies that governments and policymakers have no agency in the process of technology change, limiting their policy ambition. The aim of this paper is to provide a menu of options as an alternative to the most common IPCC-IAMs to model low carbon energy transitions and induced innovation, and how the choice of models should be dependent on their characteristics and specific policy questions that the models are supposed to address by design. In endogenously considering technology change, these models open up policy questions that might otherwise be precluded and afford agency to policymakers that is of prime importance in the transition to a sustainable economy. We invite other modellers and policy analysts to use the work proposed in this paper and suggest future pathways in this journey to a low-carbon energy transition.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Acknowledgments

The authors would like to thank the funders Department for Energy Security and Net Zero (DESNZ), Children Investment Fund Foundation (CIFF), UK Research and Innovation (UKRI) and Horizon Europe for the financial support. Thanks are also due to two anonymous reviewers for their constructive feedback during the review of this manuscript.

Funding information

This research was funded by the Department for Energy Security and Net Zero (DESNZ) and the Children Investment Fund Foundation (CIFF)—United Kingdom, project consortium Economics of Energy Innovation Systems Transition (EEIST). The University of Cambridge contribution to this work was partially funded by UK Research and Innovation (UKRI) under the UK government's Horizon Europe funding guarantee [Grant Number 10062835] for the PRISMA project that has received funding from the European Union's Horizon Europe programme under Grant Agreement No 101081604.

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