Societal Transformations in Models for Energy and Climate Policy: The Ambitious Next Step

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Whether and how long-term energy and climate targets can be reached depend on a range of interlinked factors: technology, economy, environment, policy, and society at large. Integrated assessment models of climate change or energy-system models have limited representations of societal transformations, such as behavior of various actors, transformation dynamics in time, and heterogeneity across and within societies. After reviewing the state of the art, we propose a research agenda to guide experiments to integrate more insights from social sciences into models: (1) map and assess societal assumptions in existing models, (2) conduct empirical research on generalizable and quantifiable patterns to be integrated into models, and (3) build and extensively validate modified or new models. Our proposed agenda offers three benefits: interdisciplinary learning between modelers and social scientists, improved models with a more complete representation of multifaceted reality, and identification of new and more effective solutions to energy and climate challenges.

Introduction

The feasibility and action space of reaching long-term energy and climate targets[1,2] depend on a range of interlinked factors: technology, economy, environment, policy, and society at large. Popular tools for exploring pathways and short-term actions toward these targets include integrated assessment models (IAMs) of climate change,[3] energy-system models,[4] and other sector-specific models.[5,6] IAMs are computational models that represent long-term global and regional dynamics of integrated systems, such as energy, agriculture, economy, trade, investment, technological change, water, and climate. Sector-specific models focus on one sector at a time, such as energy or transport. IAMs have been applied for quantifying emission pathways for so-called representative concentration pathways[7] (RCPs), which are used for analyzing future states of the climate and its impacts. Modelers usually come from environmental and Earth sciences, energy-system analysis, or economics, and their disciplinary knowledge can be expressed more easily in model equations. As a result, most models focus predominately on technology, environment, economy, and policy.[8,9] Broader societal developments are mostly assumed as exogenous by means of narratives that inform model assumptions. For instance, widely used shared socio-economic pathways[10] (SSPs) are narratives of global trends of population dynamics, gross domestic product, urbanization, level of cooperation in society, focus on development, and overall policy directions. The use of exogenous narratives means that societal assumptions do not interact in models with other technical, environmental, or economic factors, hence limiting the opportunities to quantitatively investigate the role of societal transformations for environmental change.

Meanwhile, a growing body of scientific literature[11–13] in social sciences (psychology, political science, geography, international relations, and many others) highlights the fundamental role of societal factors in shaping how energy and climate transformations unfold. The quick and broad transformation that is needed to meet today's energy and climate aspirations, such as the Paris Agreement's targets, means that this transformation has to be pervasive across all segments of society: from technology and infrastructures to markets, institutions, regulation, and individual practices.[13,14] The areas where IAMs, energy-system models, and other sectoral models could particularly improve can be divided into three intertwined groups:

- Behavior of all types of actors in transformations: consumer behavior and lifestyles,[15–17] material and non-material needs,[18] values,[19] preferences and utilities,[20] social acceptance,[21] governance,[22,23] geopolitics,[24] domestic politics and political discourses,[25] societal capacity to

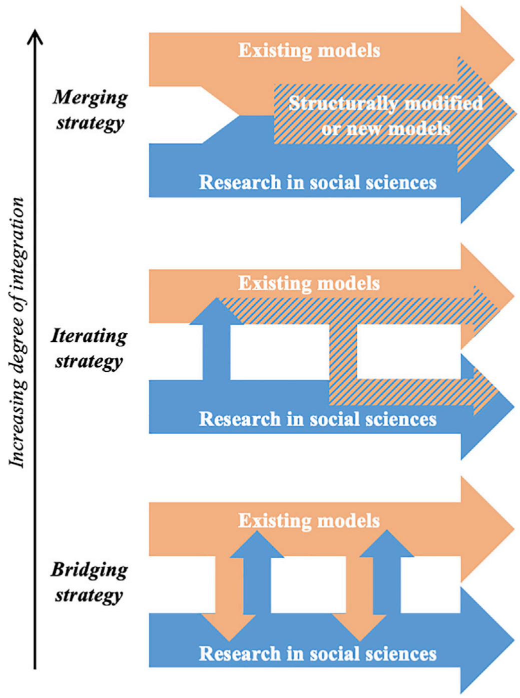


Figure 1. Three Strategies for Linking Models and Insights from Social Sciences

transform,[26] political or institutional capacity,[27] and many others.

- Transformation dynamics in time: temporal pathways to reaching the goals,[28,29] speed of transformations,[30] lock-ins,[31] path dependencies,[32] feedback loops and thresholds,[33,34] contingencies, transformation barriers, and many others.
- Heterogeneity across and within societies: contextual and environmental factors,[35,36] distributional impacts of environmental change and policies,[37] socio-economic conditions, presence of incumbents and innovators,[29] and many others.

To date, the two tracks of scientific inquiry—models versus research in social sciences—have largely evolved in parallel.[9] However, always assuming societal change as exogenous to models poses the risk of eventually missing the crucial flexibilities and thus biasing policy recommendations toward easier quantifiable technical and economic pathways. As already acknowledged by many,[11,12] closer cooperation between modelers and social scientists could potentially lead to valuable combined insights from both fields of knowledge. In this Perspective, we review the state of the art in this area and then propose a research agenda to guide experiments to attempt and integrate more insights from social sciences into models in order to cover a more complete range of technical, economic, environmental, policy, and societal factors.

State of the Art

Over the last decades, interdisciplinary research teams have started experimenting with linking IAMs and energy-system models with insights from social sciences.[9,38–40] Three types of benefits from such collaborations can be distinguished: interdisciplinary learning, increased realism of models, and new solutions to energy and climate challenges. First, modelers and social scientists who participate in such linking exercises experience mutual learning: for example, identification of missing societal factors in models,[41,42] improved consistency between narratives and models,[43,44] or at least better awareness and appreciation of the research in other disciplines.[45] Second, these interdisciplinary teams identify specific areas where the realism of models could be improved, for instance, by representing deviations from economic rationality in electricity-sector investments[46,47] or by accounting for the public acceptance bottlenecks in models.[45] Third, such interdisciplinary research also identifies new and arguably more effective and realistic levers for change in response to the urgent environmental challenges. Examples include behavior and lifestyle changes in the transport sector for emission mitigation[48] or policy measures that substitute or complement carbon-pricing policies.[49]

So far, models and research in social sciences have proved to be complementary in many aspects. Models comprehensively and simultaneously represent technology, economy, environment, and policy, whereas social scientists address the behavior of various actors, transformation dynamics in time, and heterogeneity within and across societies. Empirical social sciences are mostly based on the analysis of historical or contemporary data in the form of local to global case studies and aim to understand why and how certain societal phenomena occur. Empirically informed models can quantify, scale up, and aggregate these results beyond individual case studies or datasets and eventually develop forward-looking scenario analyses. Social science research, especially in science and technology studies or innovation studies, tends to focus on emerging innovations, be it new technologies, behaviors, or niche players.[8] Models in principle provide attention to all relevant sectors in change given that they describe competition for market share among incumbents and innovators as well as quantify the environmental outcomes. More attention in models is typically given to supply-side sectors because it is easier to quantify the relevant technical and economic factors. Demand is mostly driven by exogenous model assumptions on demographics and economic activity, or it is modeled to react to price signals and innovation dynamics.

In principle, three strategies can be adopted to facilitate collaboration between modelers and social science researchers (Figure 1):

- Bridging strategy:[45,50] models and research in social sciences proceed in parallel and establish brief exchanges (bridges), for example, only when discussing shared concepts.
- Iterating strategy:[10,43,44] this strategy is similar to the story-and-simulation approach,[51] where research in social sciences defines broad exogenous narratives, such as SSPs on population dynamics, gross domestic product, urbanization, and so on. These narratives are then translated into quantitative input assumptions used by the models. In some cases, the model outputs are also used for revisiting the narratives again.[43]
- Merging strategy:[52,53] this strategy assumes that at least the key societal factors can be modeled and hence relies

on in-depth integration of the two tracks. Insights from social sciences are used for structurally modifying existing models or creating completely new models that could altogether account for technology, economy, environment, policy, and society.

The main stronghold of the bridging and iterating strategies is that they recognize the level of complexity and context specificity of societal change that would otherwise need to be simplified in models in the case of the merging strategy.[9,43,54] The bridging and iterating strategies hence allow modelers and social science researchers to excel in their respective domains in line with the disciplinary traditions. Yet, energy and climate-policy assessments[1,2] inevitably require quantitative information from models to estimate the magnitude of technical, economic, and environmental change as well as the impacts of alternative actions. When models do not endogenize insights on societal transformations sufficiently, they can end up biasing policy recommendations toward easier quantifiable technical and economic pathways. Therefore, the main stronghold of the merging strategy is that it aspires to provide a more complete, balanced, and quantitative picture of change, including societal transformations. But this strategy also comes at a significant cost of simplifying complex descriptions from social sciences into model equations.

Three Steps for Future Research on the Merging Strategy

In this Perspective article, we focus on the options for the merging strategy (Figure 1) as a strategy that could lead to breakthroughs in how the behavior of the various actors, transformation dynamics in time, and heterogeneity within and across societies are represented in models for energy and climate policy. Although it is the most unorthodox and demanding strategy, it enables moving beyond existing disciplinary boundaries and achieving all three aforementioned benefits of collaborations between modelers and social science researchers: interdisciplinary learning, improved realism of models, and identification of new or improved solutions to the environmental challenges. First, the merging strategy requires mapping the assumptions on societal transformations that are already incorporated in the models and contrasting these assumptions against the latest knowledge in social sciences. This would lead to interdisciplinary learning. Second, it requires new empirical research on generalizable patterns and causal relationships in societal transformations in order to incorporate these patterns into models. This would improve the realism of models. Third, the improved models can be used for forward-looking policy analyses to identify new and arguably more effective solutions to energy and climate challenges.

Because the range of potentially relevant insights from social sciences is vast, we envision that the merging strategy will start with many smaller experiments and interdisciplinary collaborations that focus on one area at a time, for example, societal capacity to take bold climate action, transport behavior response to policies, or public acceptance of new technologies. As these experiments progress, their feasibility and added value can be better judged so that the priorities for more coordinated and larger-scale merging efforts can be defined. For every experiment, we suggest that all three steps, described below, be implemented in order to structure and guide the merging effectively. We describe these three steps below and give selected illustrations from the latest research. Current literature contains few merging examples with all three steps systematically carried out.

Mapping Assumptions in Existing Models

Although criticized for their focus on technology, economy, and environment, the current IAMs and energy-system models already include explicit and implicit assumptions on societal change, such as consumer behavior, limits to the speed of transformation, or heterogeneity of energy service demands across countries. Mapping, comparing, and harmonizing techno-economic assumptions are common practices among modelers in inter-model comparisons both at the front end of model assumptions[55] and at the back end of model outputs.[56] But only a handful of exercises[9,57,58] have attempted to map the assumptions on societal transformations in models. This mapping has also remained at a generic level, for instance, when it would be specified what types of actors are represented in models: aggregate social planners with or without perfect foresight, rational decision makers for investment and dispatch, households of various income, and so on. The actual implications of these assumptions on the model outcomes therefore remain unclear. Other mapping exercises or modeling critiques[59,60] have occurred outside the modeling community, and the outcomes have never been fully confirmed or internalized by the modelers. As such, no informed judgement can be made today whether the existing IAMs and energy-system models can be treated as models with adequate representations of at least the most important societal factors and, if not, what the priorities for improvement are.

Taking various social science insights that are relevant for climate and energy policy, future research should start with mapping out the related assumptions in the current models. Box 1 gives a short example of mapping assumptions on consumer behavior and lifestyles in the transport sector in IAMs. After such mapping occurs, further research should analyze whether and how these modeling assumptions are different from the latest knowledge in social sciences. Another example is presented in Box 2, which illustrates how the empirically derived framework of capacities to transform climate governance[26,61] can guide systematic assessment of missing elements in the SSP narratives and associated IAM modeling. We envision that step-by-step similar exercises of mapping and assessment exercises will be done for many societal factors. Existing theoretical frameworks in social sciences could be used as benchmarks against which the models could be assessed, and these frameworks will naturally differ depending on the issue at hand.

It is essential that such mapping and assessment involve both modelers and social science researchers on equal footing. Interdisciplinary dialogs that are essential for shared understanding and mutual learning for the merging strategy require significant effort, time, and open mindedness to the different disciplinary cultures. Some of these dialogs can be easier than others, especially if the social science discipline also uses models such as demographic research. But it is not only models that can benefit from knowing about the gaps between their assumptions and the latest insights in social sciences. Anticipating the potential quantitative role of incorporating societal factors through preliminary

Box 1. Example of Mapping Assumptions on Behavior and Lifestyles in the Transport Sector in IAMs

Changes in consumption behavior and lifestyles could contribute to mitigating climate change, especially in the transport sector.[48] These changes include one-time decision making, such as the choice of transport mode and technology, as well as repetitive behaviors, such as car usage.[17] There are various ways how behavioral considerations, their temporal evolution, and response to policy are already incorporated in IAMs:

- Transport *technology choice* is defined in IAMs by the addition of model constraints on how fast a new technology can be adopted, the addition of preference and hurdle factors to indicate attractiveness or perceived risk of a technology, the modification of assumptions on consumer risk aversion to account for social influences, or the use of multinomial logit equations that represent heterogeneity in user choice.[62–64] All these features represent technology choice in a more nuanced manner than immediate switching to a cheaper technology, which would otherwise be the default in models. A key challenge here is to find solid empirical quantification of these model features.[64]
- *Repetitive consumption behavior* is typically represented in IAMs by empirically observed trends, such as the increased usage of transport and higher preference for cars and airplanes with growing income.[65] Some models have explicitly built in theoretical concepts that are fit to represent structural change. For instance, travel-time budget and travel-expenditure budget[66–68] together result in a growing preference for higher-speed transport modes as income increases. Other assumptions are implicit and cover behavior in a very aggregated way, such as the sensitivity of transport-energy demand to income growth.[65]
- Impacts of policy on *behavior change*, i.e., moving away from default trends, in IAMs are mostly examined through scenario analyses. For example, some studies have analyzed changes in behavior over time by varying previously mentioned preference factors and quantifying their effects on vehicle adoption or modal shift.[44,69] Although it is difficult to quantify the effects of specific behavior policies, such as information campaigns, because of limited empirical data, scenario analysis at least helps to elucidate the idealized potential impact.

scenario analyses in models can help identify the most influential factors in long-term evolution of energy, climate, and environmental systems. These influential factors should be without doubt investigated further and included in the models.

Empirical Research on Quantifiable Patterns

Once there is a better understanding of which societal factors could be potentially integrated endogenously into models, these factors need to be converted into the form of generalizable and quantifiable patterns that define causal relationships. The in-depth understanding of societal phenomena and their drivers and barriers primarily falls within the scope of disciplinary research in social sciences. This disciplinary research on its own is undoubtedly crucial for effective energy and climate action, but IAMs and other global or national sector-specific models need to represent any complex real-world phenomena in stylized and simplified ways to be feasible in terms of data and computation time. That is why the empirical research on generalizable and quantifiable societal patterns for the merging strategy needs to be designed differently than for disciplinary research. The empirical research needs to look for simple yet as accurate as possible quantitative equations.

A successful and widely used example of such a pattern is the experience curve that shows how the costs of new energy technologies decrease as cumulative investment into these technologies grows.[71] The inclusion of experience curves into IAMs or energy-system models is a blueprint for the type of future research strategy that we propose. Endogenous technological learning has been studied for more than two decades.[72] Technological learning hypothesizes that the effort to expand technology's capacity depends on experience gathered in the past by a social group, such as a country.[71] Despite being a complex societal concept, experience curves have been estimated empirically and integrated in models. A strong interest in public policy, scientific curiosity, and the necessity to account for technological learning in models led to a long-lasting interdisciplinary exchange. Technological learning was a subject of many case studies in the field of industrial production in order understand the drivers and conditions for successful learning. This empirical research created the evidence base. The concept was then operationalized in measurable variables, such as cumulative installed capacity and investment costs. The data were extensively gathered for various technologies and countries and were summarized in quantitative functions between experience and improved technology. These functions and data were included in various IAMs and energy-system models, making it a common feature by now.[73,74] This integration of endogenous technological learning turned out to change the modeling results on technology choice, energy-sector developments, the economics of mitigation,[75] and regionally heterogeneous transition dynamics.[76] Subsequent scientific inquiry broadened the perspective to the inducement of learning by policy. For example, it was shown that policies to control emissions, such as carbon pricing, can trigger learning, but additional policies that directly incentivize technology deployment, such as feed-in tariffs, further facilitate emission reductions by reducing costs.[77–79]

Another recent concept is the framework of social learning for vehicle adoption, which describes the reduction of anxiety toward new technologies through social influence.[42] Other early examples of potentially quantifiable patterns that still need further investigation are the S-curves[80] or multinomial logit equations[62] for modeling technology adoption or the more general suggested laws of energy transition.[81,82] For instance, the suggested laws observe that new technologies go through exponential growth at a rate of 1 order of magnitude per decade until they reach 1% of the world's energy share and then switch to linear growth after several decades.[82] So-called stylized facts[83] have been also proposed as a model diagnostic tool. In the future, for example, it could be useful to conceptualize and operationalize in models societal capacities to take bold

Box 2. Example of Assessing Assumptions on Societal Capacity to Transform in SSP1

One of the SSPs, SSP1,[10] describes a global pathway of socio-economic development where challenges of climate-change mitigation and adaptation are low as a result of progress in sustainable development and environmentally friendly technology. When coupled with IAMs, SSP1 investigates policies that are grounded in global cooperation, efficiency, and cost-optimal implementation. The concept of societal capacity to transform[26] and its local interpretation can help identify the missing points in SPP1 and associated modeling. The table below shows several examples by using a local application of societal capacity to transform in Europe as a starting point for identifying the missing societal factors.

Societal Capacities to Transform[26]	Examples of These Capacities in SSP1 in Europe[26]	Examples of SSP1 and IMAGE Assumptions[69,70] that Are Consistent with These Capacities[26]	Examples of SSP1 and IMAGE Assumptions that Are Underrepresented
Stewarding: the ability to anticipate, protect, and recover from disturbances while exploiting opportunities for sustainability	• strong social networks and supportive social contexts • proactive long-term integrated planning • risk taking and uncertainty embracing • collective memory and learning (reflexivity and knowledge integration)	• land-use change is driven by food consumption, which in turn is driven by population, welfare, poverty reduction, and dietary changes • higher food consumption is compensated by higher yield, where land expansion leads to higher prices and incentivizes yield improvements	• underrepresented considerations of institutions and some lifestyles • missing representation of how the actors can adapt, form coalitions, and otherwise enable incentives for yield improvement beyond price effects
Unlocking: the ability to recognize and dismantle drivers of unsustainability and path dependencies	• no support for the *status quo* • effective opposition networks	• energy supply undergoes slow transition to renewable energy as a result of existing infrastructure and competition from fossil fuels • the fossil-fuel-extraction sector is constrained by restrictive land-lease and permission policies	• underrepresented considerations of perceptions and institutions • unaccounted roles of innovators to oppose the *status quo* and of existing power interests to resist innovation
Transforming: the ability to create novelties and embed them in practices	• leadership for innovation • learning from tested solutions and replicating and upscaling them	• transport-energy demand is increasingly supplied by renewable energy as a result of electric and hydrogen cars and biofuels in aviation • lifestyle changes and end-use efficiency smoothen energy demand that would otherwise grow faster	• underrepresented considerations of institutions, land-use tenure, and some lifestyles • missing representation of the role of actors to enable transformation through learning and upscaling
Orchestrating: the ability to coordinate interactor processes in order to maximize synergies	• shared, long-term development goals • collaboration across scales and sectors • good governance and engaged political culture	• inefficient bioenergy is phased out in the residential sector and is replaced by electricity and natural gas	• underrepresented considerations of institutions • missing representation of multisectoral incentives and barriers for the different actors to collaborate toward a shared goal

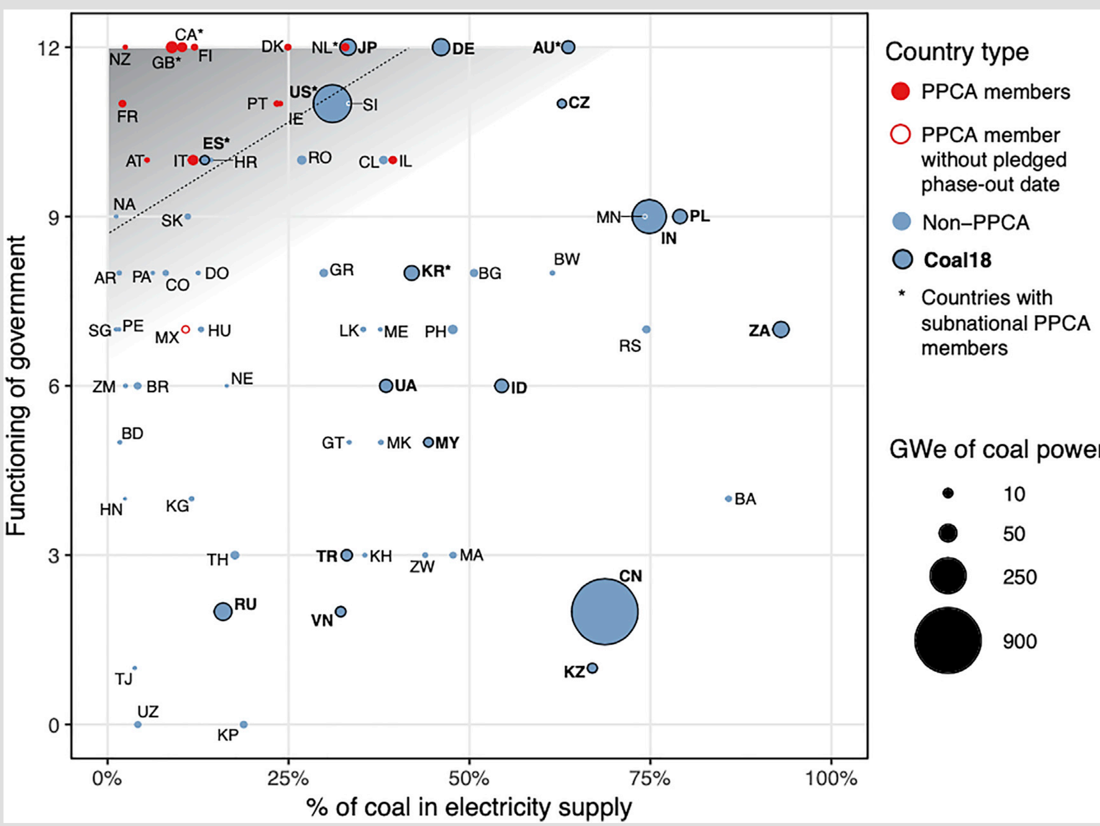
environmental action (Box 3), political feasibility,[27] or the role of governance[22] in achieving environmental targets. These and similar conceptualizations need to go hand in hand with the identification of measurable proxies that can be used in models.

In order to identify such generalizable and quantifiable patterns, empirical research is essential. A crucial requirement for such research is that it needs to ensure a broad spatial, societal, and temporal coverage including a wide variety of circumstances. Meta-analyses provide a good starting point.[90,91] As is often observed, though, evidence from social sciences usually comes from case studies that are very sparse for global and long-term coverage, segmented, and hard to harmonize as a

Box 3. Example of Empirical Research on Costs and Capacities to Phase Out Coal

To achieve the current climate targets, coal-based power should be phased out in the near future.[84] The causal relationship between the government's institutional capacities and the ability to formulate and implement energy policies has been thoroughly documented since the responses to the oil crises in the 1980s.[85] The importance of the governmental policies in supporting the persistence of the coal sector has been highlighted multiple times in the UK, Germany, and South Africa.[86–88] Governments that are free from corruption are potentially more capable of following through on the state goals, taking into account typically dispersed public concerns about air pollution and climate change, and resisting typically concentrated lobbying pressures of pro-coal interests.

Some 30 countries and over 20 sub-national jurisdictions pledged to retire their existing coal power plants by 2030 or earlier and not to build new coal plants in the initiative, known as Powering Past Coal Alliance (PPCA). An empirical analysis[89] has shown that these countries produce and use less coal, experience no or negative growth in electricity demand, and have older power-plant fleets. These factors make it less costly to phase out coal because there is less risk of stranded assets, lost employment, and the need to find alternative means of electricity generation. But these factors alone do not explain the membership in PPCA. The PPCA members are wealthier and have transparent governments that are independent of industrial interests. This allows their governments to formulate and execute policies in the interests of the entire society while overcoming potential resistance from pro-coal interests, including the loss compensation. These characteristics set PPCA members aside from major coal consumers, such as China and India. This insight extends beyond coal and highlights that bold climate action depends on both its political and economic costs (e.g., to compensate communities and companies affected by the coal phase out) and the government's capacities to bear these costs. As these costs and capacities evolve in time, climate policies such as the coal phase out could diffuse from their early adopters to other countries.

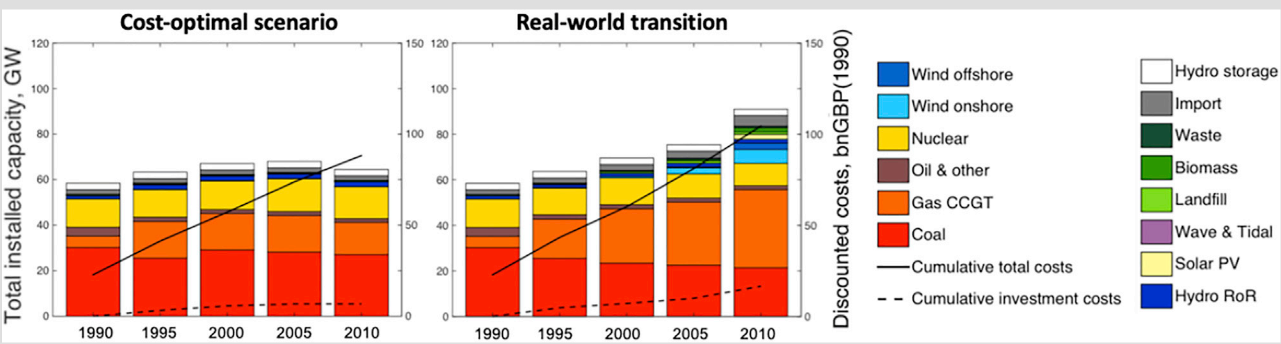


This figure plots the index of functioning of government against the share of coal in power generation in PPCA members and other countries. The size of the circles indicates the current capacity of coal power. Coal18 represents 18 countries responsible for over 90% of modern coal production; they are bolded and circled in black. The dashed line and the shaded area illustrate the results of a logistic regression analysis: the area to the left and above the dashed line shows the predicted probability of belonging to PPCA above 50%, and the shaded area shows where the probability is at least 5%. Redrawn with permission from Jewell et al.[89]

Box 4. Example of a Modified Conventional Energy-System Model

Conventional technology-rich, perfect-foresight energy-system models apply the social planner's assumption and minimize total system costs in order to quantify future energy-market scenarios by assuming perfectly competitive markets.[4] Empirical research shows that real-world transitions are unlikely to neatly follow the sole rationale of minimal system costs.[96,97] As shown in the figure below, *ex post* modeling of the UK electricity sector[46] in 1990–2014 demonstrated that, even if parametric uncertainty is kept at a minimum, the real-world transition cannot be reproduced with a conventional model because this transition has 16% higher total system costs than the cost-optimal scenario. The *ex post* modeling helps to trace back some of the reasons for this deviation from cost optimality: emergence of previously unknown environmental concerns, new technology, or conscious policy decisions with goals other than minimal costs.[46]

For prospective modeling decades ahead, even if the full spectrum of reasons for deviation from cost optimality cannot be anticipated and endogenized into models, it is meaningful for models to compute not only cost-optimal but also near-optimal scenarios. For this purpose, the existing models can use the modeling to generate alternatives (MGA) technique[46,98] and treat the near-optimal scenarios as part of the uncertainty analysis. This technique generates large ensembles of energy scenarios that are either cost optimal or within a pre-defined threshold above the minimal total system costs (such as 16% above). The threshold can be defined through empirical research[97] together with *ex post* modeling.[46] Application of this technique reduces the bias in conventional models toward unrealistic cost-optimal scenarios, and societal transformation dynamics can be broadly encapsulated by means of MGA and uncertainty analysis.



This figure plots the *ex post* cost-optimal scenario of the UK electricity sector transition against the real-world transition and its costs from the same energy-system model. Reprinted and modified from Trutnevyte[46] with permission from Elsevier.

result of diverse methodologies.[92] Such case studies are more often collected for the global North rather than the South, as has been shown for urban solutions to climate change[93] and hence for countries with liberalized market access and free trade. When such evidence from case studies needs to be synthesized and scaled up with the use of typologies,[93,94] the underrepresented types of cases either get described by imprecise relationships or are overgeneralized from just a couple of case studies. Some evidence on societal factors comes from surveys that present only a temporary snapshot of the situation at a given point in time and cannot be straightforwardly extended to the future without longitudinal data collection.[95]

Such ambitious empirical research for the merging strategy is, without doubt, costly and constrained by various practicalities. On the one hand, in the global South, public data availability is limited, local funding for case studies is scarce, and the ability to disseminate research results is low. On the other hand, large-scale harmonized studies across many countries are demanding undertakings that require substantial efforts of coordination and can be enabled only by sustained long-term funding. Yet, the previously mentioned examples of endogenous technological learning or travel time and expenditure budget (Box 1) show that even in the absence of ideally designed and truly coordinated empirical research, it is still possible to identify some generalizable and quantifiable patterns that are robust enough to be included in models. Such empirical research, first of all, enables ways to increase the realism of models and to proceed with the merging strategy (Figure 1). Then, such research serves many other purposes too: it can be used to improve conceptual and theoretical understanding of societal transformations and to gather data and insights for policy evaluation.

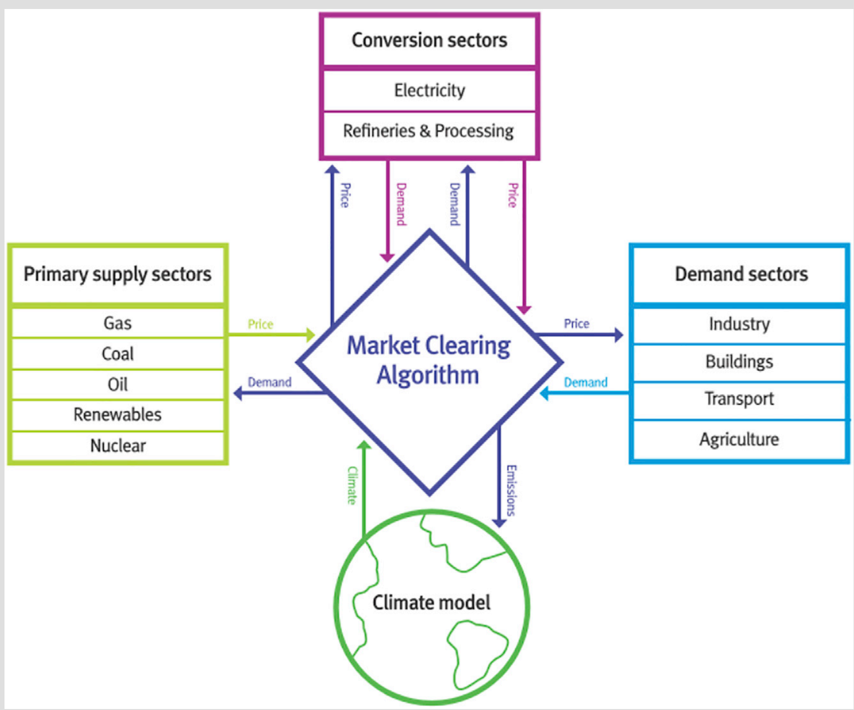
Modifying or Building New Models

When robust generalizable and quantifiable patterns are elicited, the next step is to find ways to incorporate these patterns into models by using the merging strategy from Figure 1. In principle, there are three options: (1) to use and modify existing IAMs or sector-specific models, (2) to create from scratch new societal transformation models, such as socio-technical energy transition models[53] or agent-based models (ABMs), or (3) to soft link the two and iterate between existing (reduced) models and socio-technical models or ABMs. One successful example is the integration of demographic research in SSPs.[10,44] Box 4 provides another example of how a conventional energy-system model[4] can be modified to at least broadly cover deviations from cost-optimization rationale in real-world transformations. Such a strategy of modifying an existing model has its advantages: it is more

Box 5. Example of a New ABM-Based IAM

MUSE[47] (Modular Energy System Simulation Environment) is an ABM-based tool for integrated assessment. It is explicitly designed to enable a user to simulate the decision-making processes of citizens, firms, and other societal agents in the energy-land-climate system. Agents in the end-use sectors consider commodity and technology prices and performance and then apply user-defined bespoke decision-making rules to choose between options to meet their service demands. Similarly, agents in supply and conversion sectors consider these demands, resources, and technologies available and likewise apply bespoke rules to choose between options. Their choices influence commodity prices with a knock-on influence on decisions in the end-use sectors. The model achieves a partial equilibrium by a market-clearing algorithm that iterates among end-use, conversion, and supply sectors in each region until all sectors agree on the price and quantity of each commodity. Decarbonization options are simulated via interaction with a climate module and adjustment of emissions price until the emissions budget is reached.

What makes MUSE a new approach among IAMs is its ability for modelers or model users to construct their own decision-making rules: technology search spaces that can be influenced by other agents or different objectives—such as payback time, emissions, comfort, or social prestige—or multiple ways to combine objectives to reach a decision. MUSE also allows various definitions of these features for each agent in each sector. A recent application of MUSE[47] has demonstrated that the technological makeup of future low-carbon energy systems can be strongly influenced by the decision making of citizens and firms, where non-cost features of the options bear considerable weight.



This figure shows the structure of the MUSE model.[47,99] Each sector is represented by an agent-based module. Reprinted from García Kerdan et al.[99] with permission from Elsevier.

pragmatic and allows one to build on the strengths of already established and validated modeling paradigms. Box 5 illustrates the case of a new ABM-based IAM that more fundamentally reconfigures the model structure. Overall, all kinds of experimentations with modified and new models are needed for testing the architecture and limits of these models and for understanding what can be modeled endogenously and whether that leads to substantially different model results and conclusions to justify the efforts.

Inseparable elements of building robust modified or new models that account for societal change are uncertainty analysis and model validation. Societal transformations are generally characterized by higher variability and deeper uncertainties than transformations that can be measured and validated in units of energy, land, or emissions and generally follow physical principles. The most popular practices of model evaluation[83] at the moment include qualitative assessments, verification and documentation of modeling code, stylized facts for assessing the models, model calibration, or sensitivity analysis. We argue that extensive validation through *ex post* modeling is a must for models that include societal dynamics so that it is clear whether model equations provide good representation of observed transformations.[46,100] Box 4 provides one example.

Such *ex post* modeling can ideally by combined with out-of-sample testing.[101] Advanced, rather than simple, uncertainty analysis[4,102] and model validation are increasingly applied by modelers, but these techniques have yet to become common practices.

An important gain from integrating insights from social sciences into models endogenously, as we suggest in this Perspective, is that this would allow quantifying temporal pathways toward reaching long-term energy and climate goals. When behavior of all types of actors, transformation dynamics in time, and heterogeneity across and within societies is incorporated, these models would give crisper insights on effective environmental solutions. Of course, this can be done only when truly robust, generalizable, and quantifiable evidence from empirical research and model validation are successful. In the absence of such evidence, socio-technical transition models or ABMs can be used only in a more exploratory way in parallel or soft linked to existing IAMs and sector-specific models. One particular benefit in the case of socio-technical transition models or ABMs is that modeling can result in long-term scenarios with explicit representations of various types of actors and their short-term decisions: governments, large corporations, small and medium enterprises, citizens, and so on. Current outputs from IAMs and energy-system models gloss over the implications of the actors' decisions and hence potentially effective levers of change.

Concluding Remarks

In this Perspective, we argue that IAMs, energy-system models, and other sector-specific models should experiment more with integrating insights from social sciences in order to improve the model representations of societal transformations, such as behavior of various actors, transformation dynamics in time, and heterogeneities within and across societies. There are multiple strategies for achieving this, including the bridging, iterating, and (the most ambitious) merging strategies (Figure 1). Each strategy offers a different balance of benefits: improved realism of models, more effective and realistic solutions at various time horizons, and mutual learning across different disciplines. In this Perspective, we have focused on the merging strategy, where empirical research in social sciences helps not only to elucidate societal transformations but also to extract robust generalizable and quantifiable patterns to be included in current and new modeling frameworks. The main stronghold of the merging strategy is that it enables moving beyond existing disciplinary boundaries and ideally providing quantitative assessment of technical, economic, environmental, and social change on equal footing for energy and climate policy. Even if it needs time and resources and even if it forces social scientific insights to be represented in oversimplified equations, keeping long-term societal transformations only exogenous to models means that the models will eventually miss out on crucial societal elements of initiating the necessary transformative change.

Various merging experiments are already ongoing. Given such a vast range of potentially relevant insights from social sciences, these individual experiments are the right means of identifying the most promising insights to be prioritized in modeling. In the longer run, such uncoordinated experiments are valuable but could turn out to be too fragmented to play a significant role in improving IAMs and other models for energy and climate policy. Ideally, we would need an interdisciplinary global effort with a unified goal that is structured and organized around the guidance steps that we propose here. Realistically, the success examples of experience curves or travel time and expenditure budget demonstrate that similar merging achievements can still emerge and gather momentum even without true coordination, when there is policy interest and scientific curiosity.

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AUTHOR CONTRIBUTIONS

E.T. conceptualized the overall manuscript with expertise and feedback from all authors. E.T. wrote the original draft, and N.B., A.C., A.H., O.Y.E., and S.P. wrote a box or subsection each. All authors reviewed, edited, and approved the manuscript.

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