EEIST

NEW ECONOMIC MODELS OF ENERGY INNOVATION AND TRANSITION:

ADDRESSING NEW QUESTIONS AND PROVIDING BETTER ANSWERS

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Cover image: Occupational mobility network. Full version can be found on page 122.

About

The Economics of Energy Innovation and System Transition (EEIST) project develops cutting-edge energy innovation analysis to support government decision making around low-carbon innovation and technological change.

By engaging with policymakers and stakeholders in Brazil, China, India, the UK and the EU, the project aims to contribute to the economic development of emerging nations and support sustainable development globally.

Led by the University of Exeter, EEIST brings together an international team of world-leading research institutions across Brazil, China, India, the UK and the EU.

The consortium of institutions are UK: University of Exeter, University of Oxford, University of Cambridge, University College London, Anglia Ruskin University, Cambridge Econometrics, Climate Strategies, India: The Energy and Resources Institute, World Resources Institute, China: Beijing Normal University, Tsinghua University, Energy Research Institute, Brazil: Federal University of Rio de Janeiro, University of Brasilia, Universidade Estadual de Campinas (UNICAMP) EU: Scuola Superiore di Studi Universitari e di Perfezionamento Sant'Anna.

Contributors

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Executive summary

This report represents a major effort to demonstrate the value of new economic modelling to policy questions relevant to the low-carbon transition. Through 15 real-world, global, regional and national case studies, developed in partnership with policy stakeholders, the report demonstrates how new economic modelling approaches can deliver crucial insights for decision makers. It also provides guidance on how to evaluate and choose between different modelling approaches and how to support their use.

A new generation of economic models is needed to inform successful policymaking on the energy transition. Most of the models used by governments are based on the assumption of equilibrium, in which, without external shocks, the economy is stable and the actors in it have no reason to change their strategies. This can be a suitable modelling approach for some policy questions. However, where the dynamical processes of moving between states are important, these models are not appropriate. Decarbonisation requires system transitions in each of the emitting sectors of the economy – situations in which many actors have strong reasons to change their strategies, new technologies emerge and the structure of markets changes. While equilibrium models remain valuable – for example for answering questions such as 'what could a net-zero economy look like?' – disequilibrium models are important as a complementary tool, particularly for answering questions such as 'how do we get there?'.

New models can help identify policies that will drive cost-effective decarbonisation. In general, models that simulate the processes of change in the economy arrive at different answers to policy questions compared to models that calculate and compare states of the economy at specific points in time. The case studies in this report present a range of new models and reveal a set of key findings on four types of policy questions. These are underpinned by the use of different methods, focusing on different countries: Brazil, China, India, and the UK. Table A summarises the key findings and further examples are given in the policy highlights section that follows this executive summary.

Table A: Policy questions addressed and key findings in this report

Policy questions	Key findings
Development direction: Should we decarbonise? How much will it cost? What will be the macroeconomic impacts?	• Multiple case studies, for different countries and using a range of methods, all find that decarbonisation is likely to provide net job creation and, depending on the specific economic structures of the geographies of interest, may lead to economic growth overall. • A faster transition than currently envisaged is preferable. • There may be negative impacts or costs under certain transition scenarios and we can identify the specific periods, sectors or occupations where these might be, as well as connections to other development objectives.
Technology choices: Which technologies should we focus on? What will be the sectoral impacts?	• Policymakers should minimise barriers to zero-emission technologies whose performance improves, and costs reduce, with greater deployment. These include solar, wind, electrolysers and batteries. Policymakers should shape markets to be conducive to faster innovation and growth in these technologies. • Different countries will have different technologies to focus on, depending on their current situation. • Transitioning away from fossil-fuel technologies can have predictable and manageable impacts, depending on the nature of the transition.
Policy choices: Which policies are best to support our goals?	• Investing in zero-emission technologies tends to be more effective than putting a price on fossil fuels for achieving emissions reductions and innovation in key energy technologies. • Regulation can be highly effective as a means to reallocate investment towards zero-emission technologies, accelerating their improvement and cost reduction. • Technology mandates or government procurement are effective policies to kickstart an industry and can make other policies more effective. • Carbon pricing can be helpful when used as part of a package of policies (more so when implemented as a tax than as a cap-and-trade scheme). • Timing of policy support is key, with late support increasing the chances of unwanted lock-in. • Policy support can often be revenue or fiscal-neutral.
Policy design: How should we design this policy?	• Subsidies or taxes may be particularly effective when they are set at a level that makes a zero-emission technology cost-competitive with fossil fuels. • Regulations may be more effective when they mandate uptake of a zero-emission technology than when they require increasing efficiency of fossil fuels (though both together may be best). • Emissions trading schemes need to be designed to avoid introducing a brake on emissions reductions when quick progress outstrips adjustments in permit supply.

New models can provide broader insights into low-carbon transitions. Beyond choosing a technology mix, or policies for the deployment of clean technologies, the new generation of models can also provide insights into wider societal, environmental and macroeconomic aspects of the transition. They can help to address questions such as where jobs will be gained and lost, where skill gaps in the workforce may arise, how the transition may affect the balance of trade and how tax revenues from fossil fuels could be replaced.

A new generation of models is becoming available. The case studies use a variety of modelling approaches, including: (i) data analysis approaches such as systems mapping and economic complexity; (ii) macroeconomic models such as the Energy-Environment-Economy Macro-Econometric Model (E3ME) and its evolutionary sector-specific extensions; (iii) detailed economic System Dynamics models; (iv) empirically validated agent-based models; and (v) extended energy system models. This plurality is important to ensure we do not rely on one type of modelling. What these approaches have in common is that they assume the economy is in a state of change and they simulate processes of change so that these can be understood and influenced by policy. These approaches are also underpinned by a commitment to bottom-up, structurally realistic, empirically validated economic modelling; these are delivering on the promise these methods made when they first emerged, sometimes 20 or 30 years ago.

Through this diversity of methods and policy questions, two methodological lessons emerge. First, there is enormous value in academics, analysts and policymakers working together to simultaneously co-develop suitable models and analyse real policy questions; this mode of working repeatedly delivers value and improved capacity to use new economic modelling. Second, the value of detailed policy analysis and appraisal is clear, with decision makers demanding comprehensive representation of policies and their implementation in models.

There is great potential for further improvement in economic modelling. This can come from progress of three kinds:

1. Learning what works in practice: As more applications of these new modelling approaches are completed, rich learning will be developed on what works best and how analysts and decision makers can best use these methods and build capacity.
2. Developing powerful thinking tools: The use of new economic models will support, and be supported by, the further development of economic theory on processes of innovation and structural change, from the 'Ten Principles for Policymaking in the Energy Transition' we outlined in our previous report, to the rules of thumb we can use to think about technology and economic systems, such as feedbacks, exponential change and tipping points.
3. Increasing innovation and transparency: As demand grows for new economic modelling, we expect to see new methodological innovations appearing. Transparency and clarity in model development and use will also improve, supporting wider use of the new approaches and faster innovation in their development.

Governments and international organisations can accelerate the emergence and development of these new modelling approaches. Governments are the largest customers of policy analysis; by procuring and funding the development of new models, they can stimulate the investment of time and intellectual capital by the academic community into these new approaches. Governments can improve their own institutional capability to take advantage of the new generation of models by training their officials in disequilibrium model development and complementary analytical techniques such as system mapping and risk-opportunity analysis.

The primary audience for this report encompasses the many analysts, modellers, researchers and academics conducting research within and for governments, multilateral organisations and the private sector on the energy transition and energy and climate policy. Policy teams and decision makers will also find value in this report, as it summarises the key findings of new economic modelling and helps readers understand why different types of analysis provide different insights.

EEIST

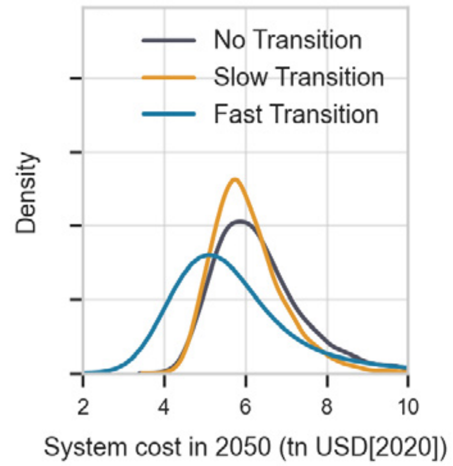
Policy highlights

Here, we present a selection of policy findings from the case studies in this report. The purpose of this section is not to provide a summary, but to give some examples that illustrate the potential of new economic models to address new questions and provide better answers to the policy problems of energy innovation and transition. Readers can refer to the case studies to find more detail on the methods, results, limitations and policy implications of each of these pieces of analysis.

The pace of the transition

The case study Empirically Grounded Energy Technology Cost Forecasts finds that a fast transition to a zero-emission energy system (including energy use across power, transport, buildings and industry) could cost less than a slow transition, and that it could save around $12 trillion compared to business-as-usual in global aggregate terms (Figure 1). This is the opposite of the traditional view that the more emissions are to be reduced, the more costs will be incurred. The reason for this difference is that our study uses a more realistic representation of the way that the costs of clean technologies fall as their deployment rises.

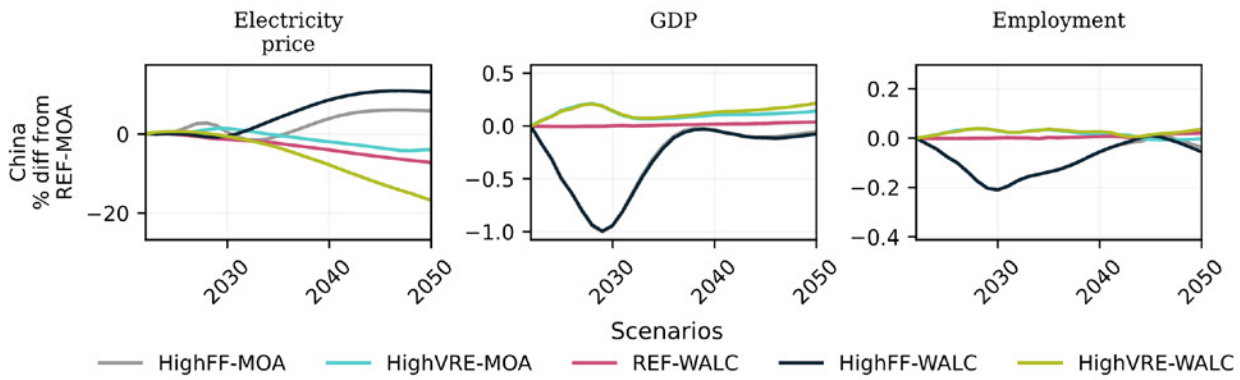
Figure 1: Forecast distributions of annual system cost in 2050.



The power sector

The case study Unstoppable Renewables and Marginal Pricing shows that choices of market design will be crucial to realising the opportunity of low-cost renewable electricity (Figure 2). While solar power with energy storage could be half the cost of coal power by 2030 in the countries we consider, the price of electricity could still be high if market prices are determined by the marginal unit of supply (likely still to be provided by fossil fuels). Alternative market designs where electricity prices reflect the weighted average levelised cost (WALC) of electricity generation could lead to lower prices, contributing to better outcomes for employment and economic growth.

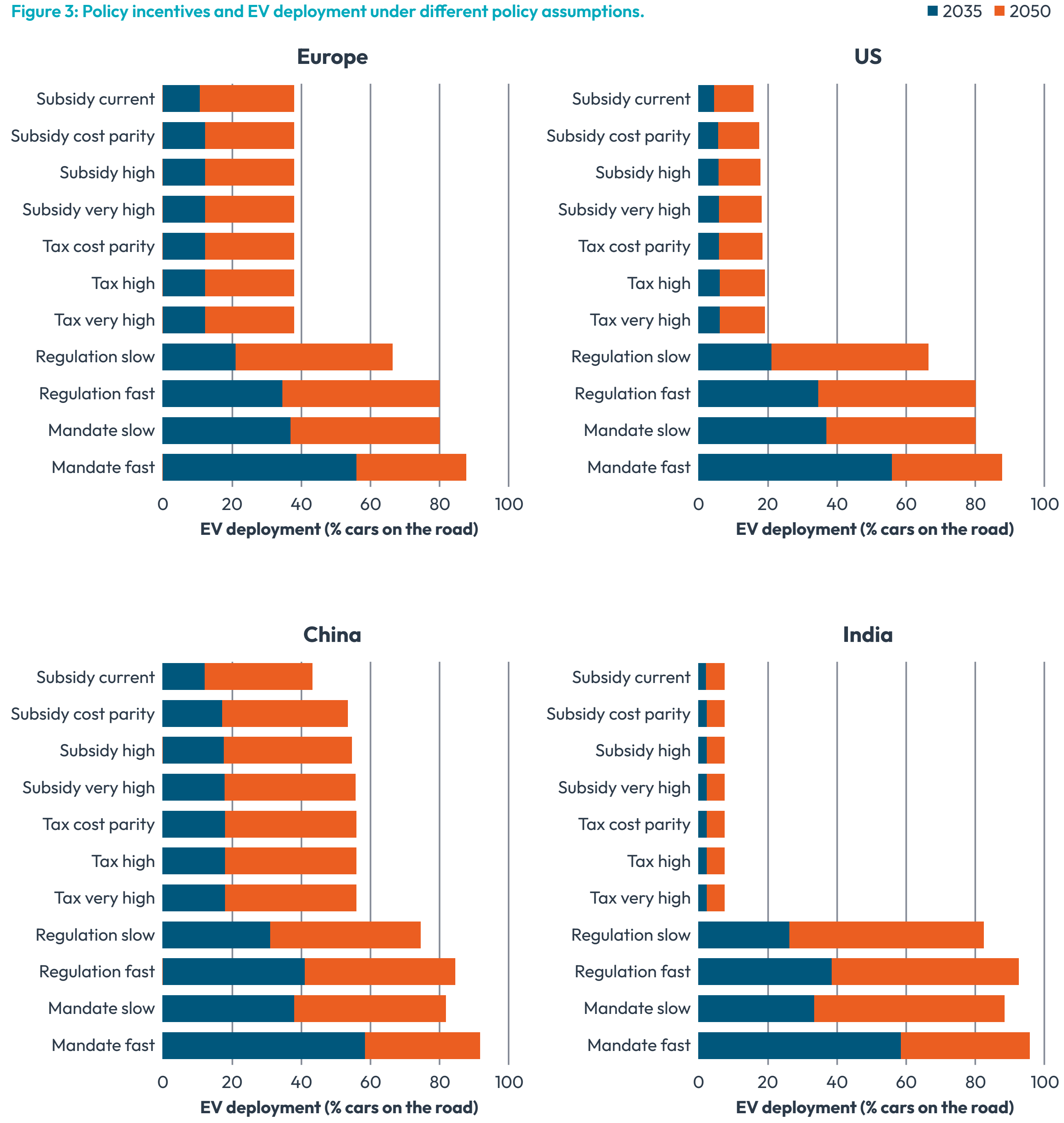
Figure 2: Comparison of electricity prices, GDP and employment, in percentage difference to the reference scenario (REF-MOA) in China. HighFF = High fossil fuels scenario; HighVRE = High variable renewables scenario; REF = Reference scenario; MOA = Merit order approach; WALC = Weighted Average Levelised Cost.



Zero-emission vehicles

The case study Activating EV Tipping Points shows how a simulation model can be used to compare policy options individually and in combination. We find that zero-emission vehicle mandates and efficiency regulations are often likely to be the most cost-effective policies for driving the transition to zero-emission vehicles, with subsidies the next best and taxes by far the least cost-effective option (Figure 3). The study also finds that policy combinations that act on both the supply and demand for zero-emission vehicles can achieve more than the sum of their parts, while other policy combinations achieve less than the sum of their parts. These findings are only possible in a model that simulates likely outcomes instead of computing 'optimal' solutions.

Figure 3: Policy incentives and EV deployment under different policy assumptions.



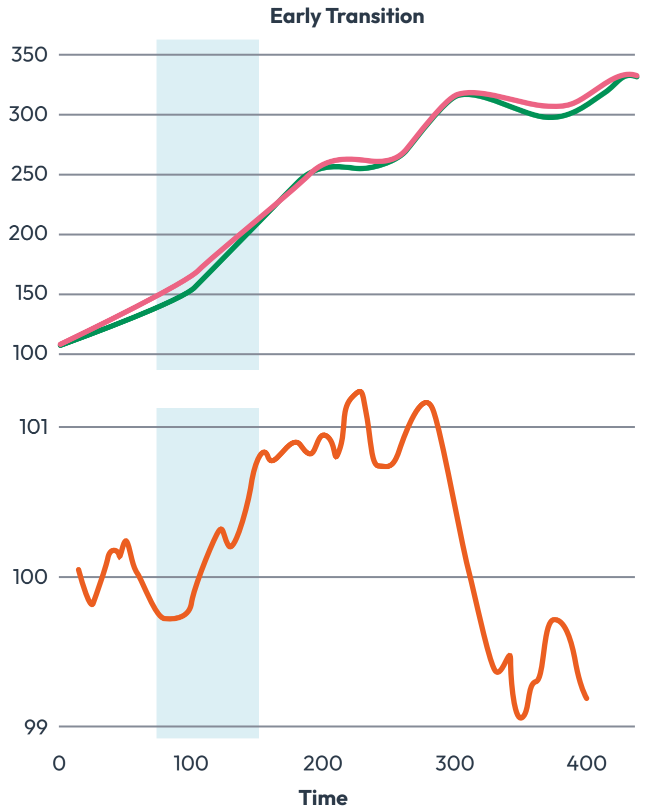
Hydrogen in power and industry

The case study Modelling Sector Coupling of Hydrogen and Ammonia in India shows the risks and opportunities arising from a policy choice about infrastructure: whether to connect hydrogen and ammonia production plants to the electricity grid, or to construct them as 'islanded' plants connected only to local industrial off-takers. The study finds that not only does the 'connected' approach result in hydrogen and ammonia produced at 10-25 per cent lower cost (Figure 4), but also reduces the need for solar and wind-generating capacity by around 200-300 GW and has significant advantages in terms of energy security and the resilience of electricity supply to weather variations, compared to the 'islanded' approach. These findings arise from the model's exploration of the dynamic interactions between the power and industrial sectors: green hydrogen and ammonia improve the efficiency of the electricity system by providing energy storage and dispatchable power; lower-cost electricity in turn enables lower-cost production of green hydrogen and ammonia. Policy choices such as how to pay for the grid connections of hydrogen plants could determine which of the alternative infrastructure configurations comes into being.

Figure 4: Levelised cost of hydrogen across scenarios.

Agriculture and land use

The case study Supporting sustainable agriculture intensification finds that, without significant policy intervention, competition between farmers for short-term profitability and market share is likely to lead to soil degradation, with serious risks to food security in the long-term. It finds that giving farmers better access to information about sustainable practices – and incentivising their uptake of new technologies – could significantly increase the chances of the agriculture system making a transition to sustainability (Figure 5). Importantly, the results suggest that policy interventions are more likely to be effective if they are introduced early in the transition; if left too late, the divergence of technological development may make it impossible to avoid a lock-in to unsustainable agricultural practices. These findings are made possible by the model's representation of farmers as economic actors with diverse resources and knowledge, acting in a context of uncertainty, whose actions influence the market and are in turn influenced by the market.



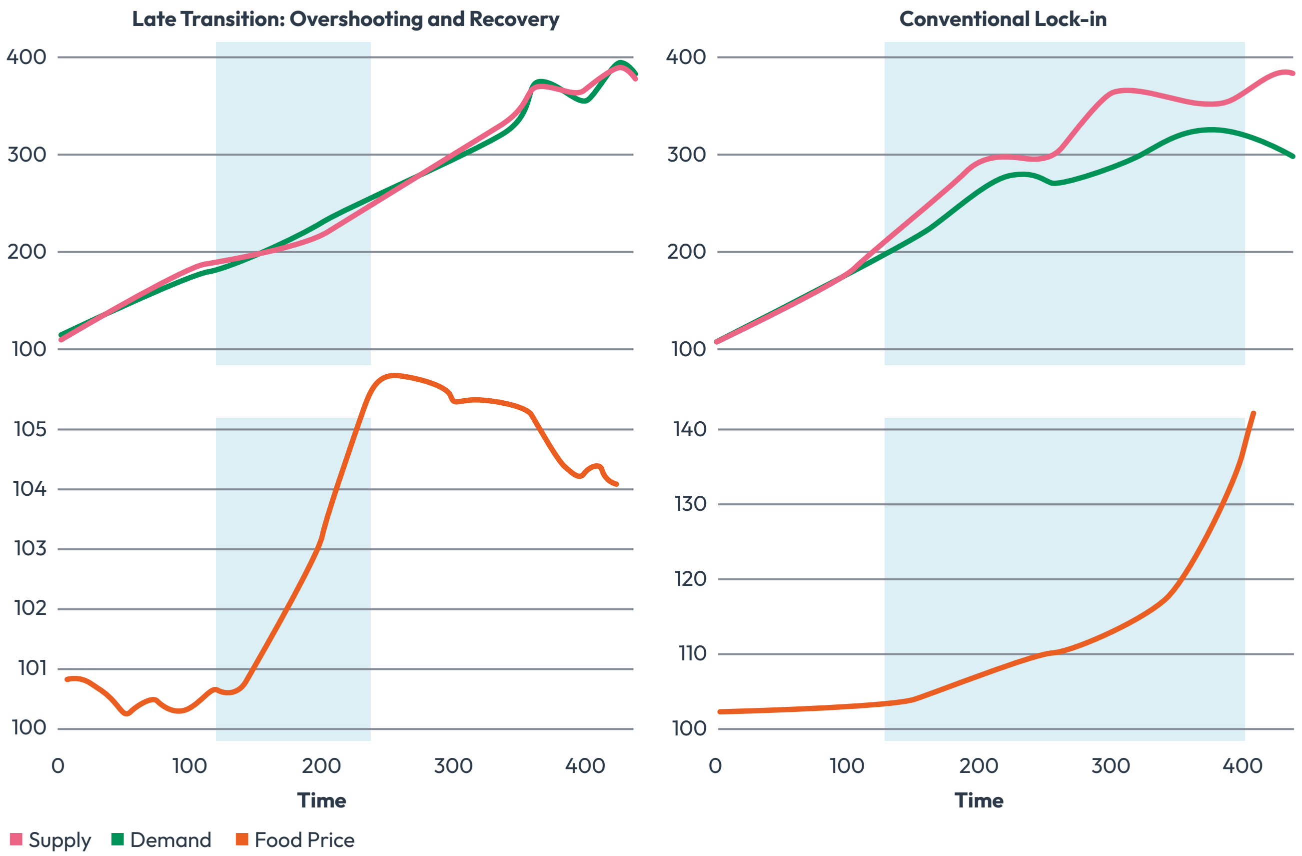


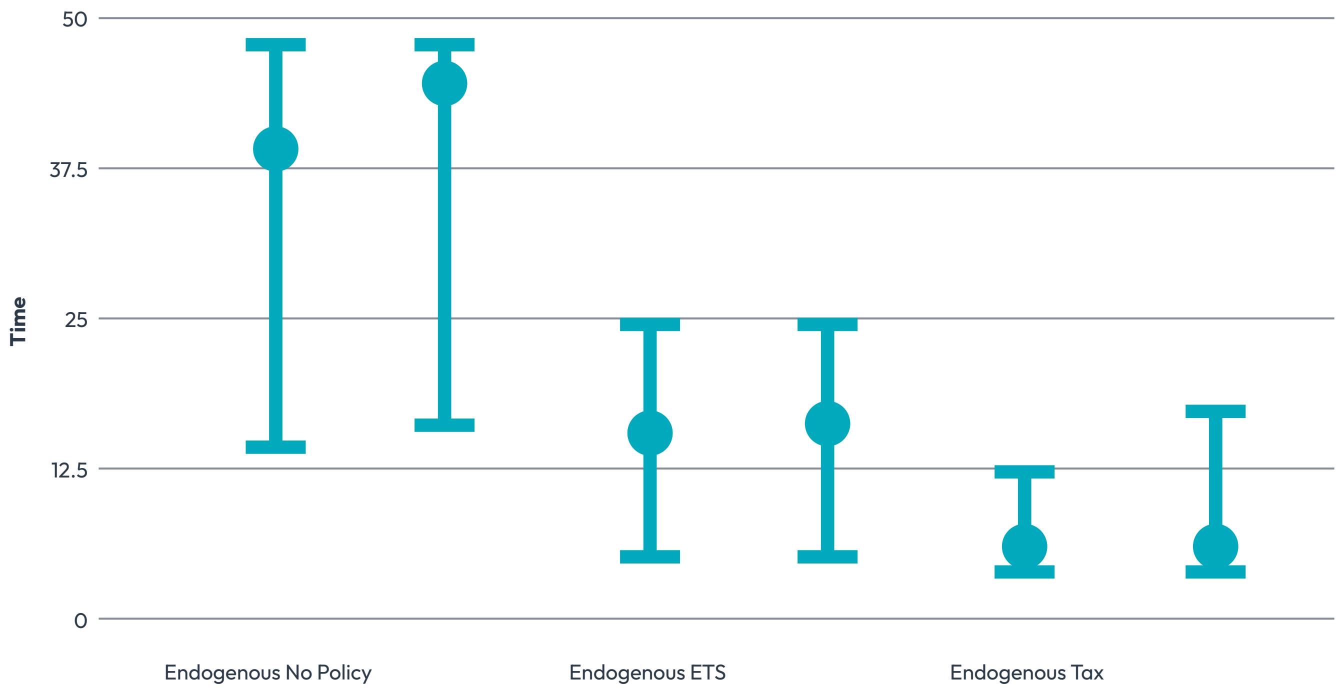
Figure 5: Three different single runs of the model, exemplifying the main types of dynamics observed in the model: rapid transition to sustainable farming, overshooting (or late transition) and conventional lock-in. For each run, the distance between total demand and supply and the food price dynamics are shown. X-axis represents time steps in model simulation, y-axis represents changes with respect to initial values (set equal to 100). Red areas correspond to periods of insufficient food.

Carbon pricing

In a previous report,[1] we noted that the traditional view that carbon pricing is the most cost-effective way to support decarbonisation depends on the assumption of equilibrium, and that this is at odds with the reality of low-carbon transitions being processes involving innovation and structural change. The case study Policy Options for Rapid, Smooth Decarbonisation and Sustainable Growth looks at carbon pricing from a global perspective. It finds that, when used alone as a policy instrument, a low level of carbon pricing is ineffective for achieving a low-carbon transition consistent with the goal of limiting temperature rise to 2°C, and that a high level of carbon pricing consistent with this goal could lead to economic instability, with a surge in unemployment, bankruptcies and recession. The study suggests that a mixture of policies including subsidies and regulation can be more effective in putting the economy on a pathway to sustainable growth.

The case study What is the Most Cost-Effective Form of Carbon Pricing? finds that, contrary to the traditional view, the two most common forms of carbon pricing – a tax and an emissions trading scheme (ETS) – are not equivalent in their cost-effectiveness. Our modelling finds that, for the same carbon price, a tax is likely to drive much faster emissions reduction than an ETS (Figure 6). The difference between these policy options also depends significantly on the structure of the markets to which they are applied. These findings are made possible by the use of models and techniques that make no assumption of equilibrium and instead explore the dynamic interactions of policies, technologies, companies and markets.

Figure 6: Time (showing min and max and mean) to reach zero emissions in the simulations (in years). The horizontal bars indicate the mean value from multiple model runs with each scenario.

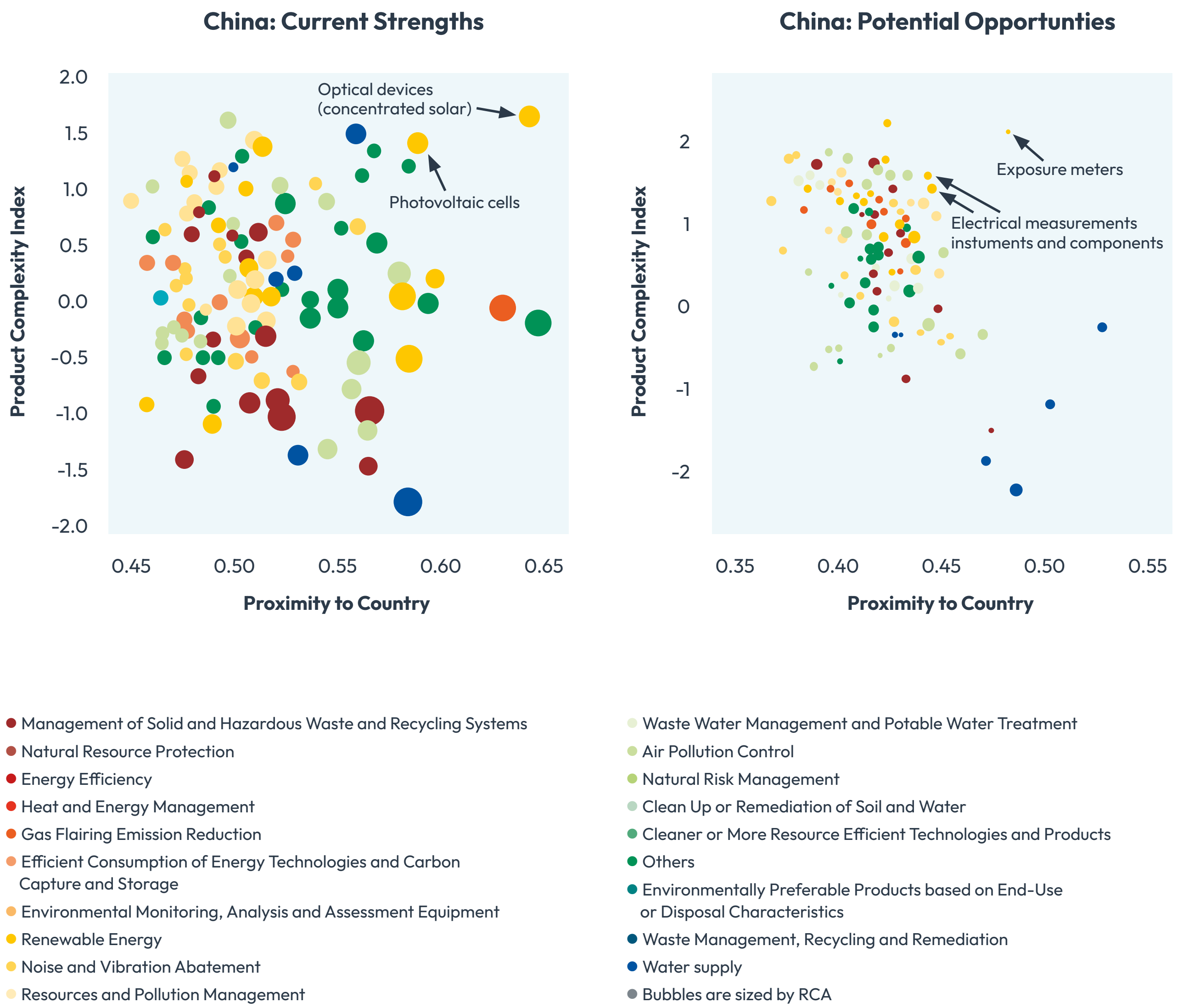


[1] Diaz-Anadon et al. (2022). Ten Principles for Policymaking in the Energy Transition: Lessons from experience.

Industrial competitiveness

The case study The Green Complexity and Competitiveness of China's Exports shows how an understanding of the network structure that relates different products in the economy to each other based on trade patterns can be used to predict new areas in which a country may be able to gain industrial competitiveness (Figure 7). We find that China's competitiveness in clean technologies exceeds its overall competitiveness in manufacturing, that it recently became competitive in exporting electric vehicles, and that areas in which it has the opportunity to increase its competitiveness include environmental monitoring technologies.

Figure 7: China's green export products divided into current strengths (left) and potential opportunities (right). Size of product circle indicates China's current revealed comparative advantage; colours represent product categories.

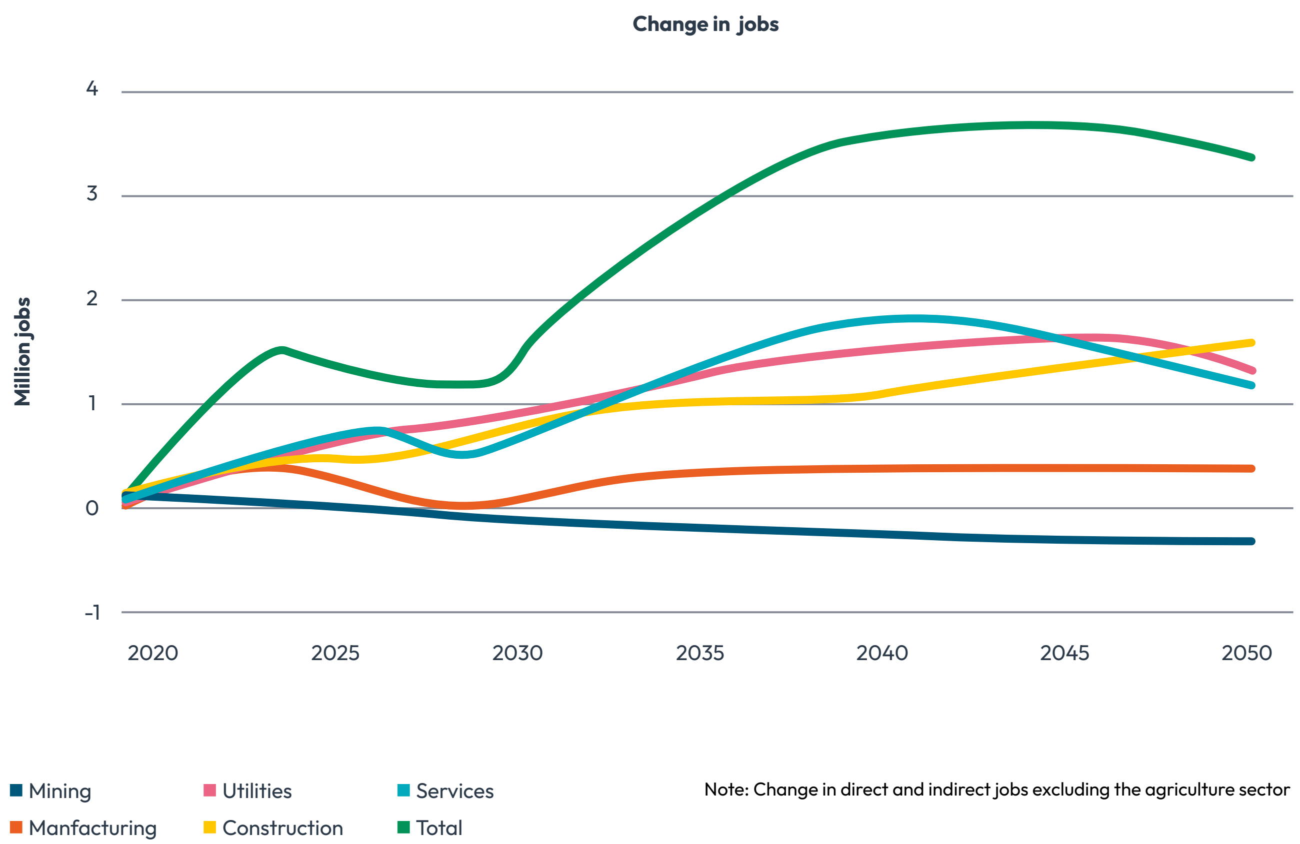


Jobs and skills

The case studies Economic Impacts of Net Zero in India and Decarbonising the Indian Economy (Figure 8), which use different modelling approaches, both find that the low-carbon transition is likely to generate additional jobs overall in India compared to a business-as-usual scenario. This finding is possible because these models do not assume that investment is optimally allocated to assets, or that people are optimally allocated to jobs, throughout the economy. Instead, the models allow for the realistic prospects of unproductive capital and unemployment. While job losses in fossil fuel sectors are likely to be substantial, these are more than offset by growth in jobs in sectors such as power generation, services and construction.

The case study Modelling Labour Market Transitions: The case of productivity shifts in Brazil considers how people's ability to move from sectors where jobs are being lost to those where they are being created will depend on their skills. Modelling the labour market with this realistic constraint provides insights into where skills gaps could be a barrier to the low-carbon transition, and where (in which sectors) unemployment is most likely to arise. The study finds that, in Brazil, the number of occupations where people could face an increased risk of unemployment due to difficulties in switching to new occupations is higher in a scenario where economic growth is driven mainly by increases in agricultural productivity than in a scenario where growth is driven mainly by manufacturing productivity. These findings could inform policies on worker retraining and economic development.

Figure 8: Macroeconomic outcomes in a long-term decarbonisation scenario, relative to the reference scenario.



Introduction

The call for change

This report represents a major effort to demonstrate and provide evidence for the value of a range of new economic modelling on specific energy topics and climate policy questions, in partnership with policy stakeholders in key countries in the global energy transition. Many researchers, policymakers and practitioners have been making the case for new economic modelling of the energy transition for some time. These calls have focused on three key areas:

1. The need for new approaches to climate policy appraisal.[2]
2. The need for better modelling of technology and innovation dynamics.[3,4]
3. The need to better model the underlying dynamics of the transition at national and global scales.[5]

These calls for new analysis are underpinned by a range of specific concerns about current analysis and decision-making frameworks, from purely technical modelling arguments to specific issues around the energy transition and how to model it appropriately, to wider arguments about how policy appraisal should be conducted and decisions made. These concerns are often overlapping and intertwined. We attempt to summarise them in Table 1. It is important to emphasise that different types of models and analysis address different subsets of these concerns; no single approach meets them all.

[2] Mercure, J-F. et al. (2021). Risk-opportunity Analysis for Transformative Policy Design and Appraisal. Global Environmental Change 70: 102359.
[3] Way, R. et al. (2022). Empirically Grounded Technology Forecasts and the Energy Transition. Joule: 6(9), 2057-2082.
[4] Peñasco, C. et al. (2021). Underestimation of the Impacts of Decarbonisation Policies on Innovation to Create Domestic Growth Opportunities. C-EENRG Working Papers, 2021-6: 1-16.
[5] Grubb, M. et al. (2021). The New Economics of Innovation and Transition: Evaluating Opportunities and Risks, EEIST report to COP26.

Table 1: Why do we need new economic modelling of the energy transition?

Theory: Energy transition domain concerns	Modelling: Conceptual and technical modelling concerns	Policy: Policy appraisal and decision-making concerns
• Marginal economic analysis is not appropriate for the transformational structural change that addressing climate change demands. • Existing theory, models and decision-making frameworks which assume equilibrium or an efficient self-optimising economy have an inbuilt bias that policy action will have costs. • Equilibrium-based theory and models often do not model structural transformation nor innovation, so assume that economic structure is static, incorrectly implying that only large price changes can prevent emissions. • We don't know the role of the private sector in the transition well, and this is often interpreted as a gap in public finance. • Real institutions should be represented.	• Models should be structurally realistic (i.e. represent the flows and relationships between economic actors as realistically as possible). • Models should capture disequilibrium[6] and path-dependent dynamics. • Models should capture feedback loops and tipping points. • Models should capture heterogeneity and interaction. • Models should capture uncertainty and 'fat-tailed' probability distributions. • Economic decision-making should be modelled using realistic individual behaviour (bounded rationality or heuristics). • Models should be empirically validated so that we can have confidence in their predictions. • Many existing models use poorly validated or arbitrary technology pathways. • Technology dynamics should be modelled endogenously. • Distributional impacts often need to be modelled.	• Decisions should be made on more than narrow 'best-guess' cost-benefit terms, to incorporate uncertainty, risks and opportunities. • A wider range of policy options needs to be considered – rather than modelling only a carbon price, we need to model the broader family of policies that are more likely to be politically feasible in the real world. This may involve implementing multiple complementary policies at the same time. • Policies should be assessed based on their likely effect on processes of change within the economy (how they affect the dynamics of innovation and structural change[7]), not just on the basis of predicted outcomes at fixed points in time. • To inform policy decisions, we need more probabilistic 'forecasting-type' models (i.e. which simulate and forecast likely futures,[8,9] as opposed to optimisation models which identify 'optimal' solutions or pathways).

In our previous EEIST reports, we have emphasised key messages on the question of how to model the energy transition. In our first flagship report, The New Economics of Innovation and Transition: Evaluating Opportunities and Risks,[10] we outlined the reasons why a new approach was needed, arguing the greatest successes achieved so far in the low-carbon transition have happened in ways that few people expected, using policy approaches that were not those recommended by standard economic analysis. If modelling for ex ante policy appraisal is to enable such successes more frequently, we need a new approach, to supplement traditional cost-benefit appraisal with new techniques, to understand the risks and opportunities of transformational changes.

[6] Here we are referring to disequilibrium as a property of complex systems, not the capability of models to be out of equilibrium or not.
[7] Peñasco, C. et al. (2021). Systematic Review of The Outcomes and Trade-Offs of Ten Types of Decarbonisation Policy Instruments. Nature Climate Change 11.3: 257-265.
[8] Meng, J. et al. (2021). Comparing Expert Elicitation and Model-Based Probabilistic Technology Cost Forecasts for the Energy Transition. Proceedings of the National Academy of Sciences 118.27: e1917165118.
[9] Farmer, J.D, and Lafond, F. (2016). How Predictable is Technological Progress? Research Policy 45.3: 647-665. 10 https://eeist.co.uk/eeist-reports/
[10] https://eeist.co.uk/eeist-reports/

In our second flagship report, Ten Principles for Policy Making in the Energy Transition,[11] we presented new evidence-based principles for policymaking in the energy transition, arguing that many of the economic principles, models and decision-making tools used by governments are designed for use within contexts of 'marginal' or incremental change, where technologies, markets and other economic structures are relatively stable. Different principles and tools are needed when, as in the energy transition, the aims and context of policy include widespread innovation and structural change.

In the main text of this report, for clarity and brevity we focus on demonstrating the value these new principles and modelling approaches can bring in practice and do not re-tread in depth the arguments about whether new approaches are needed or not. Others have done the latter already – for example, Farmer et al. (2015)[12] outline the existing taxonomy of integrated assessment models and their economic components. They discuss four key shortcomings in detail: (i) how these models deal with uncertainty; (ii) the representation of aggregation, heterogeneity and distributional impacts; (iii) representation of technological change; and (iv) the absence of realistic damage functions for the impacts of climate change on the economy. Mercure et al. (2016)[13] identify five shortcomings in existing optimisation and equilibrium economic models: (i) their normative, optimisation-based nature, (ii) their unrealistic reliance on the full-rationality of agents, (iii) their inability to account for mutual influences among agents and capture related self-reinforcing processes, (iv) their inability to represent multiple solutions and path-dependency, and (v) their inability to properly account for agent heterogeneity. In addition, Mercure et al. (2021),[14] presenting work from the EEIST project, outline an expanded form of cost-benefit analysis, called 'risk-opportunity analysis', designed for appraising policy options where the aim or context is transformational change – as is the case for policy on low-carbon transitions. They also describe how new economic modelling is needed for this type of analysis and decision support.

The IPCC has also touched on these issues,[15] outlining the spectrum between cost-benefit analyses using early integrated assessment models, the increasing emphasis on using models which can capture dynamic, rather than static, efficiency (that is, "taking account of inertia, learning and various additional sources of 'path-dependence'[16]) through to the use of complexity and systems approaches like those in this report. Others have attempted to overview and classify the large ecosystem of climate-economy models and integrated assessment models,[17] and made calls for different types of reform, such as efforts to increase understanding and participation.[18]

Delivering on the promise of new economic modelling

Calling for change is much easier than actually developing and applying the new modelling and delivering the envisaged value (i.e. more realistic, usable and fine-grained policy advice). This report represents a major effort to demonstrate and evidence the value of a range of new economic modelling on specific topics and policy questions, in partnership with policy stakeholders in key countries in the global energy transition.

This report contains 15 case studies of applications of new economic modelling approaches in Brazil, China, India, the UK and globally. Each case study describes a recent or current project in which new economic modelling was applied to live policy questions and topics with policy stakeholders. A case study approach allows us to demonstrate and reflect on the variety in modelling methods, purposes and contexts.

[11] https://eeist.co.uk/eeist-reports/

[12] Farmer, J.D. et al. (2015). A Third Wave in the Economics of Climate Change. Environ Resource Econ 62: 329–357.

[13] Mercure, J-F. et al. (2016). Modelling Complex Systems of Heterogeneous Agents to Better Design Sustainability Transitions Policy. Global Environmental Change 37: 102-115.

[14] Mercure, J-F. et al. (2021) Risk-opportunity Analysis for Transformative Policy Design and Appraisal, Global Environmental Change 70: 102359.

[15] Grubb, M. et al. (2022): Introduction and Framing. In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [P.R. Shukla. Et al (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA. doi: 10.1017/9781009157926.003 16 Ibid. page 33

[17] Nikas, A. et al. (2019). A Detailed Overview and Consistent Classification of Climate-Economy Models. In: Doukas, H. et al. (eds) Understanding Risks and Uncertainties in Energy and Climate Policy. Springer, Cham. https://doi.org/10.1007/978- 3-030-03152-7_1.

[18] Doukas, H. and Alexandros N. (2020). Decision Support Models In Climate Policy. European Journal of Operational Research 280.1: 1-24

Each explains the new modelling but, vitally, also explains the findings and their policy relevance. They each consider if and why the new modelling has given us new insights on existing questions, or developed insights on questions we could not address previously.

This report thus complements our other flagship reports, by providing the detailed new economic modelling and policy discussions many have been calling for.

Who this report is for – and how to read it

This report is more technical than our previous two. It is primarily intended for analysts and modellers working in government, international organisations, academia and the third sector; to allow them to see first-hand, and in detail, how new economic approaches can deliver value, what they can do and what they can't. We also hope that policy teams will find the report useful, providing insights on relevant policy topics, as well as illuminating the question of why different modelling approaches give certain answers and advice.

Alongside the modelling case studies, we reflect on the types of models showing most promise, considering how they differ, their strengths and weaknesses, and how we can evaluate, choose between and adopt them in our work.

- **For readers interested in the detail of what these models can do**, we recommend reading the case studies that are most relevant for you first (either by country or the policy topics they address). Next, it should be helpful to read the overview of different types of models.
- **For readers considering using any of the modelling approaches** presented here, we recommend reading our practical section on how to begin using these methods.

This report will not teach readers the technical details of how to use these models directly; it is not a manual in that sense. However, a core part of our mission is to develop the capabilities and capacity of organisations around the world to use these modelling approaches, demonstrate their value and advocate for the underlying philosophy of new economic modelling and policymaking. If you are interested in training or more detailed guidance, please go to https://eeist.co.uk/training/ or get in touch.[19]

What's in the rest of this report?

The next section focuses on types of policy questions and where new economic modelling can fit into these. Next, we explain what we mean exactly by 'new economic models', introducing the types of models. Then we move on to a practical exploration of how to choose and start using new economic modelling approaches. This section outlines what different types of models are appropriate for, but also how to adopt these approaches, how to get past technical and institutional constraints and how to advocate for new economic modelling. In the following section, we move on to the modelling case studies themselves. We group these by the broad policy themes they speak to – the global energy transition, power and industry sectors, transport, agriculture, impacts of the transition, national decarbonisation plans and finance. Each case study presents the modelling conducted, but also the policy context, the relevance of findings and the new value that these provide, in relation to previous work. Finally, we conclude with a discussion of what we can learn from the case studies as a whole and outline our vision for the next five years in new economic modelling for the energy transition.

[19] https://eeist.co.uk/contact/

Addressing the key energy and climate policy questions

Before we dive into the detail of what new economic modelling approaches are, and the applications in this report, it is important to outline the policy questions to which different approaches can be applied. Ideally, policy questions should be the driver of new economic modelling. Policy questions allow researchers to identify a topic and aim, which then in turn help us identify a suitable methodological approach (more on this below), or combination of approaches, that can provide insights on these policy questions, leading to decision-making and impact. If models are constructed or applied without policy questions as a starting point, there is a very serious risk that much time and effort may be invested without producing a tool or analysis that is useful for decision-making.

Types of policy questions

Useful analysis is rarely broad. Rather, it tends to be specific, with a narrow focus on one or all of the following: context, sector, technology, geography and policy decision. The policy decision focus can vary in scale, from macro-type questions such as, 'Will decarbonising the economy cost us money?' through to meso-level questions such as, 'Which technologies should we focus on?' or, 'Which types of policy instruments might work best?' And finally, down to micro-level questions such as, 'How should we design this specific policy instrument?' Table 2 identifies these broad types of policy questions, the relevant examples in this report and types of modelling that are well-suited to each.[20] The table is not exhaustive of all types of policy questions; there are other types, such as micro-questions about individual projects, but we do not focus on these in this report.

[20] At this stage, the types of modelling are defined on broad terms. More specific types are enumerated in the later sections.

Table 2: Types of policy question and new economic modelling applications

Nature of decision (i.e. policy hierarchy)	Scope	Example policy questions	Example case studies	Well-suited approaches[21]
Development direction and pace	Economy-wide	• Should we decarbonise or not? • How much might decarbonisation cost? • What are the macroeconomic impacts? • What are the fiscal and employment effects of phasing out fossil fuels and how should they be managed? • How fast should we transition in road transport?	• Empirically grounded energy technology cost forecasts • Decarbonising the Indian economy: policies and impacts • Socioeconomic consequences of coal phase out in China • Green complexity and competitiveness • Unstoppable renewables and marginal pricing in China, India and Brazil • Economic impacts of net zero in India	• Forecast-type models, which do not assume that the economy is self-optimising and can assess likely future outcomes in dimensions such as GDP, jobs, investment and trade. • Analytical approaches that consider the potential for a country to be competitive in emerging new technologies.
Technology choice	Within each sector	• Within the power sector, should we use solar power or coal power? • Within road transport, should we deploy electric vehicles, biofuels, hydrogen fuel cell vehicles or hybrids?	• Unstoppable renewables and marginal pricing in China, India and Brazil • Empirically grounded energy technology cost forecasts • Green complexity and competitiveness	• Forecast-type models, which can simulate the development of technologies over time and assess feasibility and likely impacts of technology choices. • Quantitative assessments of technologies' learning rates and of their compatibility with the goal of net-zero emissions. • Qualitative and quantitative assessments of the advantages and disadvantages of different technologies. • Optimisation models which can find least-cost technology mixes at fixed moments in time.

[21] See the section 'What are new economic models?' for an introduction to these types of models.

Nature of decision (i.e. policy hierarchy)	Scope	Example policy questions	Example case studies	Well-suited approaches[21]
Choice of policy	For each technology / aim	• To deploy solar, should we use tax, subsidy, technology mandate, efficiency regulation, procurement or something else? • To deploy electric vehicles, should we use efficiency regulations, EV mandates, purchase incentives, taxes or some mixture of the above?	• Decarbonising the Indian economy: policies and impacts • Activating EV tipping points	• Forecast-type models which allow detailed representation of different policy types and can simulate the effects of policies individually and in combination based on empirical evidence. • Risk-opportunity analysis[22] (as an expanded form of cost-benefit analysis).
Design of policy	For each policy	• Should a clean technology subsidy be a feed-in tariff or a contract for difference? • Should a carbon price be a tax or a cap-and-trade scheme? • How does design of electricity markets affect outcomes?	• What is the most effective form of carbon pricing? • Unstoppable renewables and marginal pricing in China, India and Brazil	• Forecast-type models which allow detailed representation of different policy designs and simulate their effects. • Qualitative models which allow us to walk through assumptions about policy design.

Where are we in the policy cycle?

Another way to think about what types of policy questions we have and where modelling approaches deliver value is to consider the policy cycle (Figure 9). We know the policy cycle is an idealised representation of the policymaking world, but it does serve a useful purpose: to break the process into different stages, which each imply different types of analysis. What it does not capture well is the iterative nature of analysis to support policy; there is often a continuous process of adjustment and improvement based on usefulness, agenda priorities and empirical data. In reality, the steps in the cycle are also not necessarily sequential – there could be arrows linking policy implementation to agenda-setting, for example. Finally, the policy cycle also obscures the importance of policy history and landscapes, where some policies can trigger others, or lock countries into certain policy paths.

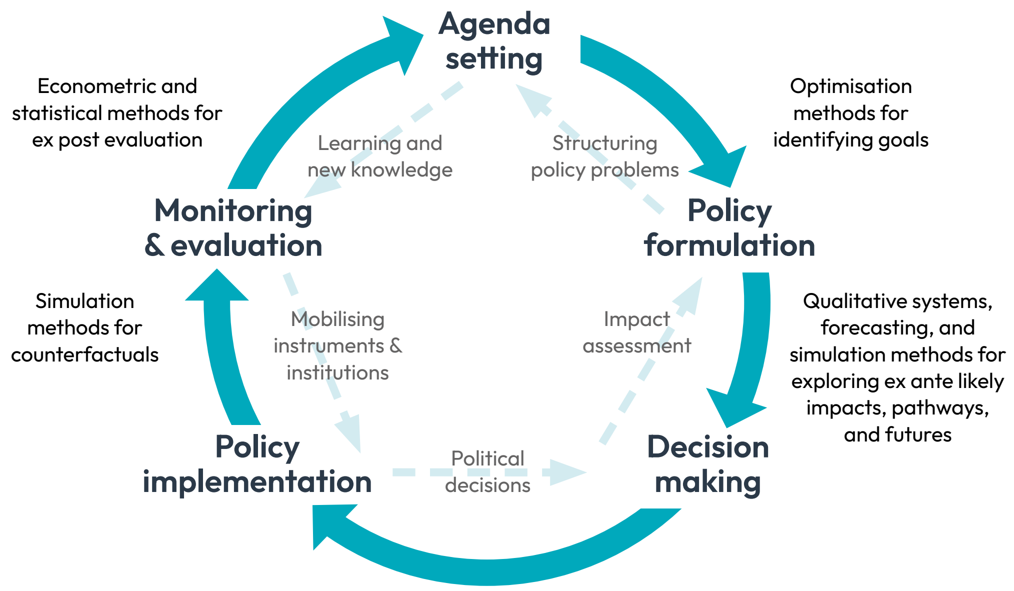
Nonetheless, the cycle helps us think about what types of analysis can be used at which stage. At the agenda-setting stage, optimisation methods (which we do not class as new economic modelling) have a role to play. Using these methods to explore what the optimal end point or goal is, in terms of costs, might be, under a set of technological constraints and assumptions, useful in setting the envelope of what we think is possible. However, as we move around the cycle, to policy formulation and decision-making, we believe new economic simulation approaches, which provide forecasts of realistic or likely futures that can result from policy actions, come to the fore. These types of models allow us to do meaningful ex-ante appraisal of policy efficacy and impacts. Importantly, they also allow us to understand the likely pathway to our goals, not just what the goal should or could be. This is simply not possible with optimisation models – it is not what they were designed for.[21]

[21] See the section 'What are new economic models?' for an introduction to these types of models.

[22] Mercure, J-F. et al. (2021). Risk-Opportunity Analysis for Transformative Policy Design and Appraisal. Global Environmental Change 70: 102359.

As we move around the cycle to policy implementation and evaluation, we begin to operate in an ex-post mode, assessing the actual impact we think a policy has had. Here, econometric and statistical methods become the most prominent, providing the data analysis techniques we need to assess impacts from real data. Econometric and statistical methods can come from new economic approaches or established approaches. A key challenge in ex-post evaluation is building a counterfactual of what might have happened without a policy. In most cases, an experimental approach with a control group to provide a counterfactual is not feasible, or ethical, for energy policy interventions. In such cases, one option is to use new economic forecast-type models to provide counterfactuals, in much the same way they assess a policy scenario in ex-ante mode.

Figure 9: The policy cycle (Adapted from Mercure, 2022[23]).



How clear are the policy questions?

Just as we know the policy process is not as simple as the policy cycle suggests, we know that, in practice, policy questions are not always expressed with clarity or certainty. Moreover, different groups or teams of policymakers may have different questions, and the questions may be contested.[25] Policymakers likely also have a long list of questions at any moment, and it is not always clear which are most important, or which might be most amenable to different methods of analysis. In this situation, it is useful to iterate quickly between policy teams and analysts exploring what type of questions we should focus on and how we should model them.

Systems mapping[26] is useful in this situation. It allows us to quickly describe the policy context and policy, to expose our assumptions to discussion, to start exploring our questions qualitatively, and to do all of this with other policymakers and groups. While this is useful in its own right, it is also much preferable to embarking on a significant piece of quantitative modelling only to realise halfway through that the policy questions were not clear enough, or the modellers had failed to bring along key stakeholders in the analysis. Where there is a lack of clarity on policy questions, we thus often recommend a systems mapping exercise as a stepping stone to more formal analysis.

[23] Mercure, J-F. (2022). Complexity Economics for Environmental Governance. Cambridge Studies on Environment, Energy and Natural Resources Governance.

[24] This point is further discussed in our previous report Ten Principles for Policy Making in the Energy Transition, pages 13 and 37. https://eeist.co.uk/eeist-reports/

[25] Royston, S. et al. (2023). Masters of the Machinery: The politics of economic modelling within European energy policy. Energy Policy 173, 113386

[26] Barbrook-Johnson, P. and Penn. A (2022). Systems Mapping: How to Build and Use Causal Models of Systems. Palgrave.

What are 'new economic models'?

What is 'new'?

'New economic models' could simply mean those that have been developed recently, but here the 'new' refers to models directly informed by the theory and methods of complexity economics and systems thinking. These academic disciplines are not brand new, but their application to an increasingly broad set of economic topics and the use of fine-grained data (i.e. firm level, different consumers, more granular technologies, more frequent temporal scales) is only just beginning. Together, they give us the conceptual frameworks and methodological approaches to address the issues identified in Table 1. They allow us to develop: models which capture disequilibrium,[27] path dependency,[28] self-reinforcing change and feedback loops,[29] and tipping points;[30] models which emphasise difference and interaction between economic agents; and models which allow for bounded rationality and decision-making rules of thumb.[31] These can be seen as extensions and complements to existing methods that are often dominated by assumptions of clearing markets in equilibrium, representative and homogenous agents, and perfect knowledge, rationality and optimal decision-making features.

Different types of models

This report draws on a variety of different models that can be hard to categorise. An important distinction is between 'data' and 'models'. Put simply, 'data' are measurements from real-world indicators; they provide context to the specific case under study and provide an anchor to the description of the real-world phenomena. 'Models' represent an explanation of the behaviour of data from a conceptual perspective – an exploration of possible future performance of these data – and are often based on assumptions that are idiosyncratic to a specific methodology. The combination of models and data can provide an analysis on a case-by-case basis and, most importantly, can allow models to challenge past performance in systems, and propose predictions on future behaviours in certain conditions.

We can differentiate new economic models between those that are based directly on data (e.g. apply analytical and statistical methods on existing data to make extrapolations to the future) and those that aim to mimic the functioning of the real world via dynamic simulations (e.g. structural relationships expected to carry meaning relative to the functioning of real phenomena) and informed by and compared with data.

In most cases, models tend to be hybrids of the two, combining elements of both data analysis and simulation modelling. However, for the purposes of enumerating a list of new economic methods, we can divide them into two categories based on their preference in formulating model structures and using data – see Figure 10 and Table 3 for overviews.

[27] In an economic context, it is simplest to think of this as models not characterised by return to equilibrium states, or using market clearing assumptions.

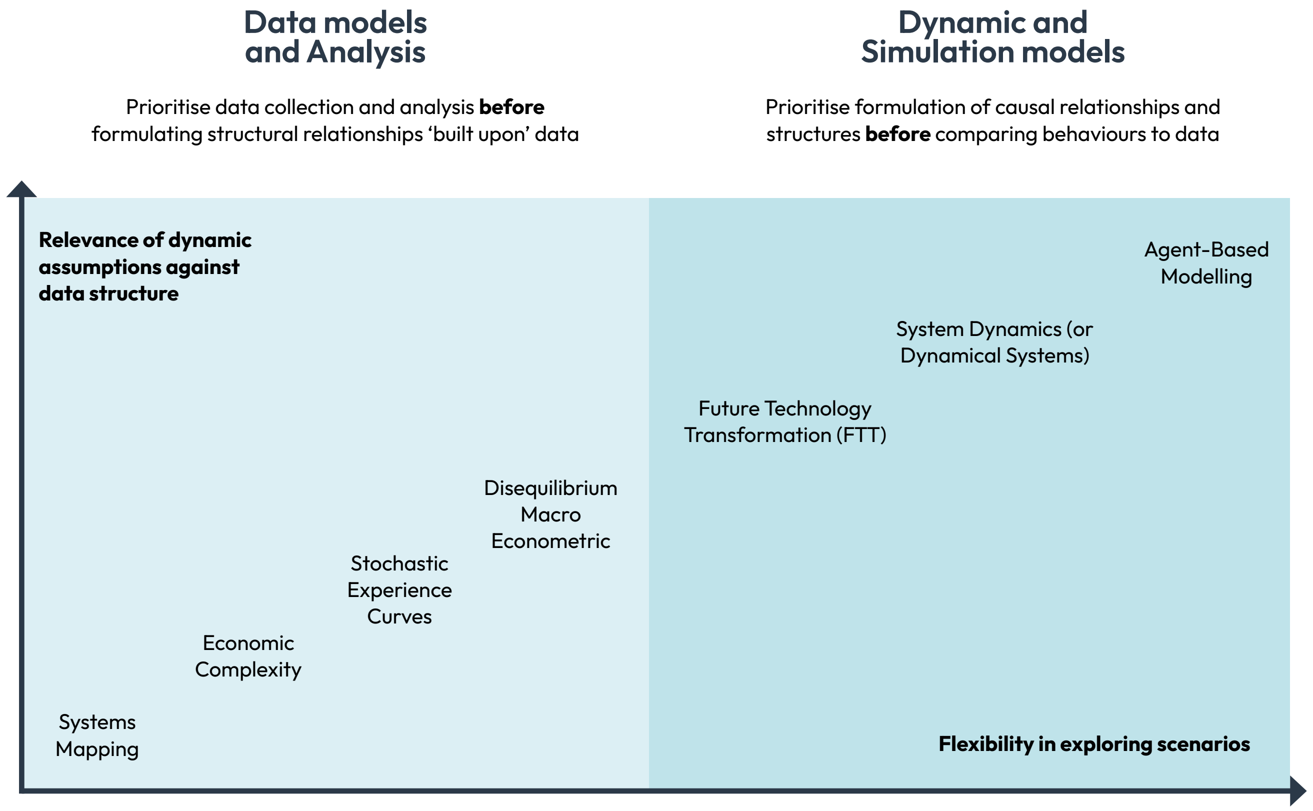
[28] Path dependency is often encapsulated by stating 'history matters'. That is, where a system has been and where it is now, constrain future directions and possibilities.

[29] Feedback loops, where an increase (or decrease) in one factor increases (decreases) another, which in turn increases (decreases) the original factor, create reinforcing or 'runaway' change.

[30] Owing to the proximity to a tipping point, small changes in a system or model can produce large or qualitatively different outcomes.

[31] Any individual model may not explicitly try to include all these aspects. This can make a model unmanageable or difficult to understand, though these trade-offs are becoming less pronounced with advances in methods.

Figure 10: Broad types of new economic models: As we move from left to right, we move from approaches which are based on looking for structure or patterns in data, through to approaches based on building structures in simulations and testing these against data. The vertical axis emphasises the importance of assumptions and theory used in approaches, which also increases as we move from left to right.



These two categories are:

1. **Models that prioritise the analysis and understanding of data before the attempt of developing model structures to explain those data.** Here, we include 'data models', often constrained by static assumptions (i.e. assumptions which do not change, or which are based on snapshots in time) – distributed on the left side of Figure 9 – and the 'disequilibrium macro-econometric' models, which, despite prioritising the analysis of data to build formal relationships, can also integrate new dynamic assumptions of real-world systems linked to non-linearity of future performance of systems.
2. **Models that prioritise the formulation of model structures to explain past events and data.** We can refer to these more generally as 'dynamic and simulation models' comprising the families of dynamical systems modelling, system dynamics models and agent-based models. The logic of these models implies that the awareness of data patterns of the past can help in identifying causal structures (of often difficult-to-quantify variables, e.g. social behaviours) that can then also be informed directly by data (i.e. parameterisation) and compared to existing time series via simulations (i.e. validation). It is worth noting that all models and methods that are built to have impact on real-world policies make use of existing data.

Table 3 further describes these classes of approaches, specifying individual modelling methods and their advantages and disadvantages.

Table 3: Specific examples of new economic models.[32]

Type Data models/analysis

Name	Description	Advantages	Disadvantages	Example case studies
Systems mapping	Uses networks to represent and analyse causal influence between factors in a system. Often used in stakeholder engagement activities.	Intuitive and accessible way of representing a range of relationships and influences in systems. Useful for identifying the dynamic effects of policies, such as differentiating between those that will be self-amplifying and those that will be self-limiting. Can utilise many sources of evidence and data. Less resource-intensive than building a simulation, but can also inform the development of dynamic models.	Though the model tries to capture feedbacks and dynamics, the model itself is static (i.e. does not explore how structure might change, or how the dynamics play out). Large maps can become unwieldy and hard to understand.	Qualitative systems mapping of ETS and carbon tax in China Data-driven systems mapping of SDGs and the energy transition in Brazil
Economic complexity[33]	Uses trade data and the economic structure it reveals to understand the direction in which an economy may be able to develop comparative advantage.	Helps understand an economy's current position and 'adjacent possible' (i.e. plausible product transition pathways). Can be used to inform industrial strategy or development strategy.	Suggests where a country could develop competitive advantage, but does not suggest how. Only based on export data, so internal consumption is missed..	Green complexity measures used to understand Chinese green technology exports
Stochastic experience curves	Uses Wright's and Moore's laws to make forecasts of energy technology costs based on past trend in deployment (or time) and costs.	Produces empirically validated probabilistic forecasts of energy technology costs. Method well-tested on a wide range of technologies and compared with expert forecasting methods.	Currently only implemented at global level. Provides no insights on why these changes are happening.	Empirically Grounded Energy Technology Cost Forecasts uses this method and plugs results into a simple energy system model.
Disequilibrium macro-econometric - E3ME[34]	Represents relationships between different economic variables and sectors as a set of equations, based on historical data patterns. Econometric model.	Can be used to identify likely macroeconomic outcomes of low-carbon transitions. Unlike CGE and DSGE[35] models, is unconstrained by restrictive assumptions such as optimal allocation of resources and full employment. Well used and documented.	A relatively aggregated model. It is not suitable to model dynamics emerging from interaction of individual heterogeneous agents. While it is not constrained by restrictive assumptions, it does not include a restriction per se on accessibility of finance, which in reality can be a constraint. Heavily dependent on data and data quality. It is not able to simulate sudden systematic change.	All E3ME-FTT case studies.

Type Dynamic and simulation models

Name	Description	Advantages	Disadvantages	Example case studies
Future technology transformations (FTT)	Uses equations that describe the S-curve of technology uptake with Wright's law. Makes forecasts of energy technology diffusion and costs, taking into account the self-reinforcing feedbacks between deployment and costs.	Can be used to simulate and predict the dynamic effects of policies – for example on technology diffusion and costs. Can test a variety of policy options and can show which policy combinations achieve more than the sum of their parts, and which achieve less.	Has limited between-sector interactions, and limited interaction between demand-side policies (in E3ME) and supply-side policies (in the FTT models)	All E3ME-FTT case studies.
System dynamics modelling (and dynamical systems modelling)	Simulation approaches which represent multiple components and structural dynamics of a system. Can simulate disequilibrium behaviour via reinforcing loops and non-linear relationships. Can capture tipping points.	Represent non-linear and disequilibrium aggregate dynamics of systems. Useful for distinguishing between policy approaches that are self-amplifying vs self-limiting, and for identifying trade-offs and synergies between policies in different sectors, or between economy, society and environment. Well-established community with norms around methodology.	Aggregated model - it is not suitable to model dynamics emerging from interaction of heterogeneous agents. Requires the dynamic structure of the system of interest to be known in advance.	System dynamics model of energy transition in India Green finance model in UK
Agent-based modelling (ABM)	Simulation method representing individual agents, their interaction with each other and their environment. Can generate emergent properties in complex systems.	'Best-in-class' structurally realistic representation of complex systems. Can show how agents such as different types of consumers, firms or investors may act in response to policy. Can be used to discover the dynamic structure of an economic system when this is not known in advance (identifying system behaviours that emerge from the interactions of different economic actors and policies). This can help to inform choices of market design.	Data-hungry (i.e. requires fine-grain data for setup, and time series data for validation), sometimes computationally heavy (i.e. slow to run). Technically difficult and time consuming to develop (e.g. difficult to trace causes and consequences of emergent phenomena).	Labour market ABM models workers as agents moving around the Brazilian labour market. Macroeconomic ABM used in Policy Options for Rapid, Smooth Decarbonisation and Sustainable Growth China carbon pricing ABM of the power sector.

[32] Most of the case studies in this report fall neatly into one of the categories in this table or are a hybrid or combination of categories. However, one does not. Modelling Sector Coupling of Hydrogen and Ammonia in India presents a 'complexity-extended' traditional energy system model, which we do not give its own category here.

[33] 'Economic complexity' here refers to the specific stream of literature on using trade data to understand the sophistication of different national economies. It is an unhelpful term because it is so generic and often confused with 'complexity economics', but it is the recognised term for this work, so we use it.

[34] Technically, E3ME and FTT are specific models, not classes of models. However, owing to their central position in the EEIST project, and new economic modelling more broadly, we give it its own category here.

[35] Computable General Equilibrium and Dynamic Stochastic General Equilibrium models. We do not introduce these well-known approaches here. For an introduction see Burfisher, M. E. (2011). Introduction to Computable General Equilibrium Models. Cambridge University Press and Wickens, M. (2012). Macroeconomic Theory: A Dynamic General Equilibrium Approach. Princeton University Press.

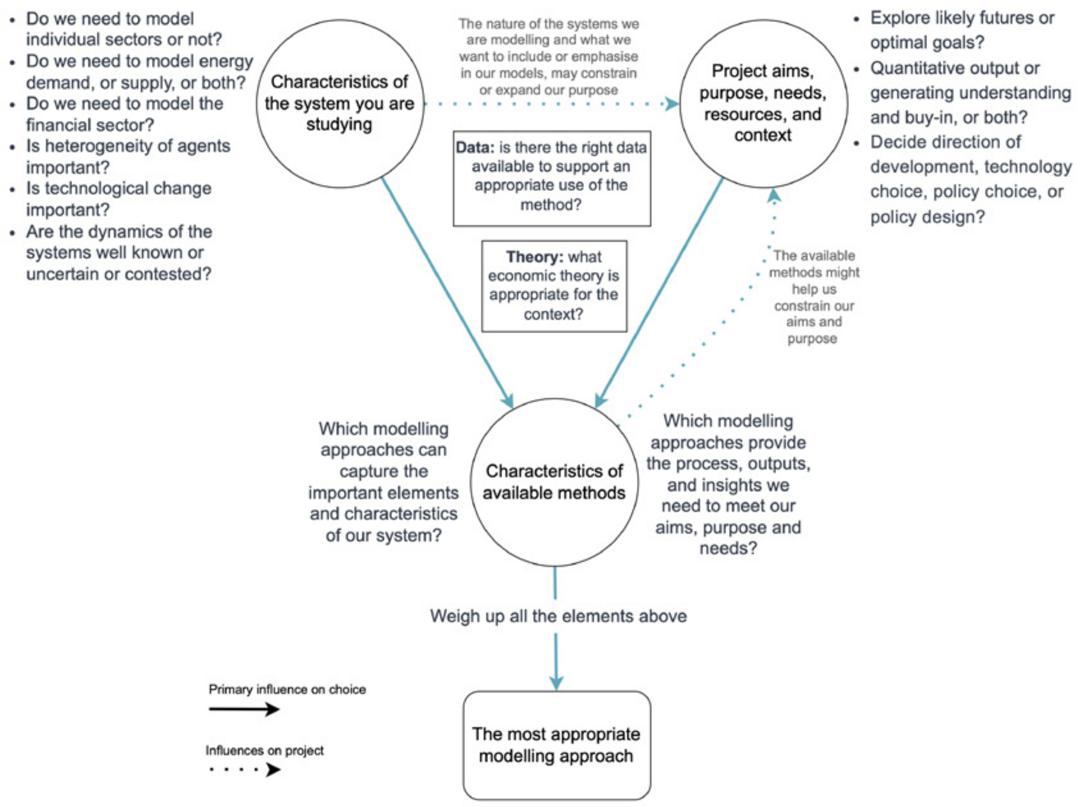
How to choose and use new economic models

Now we have a sense of what new economic models are and the types of policy questions they can be put to, in this section we outline how we can begin to make choices about which methods to use and how to start using them in practice. These choices need to be made with all methods, new or not, but since the approaches we outline in this report are less well established than others, it is worth considering these issues in detail.

Choosing the most appropriate modelling approach

There is rarely a simple best-worst choice when selecting modelling approaches to use. There will be methods that are inappropriate given specific questions and purpose, and among appropriate choices, there will be pros and cons that differ in different contexts. The trick is to find the most 'appropriate' approach given the purpose, aims, resources, data available and context – and given the characteristics of the economic and energy systems being represented. Even when taking all of those into account, there may not be an obvious choice. Where time and resources allow, it is often beneficial to deploy or combine multiple methods. This has the additional benefit of providing an indication of the robustness of results – i.e. are they the same across different methods?

Figure 11: Aspects to consider when choosing the most appropriate modelling approach.



Project purpose and aims (summarised in Table 4): These can be very different from one project to the next, and purpose can also evolve through time or be seen differently by different actors. Nonetheless, at their core, all energy transition modelling projects need to be clear on a variety of purpose questions. For example:

1. Are we trying to identify a desirable end state for the transition, given some constraints, or are we trying to identify policies that will help us get there?
2. Which do we value more: (i) a quantitative output, (ii) generating stakeholder understanding and buy-in, or (iii) both equally?
3. Are we most interested in informing development direction, technology choice, policy choice or policy design?

Beyond the immediate purpose, there is also the project resources and contexts, the needs and objectives of other stakeholders, and the availability and quality of data. These all interact with our intentions for the purpose of the project, constraining or augmenting it in different ways.

For example, the stage we are at in the policy process may affect choices. If a policy is in the early stages of being designed or discussed, we may have a more 'exploratory' purpose, which opens up more options and allows us to experiment with new methods. Whereas, if a policy design is set, and we want to appraise it in detail, or we want to understand what impacts an existing policy might have in the coming years, we will have a narrower purpose focused on exploring likely futures in detail. This will mean we are much more likely to want a tried-and-tested approach.

A key resource is data. Many modelling approaches are data-hungry and rely on the right data being available. The usefulness of models for different purposes often goes up and down with the quantity and quality of data we have to initiate and validate models. However, some methods are better suited to working in low-data contexts. When we do have data, overfitting of models (i.e. producing a model or analysis that corresponds to one particular dataset well, but not to others, or performs badly in forecasts) is a common problem to both new and traditional methods. This can happen when there are specific problems with the methods themselves being susceptible to overfitting. It can also occur where there is insufficiently developed understanding of the underlying social phenomena, leading to limited (or no) generalisability in contexts where social and economic relations are somewhat different.

Table 4: How aspects around project purpose shape the most appropriate modelling method.

Aspect	Potential situation	Most appropriate method/model
Purpose and aims	Explore likely effects of policies	Bottom-up or structurally realistic models, such as E3ME, ABMs, energy system models.
	Optimal outcomes	Process-based integrated assessment models.[36]
	Understanding, policy choice and buy-in	Simpler or qualitative models, such as systems mapping.
	Detailed policy analysis	Models which can represent different policies in precise and meaningfully different ways, such as FTT or very applied ABMs.
	Broad system behaviour	Simpler models, such as System Dynamics models, or relatively simple energy system models.
Time and money resources	High resources	Larger models such as E3ME or ABMs.
	Low resources	Relatively simpler models such as System Dynamics, systems mapping, or larger models which already fit needs closely.
Data available	Data-rich	Data-hungry models such as applied ABMs, data-driven systems mapping.
	Data-poor	Qualitative models such as systems mapping.
Context	Early in policy cycle	More scope for different methods and those less well-established; value in models that increase understanding of the behaviour of the system.
	Late in policy cycle	Pressure to use tried-and-tested models and those with quantitative outputs; greater need for specificity in policy options to be tested.
	Contested policy area	Methods which allow us to question assumptions and build buy-in, such as systems mapping; value in use of a range of models, to compare outputs with different assumptions.

[32] 36 These are the more detailed cohort of IAMs, such as AIM-Enduse, GCAM, IMACLIM, IMAGE, MESSAGE-GLOBIOM, and REMIND. For a discussion of these models, see: Wilson, C. et al. (2021). Evaluating Process-based Integrated Assessment Models of Climate Change Mitigation. Climatic Change. 166.3.

System characteristics: the energy transition is impacted by, and itself impacts, many different economic, social, ecological and technological systems. We rarely need to model all of them, and when we do, we will model some in more detail than others. We may also want to model them in different ways (i.e. representing different elements in different ways, or emphasising some parts over others) depending on our aims and how important we think specific characteristics of the systems are to our questions and purpose.

There are several sets of structural questions we should regularly ask ourselves when deciding which things to model in the energy transition:

1. Do we need to be modelling individual institutions, technologies or economic sectors, or can we aggregate them? Relatedly, is technological change important? Do we need to separately consider knowledge or technology developments outside the energy sector? Do we want to model scenarios or policies with sector-specific changes, or do we want to understand sector-specific impacts? If yes, include sectors, if not, we may be fine simplifying them away.
2. In how much detail do we need to model energy demand and energy supply? Or put another way, in how much detail do we need to model the energy system and the economy? It is likely we want to focus on one or the other, and we should not be afraid of using a simple model of one, when our focus is really the other.
3. Do we need to model the financial system? Do we believe the process of acquiring credit, or investment, is important in system behaviour? Can we do useful modelling without including the financial system?

There is also a second set of grouped questions, about how we model the systems we want to cover:

1. Do we need to model heterogeneity and interaction between actors such as consumers, firms and investors, or can we aggregate their behaviour within each of these groups? If yes, then we should probably model them, if not then we may be fine to simplify them away.
2. Do we want to model a (sub)system endogenously or exogenously? Put another way, do we want to model the internal dynamics of a (sub)system and how it is affected by other things in the model, or can we simplify it away, or treat it as static? For example, do we want to model technology innovation? Key issues here include whether we have good data and understanding of a sub-system, and how important it is to our questions or important in system behaviour. We may want to represent it endogenously and capture feedbacks between it and other parts of our model.
3. How do we want to model human behaviour and decision-making: using rational expectations, or with bounded rationality or other social rules or decision-making heuristics? Do we believe a rational expectations model of decision-making is appropriate to our context, or does it systematically miss important decisions/dynamics?
4. Which behavioural characteristics of systems – i.e. path dependency, emergent behaviour, technology complementarities and dependencies, tipping points or feedbacks – do we want to capture? Are there particular concepts we think are driving behaviour in the system and we want to understand in detail? For example, path dependency, feedbacks or tipping points.
5. How should we capture uncertainty? For many contexts, 'model structure uncertainty' can be more important than 'parameter uncertainty', so choosing a modelling approach that can represent and incorporate the former can be important. Sensitivity analysis then becomes a key tool for exploring model structure uncertainty.

Finally, it is often vital to keep in mind whether the dynamics of the system in question is well known, uncertain or contested. This can have implications for the methods that are most appropriate. Where the dynamics are contested, we might want to use a more qualitative or participatory method to help resolve open questions with stakeholders, whereas where dynamics are well agreed, we are much more likely to be able to use a quantitative simulation method successfully. Project purpose plays a big role here and should ideally always be cognisant of the status of perceptions of system dynamics and behaviour.

Reflecting on prediction, forecasting and empirical validation

In many contexts, modellers and policymakers are interested in using models to forecast how policies will affect outcomes. Having a clear understanding about expectations on forecasting and prediction is vital – users can often have different expectations about whether models can or should be used in this way. Before we can discuss this, we need to define our terms and acknowledge that they are often used in different ways. By prediction, we mean an attempt to reduce randomness by narrowing down the possible states of the world. A prediction is a statement about the likelihood of different states; it need not be about the future. For example, the ideal gas law allows us to predict the pressure of a container of gas at a given point in time if we know the volume at that same point in time. A forecast is specifically a prediction of the future.

Empirical validation can refer to many different approaches to testing if a model is giving good predictions or forecasts. We can do this by ensuring the design of the model makes sense, given some data or theory we have about the mechanisms and structure of the system. We can also validate by testing the model outputs against real data, to understand how well it forecast or predicted them. The balance between these two types of validation is often debated.

Predictions are valuable only insofar as they are accurate. This means that empirical validation is essential. Until we validate a model by using it to make predictions and testing their quality, we have no idea if it is of any use. It is essential to test against obvious benchmarks, such as random guesses, and it is surprising how many economic models fail to beat simple null models.

Models are useful for more than predictions. In many cases we may want to use a model to understand the logic of a given system. How does each part of the system affect the other parts? Sometimes qualitative models provide a good way to get started. But as modelling develops, we often want to make our models more quantitative and to make them more reliable. The key role of empirical validation is that it helps tell us whether a model has any realism – where realism is claimed, we should be suspicious of analysis based on models that do not make good predictions.

From this perspective it is important to distinguish how well a model fits data in-sample from how well it predicts data out-of-sample. By 'in-sample' we mean data that was available when the model was built and that was used to estimate its parameters. In contrast, 'out-of-sample' refers to new data that was not available when the model was built. Overfitting is the situation in which a model fits data well in-sample but produces poor predictions out of sample. From this point of view, it is often the case that a simpler model is better, it is less likely to be overfitted because it has fewer parameters to fit.

Overfitting is not just about prediction. For policy evaluation, it is always tempting to assume that complicated models that fit the available data well are more realistic, and therefore should provide better answers. However, a measure of a model's realism should not only be its design, but also the quality of its predictions. With this in mind, simple models are often more reliable, even for policy analysis.

Economic modelling is hard, so we should expect that making good predictions will require a great deal of time and effort. We are unfortunately often forced to make important decisions based on inadequate models. Our philosophy is to test models extensively where appropriate and be clear about their accuracy, managing expectations so that the user understands what a model is intended for and how reliable it is.

How to begin using these approaches

Our intention is that economists, analysts and policymakers in national governments, multilateral organisations, the private sector and civil society make more use of the modelling approaches presented in this report. There are great opportunities to develop new and timely analysis, and a growing demand for this work.

There are also potential conceptual, practical and institutional constraints that may be encountered. We have encountered these ourselves, along with our collaborators and have begun to think seriously about how to overcome them on more than just an ad-hoc basis. In this section, we consider what the barriers might be and how we can overcome them, to apply new economic modelling to generate the most value in the right settings.

Potential constraints:

The central conceptual constraint is likely to be a perception that new economic models are in direct competition with existing approaches. Existing economic approaches have been successful in many domains and are valued for their clarity and apparent quantitative rigour. Economics holds an extremely influential position in policymaking, relative to other social sciences. It also has an established set of principles and tools embedded in training and education, so has many proponents in treasury ministries, government departments and international organisations.

What matters is choosing the economic theory, models and decision-making frameworks that are appropriate for a given purpose and context. Rather than setting up different economic approaches as competitors or rivals, it is more productive to see them as complements, to be used in different contexts, depending on our purpose and how appropriate they are as theoretical lenses, or analytical tools, to the questions at hand.

Nonetheless, people advocating for new economic models are likely to encounter pushback from some economists and (more broadly) modellers, and should be ready to engage in detailed conversations about the pros and cons of using these approaches and how they sit together. In Table 5, we attempt to outline these and some of the potential constructive responses.

Practical constraints are normally more important to the quality of work we can do with new economic models than conceptual constraints. The primary practical constraint is often data. The modelling approaches presented here, especially ABMs, are data-hungry; that is, they require a lot of data, often disaggregated and through time, with which to initialise, calibrate and validate. The appendix outlines the exact data requirements of many of the case studies in this report, which we hope is useful to get a precise sense of what we mean by 'data-hungry'. Even where models are not data-hungry, they may require different data to other models, which are not immediately accessible.

Table 5: Common pushback on new economic modelling.

Pushback	How to respond and generate a constructive discussion
New economic modelling critiques a 'straw man' of economics and many of the criticisms have been addressed in recent work (i.e. critiques are made on outdated vision of mainstream economics).	This is the most important pushback to address. In whatever specific context or issue this is raised, attempt to dig deeper, to understand what the recent work is and whether it does address the critiques that new economic modelling makes. A common issue is confusion about the purpose of individual modelling projects, which clouds the discussion. Many debates can be diffused by making clear that the purpose of new economic modelling is often different to existing approaches. It is also common for misunderstandings to arise here, around terminology or use of concepts, so digging deeper and comparing approaches carefully is a vital first step. It is also often the first step to new approaches being used.
Existing economic assumptions and frameworks have been valuable so we should not get rid of them.	We are not advocating for the abolition of existing work, rather for selecting approaches that are appropriate to the contexts in which we use them. In contexts where transformational (i.e. whole-system) or structural change is needed or under way, analysis which relies upon assumptions of marginality (i.e. interventions will not affect technological capabilities, market structures or the wider economy) are not appropriate. Thus, when we are modelling the energy transition, which represents one of the primary examples of transformational change, we should be extremely careful about using marginal approaches.
New economic models are not well tested or trusted.	The complexity economics and systems approaches we present in this report have been well-tested over the last 10 years in a range of policy domains. However, it is fair to say many of the techniques we are advocating for are not well established in energy and climate change policy. However, there is a clear need for policy to make faster progress on low-carbon transitions, the limitations of currently dominant approaches are well documented, and there are strong theoretical reasons to believe that these new approaches will have significant advantages. The influence of these approaches in decision-making and the number of proponents working in national governments and international organisations is increasing. This report provides examples of these approaches being used with policymakers in important contexts. Major organisations making use of new economic models include: the UN, the OECD, the EU, the World Bank, China's Energy Research Institute, the World Resources Institute, the Bank of England, and the UK government's business and energy department.

Beyond data, new economic models may not produce the same types or precision of outputs that organisations are used to (e.g. estimates of particular indicators or variables, or plots). However, some of the precision from established methods can be illusory. New economic models are often stochastic and/or systemic in their approach and favour exploring uncertainty, so will provide ranges and estimates of outputs, not point predictions. This in turn requires a more probabilistic approach to further analysis. Before using a new method, check what outputs it produces and in what form, and think about how these might be used in organisational workflow.

Institutional constraints are a combination of practical and conceptual constraints that apply to specific organisations. Some institutions are inherently risk averse and may avoid using methods which are perceived as untested or which may be less efficient than using a method already used or well understood. Organisations may favour 'multi-purpose' models with wide applicability, since they are easier to keep and maintain than specialist models where resources and skills to maintain them, or commission when needed, will be rarer.

Organisational cultures, training and structures may also be built around an existing method or model; there may be infrastructure built up to enable its use (e.g. team structures, training, job roles dedicated to parts of models, regular reports and events organised around analysis timetables). There may also be many modelling efforts being run in parallel which are later brought together (for example, running economic forecasts at short, medium and long-term timescales). Swapping in new approaches for one of these strands may make them incompatible. These can be very serious barriers, which no method could overcome if they are seen as a direct replacement. In these situations, working in parallel is often the only way forward, but can be seen as unnecessary additional work.

How to proceed?

Given the clear opportunities, and the potential constraints, how can we proceed with adopting and using new economic modelling approaches? Here is a tentative list of suggestions based on our learning:

1. Start small and ramp up. Use pilot studies and small projects focused on specific policy questions of interest to show how new economic models can add value. This will allow organisations to learn and incrementally build up.
2. Systems mapping as an entry point.[37] Use systems mapping, an intuitive and easy-to-start method for exploring topics, to analyse the dynamics of a policy problem. This can open people's eyes to the complexity of a topic and how to think about it differently. Systems mapping, when well executed, can (i) inform policy directly, without needing a quantitative model to be built, (ii) show why disequilibrium models may be useful and (iii) be the first step in moving to a quantitative new economic model.
3. Become an advocate. Build a coalition of advocates (or users) in and around your organisation, connecting likeminded people. Practice and get used to articulating the value and complementarity of these approaches on terms that make sense to others, not just existing supporters. Build legitimacy and credibility around these methods, through pilots and partnerships with external groups who use them. Gather examples from elsewhere, of where these methods have generated value (this report, for instance).
4. Build capacity and expertise. Organisations working on the transition need people who can use these methods. Think about the training and capacity building they need to do this and how organisations can provide or access it. Consider how to fine-tune hiring or procurement processes to encourage people interested in these methods.
5. Develop bespoke guidance. There is already generic guidance out there, but bespoke guidance for individual organisations will be useful too. In particular, we recommend developing guidance for policy analysis that distinguishes between principles and tools appropriate for marginal change, and those appropriate for non-marginal (including transformational) change.

[37] Here, we are referring to the specific method 'systems mapping' (see Barbrook-Johnson, P. and Penn, A. 2022. Systems Mapping. Palgrave), but this could also apply to systems thinking more widely. For an introduction for civil servants, see https://www.gov.uk/government/publications/systems-thinking-for-civil-servants

Case studies of new economic modelling applications

This section presents the core contribution of this report: a library of 15 case studies of new economic modelling being applied to national and global energy and climate policy questions. These case studies can be read alone or in combination. They each cover key points such as the policy topic at hand, methodological details, findings and implications (including comparison to other analysis where appropriate), but they do not follow a rigid formula. Each features a description of the nature of policy engagement that was involved in the work.

Table 6 gives an overview of all the case studies in this report. We group them by the broad policy themes to which they speak: the global energy transition, power and industry sectors, transport, agriculture, impacts of the transition, national decarbonisation plans, and finance.

Table 6: Case study overview.

Group	Name	Region	Policy question	Modelling approach	Key finding
The global energy transition	Empirically Grounded Energy Technology Cost Forecasts	Global	How much will the energy transition cost?	Probabilistic energy tech cost forecasts and simple energy system model	The energy transition is likely to save the global economy trillions of US dollars.
	Policy Options for Rapid, Smooth Decarbonisation and Sustainable Growth	Global	Which climate policy packages are better at fostering and sustaining the energy transition without destabilising the economic system and the public budget?	Agent-based model	Carbon pricing alone is ineffective, but a mix of fossil fuel ban, public construction subsidies and electrification standards shows good potential for emission growth reduction while increasing growth and maintaining macro-financial stability.
Power and industry sectors	Unstoppable Renewables and Marginal Pricing in China, India and Brazil	Brazil, China, India	How can barriers to variable renewable energy uptake and the design of electricity markets affect electricity prices in power systems of the future?	E3ME-FTT:Power	Overcoming barriers to variable renewable energy (VRE) uptake likely leads to further electricity price reductions. An electricity pricing mechanism broadly in line with the weighted average levelised cost (WALC, i.e. expected lifetime costs, rather than marginal cost) might be able to accommodate further VRE uptake. The focal point for policymakers should be to minimise barriers and shape a market suitable for power systems dominated by VRE technologies.
	Modelling Sector Coupling of Hydrogen and Ammonia in India	India	Can the buildout of green hydrogen and ammonia infrastructure in India facilitate the transition to a net-zero electricity grid?	Complexity-extended energy system model	There are costs to current policy which has put us on a path towards decoupling the emerging hydrogen and ammonia sectors from the grid. There are opportunities to build more resilient, lower-cost systems if the system is designed with sector coupling in mind.
	What is the Most Cost-Effective Form of Carbon Pricing? Modelling emissions trading and a carbon tax in general and in China.	China	What is the most cost-effective form of carbon pricing in China?	A qualitative systems mapping exercise and an agent-based model	Emissions trading schemes need to be designed to avoid introducing a balancing feedback on emissions. Without this, a carbon tax will be more cost-effective. Competition in the power sector (or, more precisely, a clear price signal) is key to allowing carbon-pricing policies to work most effectively.

Group	Name	Region	Policy question	Modelling approach	Key finding
Transport	Activating EV Tipping Points in China, India, Europe and the US	China, India, Europe, US	Which policies, individually and in combination, are most effective in driving the transition to electric vehicles? How does a fast transition compare to a slow transition, in terms of costs with the road transport sector, and in terms of macroeconomic consequences?	E3ME-FTT:Transport	A cost-parity tipping point between electric vehicles (EVs), and internal combustion engine vehicles (ICEVs) is near, in major markets. An EV subsidy that closes the cost gap between EVs and ICEVs can be made revenue-neutral with only a small tax on ICEVs. Regulations and mandates are more cost-effective than financial incentives for driving the transition towards EVs when used individually and can also contribute to highly effective policy packages. A fast transition to EVs saves costs compared to a slow transition. The macroeconomic consequences of the transition to EVs are likely to be more positive for large oil-importing countries, and more negative for large oil exporting countries.
Agriculture	Supporting Sustainable Agriculture Intensification: A system-wide ABM approach	Global	Should institutions support sustainable intensification, and which factors make such intervention more urgent?	Agent-based model	Institutions should promote and incentivise sustainable farming and early support is most beneficial. If supporting policies are introduced too late, the technological gap becomes large, creating lock-in.
Impacts of the energy transition	Modelling Labour Market Transitions: The Case of Productivity Shifts in Brazil	Brazil	How would occupation-level unemployment be affected by growth paths with different drivers and emissions outcomes in Brazil?	Agent-based model	The number of occupations facing higher unemployment is lower in lower-emissions growth paths than in high-emissions growth paths. Higher productivity in manufacturing is better aligned with Brazil's NDC targets and results in fewer labour market frictions.
	China and the Social Consequences of the Coal Transition	China	What are the fiscal and employment effects of phasing-out coal power in China?	Microsimulation[38]	There are employment and fiscal losses associated with transitioning away from coal, but given current subsidies it is already likely to be a fiscal drain.

[38] Microsimulations have much in common with agent-based models, representing individual actors, but they do not typically model interactions between actors.

Group	Name	Region	Policy question	Modelling approach	Key finding
National decarbonising plans	Economic Impacts of Net Zero in India by 2070	India	What are the macro-economic impacts of achieving net zero in India by 2070?	E3ME-FTT:Power	Solar energy will become a dominant technology by 2070. The transition to a net-zero economy leads to net-positive macroeconomic impacts for India. It will also likely lead to a decimation of jobs in the fossil fuel related sectors with more than 2 million jobs at risk. However, it will support job creation in other sectors such as power generation, construction and services.
	Decarbonising the Indian Economy: Policies and impacts	India	What are the most impactful policies to decarbonise the Indian economy? What are the likely implications of these on economic growth and employment?	System dynamics model	Decarbonisation is possible while creating net savings in costs and achieving better economic growth and employment outcomes.
	Data-Driven Systems Mapping of SDGs and Energy Transition Interactions	Brazil	What risks and opportunities for SDGs will the energy transition create, and how might we manage these?	Systems mapping (data-driven)	Wind energy unexpectedly interacts with a range of health, water and sanitation outcomes.
	The Green Complexity and Competitiveness of China's Exports	China	What products do countries have comparative advantage in and how might these be affected by the energy transition?	Green complexity index/Economic complexity	Strategic long-term policies can drive a nation towards areas of potential comparative advantage. China has succeeded in doing this over the last two decades, in which its rise as a green product exporter has been even more powerful than its rise as the leading global manufacturer.
Finance	Closing the Green Financial Gap in the UK	UK	What are the macroeconomic implications of a UK low-carbon electricity transition implemented in conjunction with and without a policy designed to close the green finance gap?	System dynamics model	Closing the green finance gap policy scenario, alongside a low-carbon power scenario, leads to the co-benefits of lower power system costs and unemployment, and increases in GDP.
	Exit Options for Renewable Energy Investments in Brazil	Brazil	How might 'exit options' analysis support private financing of renewables projects.	Financial modelling.	The uncertainty in the financial evaluation of individual renewable energy projects is a key driver for the application of exit options by creditors, and despite being relatively unknown in the country this project valuation method is relevant for pushing forward the Brazilian renewables sector.

CASE STUDY:

Empirically Grounded Energy Technology Cost Forecasts

RUPERT WAY (UNIVERSITY OF OXFORD), MATTHEW IVES (UNIVERSITY OF OXFORD), PENNY MEALY (WORLD BANK/UNIVERSITY OF OXFORD), J. DOYNE FARMER (UNIVERSITY OF OXFORD)

Policy question: How much will the energy transition cost?

Region: Global

Methods: Stochastic experience curves used to produce probabilistic energy technology cost forecasts and a simple energy system model.

Key findings: The energy transition is likely to save the global economy trillions of US dollars and the savings are greater if the transition happens quickly.

Engagement: Owing to its global scope, this work has been widely disseminated with a large number of policy and media partners. Highlights include: feeding in a net zero review by the UK government, being presented at the California Energy Commission, discussions with White House and US State department officials, and being featured in media outlets around the world (e.g. BBC, Asiana Times, Guardian, New Yorker, Bloomberg).

Summary: The authors combine a well-validated data analysis approach for forecasting energy technology costs with a simple energy system model to consider how much the energy transition might cost at a global scale. In contrast to many traditional models, they find that the energy transition, and especially a fast transition, is likely to save the global economy trillions of US dollars.

Introduction

Decisions about how and when to decarbonise the global energy system are highly influenced by estimates of the likely cost. Most energy-economy models have produced energy transition scenarios that overestimate costs due to underestimating renewable energy cost improvements and deployment rates.

This case study[39] presents probabilistic cost forecasts of energy technologies using a method that has been statistically validated on data for more than 50 technologies. Using this approach to estimate energy system costs, we find that a rapid green energy transition is likely to result in trillions of net savings. Even without accounting for climate damages or climate policy co-benefits, transitioning to a net-zero energy system by 2050 is likely to be economically beneficial. This method of forecasting costs can also be useful for informing policy choices about the technologies to use for decarbonisation of different sectors.

Approach

For technologies that are experiencing improvements in costs, improvement rates are remarkably consistent.[40] For these technologies there are two dominant methods for quantitatively forecasting costs based on historical data. The first is a generalised form of Moore's law, which says that costs drop exponentially as a function of time. The second is Wright's law, which predicts that costs drop as a power law of cumulative production. We focus on Wright's law because it satisfies the basic intuition that exerting greater effort induces greater effects. However, we do repeat all our modelling experiments using Moore's law and find that the qualitative conclusions are similar.

Wright's law has usually been used to generate point forecasts, meaning that the forecast is a deterministic function of experience, with no estimate of error. Early attempts at introducing error bars did not provide a priori functional forms, which made the data requirements for out-of-sample testing prohibitive.[41 42] More recently, a priori error estimates were derived that predict forecasting accuracy as a function of historical improvement rates and volatility, and the number of data points available for forecasting.[43] Based on comprehensive backtesting, this method was shown to generate reliable probabilistic estimates of future costs. This was done by selecting reference dates in the past and then, using only the data available at the time, making forecasts over all time horizons up to 20 years into the future with respect to each reference date. Using historical data for 50 different technologies, based on roughly 6,000 forecasts, the empirically observed forecast accuracy closely matched the a priori derived estimates on all time horizons up to 20 years ahead. 2,5 Our main contribution in this work is to systematically apply this method – which we call the stochastic experience curve or stochastic Wright's law – to the energy transition.

Testing our approach to forecasting costs

To test the accuracy of the stochastic experience curve method for forecasting costs of energy technologies, we applied it to historical data for solar, wind, batteries and polymer electrolyte membrane (PEM) electrolysers (see Figure 12). Data prior to each forecast year were used to estimate parameters, then observed deployment data in subsequent years were used to generate forecasts conditioned on experience. The forecasts for solar, wind and batteries are reasonable: most of the future values lie within the 95 per cent confidence interval (CI), consistent with the a priori error estimates. Due to the short dataset and high historical volatility, forecasts for electrolysers are not as accurate, but the confidence intervals capture this.

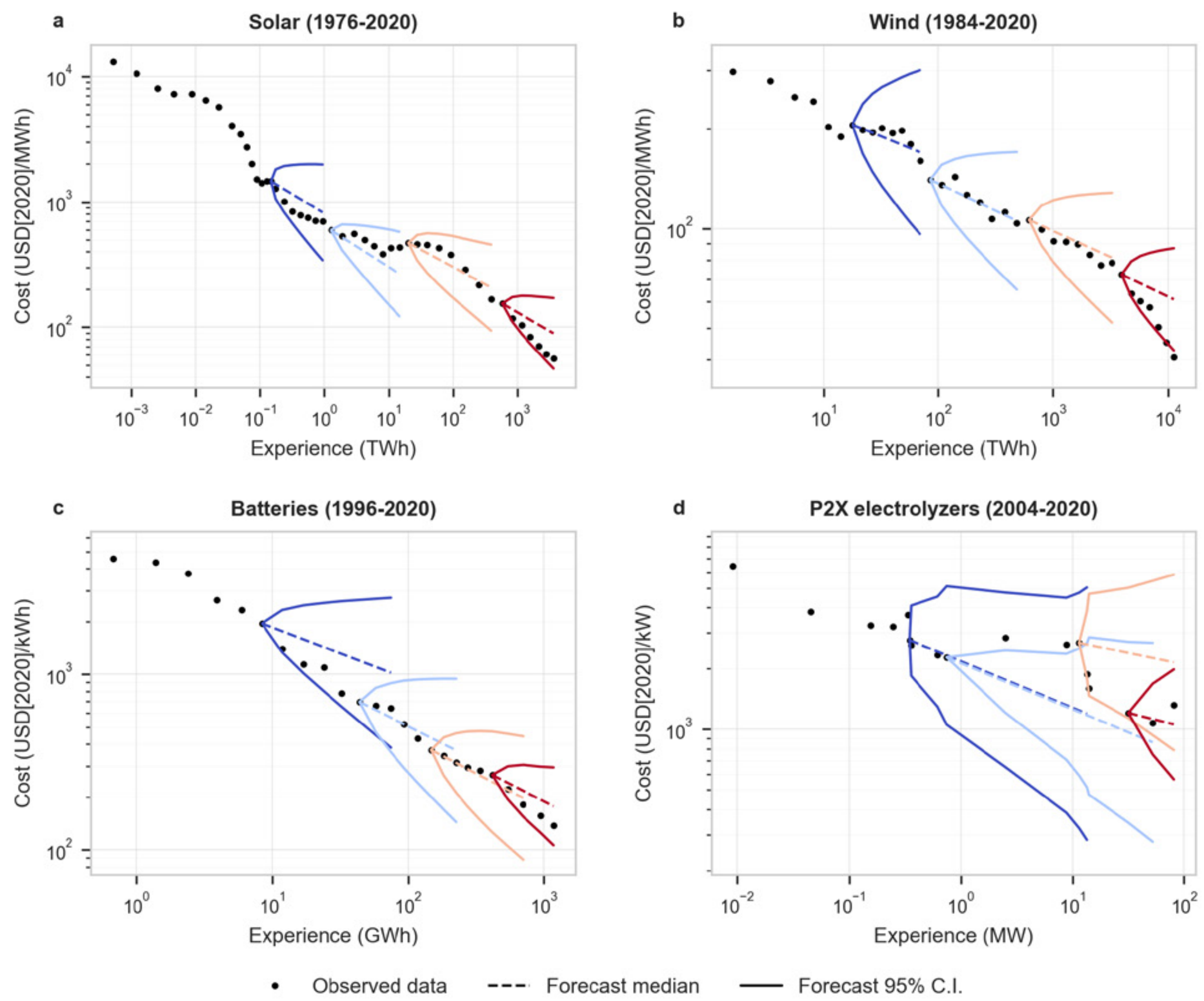
[40] Farmer, J.D and Lafond, F. (2016). How Predictable is Technological Progress? Res. Policy 45: 647-665.

[41] Nagy, B. et al. (2013). Statistical Basis for Predicting Technological Progress. PLoS One, 8 (2013): Article e52669.

[42] Alberth, S. (2008). Forecasting Technology Costs Via the Experience Curve—Myth or Magic? Technol. Forecasting Soc. Change, 75, 952-983.

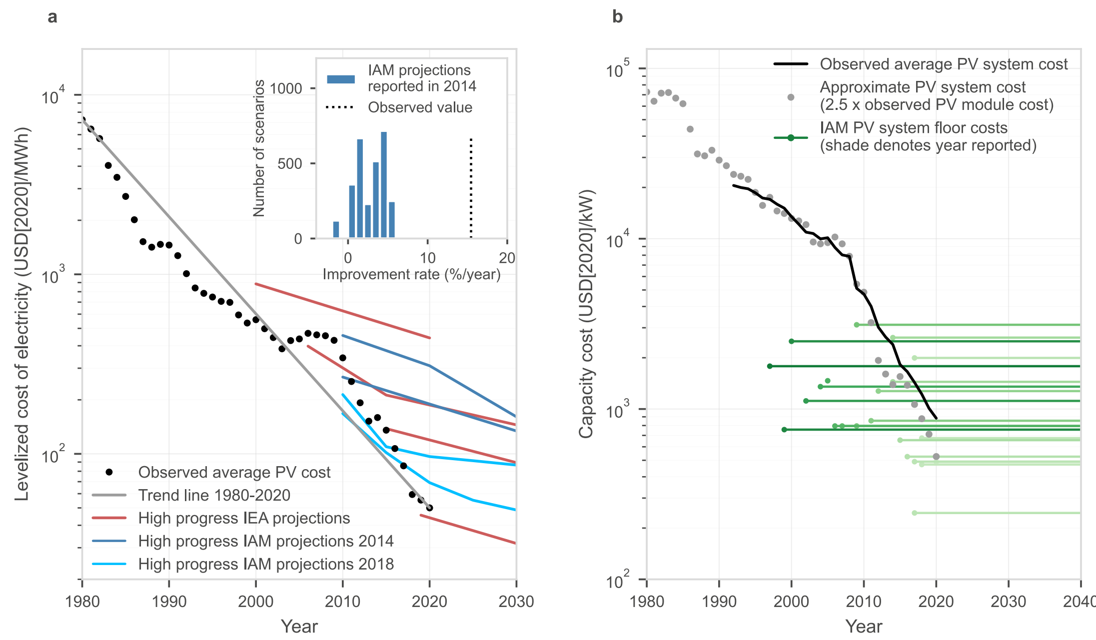
[43] Lafond, F. et al. (2018). How Well do Experience Curves Predict Technological Progress? A method for making distributional forecasts. Technol. Forecasting Soc. Change 128 (2018): pp. 104-117.

Figure 12: Historical performance of the stochastic experience curve forecasting method. Forecasts are made at regular intervals, using prior cost and deployment data to calibrate the model and 'future' deployment data to generate the forecasts. Forecast medians and 95 per cent confidence intervals (CIs) are shown, and colours denote forecast year, from earliest (dark blue) to most recent (red). Costs are LCOEs for solar and wind, and capacity costs for batteries and electrolysers. P2X electrolysers are assumed to be PEM electrolysers here. Source: Way et al. 2022. Empirically Grounded Technology Forecasts and the Energy Transition. Joule 6(9): 2057-2082.



It is instructive to compare the accuracy of these forecasts to the outputs of influential global energy-economy models. Integrated assessment models (IAMs) are used to evaluate policies and generate scenarios for deployment and cost that are consistent with given climate targets under the assumption of optimal decision-making by economic agents. Their outputs are typically called 'projections' to indicate that they are not intended to be used as forecasts. Figure 13 emphasises this point. Figure 13A shows past projections of solar PV energy costs by the International Energy Agency's (IEA) World Energy Model and several IAMs and compares them with the observed data.

Figure 13: Historical PV cost projections and floor costs. (A) The black dots show the observed global average LCOE. Red lines are LCOE projections reported by the IEA;[44] dark blue lines are integrated assessment model (IAM) LCOE projections reported in 2014;[45] and light blue lines are IAM projections reported in 2018.[46,47] IAM projections are rooted in 2010 despite being produced in later years. The projections shown are exclusively 'high technological progress' cost trajectories drawn from the most aggressive mitigation scenarios, corresponding to the largest projected cost reductions used in these models. The inset compares a histogram of projected compound annual reduction rates of PV system investment costs from 2010 to 2020 with what actually occurred (based on all 2,905 scenarios for which the data are available).[48] (B) PV system floor costs implemented in a wide range of IAMs. The colours denote the year the floor cost was reported, ranging from 1997 (dark green) to 2020 (light green). Observed PV system costs are also shown. The cost of PV modules scaled by a constant factor of 2.5 is provided as a reference. Source: Way et al. 2022. Empirically Grounded Technology Forecasts and the Energy Transition. Joule 6(9): 2057-2082.



The projections shown correspond to scenarios with the most aggressive climate policies and highest rates of technological innovation, i.e., those that produce the highest rates of key green technology deployment and the most optimistic cost declines. Nonetheless, their projected costs have been consistently much higher than historical trends.

This makes it clear that it would have been a bad idea to treat these projections as conditional forecasts. By contrast, the stochastic experience curve method produces reliable conditional forecasts of known accuracy (and a published forecast of 2020 solar costs, made in 2010 using the deterministic version of Wright's law, was indeed far more accurate than any of the IAM or IEA projections made at the time).[49] One of our goals in this work is to illustrate how such forecasts are useful for planning the energy transition.

Wright's law is widely used to generate technology cost projections in IAMs. However, it is typically used in conjunction with ad-hoc constraints such as deployment rate limits and floor costs, i.e. fixed levels that costs are assumed to never fall below. Because IAMs use costs to determine deployment (and vice versa), and many allow perfect foresight, constraints are necessary to prevent sharp cost declines due to Wright's law from leading to solutions in which key green technologies are deployed faster than is physically or socially plausible. It is difficult to know what constraints are realistic, which leads to ad-hoc choices that strongly influence the results. The imposition of excessively strong constraints is likely an important reason why the projections of these models have not corresponded to the historical record.

[44] IEA. World Energy Outlook 2021. Technical report. International Energy Agency (2021).

[45] Riahi, K. et al. (2015). Locked into Copenhagen Pledges — Implications of Short-Term Emission Targets for the Cost and Feasibility of Long-Term Climate Goals. Technol. Forecasting Soc. Change 90 (2015): 8-23.

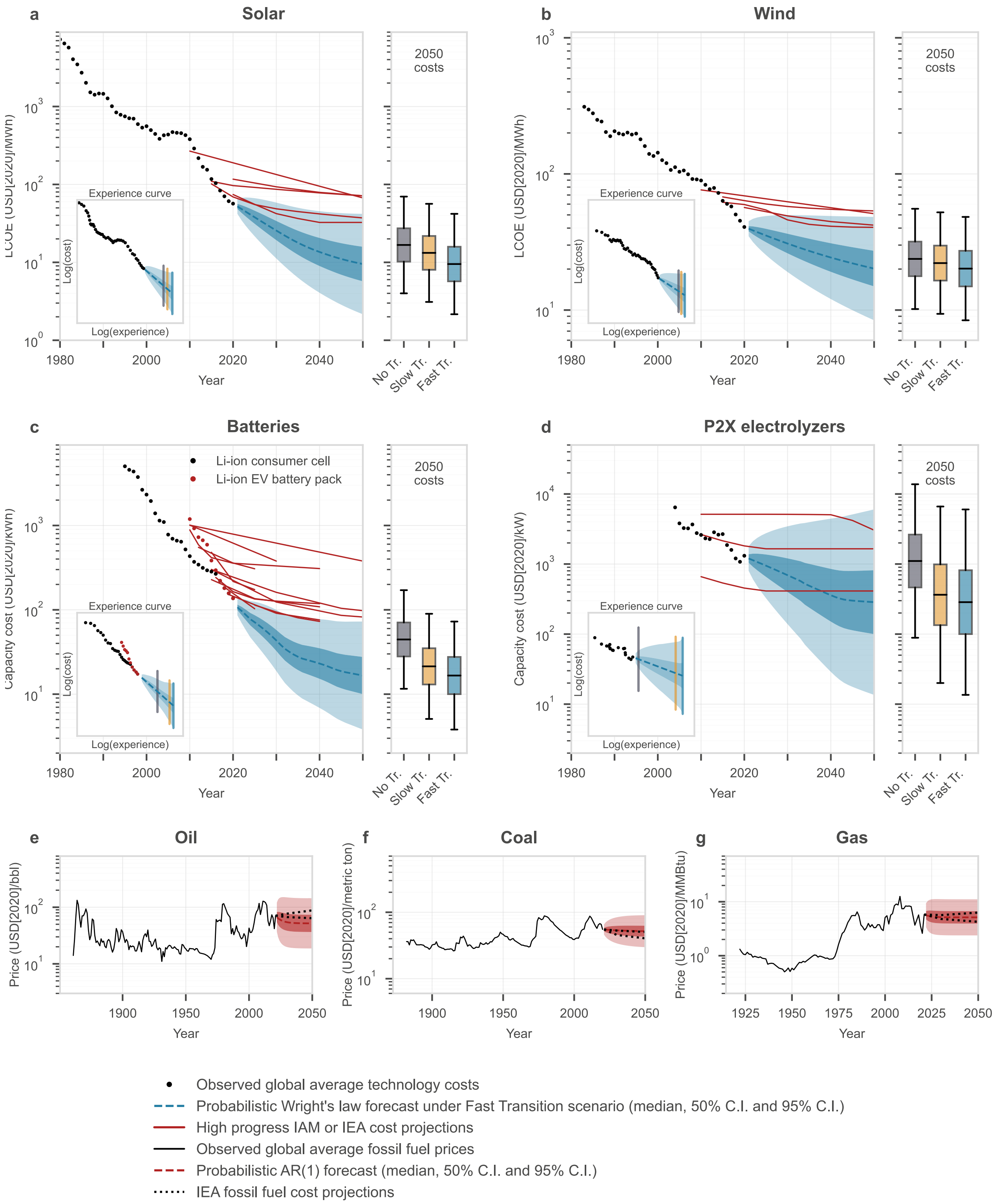
[46] Krey, V. et al. (2019). Looking Under the Hood: A Comparison of Techno-Economic Assumptions Across National and Global Integrated Assessment Models. Energy, 172 (2019): 1254-1267.

[47] Huppmann, D. et al. (2019). IAMC 1.5°C Scenario Explorer and Data Hosted by IIASA. Technical report, IIASA (2019).

[48] Riahi, K. et al. (2015). Locked into Copenhagen Pledges — Implications of Short-Term Emission Targets for the Cost and Feasibility of Long-Term Climate Goals. Technol. Forecasting Soc. Change 90 (2015): 8-23.

[49] Ferguson, C.D. et al. (2010). A US Nuclear Future? Nature, 467: 391-393.

Figure 14: Technology cost forecasts. (A–D) The main panels show cost forecast distributions under the Fast Transition scenario for solar PV, wind, batteries, and PEM electrolysers; the 50 per cent confidence interval (CI) is dark blue, and the 95 per cent CI is light blue. Also shown are several representative recent and past projections corresponding to 'optimistic' mitigation scenarios made by IAMs and the IEA (red lines) (see Figure 13). For batteries, both lithium-ion (Li-ion) consumer cells and Li-ion electric vehicle (EV) battery packs are shown, although their costs have now converged; our forecasts are based on consumer cells, whereas the IEA projections shown are based on EV batteries. The boxplots in the right-hand panels compare cost forecasts in 2050 under the No Transition, Slow Transition and Fast Transition scenarios. The insets show historical experience curves and forecasts, with learning rates that are independent of the scenario, and vertical lines that indicate how far each technology moves down the probabilistic experience curve in each scenario. (E–G) These panels show probabilistic cost forecasts for oil, coal, and gas based on the AR(1) time-series model. Source: Way et al. 2022. Empirically Grounded Technology Forecasts and the Energy Transition. Joule 6(9): 2057-2082.



Probabilistic cost forecasts for individual technologies

We applied the methods discussed so far to make forecasts of future energy costs and prices. To generate experience curve forecasts, parameters for each technology were estimated from historical data. We then specified scenarios for the future deployment of each technology as a function of time and predicted a distribution of future costs. We defined three representative deployment scenarios. The first scenario is consistent with the energy system transitioning away from fossil fuels by around 2050, and so we label this deployment scenario the 'Fast Transition'. The second scenario is consistent with eliminating fossil fuels by around 2070, so we label it the 'Slow Transition'. The final scenario is consistent with fossil fuels continuing to dominate the energy system, so we label it the 'No Transition'.

Figure 14 shows probabilistic forecasts for seven important energy technologies. The main panels of Figures 14A–D show forecasts for key green technologies in the Fast Transition scenario, which are made using the stochastic version of Wright's law. The insets show costs versus experience and emphasise that median costs develop identically as a function of experience in all scenarios. The side panels of Figures 14A–D illustrate that under Wright's law, forecast distributions depend on the scenario; as a result, in a faster transition, we are likely to reach lower costs sooner. Each Wright's law technology initially follows its current trend of exponentially decreasing costs, but then progress slows as its rate of deployment drops. To generate fossil fuel cost forecasts, an autoregressive model (AR(1)) was calibrated to observed data. For fossil fuels, model parameters depend on past data, but forecasts are independent of deployment, so each technology has a single forecast in all scenarios.

Figure 14 also shows a selection of future cost projections reported by IAM and IEA studies. As before, we show only their most optimistic projections. Consistent with the historical behaviour of these models illustrated in Figure 13, the cost projections are high relative to historical trends. They are also all substantially higher than our forecast medians.

The deployment corresponding to these cost projections is not the same as that used to make our forecasts, so they are not perfectly comparable. However, as the boxplot panels show, the disparities persist across all our scenarios, including No Transition. This makes it clear that our cost forecasts are, all things equal, significantly lower than those used in these influential energy-economy models.

From single technologies to full system costs

To forecast the likely costs of the green energy transition and explore how uncertainty in individual technology costs propagates through to uncertainty in system costs, we constructed a simple, transparent model of the global energy system based on well-defined technology deployment scenarios. We used the three transition scenarios introduced above. For more detail on these scenarios and the implementation of our simple energy system model, please see Way et al.1

To apply our probabilistic technology cost forecasting methods in a given scenario, we employed a Monte Carlo approach, simulating many different future cost trajectories, then exponentially discounting future costs to calculate the expected net present cost (NPC) of the scenario up to 2070. Figure 15A shows annual system costs through time for each scenario. The black boxplots represent the full cost forecast distributions, whereas the colored bars show median expenditures by technology group. This shows how, in the Fast Transition scenario, expenditures transfer rapidly from fossil fuels to key green technologies.

Figure 15: Scenario costs. (A) Coloured bars show median annual expenditures on fossil fuel and non-fossil fuel technologies in each scenario in trillions of dollars (tn USD). Boxplots show the median and interquartile range (IQR) of total annual expenditures, and whiskers extend from the box by 1.5 times the IQR. (B) Forecast distributions of the annual system cost in 2050 for each scenario. (C) Forecast distributions of the net present cost (NPC) of each scenario, for a fixed discount rate of 2 per cent. (D) Expected net present cost of each scenario relative to the No Transition scenario, as a function of the discount rate. The inset shows the probability that the NPCs of the Fast Transition and Slow Transition will be lower than that of the No Transition, as a function of the discount rate. Source: Way et al. 2022. Empirically Grounded Technology Forecasts and the Energy Transition. Joule 6(9): 2057-2082.

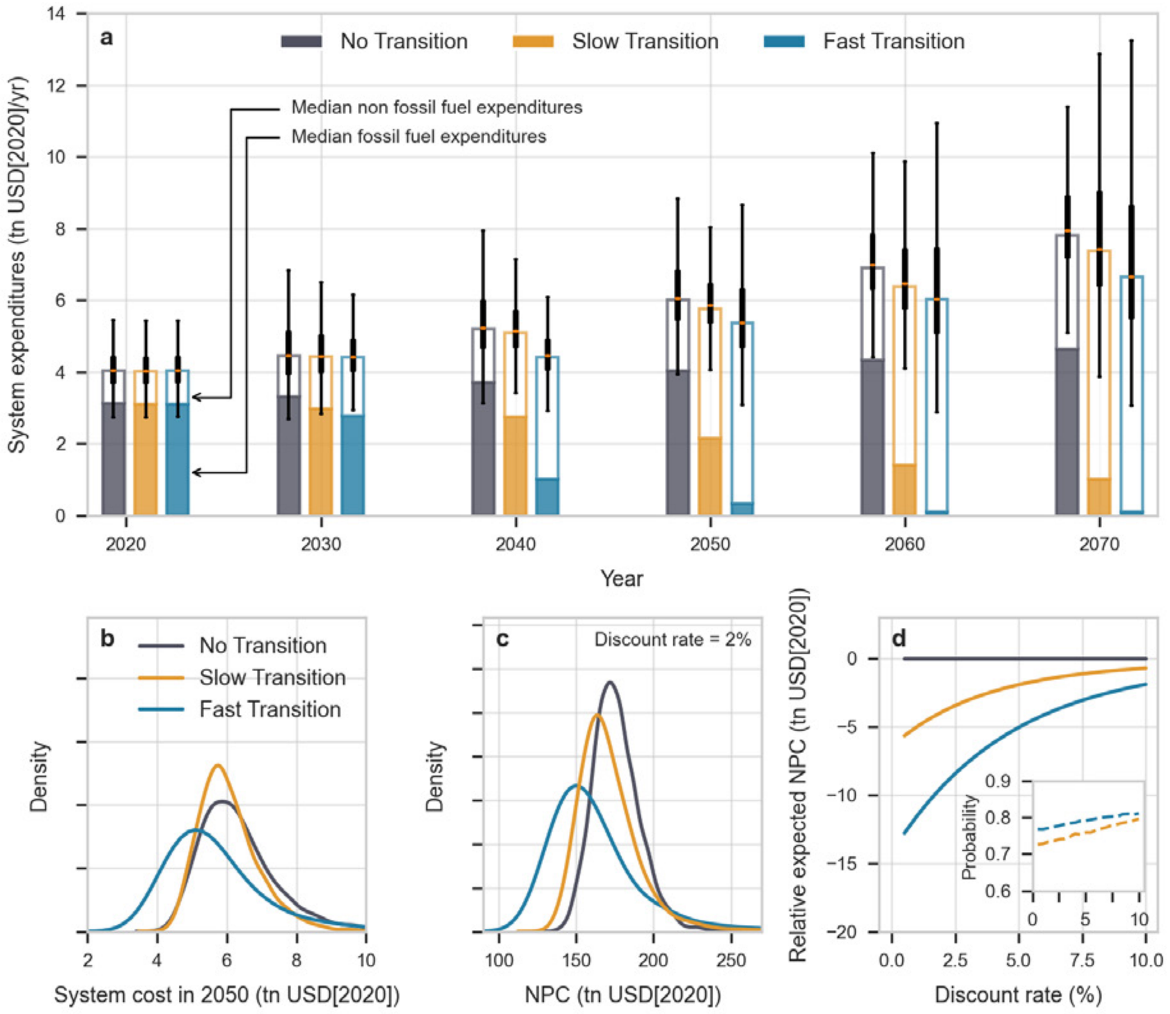


Figure 15B shows the annual system cost forecast distributions in 2050. Rapid replacement of fossil fuel technologies by low-cost key green technologies – in power and transport in particular – causes the expected annual energy system cost in 2050 for the Fast Transition scenario to be $514 billion cheaper than that for the No Transition scenario, although the distribution of possible costs for the Fast Transition is wider. After 2050, as shown in Figure 15A, while the median and interquartile range (IQR) remain relatively low, the uncertainty of the Fast Transition in relation to No Transition increases. If costs are in the upper end of the uncertainty range, cheaper alternatives would be used; we are not taking this into account, which is a drawback of our method.

Figure 15C shows the forecast distribution of the NPC of each scenario at a fixed discount rate of 2 per cent. Although there is considerable uncertainty, the NPC of the Fast Transition is likely to be quite a bit lower than that of the No Transition. By contrast, the Slow Transition is not as cheap as the Fast Transition. This is because the current high spending on fossil fuels continues for decades, and the savings from key green technologies are only realised much later. Nonetheless, it also generates savings relative to the No Transition scenario. Similarly to Figure 15B, the NPC distribution of the Fast Transition is wider than that of the No Transition. Although this is caused by higher technology uncertainty, it is important to note that this increased uncertainty is compensated for by the leftward shift in the distribution, due to expected cost declines associated with scaling up key green technologies.

Figure 15D shows how the expected NPC of each scenario varies with the discount rate relative to the No Transition scenario. The inset shows that there is roughly an 80 per cent chance that the NPC of the Fast Transition is lower than that of the No Transition, regardless of discount rate. Previous analyses have suggested that whether or not it makes good economic sense to quickly transition to clean energy technologies depends on the discount rate. But here we show a striking result: the Fast Transition is likely to be much cheaper at all reasonable discount rates. Using the 1.4 per cent social discount rate recommended in the Stern Review,[50] for example, the expected net present saving is roughly $12 trillion. At the higher discount rate of 5 per cent, the expected saving is around $5 trillion.

Conclusion

The belief that the green energy transition will be expensive has been a major driver of the ineffective response to climate change for the past 40 years. This pessimism is at odds with past technological cost improvement trends and risks locking humanity into an expensive and dangerous energy future. While arguments for a rapid green transition cite benefits such as the avoidance of climate damages, reduced air pollution and lower energy price volatility, these benefits are often contrasted against discussions about the associated costs of the transition. Our analysis suggests that such trade-offs are unlikely to exist: a greener, healthier and safer global energy system is also likely to be cheaper. Updating expectations to better align with historical evidence could fundamentally change the debate about climate policy and dramatically accelerate progress to decarbonise energy systems around the world.

While we are critical of some IAMs assumptions, we believe our approach is complementary to them, building upon historical trends directly and thus providing a counterweight to projections by IAMs. We have demonstrated that the constraints that are commonly used in IAMs are likely an important cause of the mismatch of their projections with historical data. Future work could explore how softening these constraints within IAMs changes their projections. We want to stress that, unlike IAMs, we are not attempting to find optimal solutions. There are likely other scenarios that are cheaper than the Fast Transition scenario, which was constructed to explore whether (with sufficiently rapid deployment) a rapid transition can achieve net cost savings, and if so, with what probability.

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CASE STUDY:

Policy Options for Rapid, Smooth Decarbonisation and Sustainable Growth

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Policy question: Which climate policy packages are better at fostering and sustaining the energy transition without destabilising the economic system and the public budget?

Region: Global

Methods: Agent-based model

Key findings: Carbon pricing policies alone are ineffective to stay below the 2°C target, but a mix of fossil fuel ban, public construction subsidies and electrification standards policies shows a strong potential for emission-growth reduction while increasing growth and maintaining macro-financial stability, although with a (low) fiscal impact. Nonetheless, a small carbon tax can be added to the policy mix to further speed up the transition and neutralise its impact on the public budget.

Engagement: This case study benefited from various and frequent feedback received from stakeholders, policymakers and researchers across multiple rounds of interactions, particularly in Brazil. As such, parts of the research questions, policy instruments tested and outcome variables were co-decided with policy stakeholders.

Summary: The authors use a dynamic simulation to examine how alternative climate policy combinations are able to foster and sustain the energy transition and cut emissions without destabilising the economic system and the public budget. They use a macro-financial agent-based integrated assessment model calibrated on the global economy to simulate policy packages within a complex evolving economy with heterogeneous and interacting firms, and in persistent disequilibrium.

Introduction

Climate impacts are rapidly mounting and will likely destabilise the socio-economic and natural systems under the current emission trajectory.[51 52] A mix of policies are needed to combat global warming and achieve sustainable growth; however, the currently agreed pledges are insufficient to deliver the objectives of the Paris agreement. To cut emissions, economies must reduce their carbon intensity, shift away from fossil-fuel energy and related physical capital and foster a climate-technology revolution in less than three decades. In an adverse scenario, the transition to a low- carbon economy occurs either late or abruptly, with the costs of such transformation being potentially high and systemic.[53 54 55 56] Indeed, policymakers increasingly emphasise the need of finding the right balance between a rapid transition and the macroeconomic frictions it entails,[57 58] as well as the long-run growth opportunities it can generate.[59] However, while there is widespread agreement about the urgency of climate action to mitigate risks from uncontrolled climate change, the evidence on the suitable policy package to induce an effective and orderly transition is scarce[60] and the excessive reliance on policy instruments characterised by low political acceptability, such as carbon pricing, brings about concerns for the transition outlook.[61 62 63]

Using a macro-financial agent-based integrated assessment model calibrated on the global economy as a simulation laboratory, Lamperti et al.[64] and Wieners et al.[65] compare alternative climate policy combinations within a complex evolving economy in persistent disequilibrium, examining the ability to foster and sustain the transition and exploit technological opportunities without destabilising the economic system and the public budget. Results show that carbon-pricing policies alone are ineffective to stay well below the 2°C target. Indeed, current levels of carbon taxation are inadequate to the scope, while if the only policy, carbon prices high enough to induce a rapid transition have potentially destabilising effects on the macroeconomy. Conversely, a mix of regulation and subsidies for investments and R&D in green energy technologies can put the economy on a win-win sustainable growth pathway. Our model genuinely captures endogenous technological change under deep uncertainty and path dependence, in contrast to more traditional approaches which miss these factors. Our results stem from a mix of policies that tackle a wider range of barriers to rapid system change more directly than a carbon price, which only focuses on the carbon externality and mainly acts through market signals. In this context, carbon taxation can be effectively used to finance green public spending while not hampering the growth outlook. Mission-oriented policies act as a synergic tool with climate policy and have the potential to ease the shift to a new, low-carbon growth path.[66 67] Investments to improve the government's long-term capacities and dynamic capabilities are also needed to promptly adapt the public response in face of climate change and other pressing societal challenges (Lamperti et al., 2019b). Appropriately designed credit and macroprudential policies foster macro-financial stability in the face of climate risks while mildly mitigating emission growth, though their scope is limited in absolute terms (Lamperti et al., 2021).[68] Overall, our results suggest that large packages of policies and investments grounded on credible policy targets, and mission-oriented and risk-taking attitudes of governments, have the potential to foster win-win pathways characterised by rapid decarbonisation, high employment rates and long-term sustainable growth.

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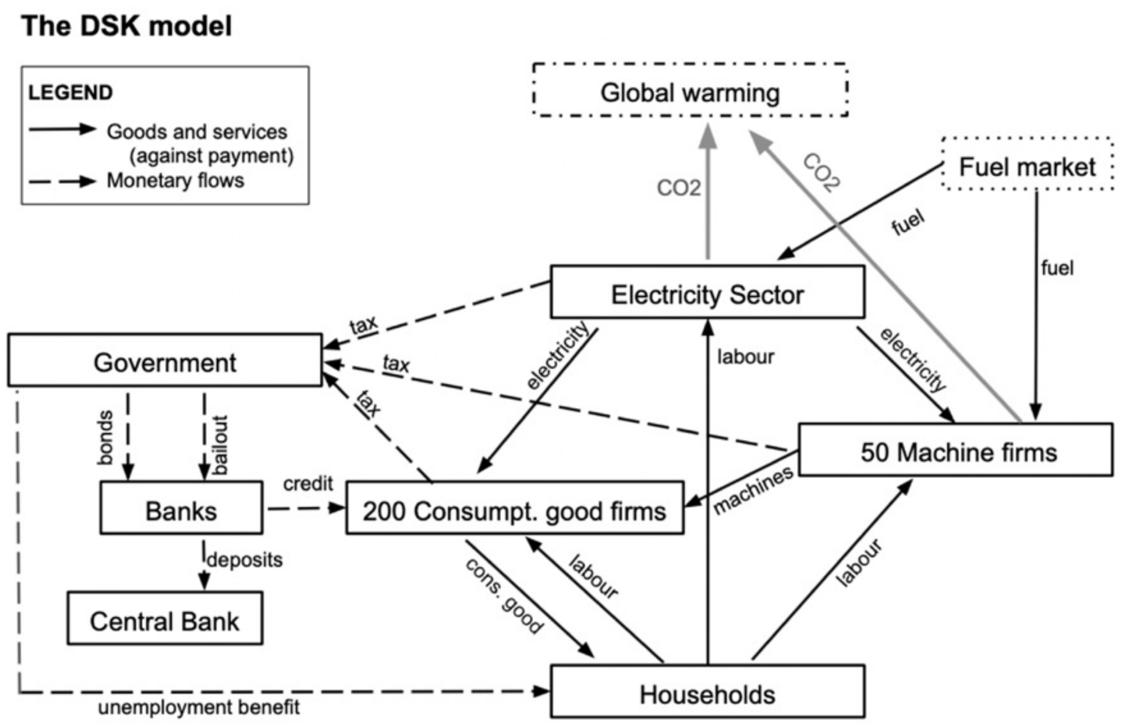
Methods

To test the risks and opportunities of alternative climate policies for the macroeconomy in the short and medium/long run, we rely on the Dystopian Schumpeter meeting Keynes (DSK) model.[69] The DSK model is an agent-based simulation laboratory representing a global economy co-evolving with dynamic interactions with the environment and the climate (see Figure 16). In particular, the model comprises heterogeneous and interacting consumption- and capital-good whose production requires energy and labor inputs, and it may need credit provided by a banking sector. Capital-good firms also carry out R&D activities aimed at improving the efficiency of production processes. In the power sector, energy plants rely either on low-carbon or fossil-fuel sources to supply electricity to the economy. Firms decide how much to produce, how many workers to hire, what investments to take, how much external financing to ask and how to search for new technologies; banks decide how much credit to offer, at which conditions and to which customers and, in addition, they demand government bonds; differently, consumers earn wages and dividends and demand final goods.

The government implements fiscal, innovation, and energy policy, and a central bank runs monetary and macroprudential policy. Anthropogenic emissions arise from the production of goods and energy. Cumulated emissions are linked to temperature increases through a single climate model. The model has been equipped to provide a stochastic micro-foundation of climate damages, which are modeled as a series of heterogenous shocks affecting several features of firms, consumers, and energy plants (Lamperti et al., 2018, 2019).[70] The distinctive feature of the model is that it couples a Schumpeterian growth engine featuring endogenous technical change affected by Knightian uncertainty and path-dependence with a Keynesian demand management approach and a financial sector composed of heterogenous commercial banks. All these features are framed in terms of behavioral routines and decentralised interactions – which have undergone a process of empirical validation, see Fagiolo et al. (2019)[71] – among an ecology of boundedly rational agents facing an evolving environment. In this model, effective decarbonisation depends on how policies affect the pace and direction of innovation as well as how they cope with the asymmetric information affecting each market.

Figure 16: Stylised representation of the DSK model from Wieners et al. (2022).



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Results and policy insights

In Wieners et al. (2022) we analyse a number of carbon tax schedules implemented within the DSK model (see Table 7 and Figure 17). In particular, we consider carbon taxes increasing the fossil fuel price either gradually – mimicking the policies suggested by the cost-benefit integrated assessment literature – or by a constant wedge.[72] The results are crystal clear and suggest that carbon pricing – when implemented alone – can be effective and risky at the same time (see Figure 17). On the one hand, excessively low carbon taxation is largely ineffective at triggering the green transition both in the power and industry sectors. We find that the relative likelihood of meeting the 2°C target approaches zero when the policymaker relies on carbon taxes that are below 100 per cent of the fossil fuel price. In other words, a policy doubling the fossil fuel price gives an approximate minimum threshold to produce some visible effect in escaping path dependence on emission-intensive technologies. Our results point to the difficulty to overcome inertia in the process of technology search and adoption by simply raising the carbon price. Indeed, the deep uncertainty surrounding innovation and the process of search for novel technologies makes prices a poor signal to rapidly direct technological change. This is true both for energy intense sectors and, even more markedly, for those where energy costs are relatively low. On the other hand, high carbon prices are found to foster economic instability, inducing a sharp increase in unemployment rates and a surge in firms' bankruptcies translating into a transitory yet long recession. Indeed, putting a price on carbon both raises variable costs of production and makes technological adoption more difficult; these effects increase financial fragility and reduce aggregate demand. When carbon prices are sufficiently high to increase the fossil fuel price by about 2.8 times (a value which would be required to obtain a fast enough transition to comply with the 2 degrees target), a crisis becomes substantially more likely.

While revenue recycling schemes directed towards either firms (to cover costs) or households (to sustain consumption) soften such adverse effects, they do not provide full insurance to the economy. Coupling these two results, Wieners et al. find that exponentially increasing carbon pricing schedules – often advocated in DICE and other mainstream integrated assessment models (see e.g. Nordhaus, 2019, 2014)[73] – risk pairing ineffectiveness in the short term with increased economic instability in the long run, making the transition even more difficult. These findings hint at moderate and careful use of carbon pricing, and call for an ampler policy mix where carbon taxes can be coupled with other policies.

An ample set of policy instruments focusing on quantities, regulation, innovation, nudging, social influence, information disclosure and mixed approaches,[74 75] is usually left out of the macroeconomic assessment of climate policy. To fill this gap, we tested a large ensemble of combinations, including subsidies to green power plant construction, R&D subsidies to low-carbon technologies, regulations banning fossil fuel power plants and standards imposing electrification. All the instruments were further coupled with carbon taxation to single out policy synergies (see Table 7 for the main results). Our study complements the ecological macroeconomic analysis of policies for the transition,[76 77 78 79] offering a bottom-up perspective wherein the process of technical change under deep uncertainty and path dependence is the key driver of system change. Further, we offer a comparison of alternative policy schemes across multiple dimensions, which encompass the speed of the decarbonisation process and several indicators of macro-financial performance. First of all, our results reveal a positive effect of command-and-control policies forbidding fossil-fuel plant construction as well as the use of fossil fuel. Both policies (labelled as B and E in Table 7) are implemented as regulations establishing a ban to be enforced after a grace period, with non-compliant firms being fined and

[72] Specifically, we test policies that raise the fossil fuel price by a factor ranging from 1 to 15, which allows studying carbon prices coherent with IPCC scenarios limiting temperature anomaly to 2 degrees as well as more aggressive policies. When modelling increasing rates, we consider exponential tax schedules following the same fossil fuel price trajectories of Nordhaus (2017)'s DICE model. Details in Wieners et al. (2022).

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[79] Rengs, B. et al. (2020). Evolutionary Macroeconomic Assessment of Employment and Innovation Impacts of Climate Policy Packages. Journal of Economic Behavior and Organisation. 169: 332-368.

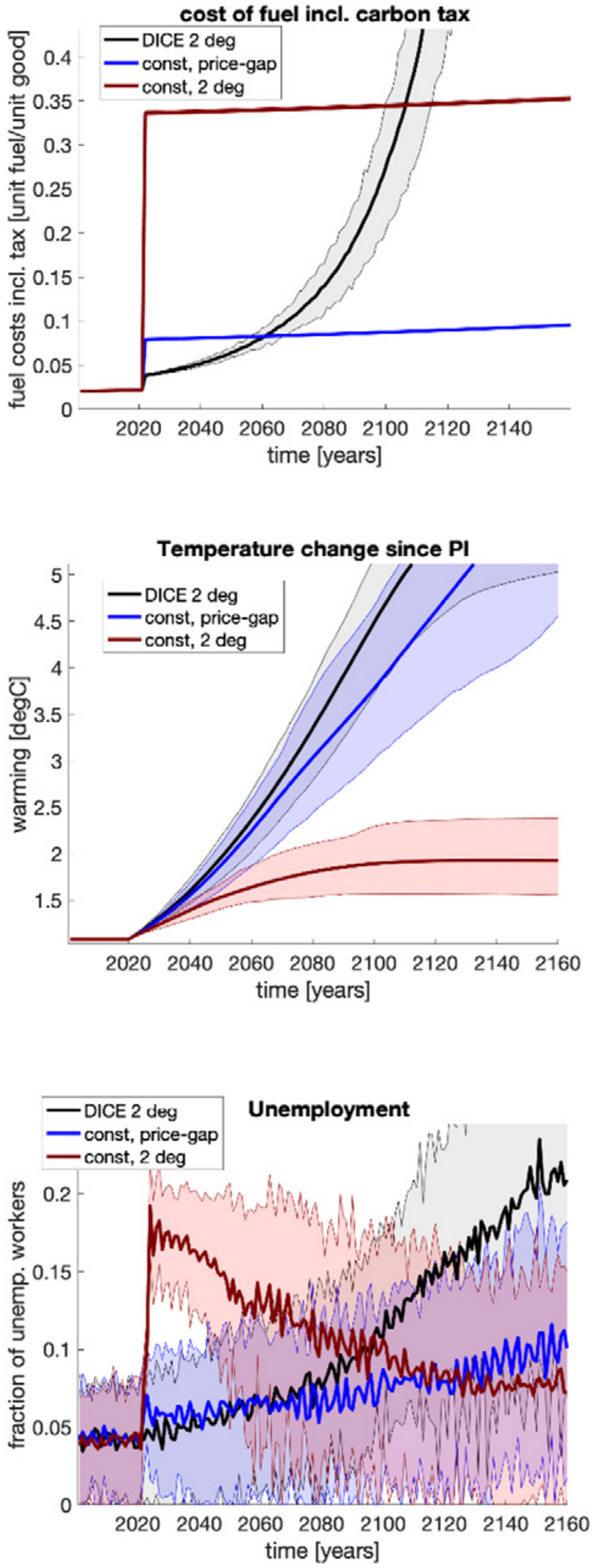
forced to leave their respective markets. Instruments of this kind are now increasingly entering the policy arena (e.g. the UK ban on gas boilers from 2025) and the macro effect they could produce at large scale needs to be uncovered. The grace period allows firms to adjust to the new regulation, which is assumed to be credible and immediately internalised by economic agents. These policies foster a higher pace of investment in low-carbon technologies, both in the energy and manufacturing sectors, and encourage a faster abandonment of emission-intensive production techniques than other policies (e.g. carbon taxation).

Public subsidies for green plant construction and green R&D are another key instrument for climate policy. They (i) accelerate the transition in the power sector, which is crucial to sustaining the adoption of electrification-based solutions, and (ii) sustain the creation of jobs. Indeed, experiment B+C+E (see Table 7) – which combines a fossil fuel ban, public green construction subsidies and electrification standards – shows a strong potential for emission-growth reduction while increasing employment and maintaining macro-financial stability, though adversely affecting public deficit. In particular, the fossil-fuel ban and electrification standards effectively re-direct the process of technological change towards low-carbon technologies, while subsidies speed up the search and uptake of innovations. The overall cost induced by non-tax-based policies on the public budget is modest (estimated at around 1.5 per cent [0.5 per cent-3 per cent] of GDP per year in a prototypical developed country). To absorb such costs, different carbon taxes were tested: in general, we report evidence of a synergic effect of mild carbon taxation. Indeed, a relatively small carbon tax can be added to the policy mix to further speed up the transition, generate revenues from high-emitting firms and neutralise the impact on the public budget that a policy mix composed of regulation and green public spending would have (experiment B+C+E+T). Numerical simulations suggest that a constant carbon tax increasing the 2020 fossil fuel price by a factor of 2.5 until 2100 can provide revenues to finance the innovation, command-and-control and green plant construction policies that are crucial in the early phase of the transition; at the same time such carbon pricing is small enough to prevent the emergence of significant transition costs at the macroeconomic level. These results suggest that a fast, smooth and employment-enhancing transition is possible, and a simple policy mix coupling price-based instruments with active industrial policy can achieve it.

Table 7: Macroeconomic consequences of different climate policies with respect to a business-as-usual (no policy) scenario. Authors' analysis based on data collected in Wieners et al. (2022). Red stands for reduced; inc. for increased; const. for constant and sub. for subsidy. Source: adapted from Lamperti and Roventini (2022).

	Emissions growth		Output growth		Financial Stability	Public deficit
Policy	**Energy**	**Industry**	**Short-run**	**Long-run**		
Const. low carbon tax (T)	mildly red.	unaffected	mildly red.	mildly red.	mildly inc.	mildly red.
Const. high carbon tax	strongly red.	red.	strongly red.	strongly red.	strongly red.	red.
DICE-like carbon tax	mildly red.	unaffected	strongly red.	strongly red.	strongly red.	red.
Sub. to green plants (C)	red.	unaffected	inc.	unaffected	mildly inc.	mildly inc.
Sub. to green R&D	mildly red.	unaffected	inc.	mildly inc.	unaffected	mildly inc.
Ban on fossil fuel use (B)	strongly red.	red.	mildly red.	unaffected	mildly red.	inc.
Electrification standard (E)	unaffected	strongly red.	strongly red.	red.	mildly red.	mildly inc.
B+E+C	strongly red.	strongly red.	mildly red.	unaffected	unaffected	inc.
B+E+C+T	strongly red.	strongly red.	mildly red.	unaffected	unaffected	unaffected

Figure 17: The effect of carbon taxes on climate stabilisation and the macroeconomy. 'DICE 2 deg' mimics a tax schedule having the same dynamics as in the DICE 2017 model; 'const, price-gap' is a constant tax (in real terms) that is sufficiently high to induce a transition by the end of century; 'const, 2 deg' is a constant tax (in real terms) that is sufficiently high to mitigate emissions and stabilise the climate in accordance with the Paris Agreement.



CASE STUDY:

Unstoppable Renewables and Marginal Pricing in China, India and Brazil

PIM VERCOULEN (CAMBRIDGE ECONOMETRICS & UNIVERSITY OF EXETER), FEMKE NIJSSE (UNIVERSITY OF EXETER), SIMON SHARPE (CLIMATE CHAMPIONS TEAM), JEAN-FRANCOIS MERCURE (WORLD BANK)

Policy question: How can barriers to VRE uptake and the design of electricity markets affect electricity prices in power systems of the future?

Region: Brazil, China, India

Methods: E3ME-FTT:Power

Key findings: (1) Overcoming barriers to variable renewable energy (VRE) uptake likely leads to further electricity price reductions regardless of pricing mechanisms. (2) An electricity pricing mechanism broadly in line with the lifetime costs of electricity supply (as a Weighted Average Levelised Cost, or WALC) might be able to accommodate further VRE uptake by lowering electricity prices in comparison to a merit order approach (MOA) equivalent. (3) The focal point for policymakers should be to minimise such barriers and shape a market suitable for power systems dominated by VRE technologies.

Engagement: This work evolved after discussions and model comparisons with Empresa de Pesquisa Energética (EPE) and other UK researchers with reference to the power sector in Brazil and was expanded to include representation for India and China. Preliminary work for India was presented at a workshop organised by The Energy Research Institute (TERI).

Summary: The authors use the E3ME-FTT:Power model to explore likely future power system configurations in China, India and Brazil, with a focus on affordable electricity and the role of market design. The model explores the potential of pricing and regulatory policies to support VRE uptake in these countries.

Introduction

Coal is the main power generation technology in both India and China.[80] Electricity in Brazil, on the other hand, is mainly supplied by hydropower plants. Over the last couple of years, variable renewable energy (VRE) technologies have been deployed at a staggering rate globally, with China recently taking the lead in the deployment of offshore wind turbines. Between 2018 and 2021, solar PV and onshore wind power nearly doubled in capacity as well in China. Solar PV uptake in the same period in Brazil also grew at a staggering rate, but the combined installed capacity of distributed and utility-scale PV was still smaller than that of onshore wind power. Historically, onshore wind power outperformed solar PV in the Brazilian setting due to the availability of great wind resources in the North-East of Brazil. VRE uptake in India has seen great gains too. Solar PV also nearly doubled in capacity, but expansion of onshore wind capacity remained behind.[81] Such rates of VRE uptake are found across the world.

It is likely that this trend of VRE deployment continues and possibly accelerates as the costs of renewables continue to decline, as they did over the past decade.[71] In most regions in the world, VRE technologies are now out competing conventional technologies in terms of the levelised cost of electricity. However, VRE uptake may face obstacles such as insufficient grid resilience, access to finance, lagging supply chains and resistance from declining industries.[83] Another hurdle to VRE uptake could be how electricity markets are designed.

A shift in power technology dominance will also likely have consequences on how electricity markets are designed. In many liberalised markets, the marginal costs of production at a given point in time determines the electricity price. This is called marginal pricing or the merit order approach (MOA) in electricity markets. It is an effective tool for clearing the market, given that most power systems are dominated by fossil fuel power generation where the costs are due to fuel purchases. Contrary to fossil-fuelled generators, the cost of VRE technologies is dominated by upfront capital investments.

Therefore, if VRE technologies continue their uptake trajectory, then the MOA could potentially lead to VRE operators supplying electricity at a loss. During very windy or sunny days, their marginal costs (which is close to zero) would set the electricity price. With a larger diffusion of renewables this would happen increasingly. This makes it likely that the MOA is not a suitable market mechanism in a future electricity system dominated by VRE. Conversely, high fossil fuel prices could lead to windfall profits for VRE companies, which pushes electricity prices up.

In markets such as India, long-term contracts for delivered electricity play an important role in the market. Here, the payment to the electricity company is more related to their levelised costs of electricity. While long-term contracts are less flexible than a day-ahead market for electricity, they do not portray the disadvantages of the MOA system described above.

Here, we seek to explore likely future power system configurations in China, India and Brazil, with a special interest on affordable electricity prices and what role market designs can play. Given the likely continued trajectory of VRE and the need for a new or updated pricing mechanism, we investigate several scenarios focused on the power systems in India, China and Brazil using E3ME-FTT:Power.

We will look at a technology diffusion scenario where VRE uptake is met by additional resistance beyond what current trajectories suggest and as a result fossil fuel use is higher (HighFF), and a set of technology diffusion scenarios where VRE could potentially be sped up by putting a cap on fossil fuel investments (HighVRE). Finally, each scenario is exposed to two different pricing mechanisms: one that mimics MOA (as often is seen in liberalised markets); and a paradigm where electricity prices are formed as the WALC which serves as an indicative alternative pricing mechanism that builds upon lifetime costs rather than short-run marginal costs. FTT:Power accounts for the cost of storage and the effect of curtailment on the LCOE. See the table below for an overview of the scenarios.

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[81] IRENA (n.d.). Data Explorer. https://www.irena.org/Data. Accessed on: 19/11/2022.

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[83] Nijsse, F. J. M. M., et al. (2022). Is a Solar Future Inevitable? Global Systems Institute Working paper series number 2022/02. https://eeist.co.uk/journalpapers/

Table 8: Scenarios focused on the power systems in India, China and Brazil using E3ME-FTT:Power.

Scenario name	Diffusion assumption	Market design
REF-MOA	Diffusion of technologies follows its current trajectory	Merit order approach (MOA)
HighFF-MOA	Greater barriers to VRE uptake, expressed as reduced diffusion rates for VRE technologies	
HighVRE-MOA	Fewer barriers to VRE uptake, expressed by a maximum capacity cap on FF technologies	
REF-WALC	Diffusion of technologies follows its current trajectory	Weighted average of levelised costs (WALC)
HighFF-WALC	Greater barriers to VRE uptake, expressed as reduced diffusion rates for VRE technologies	
HighVRE-WALC	Fewer barriers to VRE uptake, expressed by a maximum capacity cap on FF technologies	

Description of E3ME-FTT:Power

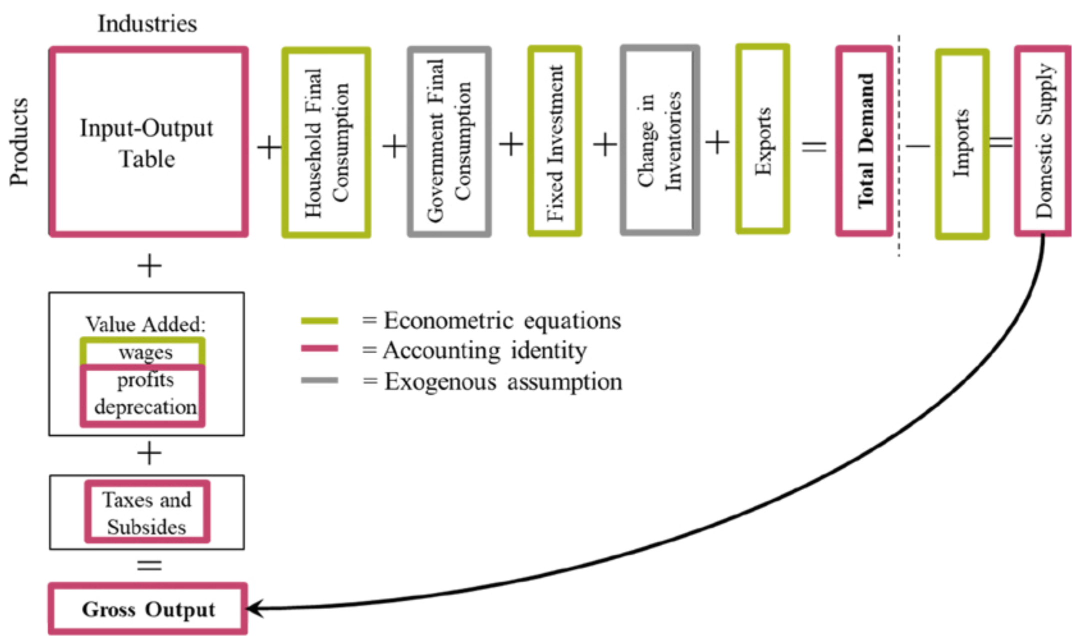
Description of E3ME
E3ME is a computer-based model of the world's economic and energy systems and the environment. Economic activity undertaken by persons, households, firms and other groups in society has effects on other groups (possibly after a time lag) and the effects may persist into future generations. But there are many actors, and the effects – both beneficial and damaging – accumulate in economic and physical stocks. A detailed description can be found online.[84]

The effects of economic transactions by economic agents are transmitted through the environment, the economy and the price and money system (via the markets for labour and commodities), and through global transport and information networks. The markets transmit effects in three main ways: through the level of activity creating demand for inputs of material, fuel and labour; through wages and prices affecting incomes; and through incomes leading in turn to further demands for goods and services. These interdependencies suggest that an E3 model should be comprehensive and include many linkages between different parts of the economic and energy systems – hence why E3ME was designed with a high geographical and sectoral resolution.

E3ME-FTT is a global model of 71 regions with major economies represented individually and distinguishes 70 economic sectors in European countries and 44 in non-European countries. E3ME is a demand-led macro-econometric model. It determines the components of demand using time-series econometrics to solve components of final demand and various other indicators. See Figure 18. The econometric parameters represent past and current behaviour in response to shocks.

[84] Cambridge Econometrics (2022). E3ME Model Manual. Available at: https://www.e3me.com/what/e3me/

Figure 18: National accounts structure of E3ME.



The energy domain is also determined by econometric relationships and builds on some of the accounting identities displayed above, but also includes responses to endogenous innovation and energy prices. The wholesale part of non-renewable energy prices is formed via a cost-supply curve approach which integrates an uncertainty parameter. Tax brackets are then added on top of that.

The role of technology in the E3ME-FTT model
Understanding why and how economic agents pick technologies is important in questions surrounding decarbonisation of the economy. Time series econometric equations require a long track of history in order to simulate the future. For novel technologies, such history does not exist and therefore econometric equations are not entirely suitable to address technology-induced transitions. This is where Future Technology Transformations (FTT) comes into play. FTT is a suite of models integrated with E3ME that describes technology decision-making in the most emission- and energy-intensive industries, such as power generation,[85] iron and steel,[86] household heating[87] and passenger vehicles.[88]

FTT follows evolutionary economics which dictates that socio-technical regimes (why something is done the way it is done) change due to internal (e.g. innovation) and external (e.g. shortages or policies) pressures, and such change is often irreversible and non-marginal. FTT incorporates uncertainty in its input parameters which represents the heterogeneous character of economic agents as well as fundamental uncertainty.

FTT determines the technology configuration to meet the demand which is determined elsewhere in E3ME-FTT. The core builds on the Lotka-Volterra replicator function, which compares all technologies on a pair-wise basis and takes investor preferences (determined as a binary logit), technology substitution frequencies and market shares of the previous year as inputs to determine market shares of the current year.[89] It includes positive feedback such as learning-by-doing based on global cumulative technology capacity additions, and negative feedback due to sectoral constraints such as VRE deployment in the power sector leading to supply-demand mismatches, or scrap availability being limited for recycling in the iron and steel sector.

[85] Mercure, J. F. (2012). FTT: Power: A global model of the power sector with induced technological change and natural resource depletion. Energy Policy 48: 799-811.
[86] Vercoulen, P. et al. (2018). Decarbonizing the East Asian steel industry in 2050. Meijo University Discussion Paper #0008.
[87] Knobloch, F. et al. (2021). FTT: Heat - A Simulation Model for Technological Change in the European Residential Heating Sector. Energy Policy 153: 112249.
[88] Lam, A., and Mercure, J-F. (2015). The Effectiveness of Policy on Consumer Choices for Private Road Passenger Transport Emissions Reductions in Six Major Economies. Environmental Research Letters, 10(6): 064008.
[89] Mercure, J-F. (2015). An Age Structured Demographic Theory of Technological Change. Journal of Evolutionary Economics, 25(4): 787-820.

How does E3ME differ from other models?
E3ME is often compared to Computable General Equilibrium (CGE) or Discrete Stochastic General Equilibrium (DSGE) models.[90 91] In many ways the modelling approaches are similar; they are used to answer similar questions and use similar inputs and outputs. However, underlying this are important theoretical differences between the modelling approaches. Models like E3ME build upon data and try to infer economic relationships from that. Most other macro-economic or integrated assessment models (IAMs) try to build upon micro foundations and theory.

In a typical CGE or DSGE framework, optimising behaviour is assumed, output is determined by supply-side constraints and prices adjust fully so that all the available capacity is used. In E3ME the determination of output comes from the demand side of the economy and it is possible to have spare economic capacity. It is not assumed that prices always adjust to market clearing levels.

The differences have important practical implications, because they mean that in E3ME regulation and other policies could potentially lead to increases in output, if they are able to draw upon the available spare economic capacity. The role of the financial sector is key.

The role of finance
E3ME is a Post-Keynesian model and within this school of thought money is endogenous – i.e. it can be created by banks through, for example, lending. This approach differs from that in many other models where the supply of money is fixed.[92] A fixed supply of money implies full crowding-out; endogenous supply of money does not, per se. E3ME is therefore agnostic on finance. The model tracks the investment needs of a given sector as a result of the econometric relationships or the FTT outcomes, but it does not provide information on whether the demanded finance is accessible.

Results

Power generation technology mix
In all countries of interest, FTT:Power simulates a continued diffusion trajectory of VRE technologies in the reference scenarios (REF-MOA and REF-WALC), in line with past diffusion dynamics and continued cost reductions (see Figure 18). Solar PV in particular gains momentum as costs continue to decline for the technology itself and for the storage technologies that facilitate VRE uptake. It is likely that solar PV will outcompete wind power or any other alternative in the near future. This is expected in Brazil, for example, where wind power has historically been the more popular VRE technology. Due to an expansion in VRE capacity, fossil fuels are set to decline, mainly in China and India.

However, if VRE technologies run into additional barriers that prevent such a deployment (see Figure 18, HighFF-MOA and HighFF-WALC) then uptake of VRE is slightly slower, which benefits fossil-fuelled power generation. The exception is Brazil. Here, a slowdown in the construction time of renewables benefits wind energy. Solar energy starts with a small market share and the industry cannot grow as fast in absolute terms as wind when construction times are long. Total VRE in Brazil is still projected to decrease, though, and fossil-fuelled power increases marginally. Less VRE also means less storage capacity is needed, which reduces electricity losses and therefore lowers the supply required to meet demand.

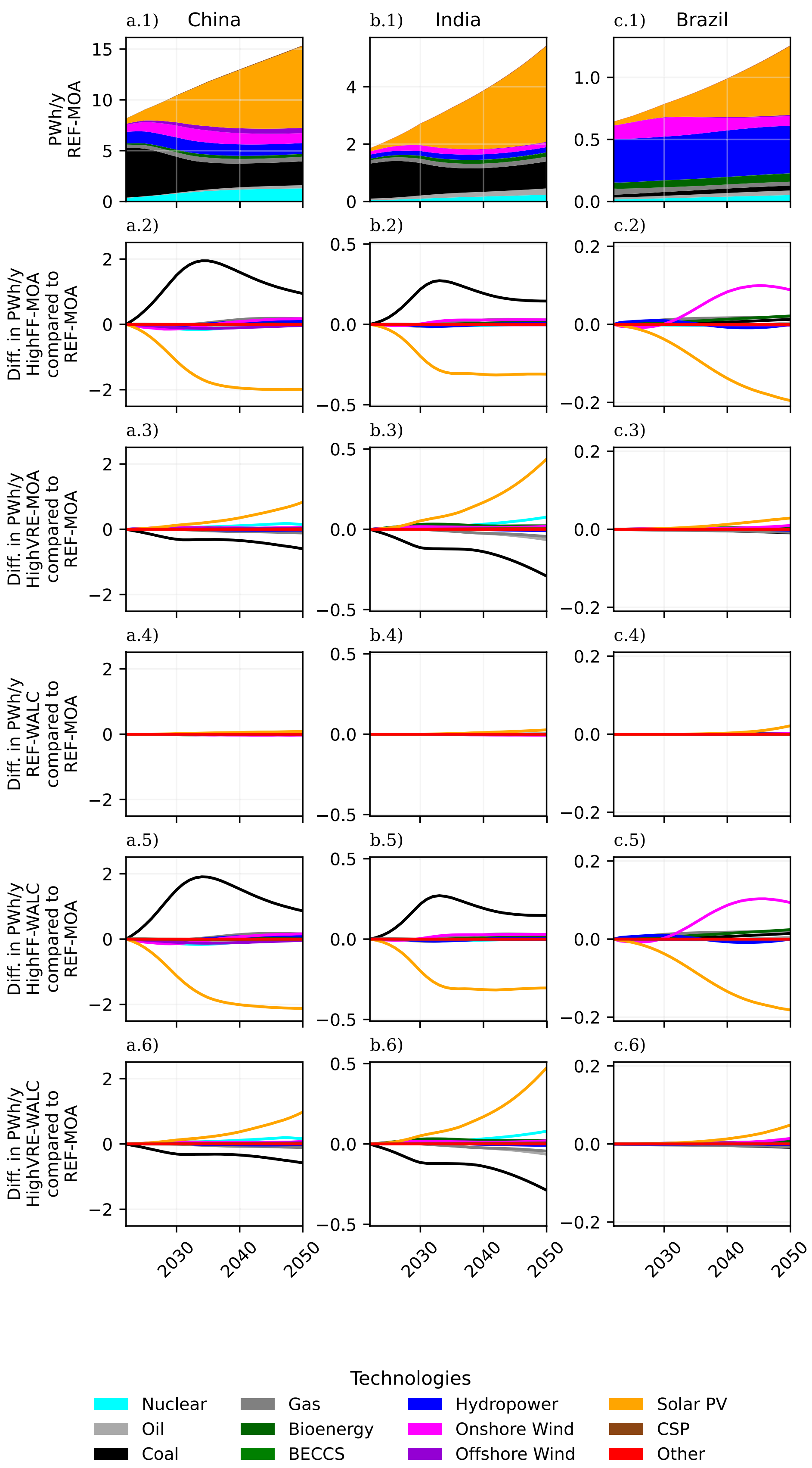
In the scenarios where VRE faces fewer obstacles and fossil-fuelled power generation is considered a less attractive investment, then – as expected – there is an increased uptake of VRE. The heightened reluctance to construct new fossil fuel plants creates space for VRE technologies. This effect is largest in India, due to the fast rate of electricity demand growth. In Brazil the effect is small as VRE technologies compete with long-lasting power projects such as hydropower plants and electricity demand grows at a slower pace.

[90] Mercure, J-F., et al. (2019). Modelling Innovation and the Macroeconomics of Low-Carbon Transitions: Theory, Perspectives and Practical Use. Climate Policy 19(8): 1019-1037.

[91] Lefevre, J., et al. (2022). Global Socio-Economic and Climate Change Mitigation Scenarios Through the Lens of Structural Change. Global Environmental Change 74: 102510.

[92] Mercure, J-F and Pollitt, H. (2018). The Role of Money and the Financial Sector in Energy-Economy Models used for Assessing Climate and Energy Policy. Climate Policy 18(2): 184-197.

Figure 19: Power generation by technology in the countries of interest. The top row shows absolute levels of generation, while all subsequent rows below show the differences in generation by technology compared to the REF-MOA scenario.



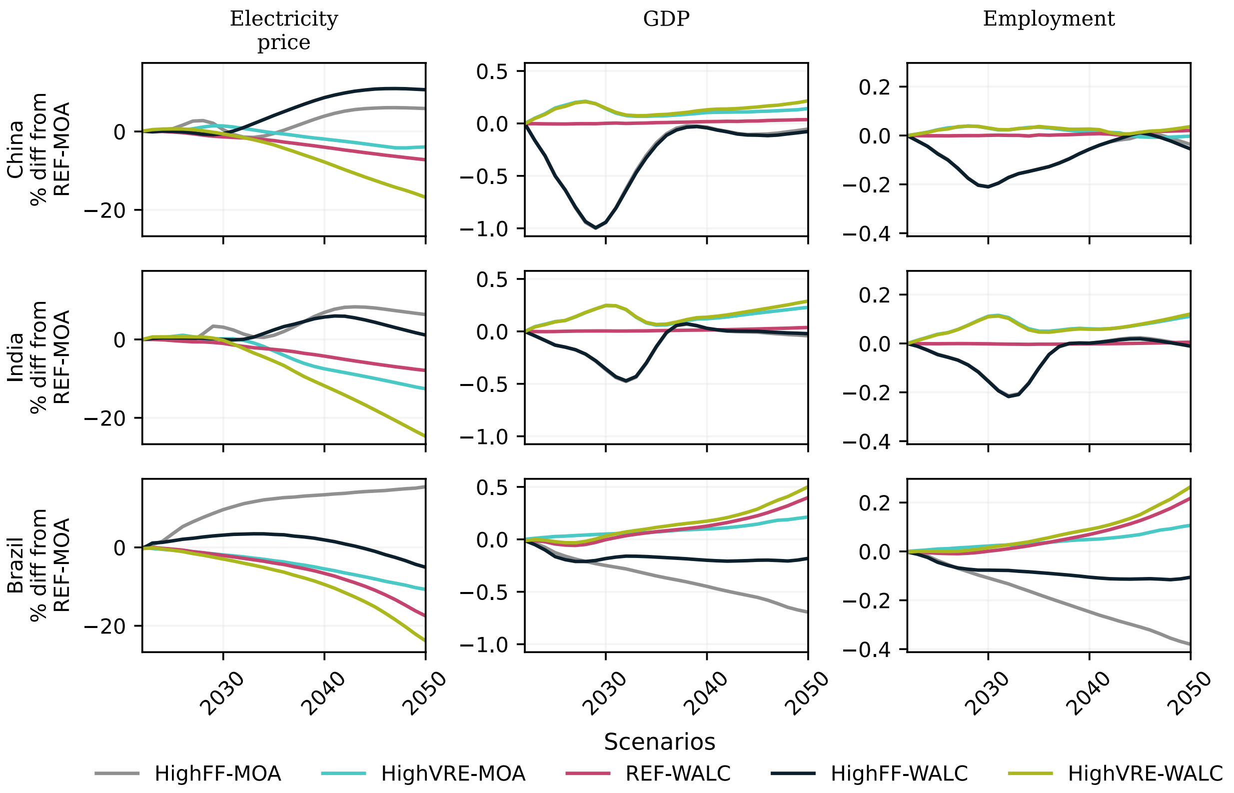
Electricity prices

The scenario and market design play an important role in the electricity price. Figure 2 shows electricity prices in the various scenarios. Electricity prices are lower in the HighVRE scenarios compared to the HighFF counterparts, regardless of market design. This is due to the lower prices of renewables and storage compared to fossil fuels.

The price mechanism also plays a role, with the WALC outperforming the MOA. The MOA price mechanism typically leads to a higher electricity price, as it relies on marginal costs for fossil fuels and can lead to large profits for nuclear and VRE when marginal fossil fuel prices are high.

It is interesting to compare the REF-WALC and HighVRE-MOA scenarios. Both show lowered electricity prices, but for different reasons. The WALC price mechanism needs to lower prices because the price is no longer determined by expensive marginal fossil fuel costs, and the HighVRE scenario shows lower prices due to the fact that variable renewables are cheaper. Only in India does HighVRE-MOA outperform REF-WALC. By 2050, India shows the highest share of solar PV in its system among the countries of interest, which means there will be a substantial number of hours in the year where the marginal costs of VRE determine the price, rather than the marginal costs of fossil fuels. This effect is not present in China and Brazil, where the alternative pricing mechanism outperforms the increased uptake of VRE.

Figure 20: Comparison of electricity prices, total employment, and GDP of each scenario in percentage difference to the REF-MOA scenario in China (top row), India (middle row), and Brazil (bottom row).



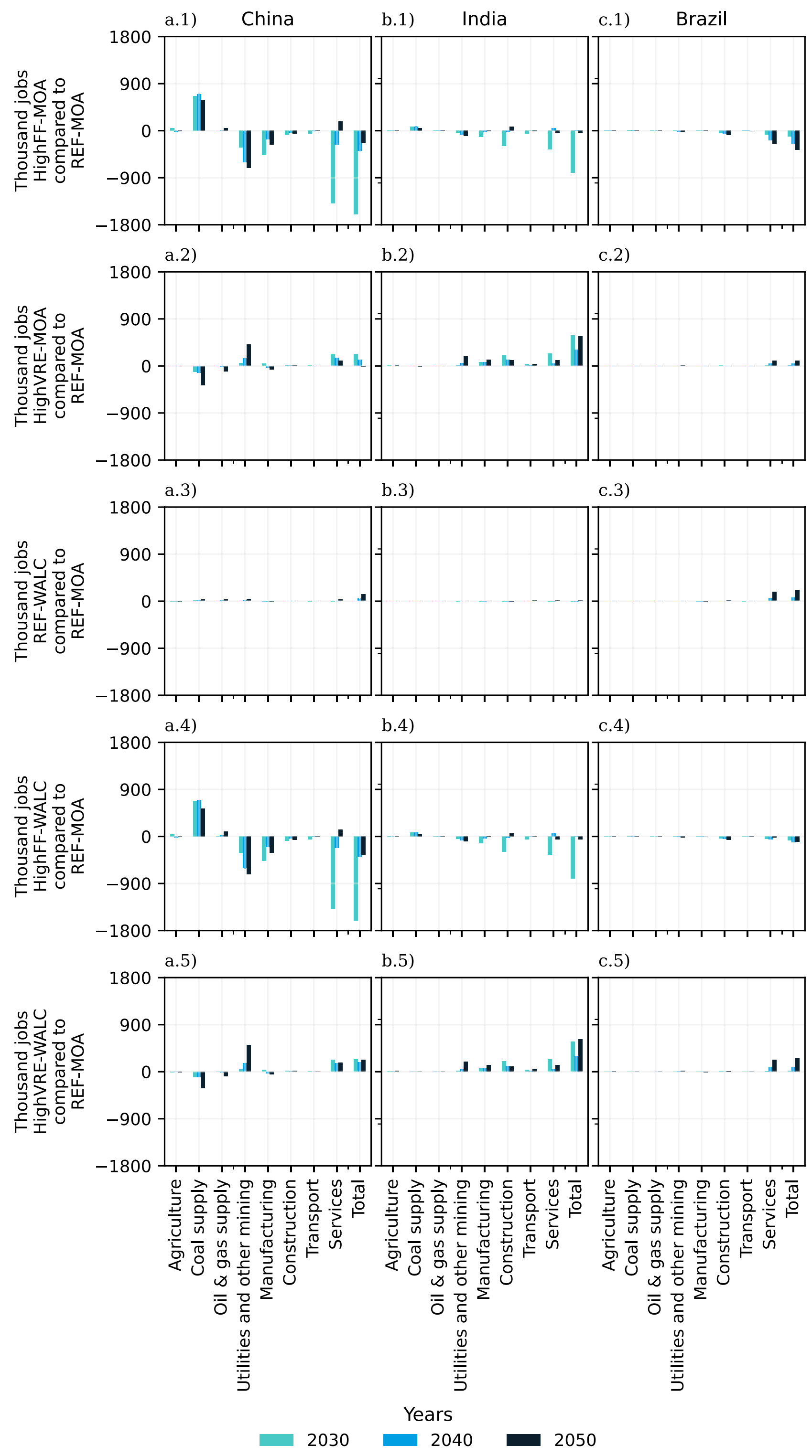
Macroeconomic effects

Changes in electricity prices lead to knock-on effects on the rest of the economy. Lower electricity prices reduce energy bills, which unlocks consumer spending. Production costs are also reduced, again helping to increase consumer spending.

Most high fossil fuel scenarios show slightly negative GDP results compared to the reference case, because high electricity prices and high costs of industrial production constrain consumption in many sectors of the economy. The impact of high fossil fuel reliance is especially negative for Brazil towards mid-century, as it means it must import more energy resources. In India and China, the GDP losses occur earlier due to a weakened construction sector from less VRE deployment. There is a positive effect on GDP in the high renewables scenarios, and this is greatest in all three countries when high renewable deployment is combined with the WALC market design.

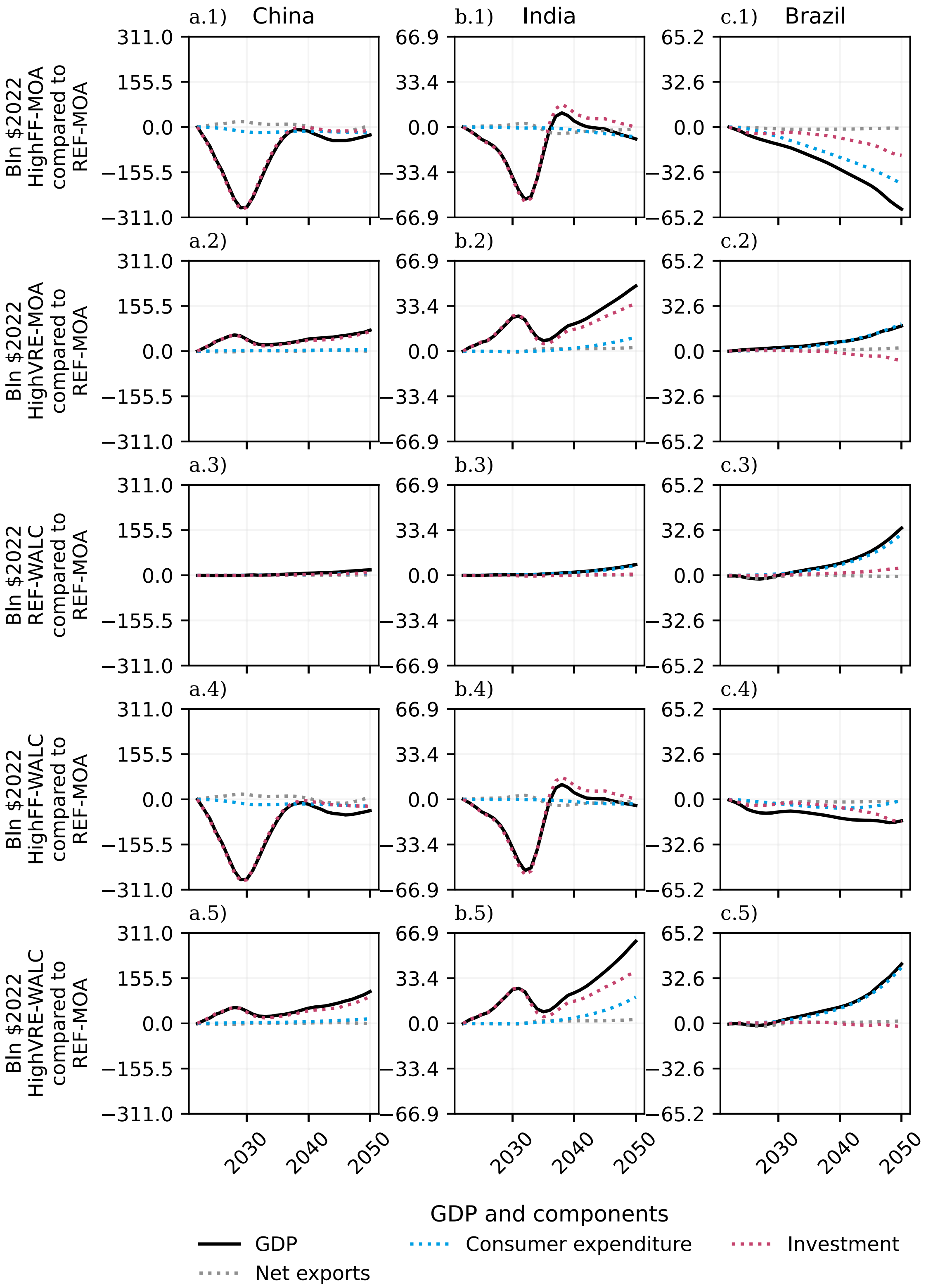
The effect on employment is similar. In the High-VRE scenarios and the WALC market design, we see increased employment in many sectors, and net gains overall. The employment gains are the highest in the scenario of high variable renewables and the WALC market design. There are significant net job gains in the HighVRE scenarios in India and Brazil, but in China the outcome is on a par with the reference case. This is because job gains in the renewables industry are offset by job losses in the domestic extraction industry. Conversely, the employment outcomes are negative for scenarios with higher electricity prices, particularly the high fossil fuel scenarios. In these scenarios, higher electricity prices weaken the demand for services in India and China and lead to lower employment (Figure 21).

Figure 21: Sectoral job impacts compared to REF-MOA scenario. Differences are in absolute terms.



When tracking the components of GDP (see Figure 22), we find that positive results in the HighVRE scenarios are driven by capital investment in additional VRE capacity. The HighFF scenarios show GDP results that are either on-par or below baseline levels by 2050. In these scenarios the negative impacts come through via increased energy imports and depressed consumer spending due to high electricity prices. The Brazilian economy responded more strongly to a change in the pricing mechanism, rather than merely to a change in power system configuration.

Figure 22: GDP and its components compared to the REF-MOA scenario. Differences are in absolute terms.



Discussion & conclusion

Policies promoting solar PV and wind power in the past have irreversibly set the scene for the diffusion we are observing today.[93] The simulations presented above build on that history and, together with a positive feedback loop based on Wright's law – the more a technology is deployed, the more its costs come down – show a continuation of past trends. Solar PV is likely to outcompete any other technology at face value.

Removing barriers to the uptake of solar PV and wind power will make countries less dependent on energy imports or domestic fossil fuel resources. Having fewer imports improves their energy trade balance, which is significant in Brazil and India. Using fewer domestic resources comes with a decline in related industries, which leads to job losses in that sector. This is notable in the Chinese context. However, this may be overcome by job creation related to installing solar PV and constructing wind turbines. Overall, a faster transition to VRE technologies leads to positive economic outcomes, which are due to suppressed electricity prices, higher investments in VRE technologies, decreased dependency on energy imports and increased consumer spending in sectors with a higher domestic content. Not removing the barriers to VRE uptake will likely perpetuate the reliance on fossil-fuelled power generation. China, India and Brazil then miss out on the opportunities that the continued energy transition provides, while China likely retains jobs in the coal supply sector.

The two pricing markets are portrayed in a stylised fashion in the model. We do not represent a potential loss of flexibility a WALC market may entail. We further do not represent the daily variations of the marginal price of electricity production in MOA. Rather, we estimate the time that either a fossil fuel technology or renewables set the price depending on the diffusion of VRE. Nonetheless, the modelling should provide a first-order indication of the advantages. Our modelling may underestimate the obstacles that (near) future power systems in China, India and Brazil face. It portrays a continuation of current trends, but it is possible that some trends are broken, so that construction times increase and the HighFF scenario would be a better reference scenario.

India and China are making moves to liberalise their power sectors. The move away from long-term contracts is an important step to ensuring the countries are not locked into fossil fuel infrastructure. However, they may use the MOA found in liberalised markets as their example. This market design may not be future-proof. A pricing mechanism broadly in line with WALC can ensure renewables get paid sufficiently.

China, India, and Brazil stand to gain by reducing the exposure to the barriers that VRE technologies may face. Past and ongoing policy support for these technologies have made them cost-competitive. The focal point for policymakers should be to minimise such barriers and shape a market suitable for power systems dominated by VRE technologies.

[93] Grubb, M. et al. (2021). The New Economics of Innovation and Transition: Evaluating Opportunities and Risks, EEIST report to COP26.

CASE STUDY:

Modelling Sector Coupling of Hydrogen and Ammonia in India

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Policy question: Can the buildout of green hydrogen and ammonia infrastructure in India facilitate the transition to a net-zero electricity grid?

Region: India

Methods: Complexity-extended traditional energy system model.

Key findings: There are costs to current policy which is putting us on a path towards decoupling the emerging hydrogen and ammonia sectors from the grid. There are opportunities to build more resilient, lower-cost systems if the system is designed with sector coupling in mind.

Engagement: This case study was presented multiple times to Indian stakeholders for feedback via the EEIST India community of practice, and other modelling forums and events.

Summary: The authors use a traditional energy system model, extended using principles from new economic modelling and ROA, to consider the potential for sectoral coupling of hydrogen and ammonia to contribute to India's net-zero targets.

Introduction

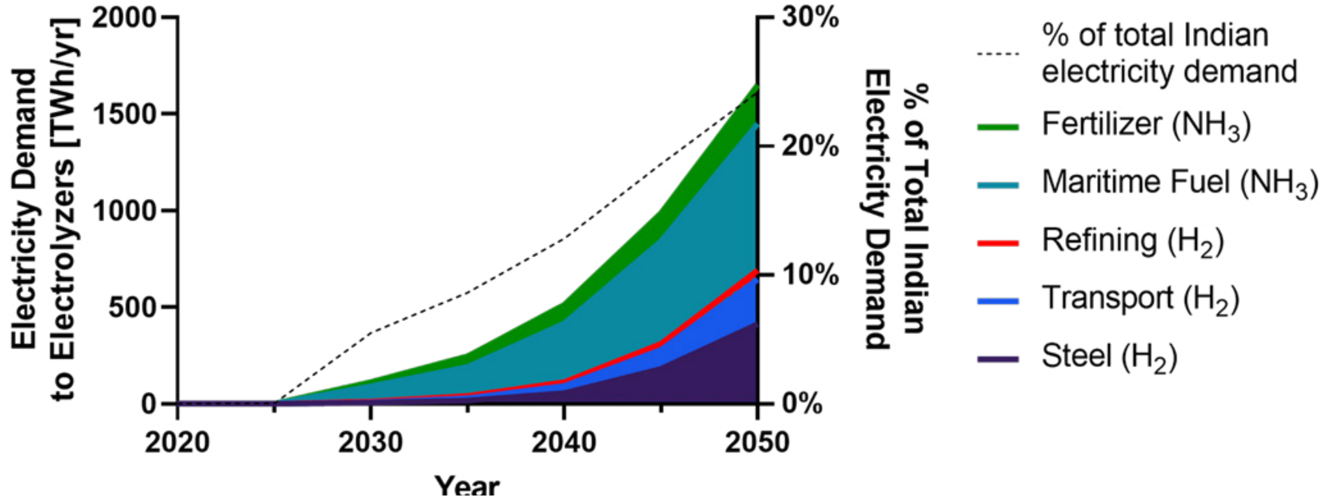
At a global level, the International Renewable Energy Agency (IRENA) forecasts that the production of green hydrogen and its derivatives (mostly green ammonia) will account for 30 per cent of the global electricity demand in 2050.[94] Yet, analyses published using Energy System Models (ESMs), the dominant tool for understanding different scenarios of decarbonisation, have systematically overlooked the dynamic integration of sector coupling of green hydrogen and ammonia for industrial demands, such as steel and fertiliser, and for heavy-duty transport fuel, such as aviation, shipping and trucking.

Simply including static demands in ESMs is not sufficient; the future potential for sector coupling is a dynamic give-and-take. Green hydrogen and ammonia are useful for taking flexible amounts of electricity from the grid via short and long-duration load shifting as well as giving dispatchable electricity back to grids via re-electrification, for example in hydrogen or ammonia-fired gas turbines. The main focus in the sector-coupled ESM literature is on short-duration, intra-daily load shifting, predominantly in the light-duty vehicle transport sector and the thermal sector, such as coordinated charging of battery electric vehicle (BEV) fleets.

In this study, the Power-to-X sector coupling potential of green hydrogen and ammonia is explored via a case study on the national-scale electricity grid of India, in which the projected electricity demands for hydrogen and ammonia production account for nearly 25 per cent of the total Indian electricity demand in 2050 (Figure 23). India is chosen as the case study due to its globally unmatched demand growth in all three relevant sectors: green electricity, green hydrogen (for steel and transport demands) and green ammonia (for fertiliser and shipping fuel demands).

This case study is based on, Cesaro, Z., Bramstoft, R., Ives, M.C., and Bañares-Alcántara, R., 2023, Facilitating deep decarbonization via sector coupling of green hydrogen and ammonia, INET Working Paper No 2023-04, https://www.inet.ox.ac.uk/publications/no-2023-04-facilitating-deep-decarbonization-via-sector-coupling-of-green-hydrogen-and-ammonia/.

Figure 23: Green hydrogen and ammonia sector-level demand in India to 2050, including comparison to total final electricity demand. Source: Cesaro et al 2023. Cesaro, Z., Bramstoft, R., Ives, M. & Bañares-Alcántara, R. (2023). 'Facilitating deep decarbonization via sector coupling of green hydrogen and ammonia'. INET Oxford Working Paper No. 2023-04. https://www.inet.ox.ac.uk/publications/no-2023-04-facilitating-deep-decarbonization-via-sector-coupling-of-green-hydrogen-and-ammonia/



[94] IRENA, Geopolitics of the Energy Transformation The Hydrogen Factor, Technical Report, International Renewable Energy Agency (IRENA), Abu Dhabi, 2022

Despite the scale of the required electrolyser fleet, there has not been a modelling effort, to the best of our knowledge, that considers the dynamic role of industrial electrification and PtX sector coupling at this scale in India. There is a large body of recent work that evaluates the role of integrating VRE into the Indian electricity system.[95 96 97 98 99 100 101 102 103] Many of these ESMs analyse the development of new generation, transmission and storage assets, as well as the best way to utilise existing assets. However, all of these studies overlook the significant role of PtX sector coupling on facilitating the integration of high levels of VRE, reducing the cost of decarbonisation, and reducing the need for long-duration storage.

India is pioneering in green hydrogen and ammonia-focused policy. The Indian government announced a target to be net zero by 2070[104] as well as the National Hydrogen Mission (NHM) to accelerate the deployment of hydrogen technologies and to establish India as a global manufacturing hub for electrolysers and fuel cells.[105] As part of the NHM, there are green ammonia obligations in the fertiliser sector, which, if achieved, would likely drive the world's fastest national green ammonia build-out. Even if the targets are not met, the momentum is building, with large green ammonia plants already announced in India.[106] However, the policy has not focused on grid integration or the interaction of these huge new electricity demands with the grid.

Model summary

We build a state-of-the-art ESM of India's electricity grid to 2050 to explore the full sector coupling potential of hydrogen and ammonia for both give-and-take services to the grid – i.e. load-shifting and dispatchable power generation. The decarbonisation scenarios in this research are compiled from other sectoral-level research and find that by 2050 over 25 per cent of electricity generated in India will be used for producing green hydrogen and ammonia, as shown in Figure 23. In this study, novel methodological approaches are added to a traditional capacity expansion ESM to better capture the transformational changes of an energy system (Figure 24).

PtX in India is an example of a sector which will cause non-marginal, transformational change to the electricity system, and therefore a good use-case for EEIST. Some of the non-marginal effects of PtX on the system include significant changes to electricity planning and system operation (the focus of this modelling effort), changes to land and water use, geographic and operational labour changes, significant reduction of imported energy, and significant potential for exported energy. Specifically, three improvements to conventional ESM are included in this modelling effort: 1) a detailed dynamic integration of PtX sector coupling and network effects (considering production, storage, transportation, industrial use and peak power generation), 2) empirically grounded technology cost forecasts based on global energy transition scenarios from Way et al.[107] and 3) representation of system resilience to interannual weather variation at high VRE penetration. These three improvements align with the ROA approaches of (i) complexity modelling, (ii) positive feedback loops and (iii) system resilience to uncertainty, respectively.

[95] Abhyankar, N. et al. (2021) Least-Cost Pathway for India's Power System Investments through 2030. Technical Report, Lawrence Berkeley National Laboratory.

[96] Palchak, D. et al. (2017) Greening the Grid: Pathways to Integrate 175 Gigawatts of Renewable Energy into India's Electric Grid. Vol. I – national study.

[97] Palchak, D. et al. (2019). India 2030 Wind and Solar Integration Study: Interim Report, Technical Report NREL/TP-6A20-73854, National Renewable Energy Laboratory. https://www.nrel.gov/docs/ fy19osti/73854.pdf

[98] Spencer, T. et al. (2020). Renewable Power Pathways: Modelling the Integration of Wind and Solar in India by 2030. TERI Discussion Paper. The Energy and Resources Institute. URL: https://www.teriin.org/ sites/default/files/2020-07/Renewable-Power-Pathways-Report.pdf.

[99] CEA. (2020). Report on Optimal Generation Capacity Mix for 2029-30. Technical Report. Central Electricity Authority. URL: https: //cea.nic.in/old/reports/others/planning/irp/Optimal_mix_report_2029-30_FINAL.pdf

[100] IEA. (2021). Renewables Integration in India, Technical Report. URL: https://www.iea.org/reports/ renewables-integration-in-india.

[101] Chernyakhovskiy, I. et al. (2021). Energy Storage in South Asia: Understanding the Role of Grid-Connected Energy Storage in South Asia's Power Sector Transformation. Technical Report, National Renewable Energy Lab (US).

[102] IEA. (2021). India Energy Outlook 2021. Technical Report, International Energy Agency. doi:10.1787/ec2fd78d-en.

[103] Lu, T. et al. (2020). India's Potential for Integrating Solar and On and Offshore Wind Power into its Energy System. Nature communications 11 (2020) 1-10.

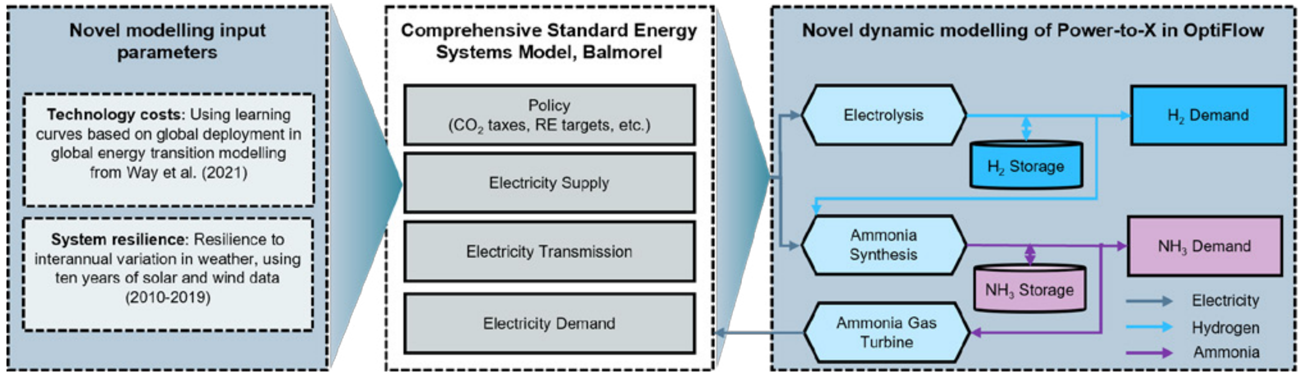
[104] Indian Ministry of External Affairs (2021) National Statement by Prime Minister Shri Narendra Modi at COP26 Summit in Glasgow.

[105] Ministry of New and Renewable Energy, Budget 2021-22 augments Capital of SECI and IREDA to promote development of RE sector. National Hydrogen Mission proposed, 2021.

[106] Pekic, Sanja. (2022). 'India's Avaada to Set up Green Ammonia Facility in Rajasthan'. Offshore Energy, 29 Aug. 2022, https://www.offshore-energy.biz/indias-avaada-to-set-up-green-ammonia-facility-in-rajasthan/.[96] Way, R. et al. (2021). Empirically Grounded Technology Forecasts and the Energy Transition, Technical Report INET Oxford Working Paper No. 2021-01, Oxford Institute of New Economic Thinking (INET), 2021. URL: https://www.inet.ox.ac.uk/files/ energy_transition_paper-INET-working-paper.pdf.

[107] Way, R. et al. (2021). Empirically Grounded Technology Forecasts and the Energy Transition, Technical Report INET Oxford Working Paper No. 2021-01, Oxford Institute of New Economic Thinking (INET), 2021. URL: https://www.inet.ox.ac.uk/files/ energy_transition_paper-INET-working-paper.pdf.

Figure 24: Overview of improvements to standard ESM. Source: Cesaro et al 2023. Cesaro, Z., Bramstoft, R., Ives, M. & Bañares-Alcántara, R. (2023). 'Facilitating deep decarbonization via sector coupling of green hydrogen and ammonia'. INET Oxford Working Paper No. 2023-04. https://www.inet.ox.ac.uk/publications/no-2023-04-facilitating-deep-decarbonization-via-sector-coupling-of-green-hydrogen-and-ammonia/



The modelling is conducted using the 'Balmorel' ESM linked with a Power-to-X model in 'OptiFlow'. Balmorel was chosen as a widely used, open-source ESM used for capacity planning and operation dispatch modelling. It is a model which has been developed over the last two decades to support analyses of the energy sector with emphasis on electricity and combined heat and power systems.[108] The base model was first written for Baltic/Nordic countries and is now used worldwide. For example, Balmorel is used by the Chinese Energy Research Institute (ERI), a member of the EEIST consortium, to model the energy transition in China in their annual China Renewable Energy Outlook report.[109] As a techno-economic model, it provides the functionality to conduct energy planning for the power and heat sector. The model is written in General Algebraic Modelling System (GAMS), an algebraic modelling language and software used to solve linear, nonlinear and mixed-integer optimisation problems. In its basic configuration, the Balmorel model linearly optimises investment in generation and transmission using hourly dispatch simulation and multi-year scenario development. Essentially, it finds the least-cost economical dispatch and capacity expansion solution for the represented energy system, subject to the provided technical and economic assumptions and constraint.

OptiFlow[110] is an open-source spatio-temporal network optimisation model which can be linked with Balmorel. OptiFlow uses node-arc relationships to represent flows such as energy, mass, economic, or environmental metrics. In this research, green hydrogen and ammonia production, storage, transport and use are modelled using OptiFlow linked with Balmorel, based on the configuration used elsewhere,[111 112] and as shown in Figure 24.

[108] Wiese, F. et al. (2018). Balmorel Open Source Energy System Model. Energy Strategy Reviews 20: 26-34. ISSN: 2211-467X. https://www.sciencedirect.com/science/article/pii/S2211467X18300038

[109] Energy Research Institute of Academy of Macroeconomic Research/NDRC, China National Renewable Energy Centre. Ea Energy Analyses and the Danish Energy Agency (2020). China Renewable Energy Outlook 2020 tech. rep. https://ens.dk/sites/e ns.dk/files/Globalcooperation/creo_2020_executive_summary.pdf

[110] Ravn, H. (2017). The OptiFlow Model Structure Technical. http://www.balmorel.com/images/downloads/optiflowdocumentation20170909.pdf (2021).

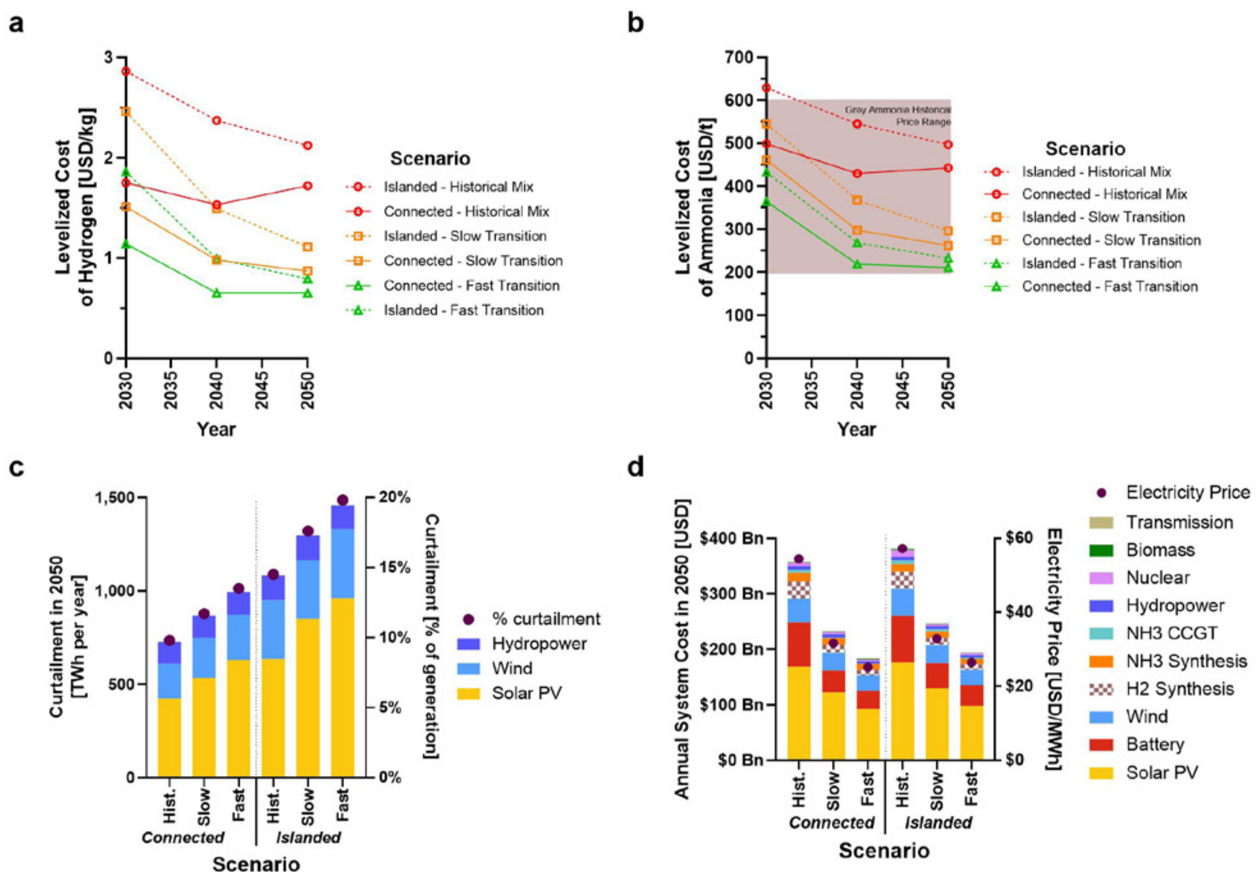
[111] Bramstoft, R. et al. (2020). Modelling of Renewable Gas and Renewable Liquid Fuels in Future Integrated Energy Systems. Applied Energy 268: 114869.

[112] Lester, M.S et al. (2020). Analysis on Electrofuels in Future Energy Systems: A 2050 Case Study. Energy 199: 117408.

Results

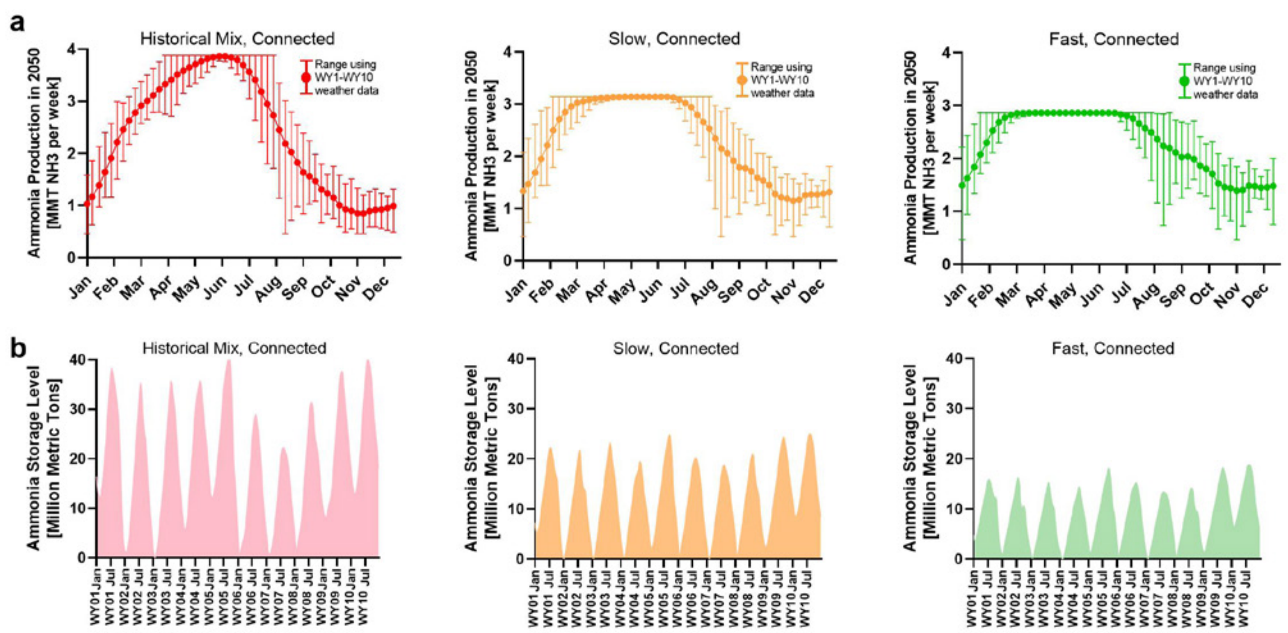
A key finding shown in the results is that there are significant benefits to connecting the hydrogen and ammonia production to the electricity grid rather than having islanded production sites. Islanded plants, which are independent from the grid and have their own dedicated renewables, are the current norm and trajectory of industry, which would require policy intervention to change. Grid integration reduces the levelised cost of hydrogen (LCOH) and ammonia (LCOA) by 10-25 per cent across the modelled scenarios (Figure 25a, 25b). The reduction in LCOH and LCOA is driven by lower electricity prices available to grid connected electrolysers because they gain access to electricity that would otherwise be curtailed. In the islanded production scenarios, 15-20 per cent of electricity generated in India in 2050 is curtailed, while only 10-14 per cent is curtailed in the grid connected scenarios (Figure 25c). In absolute terms, this saves 350 to 460 TWh of electricity from being curtailed, and 200-300 GW less PV and wind needs to be installed by 2050.

Figure 25: Key result metrics across grid connected and islanded system scenarios. a) LCOH across scenarios from 2030-2050. b) LCOA across scenarios from 2030-2050 with grey ammonia historical commodity price (Black Sea). c) Curtailment across scenarios in 2050. d) Annualised system costs across scenarios in 2050. Source: Cesaro et al 2023. Cesaro, Z., Bramstoft, R., Ives, M. & Bañares-Alcántara, R. (2023). 'Facilitating deep decarbonization via sector coupling of green hydrogen and ammonia'. INET Oxford Working Paper No. 2023-04. https://www.inet.ox.ac.uk/publications/no-2023-04-facilitating-deep-decarbonization-via-sector-coupling-of-green-hydrogen-and-ammonia/



Additionally, connecting large fleets of electrolysers into the grid infrastructure and load-shifting the industrial production – specifically green ammonia production for fertilisers and shipping fuel – is a plausible strategy towards a lower-cost, more efficient and reliable electricity grid. This envisioned least-cost system produces green hydrogen and ammonia in a seasonal pattern to match renewable surplus. Excess green ammonia is stockpiled in low-cost above-ground storage and then consumed in the seasons of lower green hydrogen and ammonia production to meet constant demands in the fertiliser and shipping sectors, as well as to provide firm generating capacity. Smaller quantities of green hydrogen are stored for intra-daily load shifting. This PtX sector coupled system configuration is not only lower cost, but it is more resilient to unfavourable VRE weather years, as shown over ten years of weather data.

Figure 26: Seasonal and interannual variation in ammonia production and storage levels to meet a constant demand. a) Country-wide weekly ammonia production in 2050 across Connected scenarios, showing the range of weekly ammonia production depending on year of solar and wind data. b) Country-wide storage levels of ammonia in 2050 over 10 weather years (WY1-WY10) of solar and wind data in simulation, corresponding to 2010-2019. Source: Cesaro et al 2023. Cesaro, Z., Bramstoft, R., Ives, M. & Bañares-Alcántara, R. (2023). 'Facilitating deep decarbonization via sector coupling of green hydrogen and ammonia'. INET Oxford Working Paper No. 2023-04. https://www.inet.ox.ac.uk/publications/no-2023-04-facilitating-deep-decarbonization-via-sector-coupling-of-green-hydrogen-and-ammonia/



In summary, the results highlighted the costs of current 'conventional wisdom' and policy decisions, which are on a path towards de-coupling the emerging hydrogen and ammonia sectors from the grid, and the opportunities to build more resilient, lower-cost systems if designed with sector coupling in mind. Crucially, this lower-cost, more resilient system depends on a new industrial paradigm of flexible ammonia synthesis with significant ammonia stockpiling, and the right market and policy measures to enable this industrial behaviour.

Policy relevance

Unfortunately, the potential benefits on this system design will not be realised unless policy steers industry-grid relations away from its historical precedence. For industry, grid connection is often associated with high grid connection charges and unreliability, which warrant onsite power backup and complete 'captive' power plants in extreme scenarios. This historical path dependency is extremely evident in India, where captive power plants at commercial and industry users accounted for 17 per cent of the country's generation in 2019-20, with over 78 GW of captive power generation installed.[113] These captive power plants are either fractionally or completely disconnected from the distribution and transmission grids to avoid the historically under-performing and expensive rates charged to industrial users.

As it stands today, electrolyser fleets for industry would likely follow in the same footsteps, with islanded systems avoiding grid connection charges and other real or perceived disadvantages. However, based on our findings, policy should steer the system towards a new paradigm of industry-grid relations which synergistically benefit both parties in the transformation towards net-zero. Recent policies announced as part of India's NHM are a step towards grid connecting PtX. One policy aims to reduce grid costs for green hydrogen and ammonia plants by waiving interstate transmission charges, among other incentives.[114] The suitability of these policies and further policy and market mechanisms need to be explored today, at the initiation of this transformation, in order to progress towards a more integrated future scenario.

Our results also inform policy on two points. Firstly, the findings support the idea that green hydrogen and ammonia can dramatically improve energy security and reduce imports. India's NHM explicitly states: "The implementation of this policy will provide clean fuel to the common people of the country. This will reduce dependence on fossil fuel and also reduce crude oil imports."[115] Indeed, the level of LCOH and LCOA achieved are more competitive than importing fossil fuels for the steel and fertiliser sectors in India. In fertiliser, India is effectively 80 per cent reliant on imports for ammonia production today: 25-30 per cent of the country's consumption of fertiliser is imported ammonia (costing more than US$ 1.3bn per year) and over 60 per cent of the domestically produced ammonia is produced used imported LNG.[116] This reliance on imports is a major strategic reason for India to shift towards domestic green ammonia production for fertilisers and the results of this ESM suggest that this is possible in the near term without a subsidy or a CO_2 pricing mechanism.

Secondly, the findings support the potential for India to use surplus VRE capacity on barren lands to produce fuels for export, such as bunkering fuel. Again India's NHM explicitly states: "The objective also is for our country to emerge as an export Hub for Green Hydrogen and Green Ammonia."[117] The findings suggest that India can indeed produce sufficient low-cost ammonia from the VRE resources (using barren and waste land-use categorisation assumptions) to, for example, easily meet the demand of over 10 per cent of the global shipping fuel demand by 2050 forecasted by the World Bank.[118]

Beyond India, the potential role of load shifting in green hydrogen and ammonia needs to be modelled for other countries and regions, which will have unique local VRE supply-and-demand mismatch, as well as country-specific PtX demands.

The real value of models such as the one we present here is not the precise results of an ESM looking toward 2050, but rather to highlight leverage or sensitive intervention points[119] and bases of system designs which dramatically alter the end-state of the system transformation. We find that hydrogen and ammonia can be one point of leverage to change our electricity grids for the better, if they are fully integrated. We hope the analysis presented here motivates and accelerates the wider research community into expanding ESMs of various regions and associated assumptions to considering the potential impacts of PtX with sector coupling.

[113] Central Electricity Authority. (2020). Growth of Electricity Sector in India from 1947-2020. Technical Report. URL: https://cea. nic.in/wp-content/uploads/pdm/2020/12/growth_2020.pdf

[114] Ministry of Power. (2022). Ministry of Power Notifies Green Hydrogen/Green Ammonia Policy. URL: https://pib.gov.in/pib.gov.in/Pressreleaseshare.aspx?PRID=1799067

[115] Ministry of Power. (2022). Ministry of Power Notifies Green Hydrogen/Green Ammonia Policy. URL: https://pib.gov.in/pib.gov.in/Pressreleaseshare.aspx?PRID=1799067

[116] IEA. (2021). India Energy Outlook 2021. Technical Report, International Energy Agency. doi:10.1787/ec2fd78d-en.

[117] Ministry of Power. (2022). Ministry of Power Notifies Green Hydrogen/Green Ammonia Policy. URL: https://pib.gov.in/pib.gov.in/Pressreleaseshare.aspx?PRID=1799067

[11] Englert, D. et al. (2021). The Potential of Zero-Carbon Bunker Fuels in Developing Countries. World Bank Technical Report. URL: https://openknowledge.worldbank.org/handle/10986/35435.

[119] Farmer, D. et al. (2019). Sensitive Intervention Points in the Post-Carbon Transition. Science 364: 132-134.

CASE STUDY:

What is the Most Cost-Effective Form of Carbon Pricing? Modelling emissions trading and a carbon tax in general and in China

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Policy question: What is the most cost-effective form of carbon pricing in China?

Region: China

Methods: A qualitative systems mapping exercise and two quantitative agent-based models.

Key findings: Emissions trading schemes need to be designed to avoid introducing a balancing feedback on emissions. Without this, a carbon tax will be more cost-effective. Competition in the power sector, or more precisely, a clear price signal, is key to allowing carbon pricing policies to work.

Engagement: This case study emerged from a long and close collaboration between policy teams and analysts in China, Chinese academics and UK researchers. As such, the topic, questions and parts of the modelling were all co-produced closely with policy stakeholders.

Summary: The authors use a qualitative systems mapping exercise, in combination with two validated quantitative agent-based models, to explore the question of how effective different carbon pricing options might be in China. The systems mapping exercise shows how an emissions trading scheme can introduce a balancing feedback on emissions, potentially slowing progress, and the agent-based models complement this by suggesting a tax may be more effective, while also demonstrating the importance of competition between energy technologies for the effectiveness of these policies.

Introduction

Carbon pricing has often been recommended as the most efficient policy to achieve decarbonisation. Previous reports[120] from the EEIST project have questioned whether this is indeed the case, noting that this recommendation is derived from an assumption of equilibrium which seems incompatible with the context of a low-carbon transition, and that consideration of feedbacks in the economy could lead to different conclusions. Nevertheless, carbon pricing is widespread: the World Bank counted 70 carbon pricing initiatives implemented in 2022, covering 47 national jurisdictions and 36 subnational jurisdictions.[121] Governments, consequently, have a strong interest in understanding what form of carbon pricing is most likely to be effective and in what situations. How can carbon pricing be used to drive a low-carbon transition rapidly and at low cost?

Carbon pricing remains a live policy issue. The European Union is considering expanding its emissions trading scheme, new schemes are under consideration in India and Brazil, and in China, where a national scheme began in 2021, there is continued debate about its impacts and the merits of different pricing mechanisms and their interaction with other policies.

While there are many ways to introduce an effective price on carbon, including auctions, shadow prices and other regulation that introduce indirect prices, most carbon pricing policies can be categorised as one of two kinds: a carbon tax, in which emissions are taxed at a fixed rate (which may be constant, rising or falling); or a cap-and-trade scheme, also often referred to as an emissions trading scheme (we use the terms interchangeably here, but primarily use the latter), in which companies buy emissions permits traded on a market, whose supply is subject to a cap (which may be constant, rising or falling).

Traditionally, advice from economists has been that these two forms of carbon pricing are fundamentally equivalent. Both are expected to incentivise companies to reduce their emissions until the point where their marginal abatement costs are equal to the carbon price. To a first approximation, the two approaches are expected to be equivalent in relation to the incentives they create for emissions reduction, and in relation to the total costs of emissions reduction.[122] Such assessments have generally concluded that the differences between the two approaches will arise from the details of their implementation. A question of preference has also been widely acknowledged: a carbon tax is seen to give certainty over the level of carbon price, which may be helpful for businesses, whereas an emission trading scheme (ETS) is seen to give certainty over the level of emissions, which may be attractive to policymakers.

In this case study, we approach the question of which is the most cost-effective form of carbon pricing from a different perspective. Since low-carbon transitions are a process of change, we do not assume equilibrium. Instead, we use analytical tools that consider the dynamics of the economy, to understand the likely effect of different forms of carbon pricing, individually and in combination with other policies.

This case study comprises three parts. Part 1 uses systems mapping to establish a basic understanding of the dynamics of the economy that may be created or influenced by different approaches to carbon pricing. Part 2 uses an agent-based model to explore the effectiveness of alternative approaches to carbon pricing in a hypothetical power sector with a competitive market for electricity generation, such as may be found in the UK or Europe. Part 3 uses a second agent-based model to consider the effectiveness of carbon pricing policy options in China. We give conclusions for policy at the end of each part.

[120] https://eeist.co.uk/eeist-reports/

[121] https://carbonpricingdashboard.worldbank.org/

[122] Stavins, R. (2019). The Future of U.S. Carbon-Pricing Policy. M-RCBG Faculty Working Paper Series, No. 2019-02. Available online: https://www.hks.harvard.edu/centers/mrcbg/publications/fwp/2019-02 (Accessed September 10, 2020.)

Part 1: Systems mapping of carbon pricing options

What is systems mapping?
Systems mapping refers to a suite of methods all designed to describe systems, or certain aspects of systems, in diagrams and models.[123] There are qualitative systems mapping methods such as Rich Pictures or Theory of Change diagrams, and quantitative methods (which may include a simulation approach) such as Bayesian Networks or Systems Dynamics. Many, but not all, systems mapping methods focus on cause and influence in systems, attempting to describe causal relationships. Methods that focus on cause and influence tend to use a network of nodes and edges to represent influence between variables or factors.

In this case study, we use a systems mapping approach called 'causal loop diagrams'. The method can be used by individual researchers, or built with groups of stakeholders, to produce maps which are organised around core feedbacks, sometimes called 'system engines'. These come in two kinds: reinforcing feedbacks, in which an increase in one variable leads to a further increase in the same variable, tending to amplify impact or accelerate change; and balancing feedbacks, in which an increase in one variable leads to a decrease in the same variable, tending to limit change or preserve stability.

Causal loop diagrams are sometimes the first step in building a System Dynamics simulation model, but not always. Sometimes, 'behaviour-over-time' (BOT) graphs are produced for causal loop diagrams which attempt to describe the expected behaviour of the feedbacks through time. Though these look like quantitative plots, they are based purely on our qualitative expectation about how feedbacks interact and are not the outputs of any quantitative analysis.

How did we build these systems maps?
To compare the dynamic effectiveness of carbon pricing policy options, we conducted a systems thinking and mapping exercise using the method developed by Meadows (2008).[124] The focus of this exercise was to use systems mapping to identify feedbacks in the economic system of interest – the power sector, its technologies and the carbon pricing policies – that would either help or hinder rapid and cost-effective decarbonisation.

The maps are based on a combination of literature reviews, expert opinion and stakeholder discussion. They are kept intentionally simple, to focus on the feedbacks at the centre of this system, rather than bringing in lots of broader information. They are not formally validated, but almost all the relationships in them are logically true (e.g. if the cost of a technology goes down, its relative cost to competitors must also decrease) and the rest are backed up by well-established concepts (e.g. deployment of technology tends to push down its price – Wright's law).

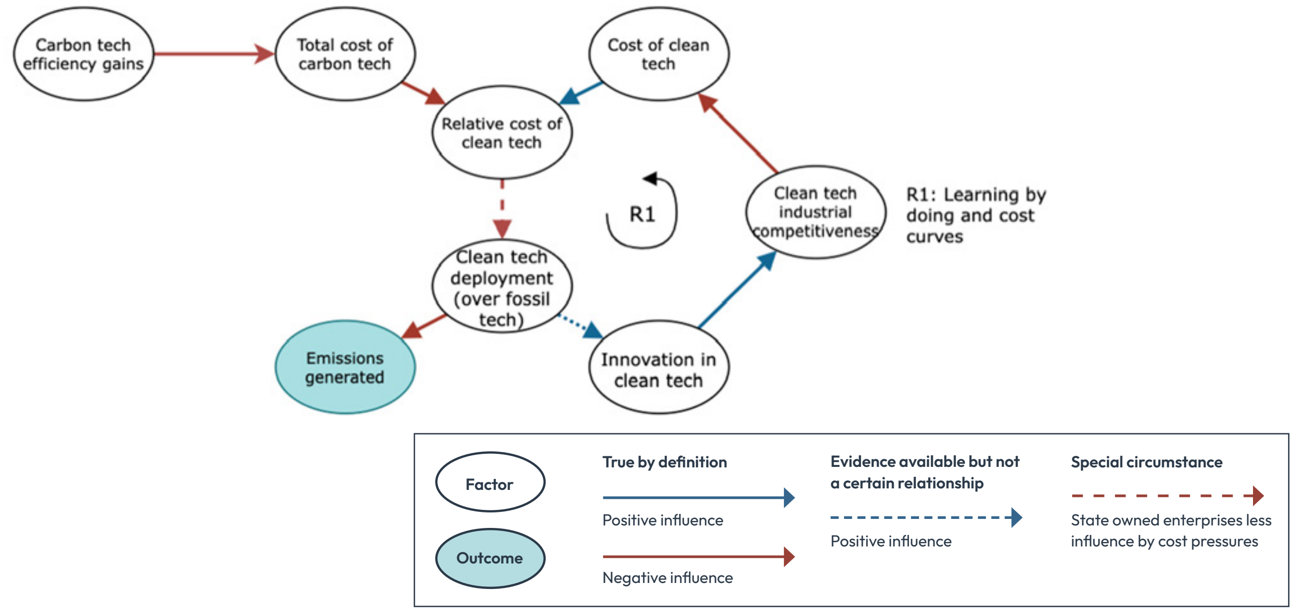
System maps of different carbon pricing mechanisms
We developed system maps of five carbon pricing policy scenarios: (i) no intervention, (ii) carbon tax, (iii) ETS, (iv) renewable portfolio standard, and (v) combinations of these. We describe only the first three here.

No policy intervention and learning-by-doing
The 'no intervention' system map (Figure 27) serves to emphasise the powerful feedback created by 'learning-by-doing' described by Wright's law, whereby deployment of a technology tends to generate learning and innovation in that technology, which decreases costs. That in turn makes the technology relatively cheaper and thus increases the likelihood of further deployment. This is a well-documented reinforcing feedback which pushes deployment of clean technologies up and drives emissions down.[125]

Beyond this feedback, the 'no intervention' map also shows the effect of another policy: the push for increased efficiency in fossil fuel technologies. This can reduce emissions from fossil-fuelled power plants; however, it may also reduce the total cost of electricity from these technologies, making them more competitive compared to clean technologies. This could weaken the reinforcing feedback of clean technology deployment and cost reduction, unless counteracted by other policies.

[123] Barbrook-Johnson, P. and Penn, A. (2022) Systems Mapping: How to Build and Use Causal Models of Systems. Palgrave.
[124] Meadows, D. (2008). Thinking in Systems: A primer. Chelsea Green, White River Junction.
[125] Way, R. et al. (2022). Empirically Grounded Technology Forecasts and the Energy Transition. Joule 6(9): 2057-2082. Note, this work also appears in this report as a case study.

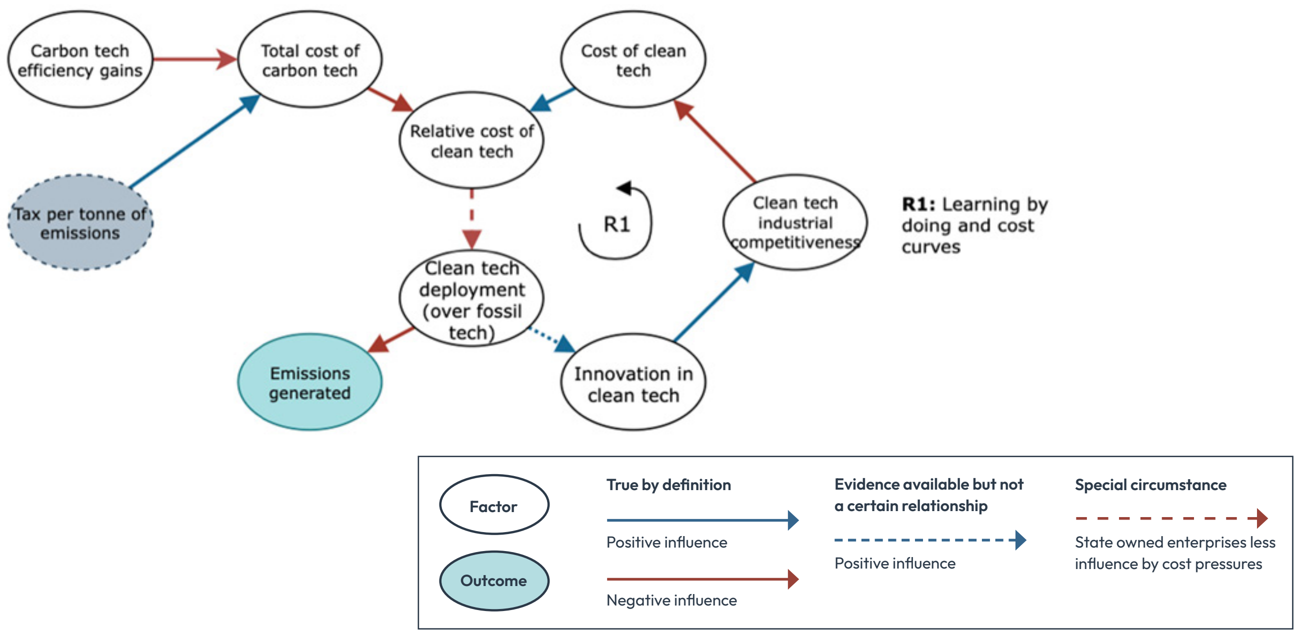
Figure 27: No intervention – historical deployment of clean tech has increased learning-by-doing and reduced costs, thus encouraging more deployment, which in turn further supports learning-by-doing in a reinforcing feedback (R1). Note: positive and negative influence refers to mathematical relationship, not a normative relationship (i.e. positive means they go in the same direction, up together or down together, not that the influence is good or desirable).



Carbon tax
Figure 28 presents the first map with a carbon pricing policy intervention: a carbon tax. Here, we see the same reinforcing feedback around learning-by-doing, with the addition of a policy factor directly affecting the cost of carbon technologies. We can see clearly that adding a carbon tax strengthens the existing reinforcing feedback loop without creating any other influences. We would expect this to accelerate the process of clean technology deployment and cost reduction, all else being equal.

In this example, there is no use of the revenue generated by the tax. However, if we wanted to include carbon tax revenue recycling, this could be done by adding in a revenue factor based on emissions generated, and then loop this round to either the cost of clean technologies (representing a subsidy for deployment) or to innovation in clean tech (representing investment in research and development). In either case, this would further strengthen the reinforcing feedback of clean technology deployment and cost reduction – either by reducing the relative cost of clean technologies, or by increasing clean technology innovation.

Figure 28: Carbon tax – the tax increases cost of carbon tech, reducing the relative cost of clean tech, further supporting the reinforcing feedback of learning-by-doing (R1).



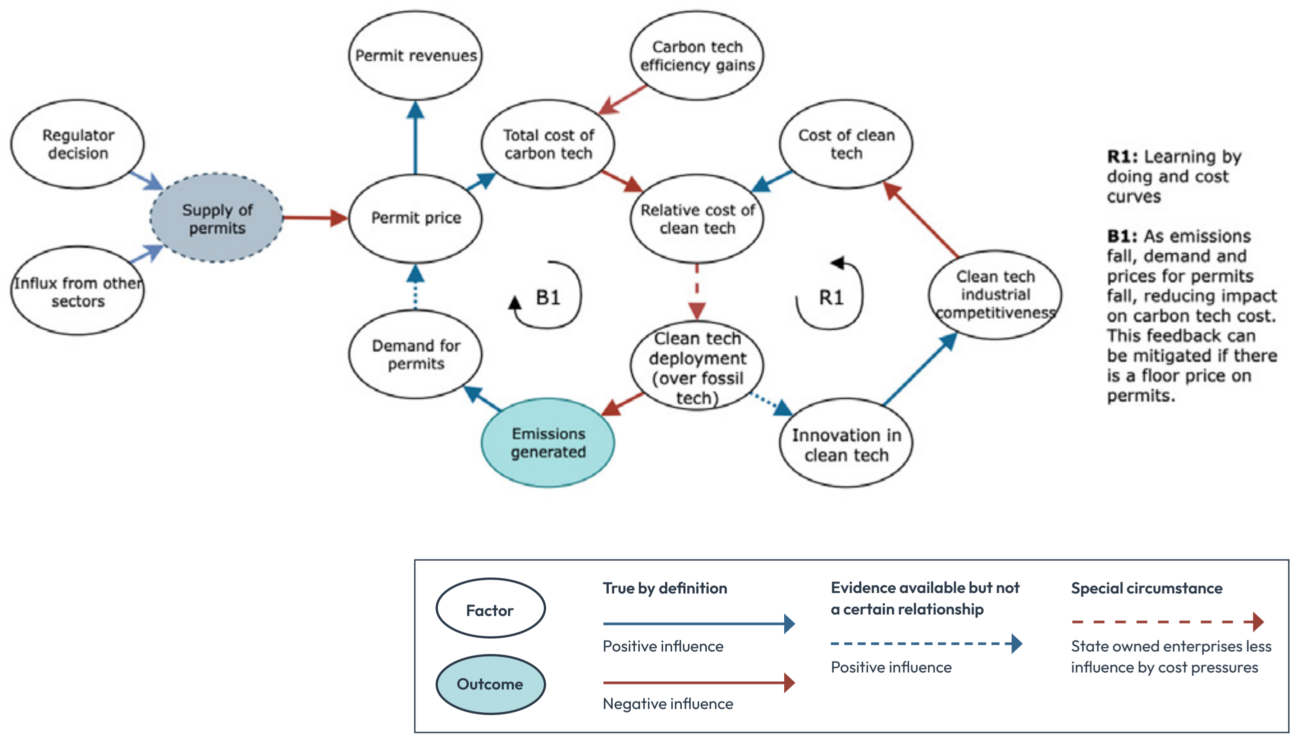
Emissions trading scheme
The next system map shows a different picture, with Figure 29 presenting the same diagram but for a standard ETS. Here the structure of the map changes, with the introduction of a balancing feedback (i.e. where a change induces an effect which in turn reverses the first change, thus acting in a self-regulating way) via the permitting system the scheme creates. The logic of this balancing feedback is that, as emissions generated falls, the demand for permits will fall, and thus the permit price will fall (since the supply of permits is fixed by the cap), which will reduce the total cost of carbon technology and thus increase the relative cost of clean tech and reduce the likelihood of further deployment. This balancing feedback counteracts the effect of the reinforcing feedback, limiting the ability of the carbon price to encourage faster clean technology deployment and cost reduction.

The logic of the balancing feedback is relatively clear, however there are a number of policy choices that will influence its effect. If the emissions cap is set to fall quickly over time, there will be a reducing supply of permits at the same time as reducing demand, with potential for the permit price to either rise or fall. The falling cap will ensure a certain level of clean technology deployment; however, the balancing feedback will continue to operate: a reduction of emissions by any actor will decrease demand for permits at any moment in time, and decrease the incentive for other actors to reduce their emissions. This dynamic makes the policy self-limiting in its effect.

Another policy option is to establish a floor price for permits, meaning the permit price cannot drop below a certain level. This would change the dynamics by limiting the range of operation of the balancing feedback. With a high enough floor price, the balancing feedback could be stopped altogether, giving the policy the same dynamic characteristics as the tax.

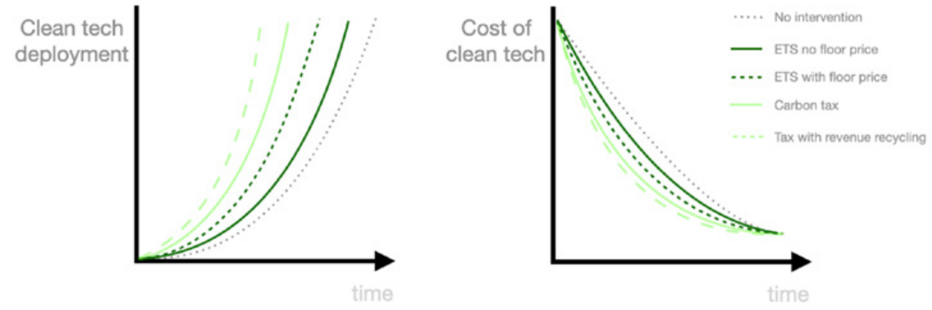
Again, there is no use of revenues shown in this map, but they could be included by adding connections from permit revenues round into either cost of clean tech (representing a subsidy) or into innovation (representing investment in research and development), as described above for a tax. Either of these would strengthen the reinforcing feedback of clean technology deployment and cost reduction; but this would be at least to some extent offset by the balancing feedback of the ETS, making any additional effect uncertain.

Figure 29: ETS – the scheme supports the reinforcing feedback of learning-by-doing (R1), but also introduces a balancing feedback. As emissions drop, there is less demand for permits, tending to reduce the effect of the carbon price on the costs of carbon tech (B1).



Behaviour-over-time (BOT) graphs
Though the system maps above make the likely effect of these policy options on the dynamics of the energy system clearer, they don't fully explain how we expect the system behaviour to unfold through time. To do this, we developed BOT graphs of clean technology deployment and cost of clean technology for the 'no intervention', tax, and ETS scenarios (including two for tax, one without revenue recycling and one with, and two for ETS, one with a floor price and one without), these are shown on one plot in Figure 30. The BOT graphs illustrate the understanding that there is an underlying reinforcing feedback which is increasing deployment and reducing the cost of clean technologies. The 'no intervention' line shows an accelerating deployment as a result. (Note, we show only the early section of what is an S-shaped curve; if we followed the no intervention line further, we would expect deployment to level out at some point.) The tax and ETS scenarios both strengthen this reinforcing feedback and so shift the curve to the left, representing quicker deployment. A revenue recycling scheme for a tax is shown as further reinforcing this dynamic. However, the balancing feedback created by the ETS limits its effect, so that deployment is increased to a lesser extent. The disadvantage of the ETS is reduced in the scenario where a floor price is implemented. The same dynamics are shown in the cost of clean technology plot, with costs decreasing faster in the tax scenarios, and slowest (of the interventions) with an ETS with no floor price.

Figure 30: Behaviour-over-time (BOT) graphs for clean tech deployment and costs under tax and ETS scenarios.



Policy conclusions from the system mapping exercise
The most important conclusion of the system mapping exercise is that the two policy options are fundamentally different in their dynamics. The carbon tax creates no new feedbacks, but strengthens the reinforcing feedback of clean technology deployment and cost reduction. The ETS creates a balancing feedback, and so strengthens the reinforcing feedback of clean technology to a lesser extent. Before any other considerations are taken into account, this suggests the carbon tax is likely to be the more cost-effective policy, since it does not create self-limiting dynamics. There are several issues that are also likely to be important to the relative effectiveness of the policy options. These include:

- Policy strength: In this exercise to compare the dynamics of the two policies, we assume they are implemented with equal 'strength'. In practice, a policy's effectiveness will depend on its stringency as well as its dynamic structure. A weak carbon tax that leaves fossil fuels as the most competitive option may do little or nothing to strengthen the reinforcing feedbacks of clean technology deployment and cost reduction. A rapidly falling cap in an ETS may achieve rapid emissions reduction despite the balancing feedback it creates (although not necessarily in the most cost-effective way).
- Policy modifications: The system mapping suggests that a carbon floor price in an ETS can limit the range of operation of the balancing feedback, improving the dynamics of the policy. However, since a strong floor price makes the scheme operate more like tax, this begs the question of why an ETS would be preferable if it operates in the same way, but with a larger administrative burden due to its more complex design. Revenue recycling appears likely to add to the effectiveness of a carbon tax, while its additionality when used with an ETS is less certain.
- Market design: In this exercise we assumed that there is competition in the electricity market between clean technologies and fossil fuel technologies. The connection between the relative cost of clean tech and the clean tech deployment depends on energy companies choosing technologies in response to price signals. In a market where this does not happen – either as a result of regulatory structure or because of other objectives and constraints driving the decisions of energy companies, this link may be weaker or even non-existent. Without such a link, it will be difficult for any carbon tax to have an effect, and if an ETS has an effect, it is likely to be functioning in a manner equivalent to a regulation (i.e. its effect is independent of price).

The relative merits of the two policies may also depend on outcomes or factors wider than those we have discussed here – for example, their effect on electricity prices, their ability to mobilise investment in new power-generating capacity, or the degree to which they can win acceptance among political, industrial and social stakeholders.

Part 2: simulation of carbon pricing policy options using an agent-based model in a competitive market

In this exercise, we compared the same two policy options – a carbon tax and ETS using an ABM building on earlier work by Chappin.[126] This is a different and complementary approach. In systems mapping, the dynamics of the system are understood by mapping the relationships between variables – based on logical reasoning or underlying evidence – and identifying feedbacks. In an ABM, the dynamics of the system are discovered by simulating the interactions between economic agents, where each agent's behaviour is driven by a set of decision-making rules that it is assumed to have. The difference between these methods means that they can provide a helpful cross-reference when applied to the same policy problem.

Design of the agent-based model

The ABM that we present recreates an abstract closed electricity market composed by 10 companies, that produce electricity for an unidentified number of consumers which are represented by a demand trendline. All electricity demand is met by supply within this market, which can be imagined as representing a stylised version of an isolated country or of the whole world (i.e. there is no trade outside the market). Companies can use four technologies to generate electricity: coal, natural gas, wind and solar PV.

The model runs three scenarios:

1) No policy, where no policy is implemented and companies continue to produce and invest along a 'business as usual' trajectory (BAU).

2) The ETS scenario, where a policy based on the EU ETS is introduced.

3) The tax scenario, where a carbon tax is introduced (where we assume that the tax is introduced as a flat rate and the market assumes it will remain at this rate over the planning periods).

The model is partially empirically grounded, meaning that part of the data fed into the model as well as the parameters used have been informed using real data gathered from available literature. In particular, the parameters defining the costs of different electricity generating technologies, and the rate at which these technology costs fall in response to deployment in the model have been taken from Mercure (2012),[127] and the rate of decrease for the emissions cap used to simulate the ETS scenario has been taken from the real functioning of the EU ETS.[128]

The model simulates a competitive electricity market, where electricity from the cheapest units of generation is sold first, and then electricity from increasingly expensive units is sold until the point where supply meets demand. Demand is set exogenously and is assumed to increase at 5 per cent per year. Electricity demand is assumed to be always met and so defines electricity supply. Any surplus generating capacity is left unused. The price of electricity is set by the cost of the marginal unit of supply. The cost of each unit of supply is a levelised cost of electricity that includes capital costs (depreciation), operating costs (fuel and maintenance) and any carbon pricing costs.

The agents in our model are the energy companies who make decisions on what, when and how much to invest in new electricity generation technology deployment. Each company can choose from the following generation technologies: coal, gas, wind and solar. Each starts with a different mix of these technologies and has different expectations about the future. These expectations allow each company to project forward one and seven-year trends in market price, investment costs and policy-related variables (i.e. permit price or tax) to anticipate profit. They then make a decision on which technology to invest in, based on different criteria which define their expectations, including attitude towards market leadership (being more or less aggressive in trying to grow their market share), expectations towards technology (being more or less of the view that the market will favour renewables, and therefore that their cost will decrease more or less rapidly), company preference (whether a company views renewables more favourably, which could be due, for example, to its own historic experience or investor pressure), and view of the effectiveness of policy (what a company believes about how fast the permit price on the emissions trading scheme will increase). See Sharpe et al. forthcoming, for more details.[129] As companies aim to maximise their profits, their decisions are a function of the expected returns and capital constraints.

[126] 126 Chappin, E. (2011). Simulating Energy Transitions. Next Generation Infrastructures Foundation, Delft, The Netherlands. Available online: http://chappin.com/ChappinEJL-PhDthesis.pdf

[127] Mercure, J-F. (2012). FTT:Power: A Global Model of the Power Sector with Induced Technological Change and Natural Resource Depletion. Energy Policy 48: 799-811. Note: Values have been converted from $ to £ for consistency for all four technologies (based on 2020 exchange rate). Due to the age of the paper (2012), the parameters related to current cost of renewables were outdated. Therefore, these were cross-checked with current values associated with the trend's position on the cost curves.

[128] EU. (2013). The EU Emissions Trading System (EU ETS). https://ec.europa.eu/clima/sites/default/files/factsheet_ets_en.pdf

[129] Sharpe, S. et al. (Forthcoming). Stuck in First Gear: Why Cap and Trade Causes Decarbonization at Maximum Cost.

The model can be run with either of two settings governing innovation. In the 'exogenous' setting, the cost of clean technologies reduces as a function of time, following a Moore's Law relationship based on historical data. This can be thought of as representing a market that is too small to significantly influence clean technology costs (a simplification; in reality, factors such as installation and finance costs are likely to be influenced by local policy, even if the core technology costs are not). In the 'endogenous' setting, the cost of clean technologies reduces as a function of their cumulative deployment, following a Wright's Law relationship based on historical data. This can be thought of as representing the global market, within whose boundaries all clean technology innovation takes place.

The model is initialised with a list of parameters whose values are based on either assumptions or empirical literature. In line with established model-development techniques, we introduced randomness in the 92 initialisation values for some parameters and variables, where their values are not completely certain (especially where they relate to behavioural responses), which allows emergent behaviour to appear. The results from many runs can then be compared to give ensemble averages, which ensures that outcomes are not driven by particular choices of variables. In addition, we further use a range of values for some variables, where the typical ranges are known, to test the sensitivity of the outputs to these changes.

Results

For our simulations we investigate the effectiveness of each policy in reducing emissions. We also compare this with a no-policy option. We run this comparison under the model's two innovation settings: endogenous and exogenous. To ensure a fair comparison between the two policies, the carbon tax is set by calculating the average cost of carbon over the simulation run from the ETS (therefore the average cost of carbon under each simulation is identical). For example, if the average (mean) carbon price paid under the emissions trading scheme within the endogenous scenario is 68 Euro/tonne, then the tax for the endogenous scenario is set at this level.

The output variables of interest are the time taken for emissions to reach zero, and the total emissions over the duration of the run. Figure 31 and Table 9 summarise the results.

Figure 31: Time (showing min and max and mean) to reach zero emissions in the simulations (in years). The horizontal bars indicate the mean value from multiple model runs with each scenario.

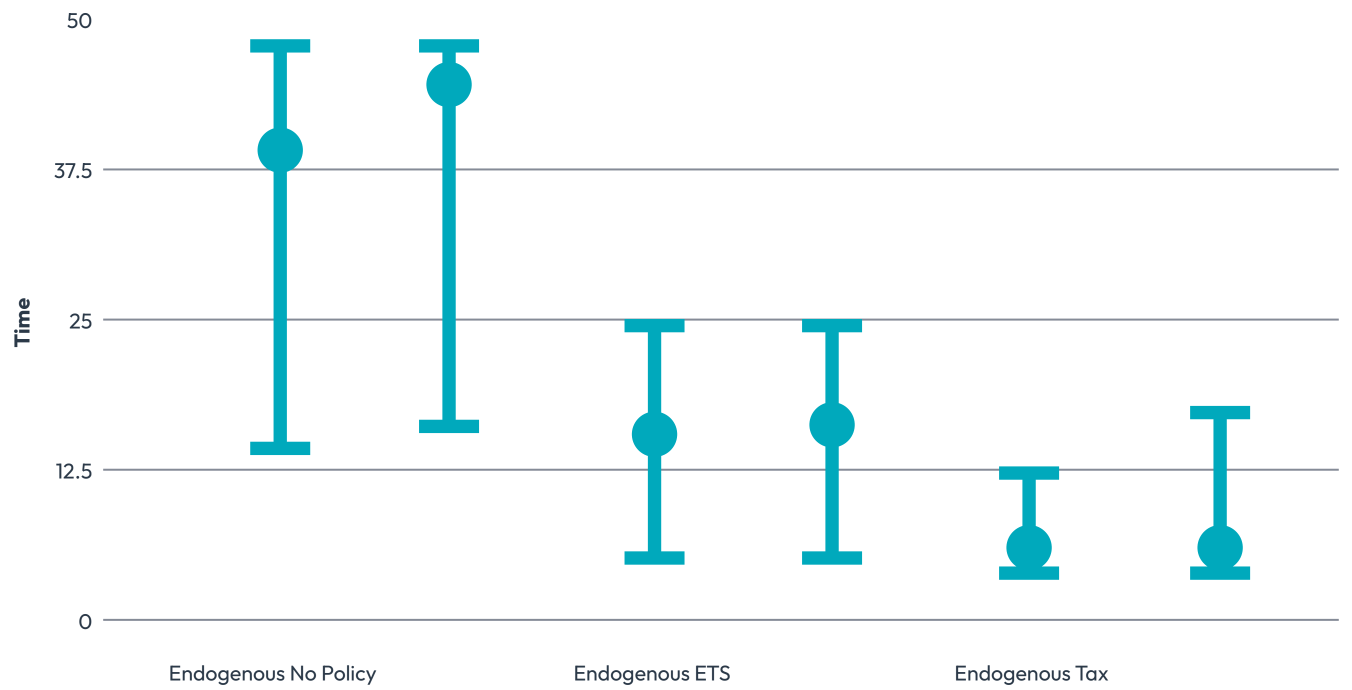


Table 9: Cumulative emissions (range) before reaching zero emissions (in tons CO2).

Scenario		Min	Medium	Mean	Max
Endogenous	No-policy	2.9 million	161 million	332 million	1.9 billion
	ETS	3.0 million	26.8 million	29.2 million	130 million
	Tax	3.0 million	8.6 million	8.4 million	25.8 million
Exogenous	No-policy	3.0 million	213 million	413 million	1.9 billion
	ETS	3.1 million	28.1 million	30.2 million	138 million
	Tax	3.1 million	8.6million	8.5 million	26.3 million

As can be seen, the tax performs much better than the ETS in reducing emissions. With the same average carbon price, the mean time to get to zero emissions is about three times as long under the ETS as under the tax. Cumulative emissions were also about three times higher under the ETS than under the carbon tax. These ratios were roughly the same under both endogenous and exogenous innovation settings, implying that the difference in performance between the two policies may be independent of market size.

Discussion
These findings appear to support the main conclusion of the systems mapping exercise: that the carbon tax is dynamically superior to the ETS. The performance of the ETS is limited by its balancing feedback; the tax, without this limitation, brings about a faster transition.

The outcomes of the scenarios presented in this Agent Based Model are driven by the dynamics of the interplay between different agents which have differing future expectations of technology costs and (in the ETS scenario) permit prices. Within the model there is a range of allowed future expectations of renewable technology costs and future permit prices. (As the tax is fixed all agents have the same – correct – expectation for the carbon price in the tax scenario). No company has perfect foresight, so although on average their expectations may be consistent with what actually happens, individually their expectations will diverge. These results depend on the degree of divergence in agents' expectations, with a reinforcing feedback rewarding early investment in the tax scenario and a balancing feedback offsetting this effect and delaying this investment in the ETS scenario.

It is important to note that these results are subject to the caveats mentioned at the end of part 1 of this case study: policy strength, policy modifications, and market design will all affect the relative effectiveness of a carbon tax or an ETS. In this study we assume no policy adaptation during the lifetime of the policies, since this allows a clear comparison between the alternatives. In reality, policy modifications can of course be made during implementation of a policy, as well as during policy design.

Part 3: Simulation of carbon pricing policy options in the Chinese power sector using an agent-based model

In this final part of the case study, we develop an agent-based model to compare carbon pricing policy options in China, where the electricity market structure differs significantly from the competitive market simulated by the model used in Part 2.

Context and history of carbon pricing in China
China has a long history of meeting its national policy targets using planning, regulation and other 'command and control' approaches. The climate change mitigation targets, outlined in the country's 'nationally appropriate mitigation actions' up to 2020, and its 'nationally determined contribution' to 2030, are no exception. However, since the 11th Five Year Plan (2006-2010), there have been calls for greater use of 'market-based' instruments.

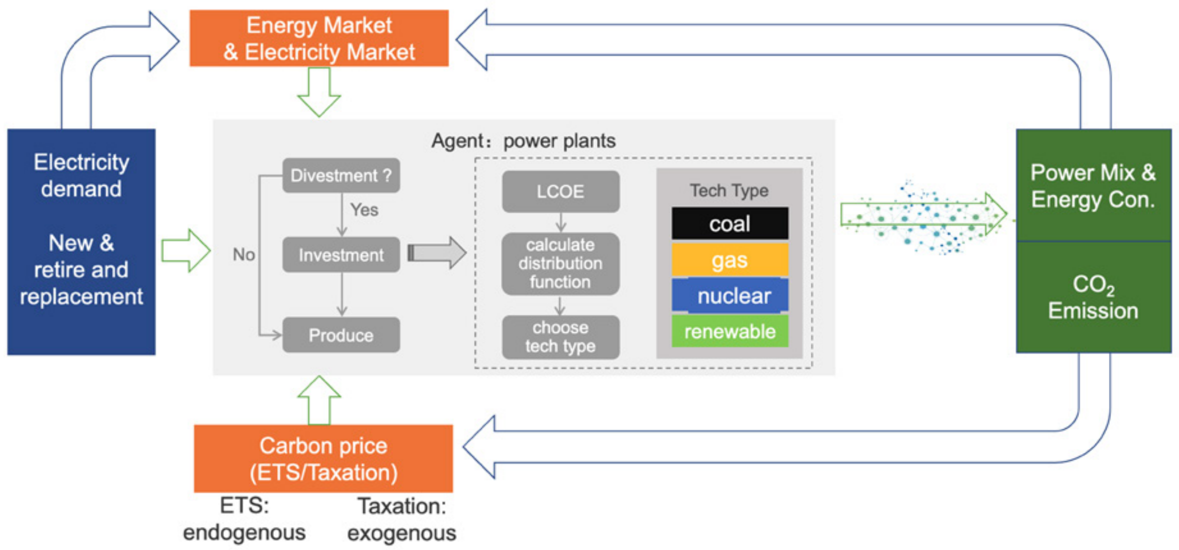
Regional ETS pilots were initiated in 2013 after a few years' preparation, and a national scheme was formally launched in July 2021. At present, this only covers the power sector, which accounts for over 40 per cent of China's CO2 emissions. The design of the scheme differs from that of the EU in two important respects. First, there is no 'hard cap', in which the supply of emissions permits is decreased linearly over time. Instead, the supply of emissions permits each year is a function of the 'benchmark' emission intensity and of total electricity generation. Second, emissions permits are allocated to each power plant (based on its own output, multiplied by the benchmark emissions intensity) freely, instead of through an auction. Compared to the EU ETS, where the benchmark level is set at the most efficient 10 per cent of coal power plants in the market, the Chinese scheme is relatively conservative, set around 50-60 per cent of the 'most' efficient plants, to avoid a gap between permit supply and demand. This is understandable in this initial stage.

The progress of the national ETS has been described as positive (MEE, 2022),[131] but it has also been argued that the policy has done more to stimulate competition between fossil-fuelled power plants (promoting greater efficiency) than it has done to promote deployment of renewable technologies (IEA,2022).[132] Consequently, there remains discussion on how to reform the scheme, and on whether a carbon tax would do a better job.

Previous studies
Many studies have compared these two carbon pricing instruments in applied contexts. Some have focused on specific issues such policy efficiency, cost-effectiveness, institutional feasibility or distributional impacts,[133 134] while others have used modelling approaches, such as equilibrium models or cost-optimised models, for assessing policy options.[135 136 137] There are studies of carbon pricing specifically in China using ABM to look at this ETS,[138 139] as well as IEA and Tsinghua University's work on the scheme.[140] However, all these studies focus on only one policy option at a time, and do not compare tax and ETS.

Design of the China agent-based model
The structure of the model is illustrated in Figure 32. The model simulates the decisions of agents representing operators of individual power plants. (This is an important difference from the model described in Part 2, in which agents are companies that invest in a portfolio of power plants using different technologies.) Agents decide each year whether to continue operating their power plant, or to decommission it and invest in a new one. New agents enter the market if demand for power would otherwise exceed supply. When an agent enters the market or invests in a new power plant, it can choose between the technologies of coal, gas, biomass, nuclear, hydro, solar, onshore wind and offshore wind.

Figure 32: Illustration of ABM-power transition model.



[131] Ministry of Ecology and Environment. (2022). Annual report on China's policy and actions to address climate change. Available at: https://www.mee.gov.cn/ywgz/ydqhbh/syqhbh/202210/W020221027551216559294.pdf [Accessed October 27, 2022].

[132] IEA. (2021). The Role of China's ETS in Power Sector Decarbonisation. https://iea.blob.core.windows.net/assets/61d5f58d-4702-42bd-a6b6-59be3008ecc9/The_Role_of_China_ETS_in_Power_Sector_Decarbonisation.pdf

[133] Stavins, R. (2019). The Future of U.S. Carbon-Pricing Policy. M-RCBG Faculty Working Paper Series. Available online: https://www.hks.harvard.edu/centers/mrcbg/publications/fwp/2019-02 (Accessed September 10, 2020.)

[134] Mathur, A. and Morris, A. (2014). Distributional Effects of a Carbon Tax in Broader U.S. Fiscal Reform. Energy Policy 66: 326-334.

[135] Fan X. et al. (2022). Is Price Commitment a Better Solution to Control Carbon Emissions and Promote Technology Investment? Management Science. https://doi.org/10.1287/mnsc.2022.4365

[136] Hagmann, D et al. (2019). Nudging Out Support for a Carbon Tax. Nat. Clim. Chang. 9: 484-489.

[137] Li, W. et al. (2018). The Impact on Electric Power Industry under the Implementation of National Carbon Trading Market in China: A dynamic CGE analysis. Journal of Cleaner Production 200: 511-523.

[138] Maosheng, D. and Wang, B. (2022). Consignment Auctions of Emissions Trading Systems: An Agent-Based Approach Based on China's Practice. Energy Economics 112: 106187.

[139] Tang, L. et al. (2015). Carbon Emissions Trading Scheme Exploration in China: A multi-agent-based model. Energy Policy. 81: 152-169.

[140] https://www.iea.org/reports/enhancing-chinas-ets-for-carbon-neutrality-focus-on-power-sector

Agents' decisions on whether to operate or decommission an existing plant are based on their profitability. If the plant is profitable, the agent will continue to operate it. Agents have bounded rationality, not perfect foresight, so make their decisions probabilistically. If a plant is unprofitable, then the longer the period of loss-making is, the greater the probability that the agent will decide to decommission it.

When agents decide which technology to use for a new plant, this decision is based on the expected profitability of different technologies, calculated using their LCOE generation. This decision is similarly probabilistic. Agents are heterogeneous in their risk preferences: some are risk averse, preferring to stick with the technology they have (generally coal) and others are more willing to experiment with new technologies, even when their costs are higher. For more detail, see the appendix.

An important aspect of the first decision-making rule in this model is that, for an agent to continue operating a plant, the plant only has to be profitable now, without any consideration of whether a shift to an alternative plant using a different technology might be more profitable in future. This means that there is significant inertia in the stock of existing power plants, with strong competition between technologies only applying to investment in new power plants. We use this as a rough proxy for the actual situation in China's electricity market, where the interests of some large-scale power utilities are often aligned with continuing to run existing coal plants despite the potential for alternatives to be more profitable. Concern to maintain security of electricity supply, for which coal power is seen as a safe option, is one significant factor reducing the motivation of operators of existing power plants to replace them with alternative technologies. The relatively low risk and low difficulty of increasing the efficiency of coal power, compared to replacing coal plants with a different technology, may be another.

Electricity demand is exogenous to the model and is assumed to increase over time.[141] Agents' decisions collectively determine the electricity generation technology mix, and therefore also the total emissions.

The model begins with 14,960 power plants, including both fossil (around 3,000 of which are covered by the ETS) and non-fossil based, with a total capacity of 2,200 GW and total electricity generation of 7,700 TWh in 2020 (the first year). CO2 emissions in the first year are around 4,500 Mt. Attributes of power plants include capacity, fuel type, construction year, lifespan, average working hours per year, energy efficiency, and emission intensity, based on open information sources and related assumptions. Technological progress in renewable technologies (and thus, cost assumptions) is treated as an exogenous variable, based on learning curves. The capacity, power generation and CO2 emission distribution in the base year are shown in the appendix.

The following policy options were tested in the model:

a) No policy (business as usual).

b) A carbon tax at CNY 30/tCO2 (~US$4.3/tCO2).

c) A carbon tax at 50 Yuan/tCO2 (~US$7.2/tCO2). Note: these two levels for the carbon tax have been chosen to be similar to the average carbon price currently generated by China's ETS (CNY 51.20/tCO2 over the period July 2021 to December 2021).

d) An emissions trading system with a soft cap (using the benchmark approach as described in Zhang et al, 2022) and free allocation of permits. This is the closest fit to the carbon pricing policy currently implemented in China.

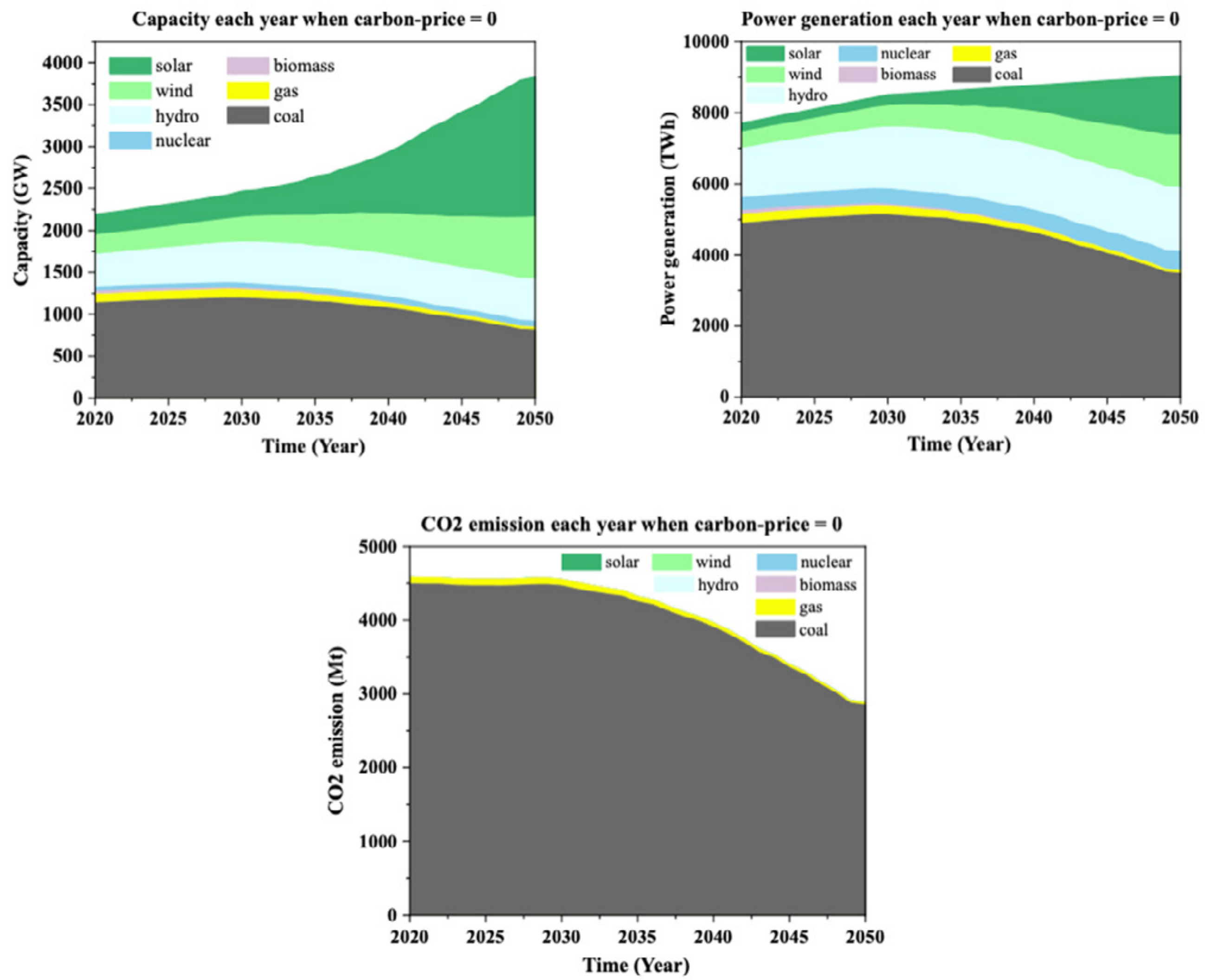
e) An ETS with a hard cap and permits allocated by auction (see appendix for details on the auction design used in the model).

In all cases, the base year was 2020, and the model simulated the evolution of the power system until 2050.

Results and discussion

Business as usual
In the BAU scenario, there is no carbon pricing or other policy intervention. The power capacity, power generation and CO2 emissions by fuel type are shown in Figure 33.

Figure 33: Technology evolution over time in BAU scenario: capacity (top left), power generation (top right), CO2 emission (bottom).



The overall trend is, not surprisingly, a slow transition. Fossil-fuelled capacity, particularly coal, decreases over time, while non-fossil capacity expands. Solar and wind become dominant as the new technologies, while total power capacity grows to 2,500 GW in 2030 and to nearly 4,000 GW in 2050.

The turning point of solar power development, due to its rapid innovation rate, is around 2035, after which its growth is accelerated. The contribution of coal generally keeps stable till 2030, then starts to decrease. By 2050, the major technologies' shares of power capacity have changed significantly compared to 2020: coal's share falls from 52 per cent to 21 per cent; wind's share rises from 11 per cent to 19 per cent, and solar's share rises from 11 per cent to 44 per cent. The role of gas-fired units, hydro power and nuclear are relatively unchanged.

The technology mix of power generation follows the same pattern as that of power capacity, since the model assumes the load factor of each technology remains unchanged. CO2 emissions, which mainly come from coal and gas power plants, especially coal, tend to keep stable before 2030 and then decline significantly to below 3,000 Mt in 2050 – about two thirds of the level in 2020.

[141] The relevant assumption is from Jiang and Chen (2021) where the demand in 2030 and 2050 is up to 8,500 TWh and 9,000 TWh, respectively. These assumptions might be much lower than latest predictions. Jiang K and Chen Y eds. 2021. China Climate and Environment Evolution 3.

Carbon tax

Figure 34 shows the power capacity, power generation and CO2 emissions over time in the low carbon tax scenario (CT-30). Figure 35 shows the same for the high carbon tax scenario (CT-50). Bottom right of Figure 35 compares emissions over time for the carbon tax at low and high levels, and for the BAU scenario.

The results show the low carbon tax has a limited effect in accelerating the transition before 2030, compared with the BAU scenario. The reason is likely to be that this low tax is only sufficient to nudge the very oldest and least-efficient coal plants towards decommissioning, while most of the coal fleet remains profitable and continues to operate. As the costs of wind and solar fall, the low carbon tax moderately increases their advantage over coal in the competition for investment in new capacity, and this leads emissions to diverge further from BAU. Even so, emissions in 2050 are around 2,500 Mt, only about one sixth lower than their BAU level in that year.

Figure 34: Technology evolution over time in CT-30 scenario: capacity (top left), power generation (top right), CO2 emission (bottom).

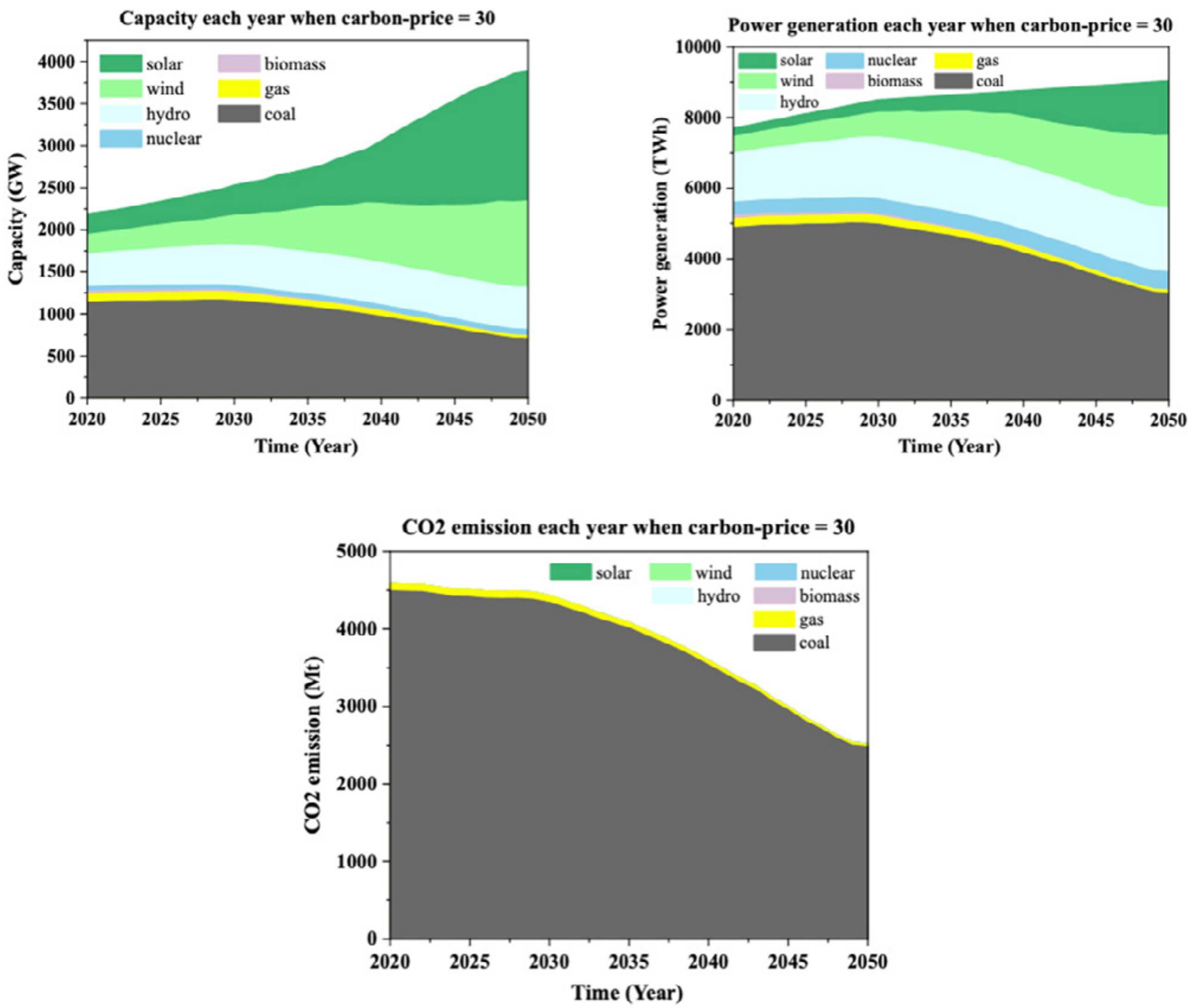
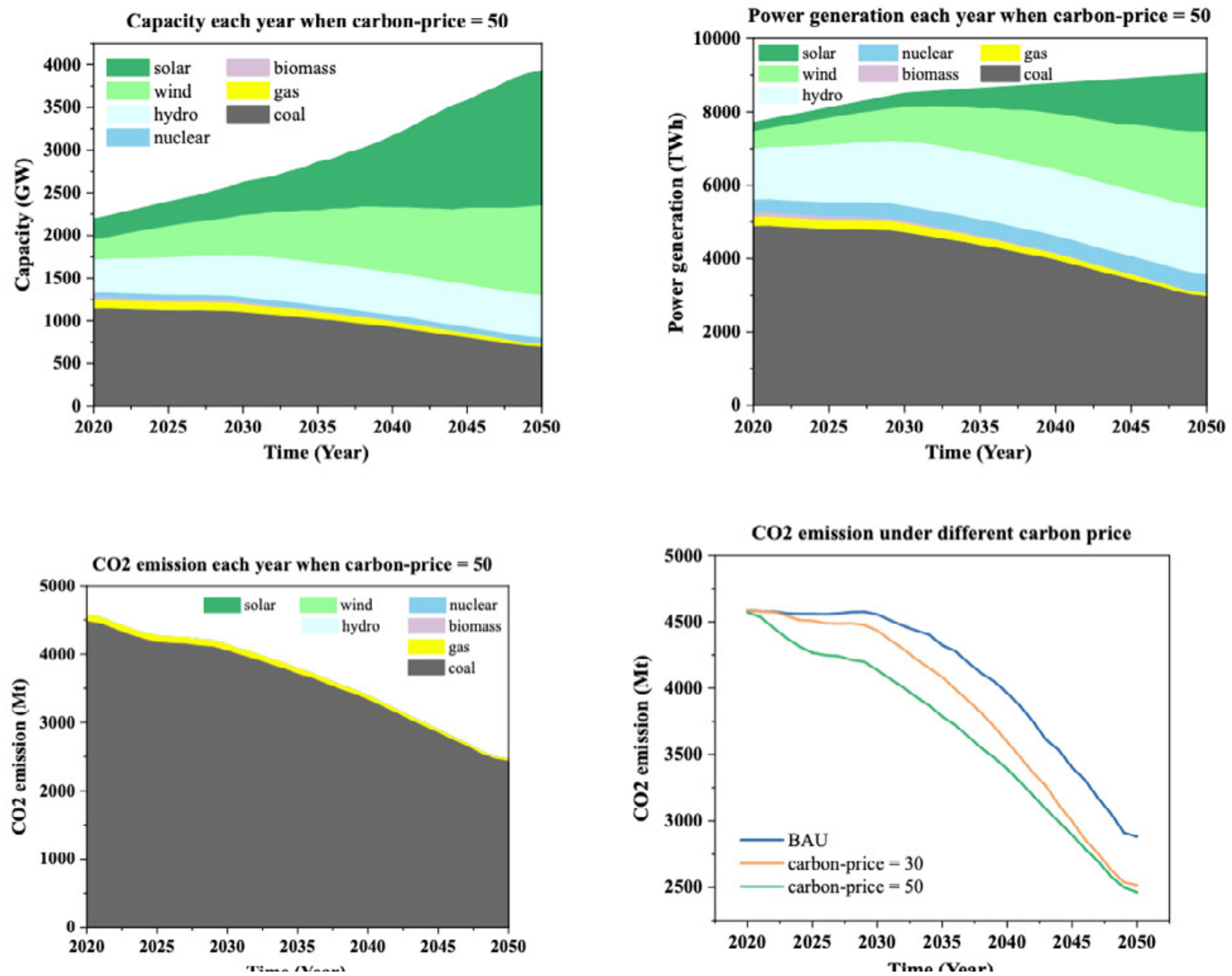


Figure 35: Technology evolution in CT-50 scenario: capacity (top left), power generation (top right) and CO2 emission (bottom left); comparison of BAU, CT-30 and CT-50 on CO2 emission (bottom right).



The high carbon tax has much greater impact in the first decade, with emissions declining quickly in the period of 2020-2030, during which the low carbon tax has little influence. However, the advantage of the high carbon tax decreases in later years, with its impact on the technology mix and annual emissions almost converging with that of the low carbon tax by 2050. The reason may be that, by the late stages of the transition, solar and wind already outcompete fossil fuels for new power capacity investments without any need for a carbon price. At the same time, even this 'high' carbon tax (of CNY 50 or US$7.2/tCO2) is too low to stop most coal plants being profitable, though the profits are inevitably shrinking; consequently, most of the existing coal fleet continues to operate unaffected.

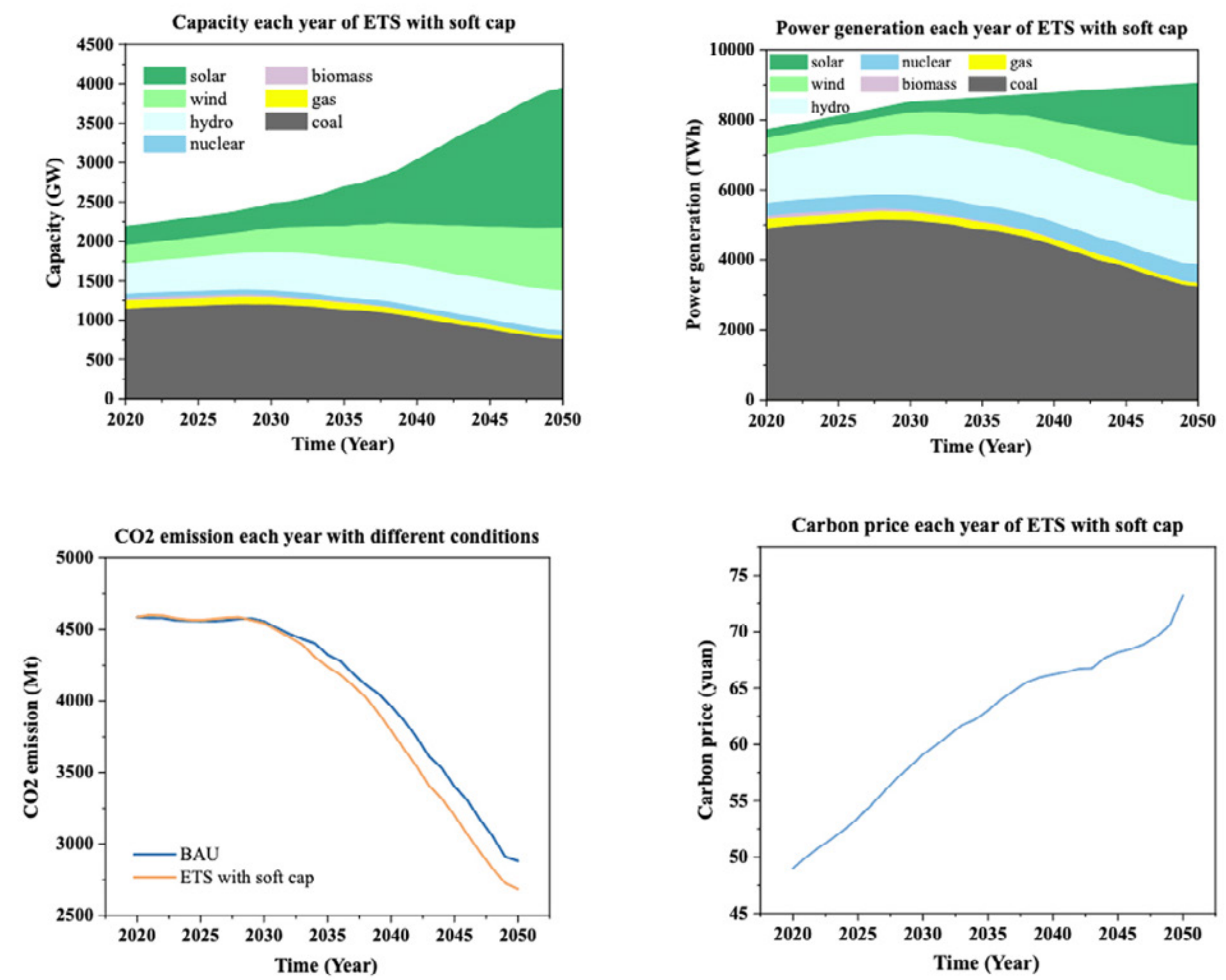
A conclusion for policy is that, in a market where there is little competition between technologies for existing generation, the carbon tax will only have a substantial and sustained impact on emissions if it is high enough to make a typical coal plant unprofitable. In our simulation, that would require a carbon tax of around CNY 120/tCO2 (or US$17/tCO2).

ETS with soft cap and free allocation

In this scenario, each agent is assigned emissions permits based on its output of electricity and the benchmark carbon intensity as described above. The benchmark decreases gradually over time, as the efficiency of the most-efficient plants improves. The permits are allocated freely and can be traded between agents. When a less-efficient plant has a shortage of permits due to the falling benchmark, it must purchase credits in the market. The carbon price that emerges from this trading in permits is calculated using an empirical formula developed by Chappin (2011)[142] (see appendix for details).[143] For the less-efficient coal plants, this represents a cost; for the highly efficient coal plants it represents a source of income.

The modelling outputs for power capacity and power generation by each technology, and CO2 emissions, are illustrated in Figure 36. Bottom right of Figure 36 shows the how the permit price changes over time.

Figure 36: Technology evolution over time in ETS scenario: capacity (top left), power generation (top right), CO2 emission (bottom left) and carbon price (bottom right).



As can be seen from Figure 36 (bottom left), the ETS with soft cap and free allocation has almost no effect on emissions over the period 2020-2030, compared to BAU. After 2030, there is some effect, but it remains extremely limited, with emissions in 2050 being less than 10 per cent below their BAU level for that year, despite a steadily increasing carbon price.

Figure 37 compares the emissions over time of the ETS with soft cap and free allocation to the emissions trajectories of the two tax scenarios, as well as BAU. This shows the effect of the ETS is even less than that of the low carbon tax.

[142] Chappin, E. (2011). Simulating Energy Transitions, Next Generation Infrastructures Foundation, Delft, The Netherlands. Available online: http://chappin.com/ChappinEJL-PhDthesis.pdf

[143] In order to validate the formula, the permit price was calculated for the base year, using the benchmark of 877gCO2/kWh. The result gives an average carbon price of CNY 54.2/tCO2 (with a soft emissions cap of around 4,280MtCO2). These outcomes are close to their actual values in China, providing confidence in the applicability of this formula (which was originally designed for simulating the EU ETS).

Figure 37: Illustration of CO2 emissions in all scenarios.

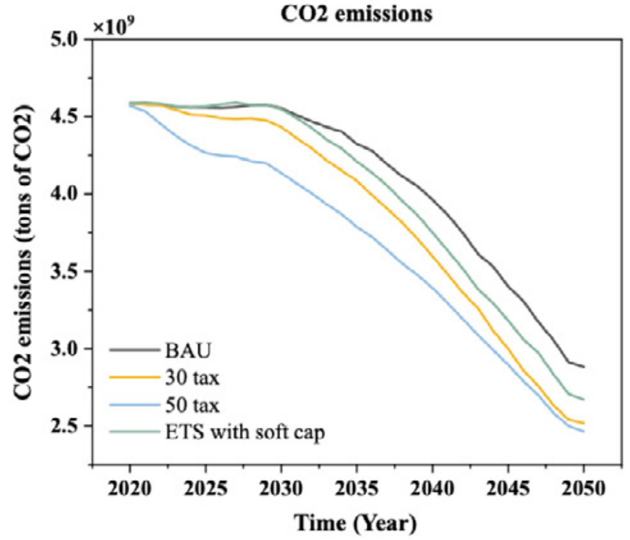
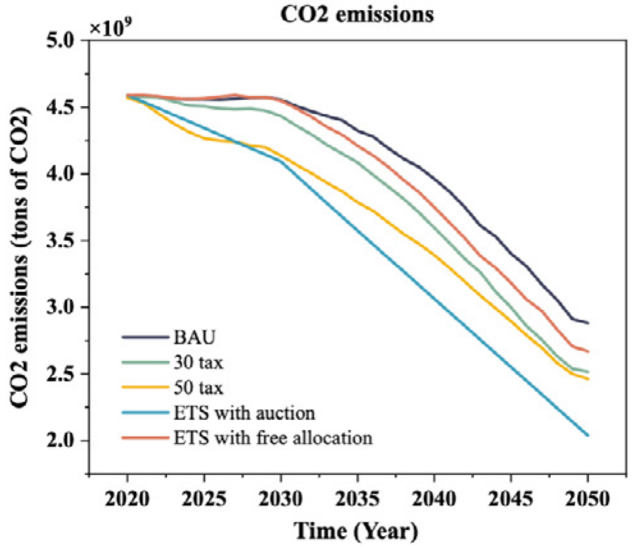


Figure 38: Emissions over time for the ETS with permits allocated by free allocation and auction, compared to low and high carbon taxes and BAU.



The explanation for this lies in both aspects of the design of this version of the ETS. Free allocation of permits means that only a small proportion of emissions are subject to any carbon price. Even the oldest and least-efficient coal plants only have to pay to top up their allocated permits to the total number of permits needed; the emissions covered by their free allocation are not priced. At the same time, the effect of having a soft cap based on the benchmark carbon intensity is that the most efficient coal plants pay no carbon price on any of their emissions, and instead receive a bonus from selling their freely allocated permits. Instead of providing a strong push to the transition, the policy gives only a small nudge.

A conclusion for policy is that significant design changes are likely to be needed for the ETS to have a substantial impact on emissions. These could be, for example, a hard cap on emissions that reduces over time, and/or emissions permits allocated by auction instead of freely.

ETS with hard cap and auction for permits

In this scenario, the ETS has a hard cap: the total supply of permits is set by the government. In our example, the cap is set roughly in line with China's targets of peaking emissions by 2030 and achieving carbon neutrality by 2060. The trajectory fixed by the cap is a linear decrease from the current level of emissions to 4,000 Mt in 2030, and then a steeper linear decrease to 2,000 Mt in 2050. (Meeting the carbon neutrality target would require a further steepening of the trajectory between 2050 and 2060.[144]) Agents bid for the permits they need in an auction, with the bid for the final permit setting the carbon price for the whole market, each year. Details of this process are described in the appendix.

Figure 38 shows that this version of the ETS is significantly more effective than the free allocation. For the period 2020-2030 it performs similarly to the high carbon tax. During the period beyond 2030, it outperforms the high carbon tax, resulting in annual emissions being nearly a third lower than BAU in 2050. The reason for this is straightforward: the hard cap on emissions limits the amount of fossil-fuelled power that is allowed to operate. Coal plants are gradually forced out of the market, beginning with those that are least efficient, and emissions fall in line with the cap.

[144] This is only one possible trajectory for power sector emissions towards meeting the 2060 target. We are not suggesting that it is the most cost-effective trajectory.

It is worth considering the extent to which this ETS is functioning as a 'market-based' policy. Because there is limited competition between technologies for existing power generation, coal plants continue to operate longer than they would in a more competitive market. This means that demand for emissions permits is always higher than supply, as shown in Figure 39, and the carbon price steadily rises over time, as shown in Figure 40. (This is markedly different from the fluctuating carbon price seen in the EU ETS). Despite this steady increase, the carbon price never reaches the level that would make a typical existing coal plant unprofitable (around CNY 120/tCO2). Given these characteristics, it appears that the ETS is functioning rather as a regulation: a similar effect could be achieved by a regulation that set a limit on the allowable carbon intensity of power plants, which decreased over time.

Figure 39: Ratio of demand and supply for emissions permits through time. A ratio of more than 1 indicates that demand is higher than supply.

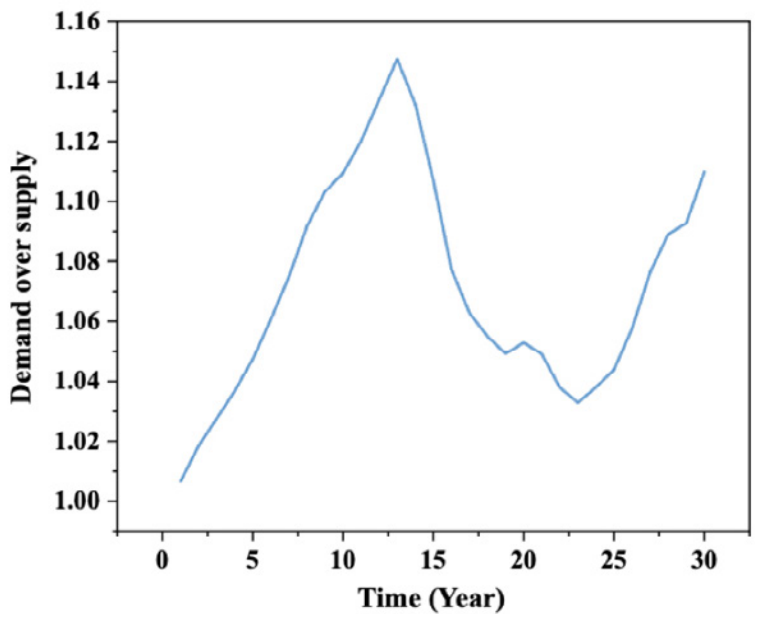
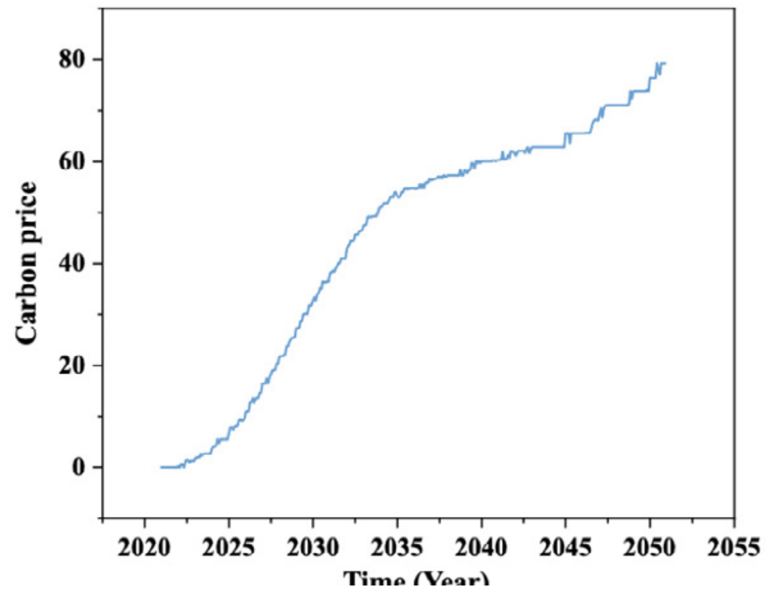


Figure 40: Carbon price through time.



Policy conclusions from Part 3

The lack of competition between technologies in the market for existing power generation (as opposed to investments in new capacity) limits the effectiveness of either form of price-based policy. A large amount of existing coal-power generating capacity is difficult to shift. Referring back to Figure 27, the link between relative cost of clean technology and clean technology deployment is weakened, and this weakens the reinforcing feedback of clean technology deployment and cost reduction.

In such a market, a carbon tax can contribute to reducing emissions by influencing the choice of technology for new power capacity, but this contribution is modest. A carbon tax appears likely to have a substantial and sustained impact on emissions only if it is high enough to make existing coal plants unprofitable, so that they are increasingly replaced with zero-emission technologies.

In this market, an ETS with a soft cap, loose benchmark level and free allocation of permits leads to emissions similar to BAU. An ETS with a hard cap and an auction for permits can have a stronger effect, but its functioning appears to be similar to that of a carbon intensity regulation. Arguably, a regulation would be an administratively simpler way to achieve the same result.

China's ETS experiment in the power sector must be cautiously designed in order to avoid disturbance to power generation, energy supply and economic growth, given the context of the country's development goals, geopolitical tensions and impacts of the Covid pandemic. The observed progess in these two years (2021-2022), and the simulated outputs described above, look relatively modest; however, more significant progress could be expected when the system is incorporated and coordinated well with deepening electricity market reform.

Introducing greater competition into the electricity market is likely to be desirable in any case, to enable greater deployment of low-cost, low-emissions power-generating technologies. If China's market is reformed in this direction, the carbon pricing policy options will increasingly resemble those described in Part 2, such that a carbon tax is likely to drive faster progress in the transition than an ETS of equivalent strength.

CASE STUDY:

Activating EV Tipping Points in China, India, Europe and the US

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Policy question(s): Which policies, individually and in combination, are most effective in driving the transition to electric vehicles? How does a fast transition compare to a slow transition, in terms of costs with the road transport sector, and in terms of macroeconomic consequences?

Region: Global

Methods: E3ME-FTT:Transport

Key finding(s): A cost-parity tipping point between electric vehicles (EVs) and internal combustion engine vehicles (ICEVs) is near, in major markets. An EV subsidy that closes the cost gap between EVs and ICEVs can be made revenue-neutral with only a small tax on ICEVs. Regulations and mandates are more cost-effective than financial incentives for driving the transition towards EVs when used individually and can also contribute to highly effective policy packages. A fast transition to EVs saves costs compared to a slow transition. The macroeconomic consequences of the transition to EVs are likely to be more positive for large oil-importing countries, and more negative for large oil-exporting countries.

Engagement: This study was informed by interactions with governments in several of the EEIST partner countries in which policymakers expressed interest in knowing the level at which EV subsidies would be effective, the relative cost-effectiveness of different policies, and the effect of implementing a given policy with varying levels of stringency.

Summary: The authors use the E3ME-FTT:Transport model to consider how a set of policies used individually and in combination can accelerate the transition to zero-emission vehicles in India, China, the US and Europe.

Introduction

The transport sector represented 23 per cent of global CO_2 emissions from fuel combustion in 2021.[145] Private passenger road transport generates 45 per cent of transport emissions and 30 per cent of its growth, and thus requires urgent attention from policymakers.[146] Electric vehicles (EVs)[147] have been seen as a major component of the solution for decarbonising private passenger road transport.[148] Due to sustained EV policy support already introduced around the world, the number of EVs on roads has increased dramatically, with about 16.5 million EVs globally in 2021. At the same time, battery prices have fallen significantly from US$1,100/kWh in 2010 to US$137/kWh in 2020[149] – an 88 per cent drop that is largely a result of economies of scale in production and innovation through various forms of learning as production and sales increase. However, after a decade of declines, battery packs across all sectors have increased in cost to around US$150/kWh in 2022, as a result of material prices elevation.[150]

As EV sales increase, a number of countries have set targets to make all new cars zero emission.[151] For instance, the EU has now agreed to require all new car sales to be zero emission by 2035. However, some leading markets, including the US and China, have so far only set interim targets – aiming for EV shares of car sales by 2030 of 50 per cent and 40 per cent respectively. Their decisions on the pace of the transition are likely to take into account perceptions of feasibility, estimates of the future affordability of EVs[152] and expectations of the impact of policies on industrial competitiveness, jobs, energy security and economic growth.

This case study presents evidence that major markets are nearing irreversible EV diffusion tipping points. It also identifies policy packages that could accelerate the transition to zero-emissions vehicles (ZEVs) and that could accelerate reductions in their cost; and it highlights the macroeconomic benefits of a fast transition (leading to 100 per cent ZEV sales in 2035 in the leading markets) compared to a slow transition. Early policy success in the leading car markets could induce an EV transition in the rest of the world by increasing the affordability of EVs, while at the same time, the adoption of EVs in the rest of the world could bring forward cost parity between EVs and fossil-fuelled cars in the leading markets. These projections were simulated using FTT:Transport on the basis of observed cost for more than 2,000 vehicle models, and diffusion data for the past 12 years. The E3ME model was used to estimate macroeconomic outcomes.

FTT:Transport model description

Overview

The Future Technology Transformations (FTT) model is a loose framework method that models technological diffusion dynamically, based on technological competition in markets. The FTT:Transport model assumes the presence of an adaptive, evolving, path-dependent vehicle market with consumers who are heterogeneous agents, and vehicle manufacturers who supply the market in response to demand. We assume revealed preferences, in that the observed cost distribution for recent vehicle sales corresponds to the heterogeneity of consumer preferences and choices.

The FTT framework models technological diffusion by a set of logistic differential equations of the LotkaVolterra family, which represent gradual technological substitution processes. The diffusion processes are path-dependent and involve positive feedbacks which are captured by the FTT framework. Under the FTT framework, consumers are more likely to choose a technology that has lower costs, and that has a higher market share as a result of availability, visibility, social influence and network effects, as well as if it is cheaper.

Modelling heterogeneity with the discrete choice theory

Consumers in the vehicle market are heterogeneous and choices are made in a probabilistic fashion. We assumed that the market heterogeneity can be derived from consumer's 'revealed preference' (i.e. their vehicle choices). This is simulated by consumers making purchases based on the availability and cost of car models in the market and the model

[145] IEA. (2021). World Energy Outlook.

[146] IEA. (2021). World Energy Outlook.

[147] EVs include both battery electric vehicles (BEVs) and plug-in electric vehicles (PHEVs).

[148] IEA. (2022). Global EV Outlook 2022.

[149] Bloomberg NEF. (2021). Electric Vehicle Outlook.

[150] Bloomberg NEF. (2022). Electric Vehicle Outlook.

[151] UK Government. (2021). COP26 declaration on accelerating the transition to 100% zero-emission cars and vans. https://www.gov.uk/government/publications/cop26-declaration-zero-emission-cars-and-vans/cop26-declaration-on-accelerating-the-transition-to-100-zero-emission-cars-and-vans

[152] Bloomberg NEF. (2021) Hitting the EV Inflection Point.

implicitly assumes that car manufacturers supply the market in a way that matches consumers' preferences. In the discrete choice theory, consumers have heterogeneous taste and place different utility weights on different product characteristics.

The FTT model uses a modified version of discrete choice theory in the form of an evolutionary theory. It uses observed distributions of costs to represent agent heterogeneity (a form of revealed preferences). Consumer decisions are modelled with chains of binary logits. In the discrete choice, choices are made in a probabilistic fashion, which means that unobserved factors such as taste variation and interpersonal heterogeneity are taken into account in the discrete choice model. In terms of transport, the probability of choosing a particular vehicle is influenced by the width of the cost distribution for each segment of car technology and the market share of the technology. Hence, a policy does not lead to an instant diffusion of EVs and consumers do not respond to the incentives simultaneously.

The levelised cost of transportation (LCOT)
For the decision-making component of this model, we separate the investor in transport technology from the consumer of transport services. We think of them as separate entities for clarity, even though in some cases they might be the same person. Whether the roles are fulfilled by the same actors or not, they are quite distinct, where the investor purchases a vehicle to sell a transport service to the consumer. This is done to clarify the distinction between technology investment and associated market competition, and the consumption of the service that technologies produce. It also allows for the possibility that a person who purchases a car can still travel by train or plane and not use the car they purchased. The mode choice is distinct from the technology choice, even when performed by the same person. The cost of the vehicle, as perceived by the investor purchasing a vehicle or unit of transport technology, must be taken to include all components relevant to the decision making. Many of the components are easy to quantify from available data. Others are not straightforward, and we show here how this is done. When a vehicle is purchased, an initial investment is made, or a loan is obtained, for the capital cost, and henceforth fuel and maintenance costs are:

$$LCOT_i = \sum_t \frac{\frac{(I_i - EVS_i)}{CF_i} + \Sigma_t \frac{\frac{RT_i(t)}{CF_i} + (F_i(t) + FT_i(t)) * (FE_i(t) * Dist_t) + MR_i(t)}{(1+r)^t}}{\Sigma_t \frac{1}{(1+r)^t}}$$

Figure 41: Equation showing the levelised cost of transportation. Here I_i , F_i, and MR_i and are the mean capital costs (in US$), fuel cost (in US$/litre) and maintenance cost (in US$/km), respectively. EVS_i represents EV subsidies, paid to car purchasers (and therefore, negative cost) at the purchase time. FT_i is the fuel tax, in USD/litre. The fuel cost depends on the fuel consumption $FE_i(t)$ and the distance travelled each year ($Dist_i$). RT_i is the annual registration tax, which is vehicle and class-specific, paid by car owners once per year. CF_i is the capacity factor, in km/y.

As inferred from the price distribution of sales, transport costs are not the only factors that consumers consider when purchasing a vehicle. Many additional aspects (e.g. comfort and luxury) are valued by the consumer, of which we have little information beyond the price distribution of what is purchased. We keep in mind that technologies have different pecuniary costs, particularly across engine size classes; despite this, higher costs are in effect compensated by higher perceived benefits, such that higher-cost luxury vehicles co-exist alongside much cheaper economic vehicles.

Were we to simulate technology diffusion based on bare LCOT distribution comparisons, the lowest LCOT technologies would diffuse more successfully, which is not consistent with our historical data. Clearly, components would be missing in the LCOT – for instance, comfort, acceleration and style – which we may call the 'intangibles'. We define intangibles for this model as the difference between the generalised cost, which leads to observed diffusion, and the LCOT, as calculated from pecuniary vehicle properties for which we have data. The value of the intangibles is an empirical parameter obtained from making the FTT diffusion trajectory match the trajectory observed in our historical data, at the year of the start of the simulation.

Vehicle population projection
Car ownership models are used to forecast transport demand, energy consumption and emission levels. Among the different model types, one of the most well-known approaches is an econometric estimation of an income-car stock model based on a logistic function. Historically, GDP growth and economic development are associated with an increase in vehicle ownership. Past studies have made projections of passenger car ownership based on GDP.

The Gompertz curve is an S-shaped growth curve that relates per capita vehicle ownership to GDP per capita. While vehicle scrappage is not explicitly included, it has been tested empirically to represent growth trend of vehicle stock.[153] We examine trends in the growth of vehicle stocks for a large sample of countries and employ the Gompertz function to estimate the relationship between the number of vehicles and per capita income.

$$V_{i,t} = V_i^* e^{\alpha e^{\beta EF_{i,t}}}$$

Figure 42: Following the previous studies, we estimate car stock with a Gompertz model.

Passenger transport demand projection
Transport demand is driven by income, population, urban density, family structure and other demographic factors. The demand estimation in this section consists of two parts. The first part is the construction of an econometric model that predicts the demand for passenger light-duty vehicles (PLDVs) (in km per vehicle) using fuel prices, income, urbanisation, road infrastructure, urban density and fuel economy. Then we use the econometric model to predict the future private passenger vehicle transport demand (per vehicle). In the second part, we develop a model for vehicle stock and project future car ownership, which is then used to make projections for the total demand for PLDVs.

Policy simulations and interactions in the FTT:Transport model
Financial incentives such as EV subsidies, road tax and fuel tax affect the cost of operating a vehicle and are calculated in Figure 41 directly. Fuel economy regulation is modelled by influencing the flow of share values in the technology category for old inefficient vehicles, while new ICEVs continue to be sold. When a fuel economy regulation is introduced, sales of vehicles that fail to meet the required standard of efficiency are prevented. The stock of vehicles on the road will gradually be replaced by more energy-efficient vehicles as a result.

For EV mandates, it is assumed that the policies exogenously change the shares of vehicle types at a specific point in time. We assume that market shares flow from conventional cars to EVs by assigning the minimum exogenous shares corresponding to the mandate to the new vehicle technology. This approach models mandates with targets that require manufacturers to achieve specific percentages of EVs in their sales. This represents the simplest version of the policy, and is not exactly the same as some of the real-world EV mandates, where the government sets an EV production quota and this can be met through a system of credits. Here we assume the EV mandate is effectively enforced, so that the EV share of car sales follows the target trajectory set by the government.

In the FTT model, each layer of policy plays a specific role in the decarbonisation of the transport sector. When the policies are simultaneously simulated in the model, they influence each other's effectiveness. For example, taxing high-emission vehicles with a vehicle tax will encourage consumers to purchase low-emission vehicles. In a consumer market with limited EV models available, a consumer will be more likely to choose a lower-emission petrol car rather than an EV. However, in the presence of the EV mandate, manufacturers are encouraged to accelerate the deployment of EVs, which increases choice for consumers. This then makes the tax more effective at guiding consumer choices for reducing emissions than would be the case without the mandate. Furthermore, when more EVs are produced, their costs fall more quickly, leading to a higher rate of diffusion. In this way, the model represents the S-shaped technological diffusion curve. Hence, policy interactions emerge endogenously in the FTT:Transport model.

Nearness of EV tipping points

Although EV purchase prices at present can be higher than those of petrol and diesel vehicles, EVs are easier to maintain and cheaper to operate. This combination means that battery costs are declining rapidly and EVs appear soon likely to become the cheaper option in terms of total ownership costs, which could lead to a social 'tipping point' where EVs become the preferred option for the majority of consumers.[154] Several studies have analysed projected EV and ICEV costs for representative models[155 156 157 158] and concluded that EV cost parity[159] (total cost of ownership) begins to be reached in the 2022-2027 timeframe in Europe, the US and China. However, depending on the discount rate and other factors influencing decision-making, parity of upfront purchase price can be a more important consideration than parity of total cost of ownership, for the consumers.

[153] Meyer, I. et al. (2012). Scenarios for Regional Passenger Car Fleets and their CO2 Emissions. Energy Policy, 41: 66-74.

[154] Sharpe, S. and Lenton, T. M. (2021). Upward-Scaling Tipping Cascades to Meet Climate Goals: Plausible Grounds for Hope. Climate Policy 21: 421–433. https://doi.org/10.1080/14693062.2020.1870097

[155] Bloomberg NEF. (2021) Hitting the EV Inflection Point.

[156] Lutsey, N. et al. (2021). Evaluating Electric Vehicle Costs and Benefits in China in the 2020-2035 Time Frame. International Council on Clean Transportation (ICCT).

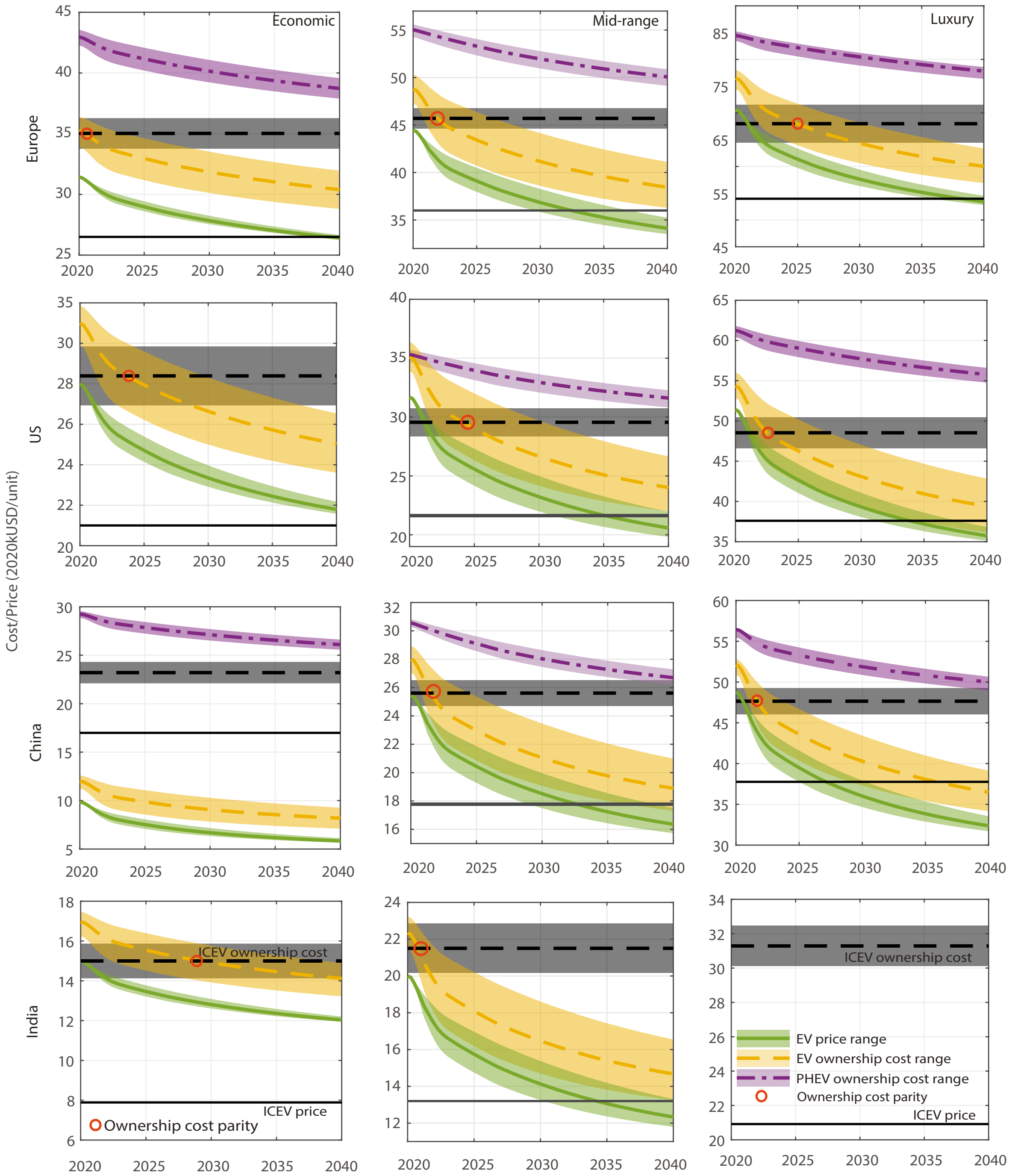
[157] Lutsey, N and Nicholas, M. (2019). Update on Electric Vehicle Costs in the United States through 2030.

[158] Lam, A. and Mercure, J-F (2022). Evidence for a Global Electric Vehicle Tipping Point. GSI Working paper series number 2022/01. https://www.exeter.ac.uk/media/universityofexeter/globalsystemsinstitute/documents/ Lam_et_al_Evidence_for_a_global_EV_TP.pdf

[159] Cost parity does not happen for all EV models at the same time because this depends on the model size and specification. "Initial cost parity" is triggered when cost parity is first reached for some vehicle models, in a given market.

Figure 43 shows the projected EV ownership costs and prices, according to the combined Rogers-Wright law (on diffusion and experience curves), against ICEVs in all four major car markets until the policy horizon of 2050 for three different segments, given observed trends, existing uncertainties and assuming that current policy frameworks are maintained.

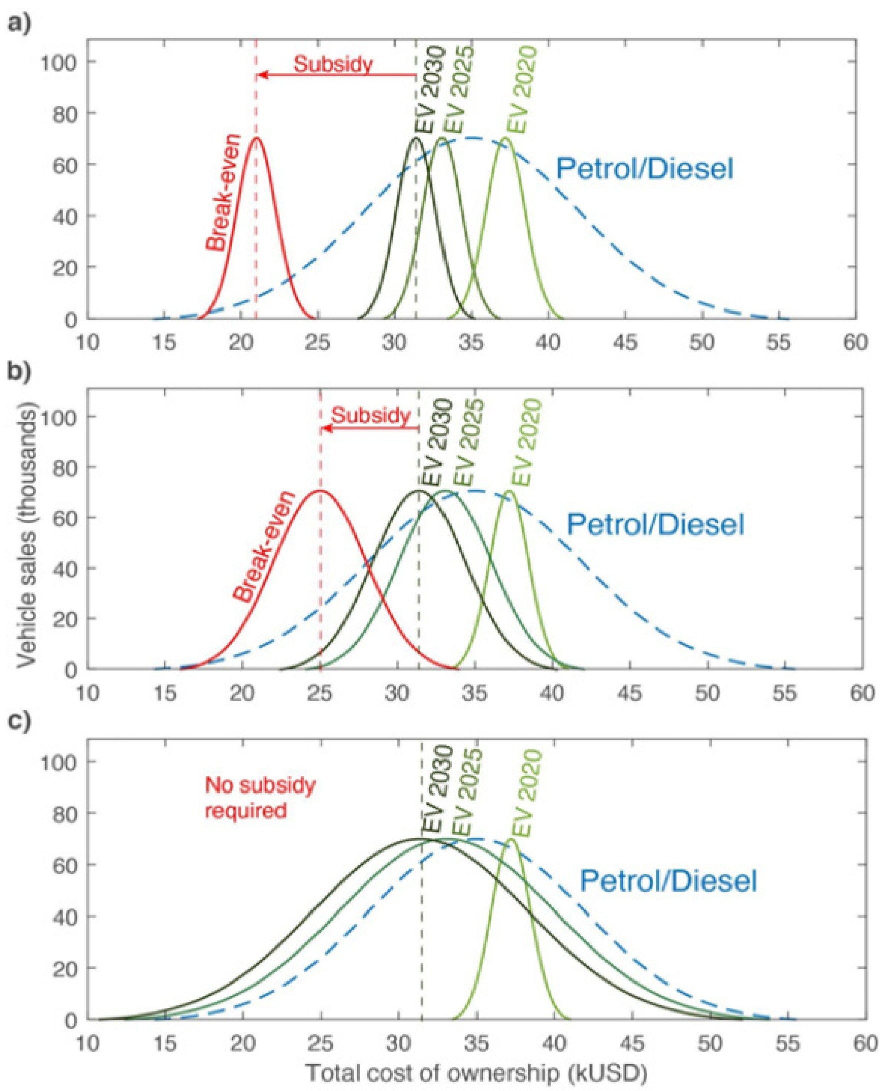
Figure 43: Trajectory of total ownership costs (dashed lines) and prices (solid lines) of BEVs/PHEVs/ICEVs (median and 95 per cent confidence range learning rates).[160]



Battery electric vehicles (BEVs) begin to reach cost parity within 2022-2025 for all segments. For Europe, the US and China, cars at the lower end of the price range reach cost parity the earliest, with both prices and ownership costs for BEVs already lower than ICEVs in China. For a mid-range or luxury car, ownership costs of BEVs can achieve parity with ICEVs between 2023 and 2025 in China, India, Europe and the US (Figure 43). However, plug-in hybrid electric vehicles (PHEVs) never achieve cost parity with ICEVs and are absent in India. This is because PHEVs are on average more expensive to own than BEVs (consuming fuel as well as electricity) and cost more to purchase than ICEVs (having a battery and electric drivetrain as well as a motor). Also, cost reductions for BEVs, which have larger batteries than PHEVs, are steeper.

BEV purchase price parity is likely to be achieved later than ownership cost parity, and could occur in the 2028-2035 timeframe. In some cases (e.g. the low-cost segment of the market in India), purchase price parity is not achieved before 2040 based on existing data, because the few BEV models that are available remain a lot more expensive than the comparable ICEVs. To convince consumers to switch to BEVs in markets where their variety is low, the subsidies that could break even on a cost basis must bridge potentially wide gaps between the prices of some conventional vehicle market segments and those of scarce zero-carbon alternatives (see Figure 44). Alternatively, supply-side policies such as ZEV mandates could increase model variety on the market and reduce the need for subsidies.

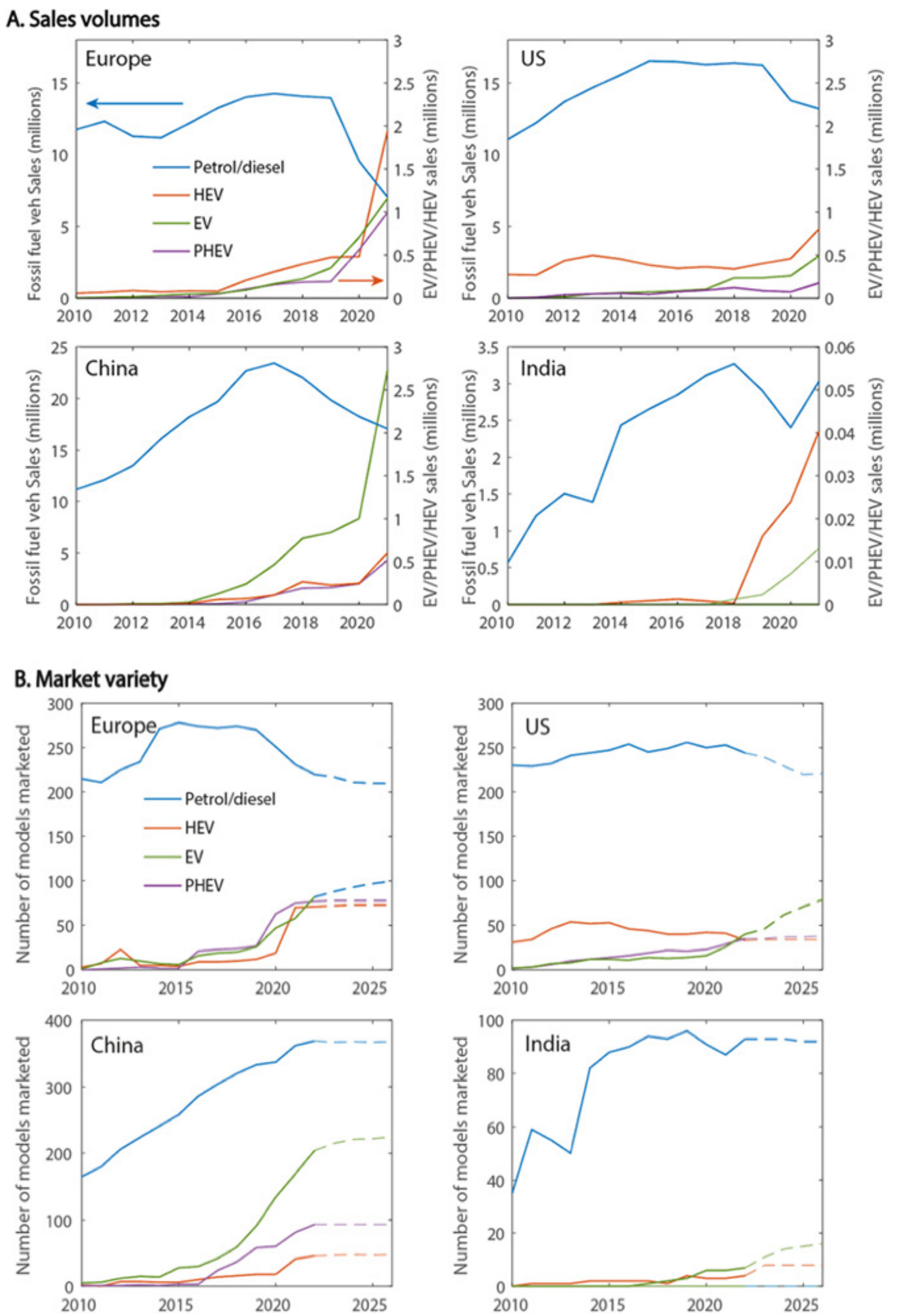
Figure 44: Relationship between model variety and the breakeven subsidy in 2025 and in 2030. The red curve represents the subsidy required for an EV to cost less than most of the comparable ICEV models in every cost category in the market. This breakeven subsidy reduces as costs decline with rising diversity, for (a) constant BEV variety, (b) doubled BEV variety and (c) BEV variety matching the current variety of petrol/diesel vehicles. In (a), the subsidy required to narrow the cost difference is larger than in (b) and (c) because there are a significant number of less costly ICEV models on the market. When the diversity of EVs reaches that of the ICEVs (in c), it becomes possible for consumers to purchase a comparable EV model without subsidies.



[160] Lam, A., Mercure, J-F (2022). Evidence for a global electric vehicle tipping point. GSI Working paper series number 2022/01. https://www.exeter.ac.uk/media/universityofexeter/globalsystemsinstitute/documents/Lam_et_al_Evidence_for_a_global_EV_TP.pdf

In the leading markets, more EV models becoming available has made EVs more attractive to consumers. We observe rapidly rising sales and an increase in variety for both BEVs and PHEVs. BEVs have recently far outpaced PHEVs in their growth, with the latter stagnating in 2019-2021. Crucially, EV sales have been entirely unaffected by the COVID-19 pandemic. While EV sales are still lagging in developing countries such as India, where only a few models are available (Figure 45), sales of electric two and three-wheeler vehicles have been consistently on the rise. The variety of EVs will need to continue to increase in all markets to ensure a successful and cost-effective transition. Targeting EV purchase incentives at popular ICEV segments where EV models are lacking could help to increase the variety of EVs available. In the case where very few EVs are available in the market, it may also be helpful to develop a trade policy conducive to increasing imports, or to strengthen the EV supply chain domestically.

Figure 45: Evolution of vehicle markets and prices. Price distribution time series for conventional petrol/diesel vehicles, BEVs and PHEVs in Europe, the US, China and India.[161]



[161] Lam, A., Mercure, J-F (2022). Evidence for a Global Electric Vehicle Tipping Point. GSI Working paper series number 2022/01. https://www.exeter.ac.uk/media/universityofexeter/globalsystemsinstitute/documents/Lam_et_al_Evidence_for_a_global_EV_TP.pdf

Individual policies to support EV deployment

The nearness of EVs to achieving cost parity does not guarantee a transition to electric mobility that is compatible with a country's economic, industrial or climate change goals. We analysed the effectiveness of four of the main policy instruments for supporting the deployment of EVs: EV subsidy, vehicle tax, vehicle efficiency regulation and EV mandate. We compared outcomes in terms of cost effectiveness of EV deployment; cost effectiveness of emissions reduction; and cost reduction of EVs achieved over the period. We also compared the macroeconomic impacts of fast and slow transition scenarios, in terms of economy-wide energy consumption, GDP, imports and employment.

For the purpose of comparison, we defined individual policy instruments as follows:

- Subsidies: 'Subsidy current' is an EV purchase subsidy at its current level in the specified market. 'Subsidy cost parity' is an EV purchase subsidy set at the level required to achieve ownership cost parity with an equivalent ICE vehicle in the year 2022. 'Subsidy high' is a subsidy at 150 per cent of the baseline/2020 level. 'Subsidy very high' is a subsidy at 200 per cent of the baseline/2020 level.
- Taxes: 'Tax cost parity' is a tax on ICE vehicles set at the level required to achieve ownership cost parity with an equivalent EV in the specified market in the year 2022. 'Tax high' is a tax at 150 per cent of the baseline/2020 level. 'Tax very high' is a tax at 200 per cent of the baseline/2020 level.
- Regulations: 'Regulation slow' is an efficiency regulation that requires the carbon intensity of new vehicles, measured in carbon emissions per kilometre, to reduce linearly from its level in 2022 to 50 per cent of that level by 2035. 'Regulation fast' requires the carbon intensity of new vehicles to reduce linearly from its level in 2022 to zero by 2035.
- Mandates: 'Mandate slow' requires 50 per cent of new vehicles to be zero emission by 2035. 'Mandate fast' requires all new vehicles to be zero emission by 2035.

Figures 46 and 47 compare the effectiveness and cost of these individual policy instruments for promoting the deployment of EVs in Europe, US, China and India.

The results indicate:

- **In terms of pure effectiveness at driving the transition to electric vehicles, mandates are the most effective policy in all four regions.** This is not surprising: mandates are designed to ensure a shift to the new technology. Efficiency regulations, even when they have equivalent stringency (requiring a full shift of new vehicle sales to zero-emission technology by the same date), may achieve less of a shift to electric vehicles on the road, because at least for some period they can be complied with through sales of more efficient petrol or diesel cars.
- **Subsidies and taxes, when used without the support of regulations or mandates, are relatively ineffective.** Increasing their level beyond that required to achieve cost parity between EVs and ICE vehicles has relatively little additional effect on deployment. This is because the tax or subsidy at cost parity level is not necessarily enough for many consumers to favour EVs, especially in the absence of what are perceived as comparable models or sufficient numbers of charging stations. Without regulations or mandates pushing the pace of diffusion, too few consumers are aware of, or have access to, the new technologies and therefore few will take advantage of the fiscal incentive until diffusion levels are higher.
- **Regulations are generally more cost-effective than financial incentives, for driving the transition to electric vehicles.** This is due to a combination of factors. Regulations and mandates achieve a larger shift to EVs by acting decisively on supply and imposing hard requirements that manufacturers have to meet. In contrast, financial incentives – which focus on narrowing the cost differences – encourage a change in behaviour by consumers but do not require it, and the diverse preferences of consumers mean that some will remain unpersuaded. At the same time, the cost of regulations and mandates (more vehicles bought with higher purchase price) is offset by the lower operating costs of EVs and more efficient ICE vehicles. In China, the cost of regulation is negative because the ownership costs for EVs are already lower than those of ICEVs. An exception to the rule is seen in Europe, where regulations have already been in place for some time and the EV market is relatively mature and varied. In this context, subsidies can be cost-effective.

- **In all cases, taxes are far less cost-effective than subsidies.** This is because to achieve the same effect of cost parity between EVs and ICEVs, an EV subsidy only has to be applied to the small share of the market currently accounted for by EV sales, whereas a tax must be applied to the far larger share of the market made up by ICEV sales.

Figure 46: EV deployment in 2035 and 2050 in major markets resulting from different policies used individually.

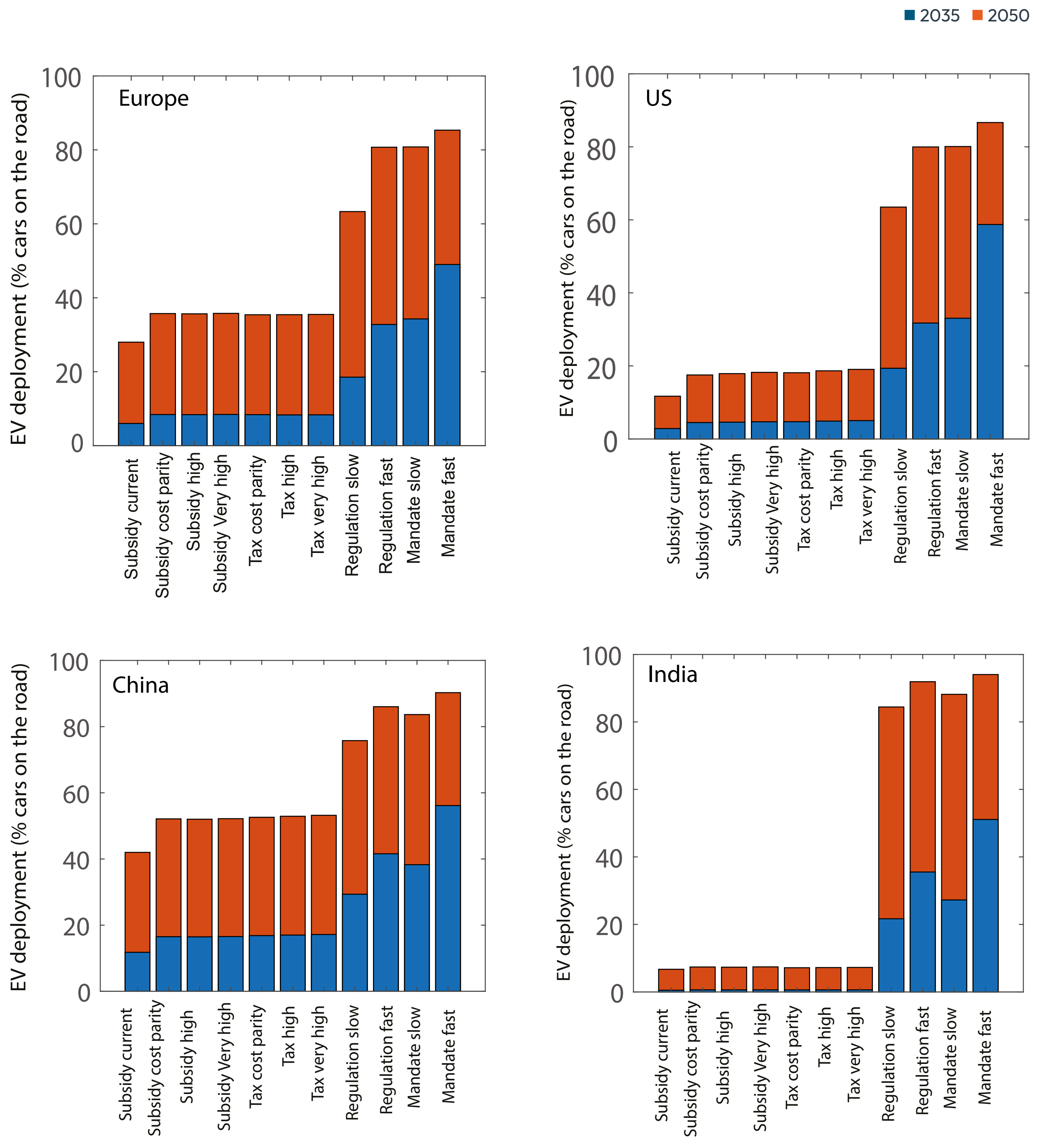


Figure 47: The cost of EV deployment as a result of different policies used individually.

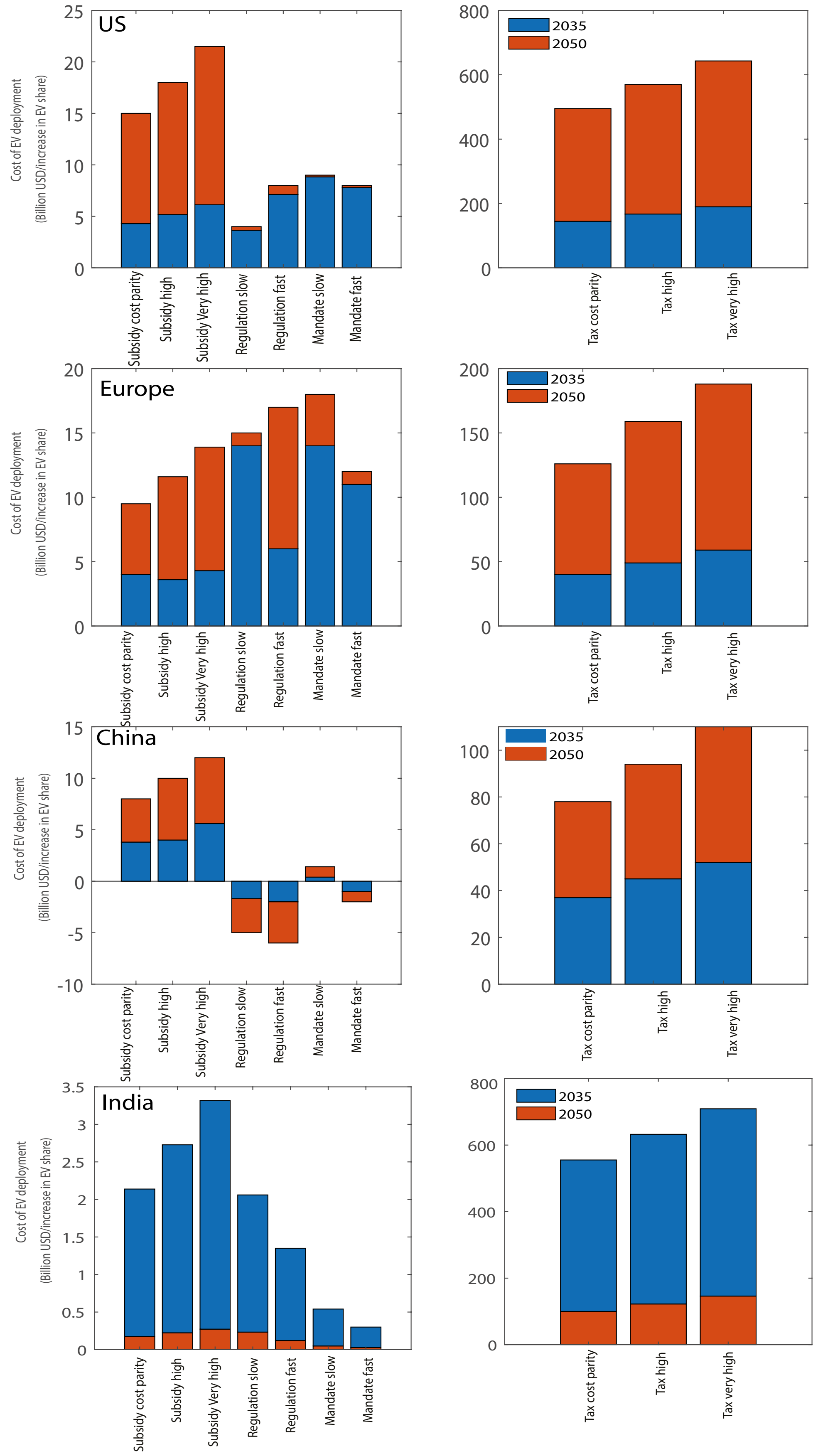


Figure 48 compares the cost effectiveness of the policies in terms of a different outcome: emissions reduction. The overall pattern is similar. Regulations and mandates generally achieve cumulative emissions reductions over the period more cost-effectively than financial incentives. Subsidies achieve emissions reductions more cost effectively than taxes.

Whether the goal is deployment of EVs or reduction of emissions, we find that a fast transition is more cost effective than a slow transition (Figures 47 and 48). Because the system is highly path-dependent, a fast transition scenario in the short run leads to higher EV diffusion in the long run, and hence it achieves significantly more than a slower transition scenario in terms of EV deployment and CO2 emissions reductions. Because EVs become cheaper to operate than ICEVs relatively early in the period, a faster transition yields greater overall cost savings.

Figure 48: Cost of CO2 emissions reduction under different policy assumptions.

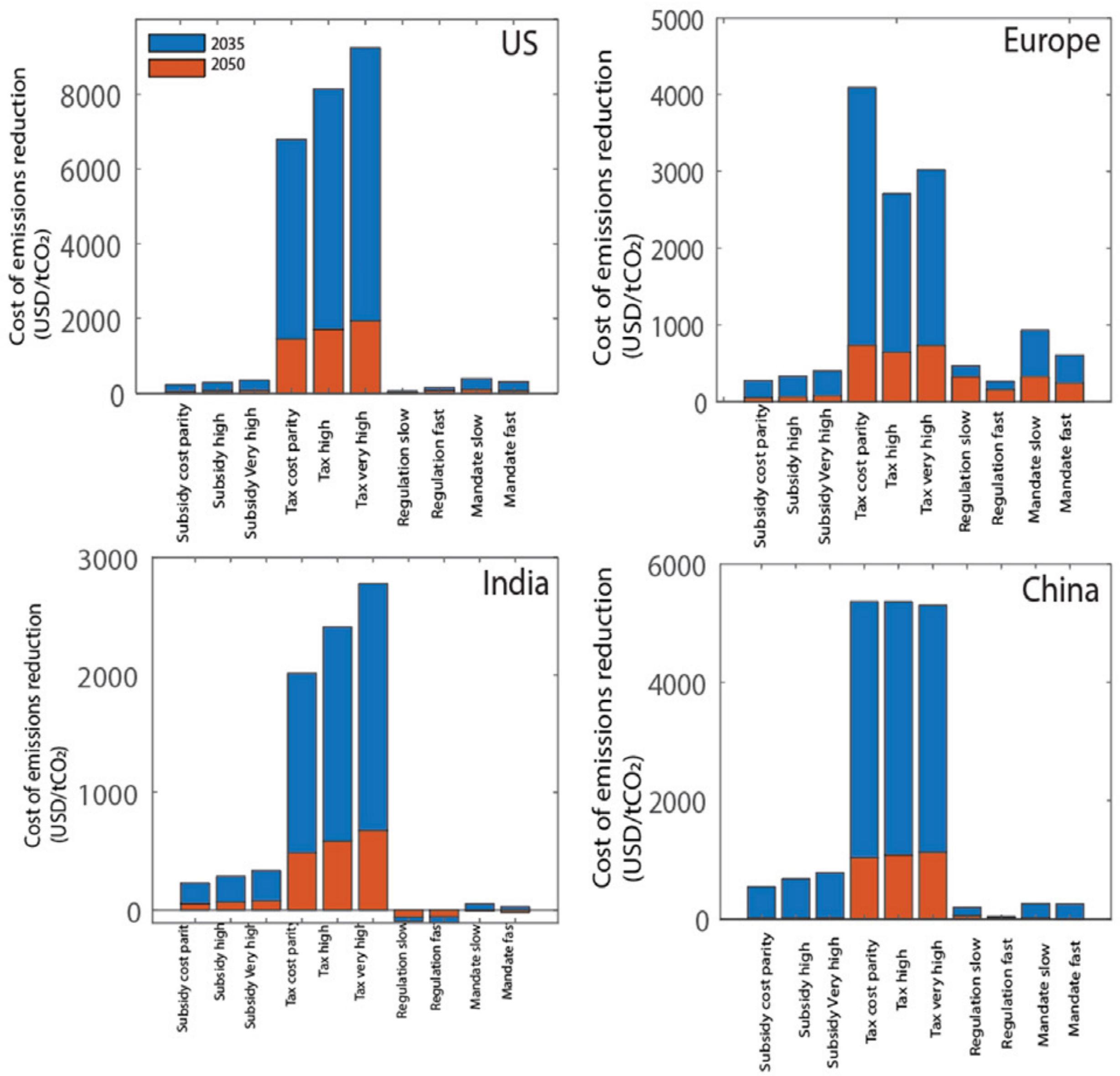
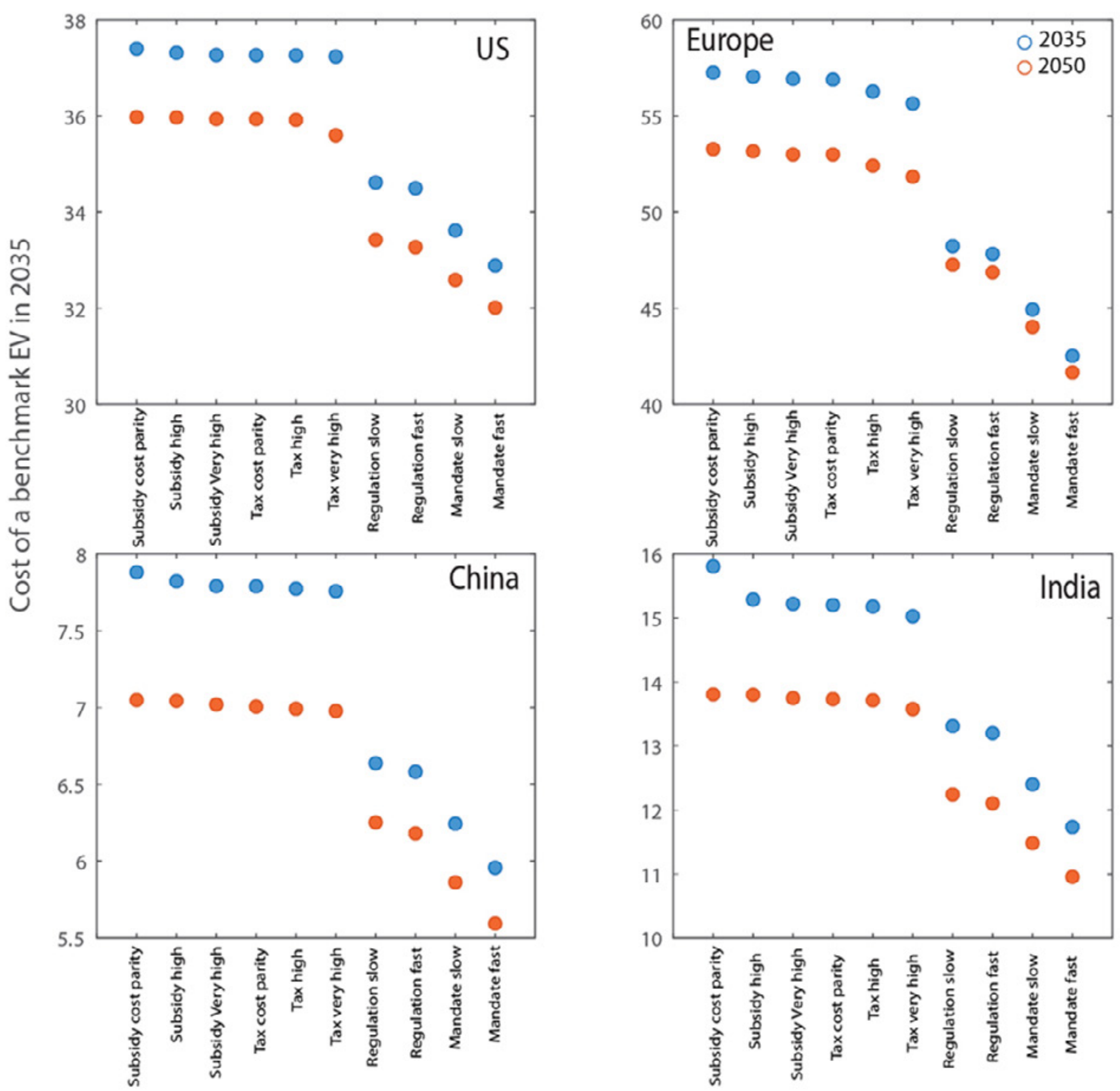


Figure 49 shows the effectiveness of policies in driving down EV costs over time. This happens as deployment drives learning and economies of scale. Regulatory policies are more effective than the financial incentives because they are more effective in increasing EV deployment. In all cases, the EV mandate drives the greatest cost reductions because it achieves the highest cumulative deployment of EVs (as shown in Figure 45).

Figure 49: Cost of benchmark EV under different policy assumptions.



Figures 50 and 51 illustrate the cumulative energy consumption and CO2 emissions reduction under different policy scenarios. Overall, our results indicate that regulations and mandates are significantly more effective in reducing CO2 emissions than financial incentives and are also more effective at reducing energy consumption.

Figure 50: Cumulative energy consumption under different policy assumptions.

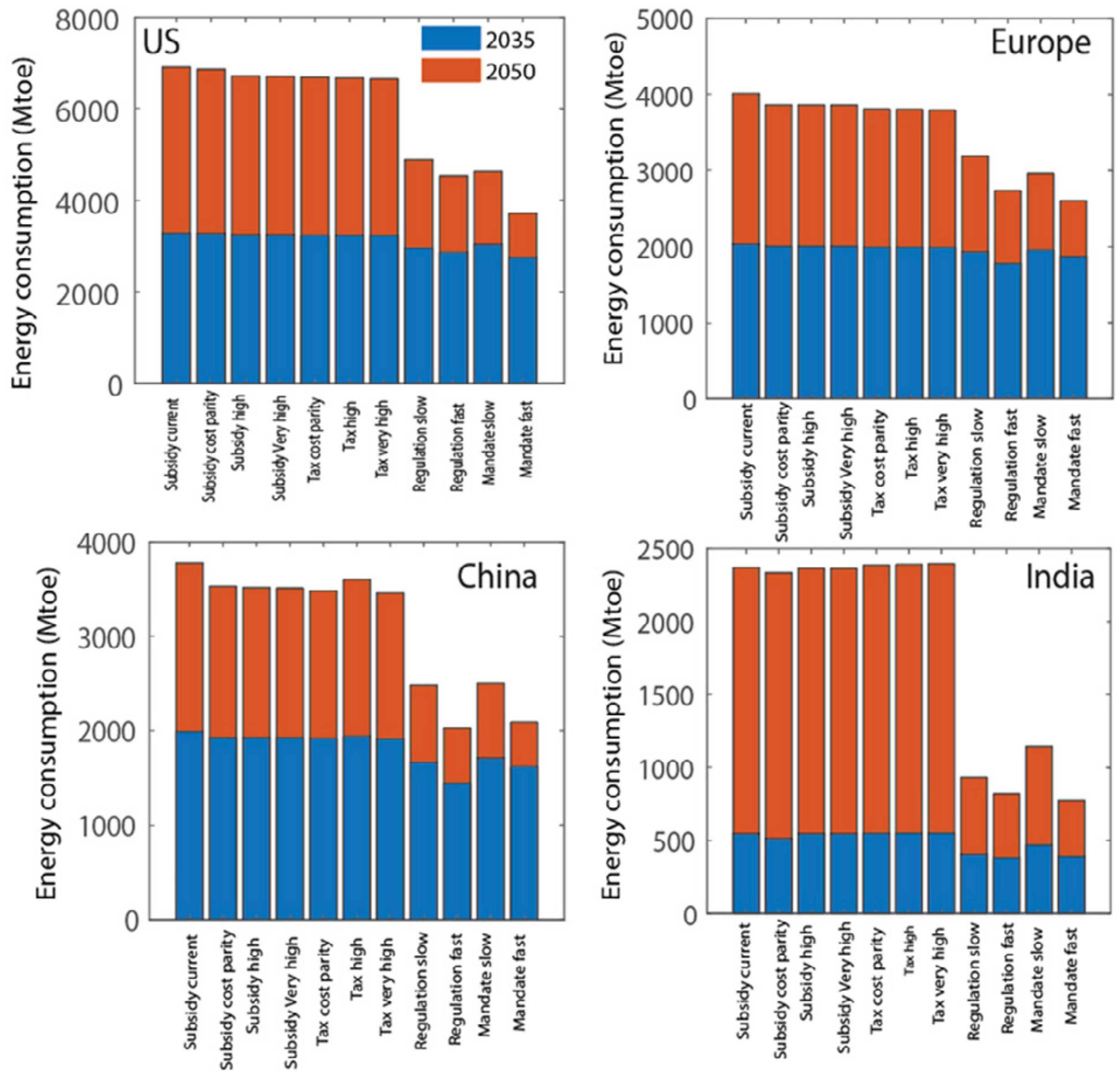
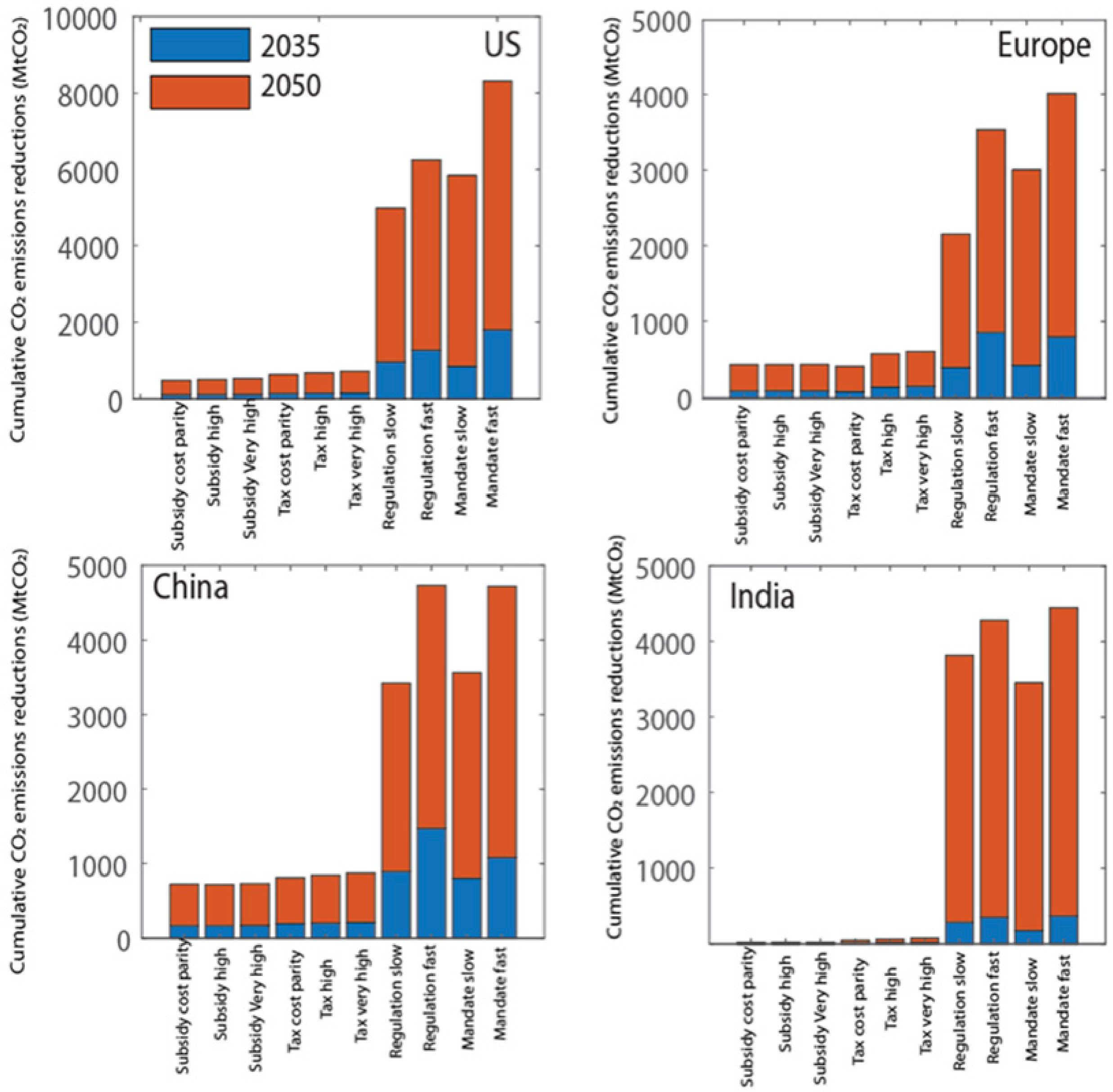


Figure 51: Cumulative CO2 emission reductions under different policy assumptions.



Policy packages to support EV deployment

In reality, individual deployment policies are rarely used in isolation. Typically, there are advantages from implementing different policies simultaneously. However, the effectiveness of policy packages can vary widely.

Figure 52 shows that the combined effectiveness of two policies is generally not equal to the sum of their individual effectiveness, but can be either smaller (trade-off effect) or larger (reinforcement effect). The strongest reinforcement effects are observed when EV mandates are used together with efficiency regulations; and when EV mandates are used together with road taxes. Trade-offs are observed when efficiency regulations are combined with road taxes or fuel taxes: these combinations achieve less than the sum of their parts.

Figure 52: Policy scenarios to achieve rapid transport decarbonisation under different policy scenarios.[162]

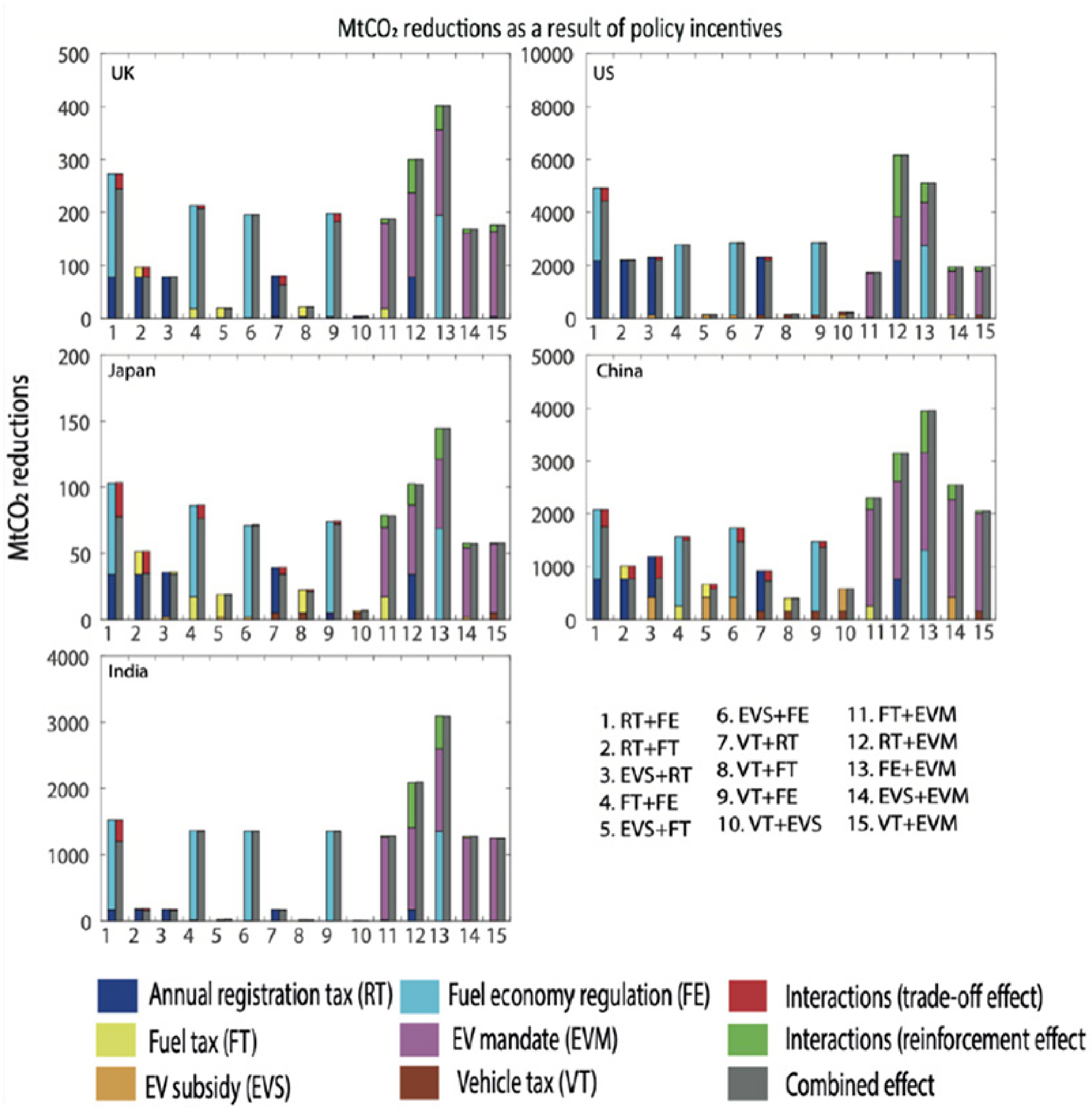
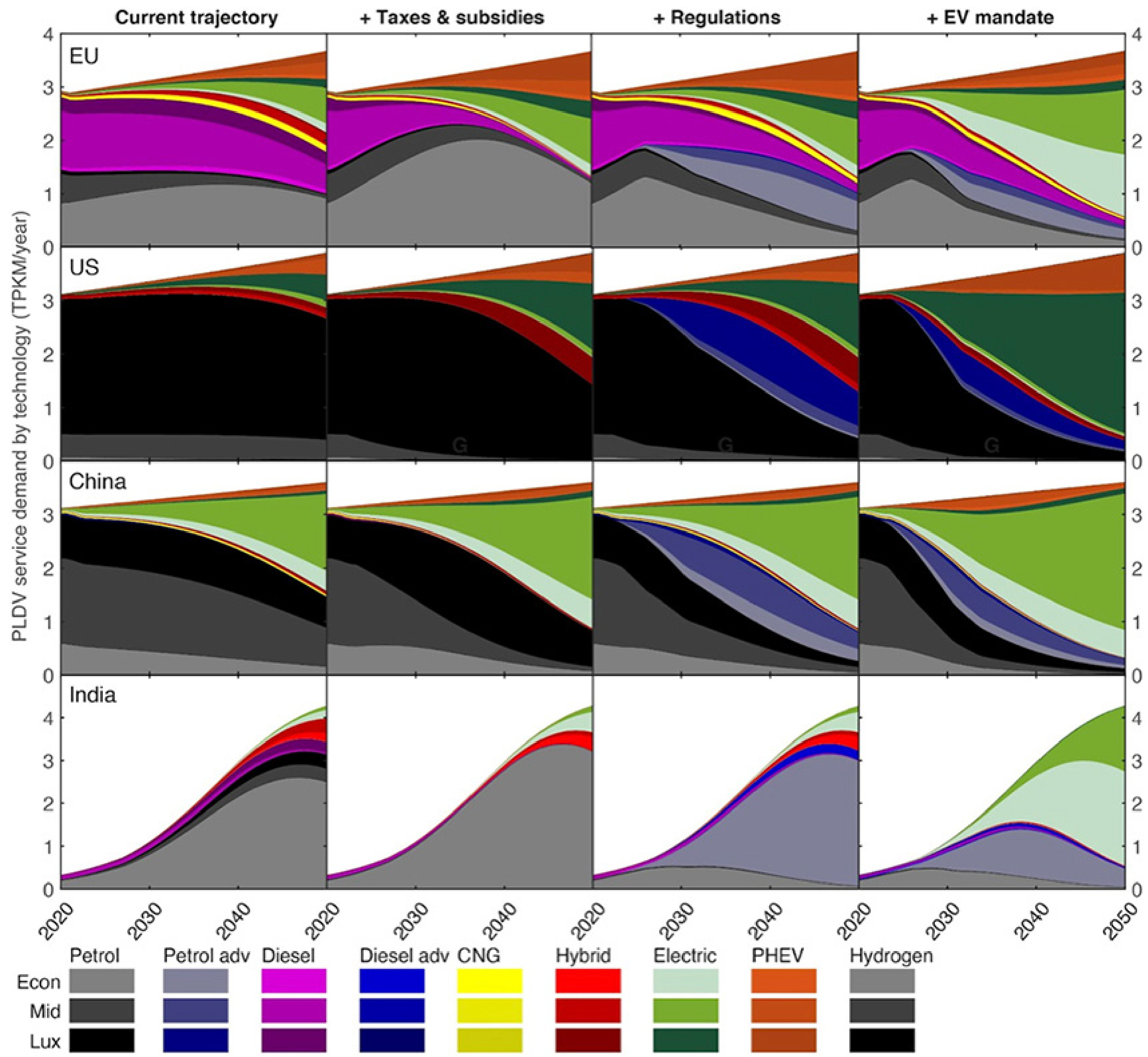


Figure 53 shows the effect of combining more policies in a package, based on simulated scenarios of fleet compositions in the four leading markets. Current trajectory (A) indicates where markets are headed without additional policies. (B) The addition of more stringent road and vehicle taxes and EV subsidies have limited impacts. (C) Fuel economy regulations accelerate conventional vehicle emissions reductions but have limited impacts on the diffusion of EVs. (D) Adding ZEV mandates magnifies substantially the effect of the other policies as it expands their effect across vehicle users. In the current trajectory scenario (Column A), we assume there are no new policy incentives in place. The results show that the transition to 100 per cent EV sales by 2035 will not happen without sustained policy.

Figure 53: Simulations of comprehensive EV policy scenarios for all major car markets. Current trajectory (A) indicates where markets are headed without additional policies. (B) The addition of more stringent road and vehicle taxes and EV subsidies have limited impacts. (C) Fuel economy regulations accelerate conventional vehicle emissions reductions but have limited impacts on the diffusion of EVs. (D) Adding ZEV mandates magnifies substantially the effect of the other policies as it expands their effect across vehicle users.[163]



[162] Lam, A. and Mercure, J-F. (2021). Which Policy Mixes are Best for Decarbonising Passenger cars? Simulating interactions among taxes, subsidies and regulations for the United Kingdom, the United States, Japan, China, and India. Energy Research and Social Science 75. https://doi.org/10.1016/j.erss.2021.101951

[163] Lam, A., Mercure, J-F (2022). Evidence for a Global Electric Vehicle Tipping Point. GSI Working paper series number 2022/01. https://www.exeter.ac.uk/media/universityofexeter/globalsystemsinstitute/documents/Lam_et_al_Evidence_for_a_global_EV_TP.pdf

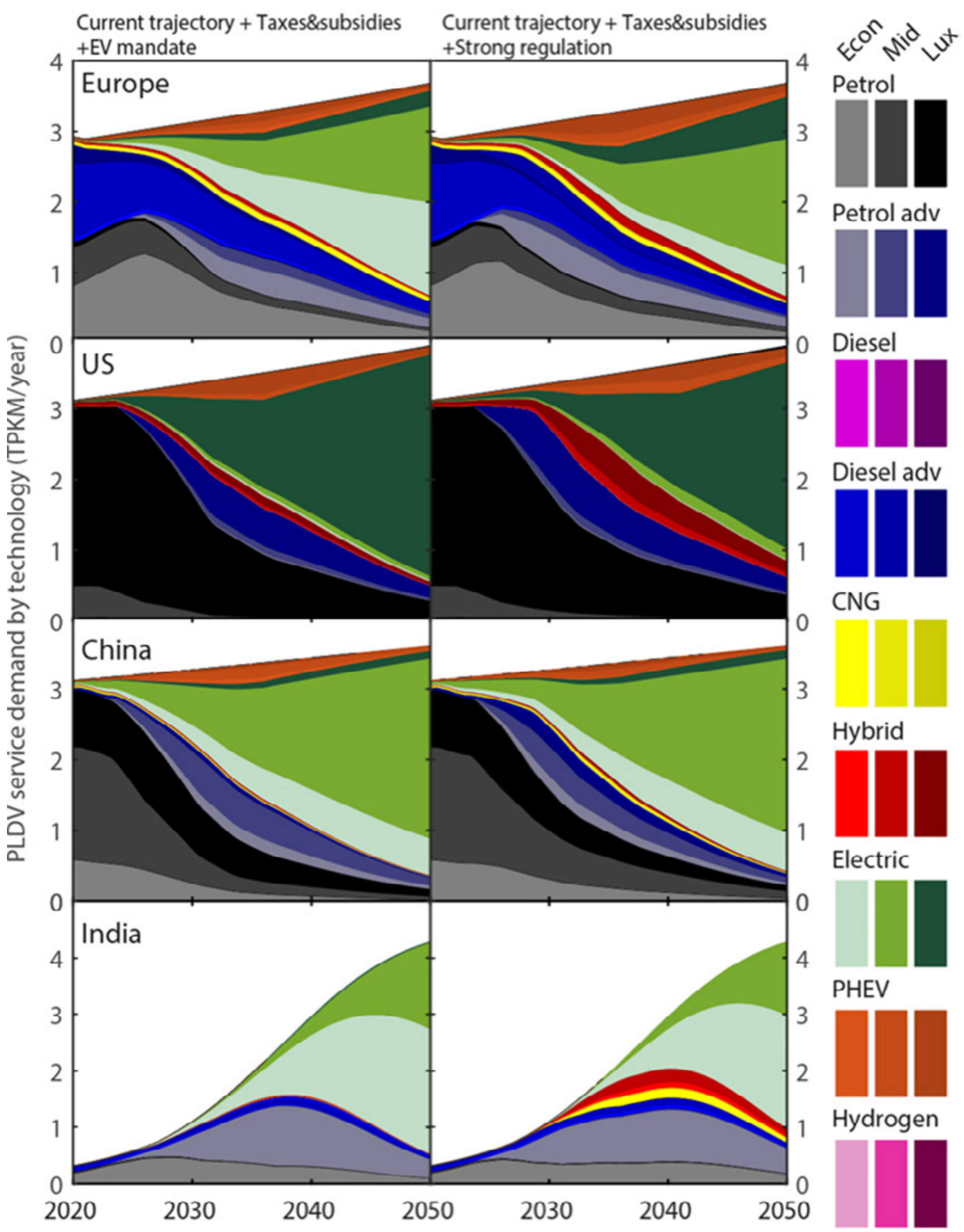
Financial incentives that achieve cost parity between EVs and fossil fuel cars can help, as discussed above. We demonstrate that it is possible to achieve this without putting financial pressure on the government by considering a revenue-neutral feebate. Table 10 shows the BEV subsidies required to break cost parity with different segments of ICEVs in the leading markets in 2023. Subsidies are funded through taxes applied to ICEVs at the point of purchase. With the range of subsidies on fossil fuel cars listed in Table 10, the incentive structure can create a revenue-neutral mechanism to fund BEV subsidies that bridge the cost gaps between ICEVs and EVs in 2023 in Europe, the US and India. The Chinese government is no longer providing subsidies to buyers of EVs so EV subsidy in China is not considered here. Because EVs are currently only a small share of the market, a small tax on each fossil fuel vehicle sold is enough to fund a high subsidy on each new EV.

We found that adopting subsidies to break cost parity with ICEVs is not enough to make all new vehicles zero emission by 2035 for the reasons stated above (Figure 53, Column B). Resolving the supply problem of BEVs can be accelerated using ZEV mandates or strong efficiency regulations. A number of existing studies[164] [165] [166] find that well-designed combinations of policy instruments can lead to a greater rate of transition than may be achieved through the application of any individual instrument. In particular, there is a reinforcement effect between ZEV mandates and other financial incentives (i.e. the presence of two policies offers a larger CO2 mitigation benefit than the sum of the effectiveness of either policy alone).[167]

Given that there is a reinforcement effect between the ZEV mandates and other financial incentives, we sequentially add EV subsidies, regulations and ZEV mandates in panels B-C-D in Figure 53. Adding ZEV mandates that guide manufacturers towards supplying specific shares of ZEVs going gradually towards 100 per cent ensures, in tandem with the other policies, that zero emissions at the tailpipe can be achieved by 2050 or earlier.

We compare the results of a gradual tightening of the efficiency regulation that leads towards zero emissions with a ZEV mandate that leads to 100 per cent BEV sales in 2035. As shown in Figure 54, a ZEV mandate leads to more rapid diffusion of BEVs than a gradual tightening of fuel economy regulations. This is because the fuel economy standard is technology-neutral and allows the diffusion of low-emission vehicles such as hybrid electric vehicles (HEVs) and PHEVs. In particular, in countries where the populations of PHEVs and HEVs are much larger than BEVs in the current trajectory scenario (e.g. the US and India), a gradual phase-out of conventional vehicles sees the opportunity for the diffusion of PHEVs and HEVs, due to the strong path dependence of technological diffusion. Meanwhile, a ZEV mandate that requires automakers to produce and sell a certain number of BEVs is a more direct measure for encouraging a rapid diffusion of BEVs. Given BEVs have no tailpipe emissions, more emissions reductions can be achieved with a ZEV mandate when it is combined with a gradual tightening of fuel economy regulation over the simulated period.

Figure 54: Simulations of strong regulations and ZEV mandates. Column A shows simulated scenarios of fleet composition assuming the adoption of ZEV mandates on top of taxes and subsidies. Column B shows the simulated scenarios of fleet composition assuming the adoption of a gradual tightening fuel economy regulation to phase out ICEVs, in addition to taxes and subsidies.[168]



[164] Axsen, J. et al. (2020). Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. Nature Climate Change 10: 809–818. https://doi.org/10.1038/s41558-020-0877-y

[165] Bhardwaj, C. et al. (2020). Why have Multiple Climate Policies for Light-Duty Vehicles? Policy mix rationales, interactions and research gaps. Transportation Research Part A: Policy and Practice 135: 309–326. https://doi.org/10.1016/j.tra.2020.03.011

[166] Lam, A and Mercure, J-F. (2021). Which Policy Mixes are Best for Decarbonising Passenger cars? Simulating Interactions Among taxes, Subsidies and Regulations for the United Kingdom, the United States, Japan, China, and India. Energy Research and Social Science 75. https://doi.org/10.1016/j.erss.2021.101951

[167] Lam, A and Mercure, J-F. (2021). Which policy mixes are best for decarbonising passenger cars? Simulating interactions among taxes, subsidies and regulations for the United Kingdom, the United States, Japan, China, and India. Energy Research and Social Science 75. https://doi.org/10.1016/j.erss.2021.101951

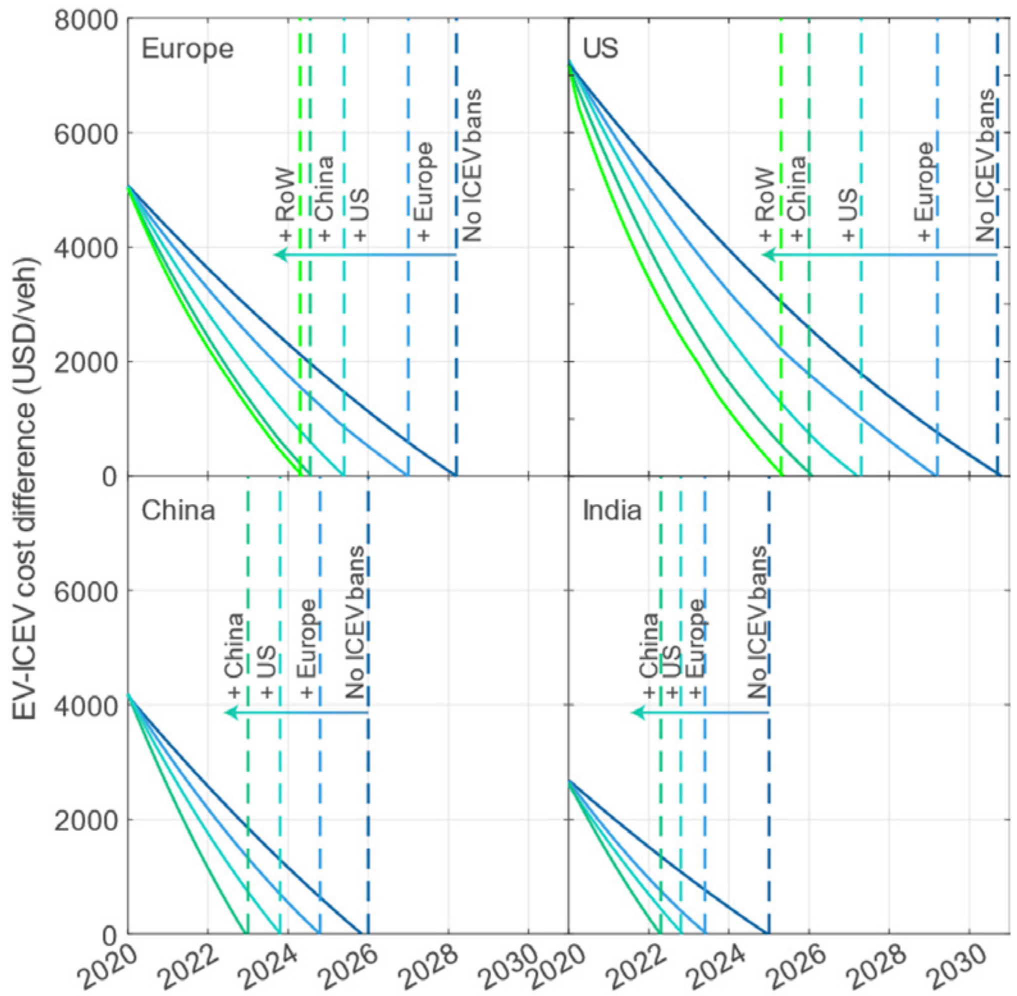
[168] Lam, A., Mercure, J-F (2022). Evidence for a Global Electric Vehicle Tipping Point. GSI Working paper series number 2022/01. https://www.exeter.ac.uk/media/universityofexeter/globalsystemsinstitute/documents/Lam_et_al_Evidence_for_a_global_EV_TP.pdf

International coordination brings forward BEV cost parity

The Breakthrough Agenda, agreed by 45 countries at COP26 in Glasgow, aims to see countries coordinate their actions to accelerate the development and deployment of clean energy technologies in order to bring down their costs more quickly. Even with recent successes of EV deployment in the leading markets, reaching a trajectory consistent with climate targets requires strong policy action from all countries.

Figure 55 shows the cost differences between BEVs and ICEVs in different scenarios of international cooperation by the leading markets. Assuming that no regions implement strong policies towards all new vehicles being zero emission induces the slowest rate of BEV cost reductions. The adoption of policy frameworks that achieve 100 per cent of new vehicles being zero emission by 2035 in the leading markets (Europe, the US, China) brings forward the year at which cost parity is achieved by two to five years in Europe, the US and China, significantly increasing the chances of meeting climate targets. In this simulation, we implicitly assumed that the battery and EV production capacity is sufficient to meet the demand for EVs that results from this policy. Meanwhile, BEV adoption in the rest of the world could enable further expansion of production, and drive costs down even further in the leading markets. This coordination gain justifies strong and coordinated action between the major markets, and financial and technical support to promote BEV deployment in developing countries. Due to diminishing returns in price reductions, early policy success has a larger effect on accelerating cost reductions. This suggests that policy action in Europe, China and the US could be particularly important in enabling transitions to ZEVs in the rest of the world.

Figure 55: International cooperation brings forward cost parity. Analysis of cost parity between ICEVs and BEVs for different scenarios of international cooperation to bring BEV costs down. The more countries join in, the sooner the cost difference between BEVs and ICEVs reaches zero. The impact of adding the rest of the world (RoW) is only visible for Europe and the US, where cost parity is reached later. The impact of adding India is not shown as induced differences are small, the market remaining small relative to others shown.[169]



[169] Lam, A., Mercure, J-F (2022). Evidence for a Global Electric Vehicle Tipping Point. GSI Working paper series number 2022/01. https://www.exeter.ac.uk/media/universityofexeter/globalsystemsinstitute/documents/Lam_et_al_Evidence_for_a_global_EV_TP.pdf

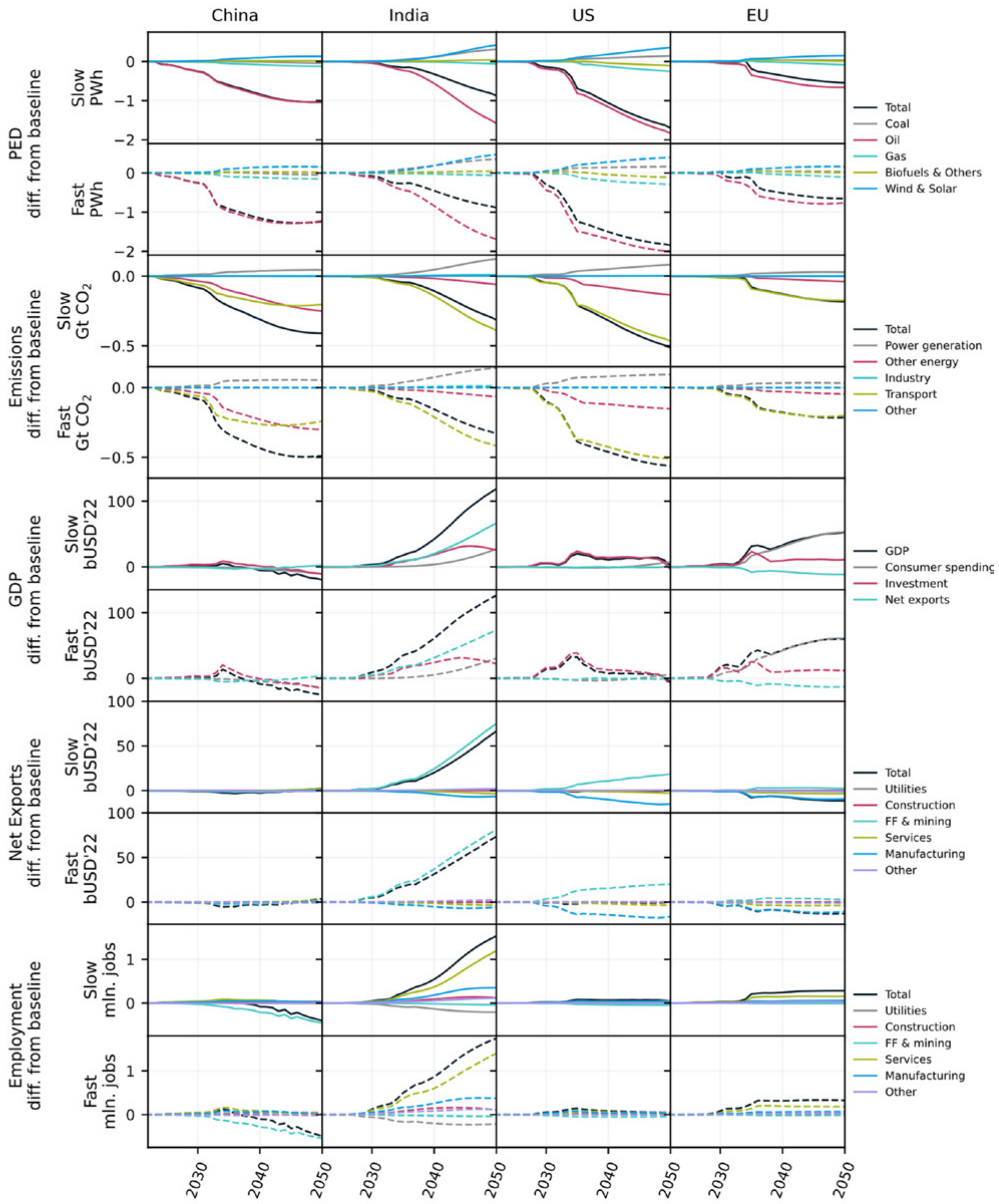
A fast transition to ZEVs can lead to positive macroeconomic impacts, though this depends on the context

We used the E3ME model to investigate the effects of the transition to EVs and its pace on various macroeconomic indicators. Figure 56 displays the impacts of a slow and fast transition compared with the reference scenario where such transition does not occur. The top row displays the economy-wide differences in primary energy demand of both scenarios compared to the reference. Electrification of the vehicle fleet leads to a large reduction in the demand for oil, which is greater in the fast transition scenario. In China, oil demand in 2035 falls by 8 per cent in the slow transition and by 12 per cent in the fast transition, compared to the baseline scenario in 2035. In India, the equivalent numbers are 4 per cent and 8 per cent. However, the transition also requires additional electricity, which requires various primary energy sources. In all regions we note an increase in demand for electricity, which generally includes a mix of renewable energy and fossil fuels, depending on the local energy mix. This is reflected in power sector emissions, which increase in India and the US; however, this is more than offset by emission reductions in the transport sector and the fuel manufacturing sector (contained in the 'other energy' group). The reason for this is that fossil fuel electricity plants and electricity transmission together are generally more efficient than internal combustion engines of cars in generating movement.

Looking at GDP, we notice subtly different stories for each country. India and the EU show additional growth due to the transition to EVs, and the increase is higher in the fast transition scenario than in the low transition scenario (by US$126bn2020 for India and by US$60bn2020 for the EU, compared to the reference scenario in 2050). In contrast, the US and particularly China show lower GDP outcomes when undergoing a fast transition compared to the reference. China is the only region with negative GDP impacts in the slow transition scenario as well. These results are driven via a combination of changes to consumer spending, industrial investments and net exports. Consumer spending is affected by employment, wages and prices. In China the model shows a large decrease in employment in the fossil fuel and mining sectors (particularly oil and gas) which suppresses consumer spending. Lower consumer spending leads to lower demand and therefore slows down investments, while net exports are also down, despite an interplay of fewer imports of crude oil and fewer exports of refined oil products. The story is the opposite for India. India relies much more heavily on crude oil imports than the other countries and so a decline in oil demand leads to improving the trade balance (expressed as net exports), leaving income to spend domestically, with consequent benefits for GDP and jobs. The US is a large producer of crude oil and refined products, and mainly sees negative impacts due to reduced crude exports. Finally, the EU is not a large producer of crude oil and it has sizeable oil-refining capacities to meet demand within its own market. Hence, the negative trade impacts are lower. Across all countries and scenarios, the bandwidth of relative GDP impacts is relatively small, ranging from approximately -0.1 per cent to +0.6 per cent.

An important limitation of the model is that it does not differentiate between economic activity and jobs generated through the manufacturing of EVs and those generated through the manufacturing of ICEVs. It also does not determine for each country whether EVs are imported or domestically manufactured. This means it does not capture the economic gains or losses that may arise through a country increasing or decreasing its share of global vehicle sales as the sector makes the transition from fossil fuels to EV technology. This may lead to an understatement of the economic benefits of policies that stimulate the growth of EV supply and demand within a country's domestic market.

Figure 56: Impacts of slow and fast transitions compared to the reference on primary energy demand (PED), emissions, GDP, net exports and employment.



Conclusion

With rapidly falling costs of batteries for EVs, cost parity with fossil-fuelled vehicles could be reached in many countries in the near future. Once cost parity is crossed, EVs could deliver substantial cost savings to the economy. Governments have an interest in identifying the policies that can maximise those savings.

An EV subsidy that closes the cost gaps between EVs and ICEVs can make EVs more attractive to consumers and can be made revenue-neutral with only a small tax on ICEVs. However, financial incentives alone are not sufficient to drive a fast transition when individual preferences vary, and choices are limited. Policy measures such as ZEV mandates and efficiency regulations that increase the supply of ZEVs to the market can be more cost effective individually and can be used together with financial incentives to create highly effective policy packages. The transition towards EVs can be further accelerated through international coordination. The most significant macroeconomic consequence of the transition may be the reduction in oil consumption, which may affect countries positively or negatively depending on their status as an importer or exporter.

Table 10: Revenue-neutral approach to support the transition towards EV. a) EV subsidy required to break cost parity with ICEVs. b) Revenue-neutral tax levels in the leading markets in 2023.

A. Subsidy required per vehicle in 2023 (US$)	Europe	US	India
EV Low-cost	0	1900	1000
EV Mid-range	1600	3000	0
EV Luxury	4800	4500	NA
B. Revenue-neutral tax per vehicle in 2023	**Europe**	**US**	**India**
ICEV lower-case	0	90	7
ICEV mid-range	160	200	0
ICEV luxury	310	260	NA

CASE STUDY:

Supporting Sustainable Agriculture Intensification: A system-wide agent-based modelling approach

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Policy question: Should institutions support sustainable agricultural intensification, and which factors make such intervention more urgent?

Region: Global

Methods: Agent-based model

Key finding(s): (1) Institutions should promote and incentivise sustainable farming; (2) their protection and nurturing is particularly beneficial when done in the early stages of the simulation; (3) supporting policies can involve a mixture of tax-based and command-and-control instruments; (4) if supporting policies are introduced too late, the technological gap might become so large that it becomes impossible to avoid a lock-in scenario in unsustainable agricultural practices.

Engagement: This case study emerged from a long and close collaboration between research teams at the Institute of Economics, the Institute of Life Science and the Center of Plant Sciences at Scuola Superiore Sant'Anna. Topic, questions and parts of the modelling were closely debated during stakeholder meeting, including Brazilian government officials and representatives of the Brazilian Development Bank (BNDES). As such, outputs of the case study were co-produced closely with policy stakeholders.

Summary: The authors use an ABM to consider a number of policies in support of the productivity gap of sustainable farming. Specifically, the study presents the agriLOVE model, which is characterised by high level of uncertainty, reinforcing feedback loops modelling competitions between firms/farms, and heterogeneity.

Introduction

With the global population projected to increase steadily during the next century and soil degradation already affecting the cultivation of major crops worldwide,[170] agricultural systems are in need of finding sustainable intensification strategies quickly to ensure viable food security pathways.[171 172 173 174] Supporting sustainable agriculture intensification has become a crucial need, as the agricultural sector is slowly eroding crucial environmental resources, contributing to dangerous crossing of environmental boundaries, and possibly activating positive/negative tipping points.[175] Here we investigate which factors might impede or foster such transition while ensuring food security, and the subsequent policy implications. More explicitly, from a policy perspective, this translates into the following question: should institutions support sustainable intensification, and which factors make such intervention more urgent?

Modelling approach

With respect to canonical Integrated Assessment Models (IAMs), ABMs can offer a valid alternative paradigm to investigate these issues. They are increasingly employed in the domain of agricultural economics, because of the inherent complexity of socio-environment interactions.[176 177 178 179] In addition, they can easily accommodate realistic representations of boundedly rational decision making, complex-social interactions among different actors (e.g., networks or property structures), the presence of self-reinforcing feedback loops, genuine and built-in path dependency, the integration of biophysical sub-models, and an explicit representation of non-trivial spatially based interactions.

To investigate which factors might help or impede transition to sustainable agriculture, we employ the agriLOVE model.[180] Unlike other agricultural ABM models, a key feature of agriLOVE is to explicitly model endogenous technical change in agriculture, thus allowing for the investigation of different, path-dependent trajectories of evolution of technical paradigms, their uptake by agents and their aggregate outcome – in terms of food security and depletion of natural resources. As such, the model constitutes a testbed for alternative policy, institutional and environmental scenarios and the assessment of their relative risks and opportunities. Our approach is in line with the Risk-opportunity analysis (ROA) framework.[181] In particular, the model embeds core concepts of the ROA approach, including i) radical uncertainty (agents do not know the distribution of the possible states of the world, whose support cannot be known a priori), ii) path-dependency, where endogenous scenarios emerging in the model diverge from each other, and crucially depend on actions taken and states of the system observed in the past, ii) persistent disequilibrium, since the model economy has no super-imposed tendency to reach an equilibrium, but gravitates around stable trajectories as the result of continued coordination efforts among highly heterogeneous actors and iv) disproportionality of cause and effect, where small perturbations to the system can lead to drastically different trajectories via path-dependence and highly non-linear dynamics. At the current stage the model is not parameterised to a specific area but is instead representative of macro-regions mainly characterised by smallholder farming.

The model is characterised by a collection of agent farms, operating on a spatially explicit grid, representing arable lands as well as natural resources – virgin lands or forestry (Figure 58C). Each farm combines labour and land to produce a homogeneous bundle of food. Farms are owned by firms, which collect the output produced and sell it on a centralised, monopsonistic market. Market outcomes, in turn, influence future decisions carried out by agent farms/firms. Given the strong technological and environmental uncertainty,

[170] Ray, D.K. et al. (2012). Recent Patterns of Crop Yield Growth and Stagnation. Nature communications, 3: 1293.

[171] Rockström, J. et al. (2017). Sustainable Intensification of Agriculture for Human Prosperity and Global Sustainability. Ambio, 46(1): 4-17.

[172] Ramankutty, N. et al. (2018). Trends in Global Agricultural Land Use: Implications for Environmental Health and Food Security. Annual Review of Plant Biology 69: 789-815.

[173] Tilman, D. et al. (2002). Agricultural Sustainability and Intensive Production Practices. Nature, 418(6898): 671-677.

[174] Howden, S.M. et al. (2007). Adapting Agriculture to Climate Change. Proceedings of the National Academy of Sciences, 104(50): 19691-19696.

[175] Steffen, W. et al. (2015). Planetary Boundaries: Guiding human development on a changing planet. Science, 347(6223): 1259855.

[176] Filatova, T. et al. (2013). Spatial Agent-Based Models for Socio-Ecological Systems: Challenges and Prospects. Environmental Modelling & Software 45: 1-7.

[177] Berger, T. (2001). Agent-based Spatial Models Applied to Agriculture: A simulation tool for technology diffusion, resource use changes and policy analysis. Agricultural Economics 25(2-3): 245-260.

[178] Bert, F. E. et al. (2011). An Agent Based Model to Simulate Structural and Land use Changes in Agricultural Systems of the Argentine Pampas. Ecological Modelling, 222(19): 3486-3499.

[179] Berger, T. and Troost, C. (2014). Agent-based Modelling of Climate Adaptation and Mitigation Options in Agriculture. Journal of Agricultural Economics, 65(2): 323-348.

[180] Coronese, M. et al. (Forthcoming). Agrilove: Agriculture, Land-Use and Technical Change in an Evolutionary, Agent-Based Model. Ecological Economics.

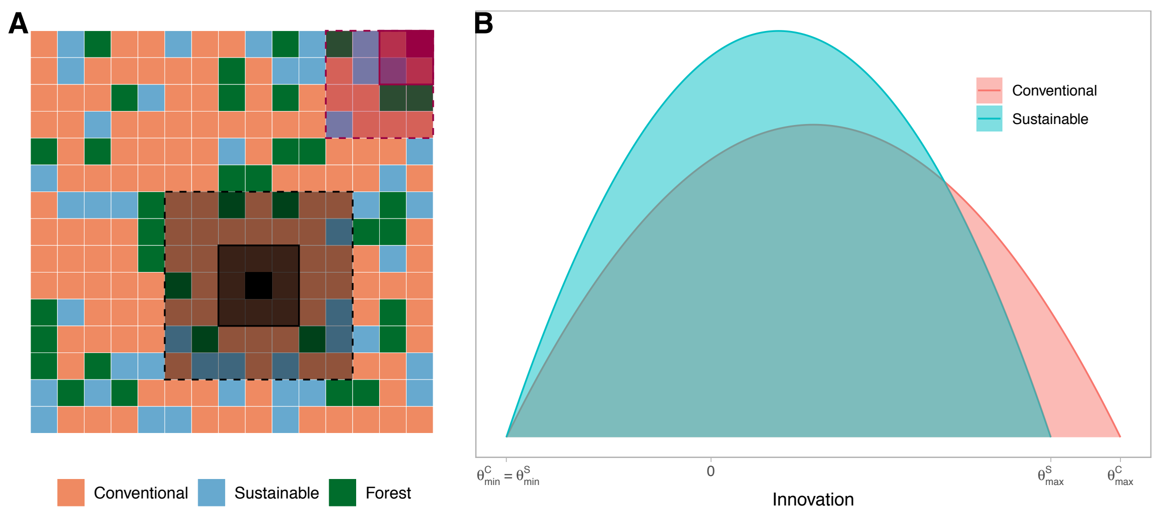
[181] Mercure, J-F. et al. (2021). Risk-Opportunity Analysis for Transformative Policy Design and Appraisal. Global Environmental Change, 70: 102359.

agents learn and adaptively employ heuristics which guide their decisions on engaging in innovation and imitation activities – for instance, they dynamically adjust the amount of resources devoted to these costly activities depending on their cash flow, and actively select best-performers among neighbouring farms to imitate. They also hire workers, acquire new farms, deforest virgin areas and abandon unproductive lands, adaptively trying to adjust production in order to meet perceived, possibly inaccurate, future levels of demand. Innovation and imitation activities capture, in an evolutionary fashion, the salient aspects of the costly process of search for productivity-enhancing new discoveries, including dynamic learning and knowledge diffusion patterns along distinct dimensions (technological proximity, spatial proximity and network effects).

We focus here in particular on modelling the dichotomy between conventional vs sustainable agricultural techniques – as commonly taxonomised in the literature[182] – and investigate the dynamic diffusion and learning patterns among these different technological trajectories. Typically, conventional farming refers to those practices which use synthetic chemicals and fertilisers to maximise the yield of a particular set of crops, often genetically modified and characterised by mono-cropping. These methods require a significant amount of chemical and energy input and may weaken the ecology of a landscape.[183] Sustainable farming is instead a broad definition, usually identifying all those agricultural paradigms which reintegrates soil nutrients during the production process. It relies on ecological processes, biodiversity and cycles adapted to local conditions, rather than the intensive use of chemical inputs.[184] It often triggers positive externalities for the environment as a whole.[185]

In order to do so, we assume that conventional techniques tend to achieve more productivity-enhancing innovation discoveries than sustainable ones (Figure 58B) – reflecting their historically higher yields – and that conventional techniques can result in greater exploitation of available natural resources such as forests. However, prolonged usage of conventional techniques will lead to a loss of productivity due to soil degradation, possibly leading to stagnating yields, observed in the real world. On the other hand, sustainable techniques have less growth potential, but they do not lead to soil depletion. Agents dynamically choose which technology to employ, basing their decision on the perceived productivity of a given technological option in neighbouring areas (Figure 58A).

Figure 57: Panel A: An example of farms with different observational horizons (and thus different information sets) from distinct locations on the model spatial grid, when evaluating relative performances of different technological options. Panel B: Distribution of innovation outcomes for conventional and sustainable farming. X-axis represents gains in productivity, y-axis represents their relative probability. Conventional farming displays a larger set of innovation opportunities, leading to higher innovation potential and yields (without considering soil degradation).



[182] Saifi, B. and Drake, L. (2008). A Coevolutionary Model for Promoting Agricultural Sustainability. Ecological Economics, 65(1): 24-34

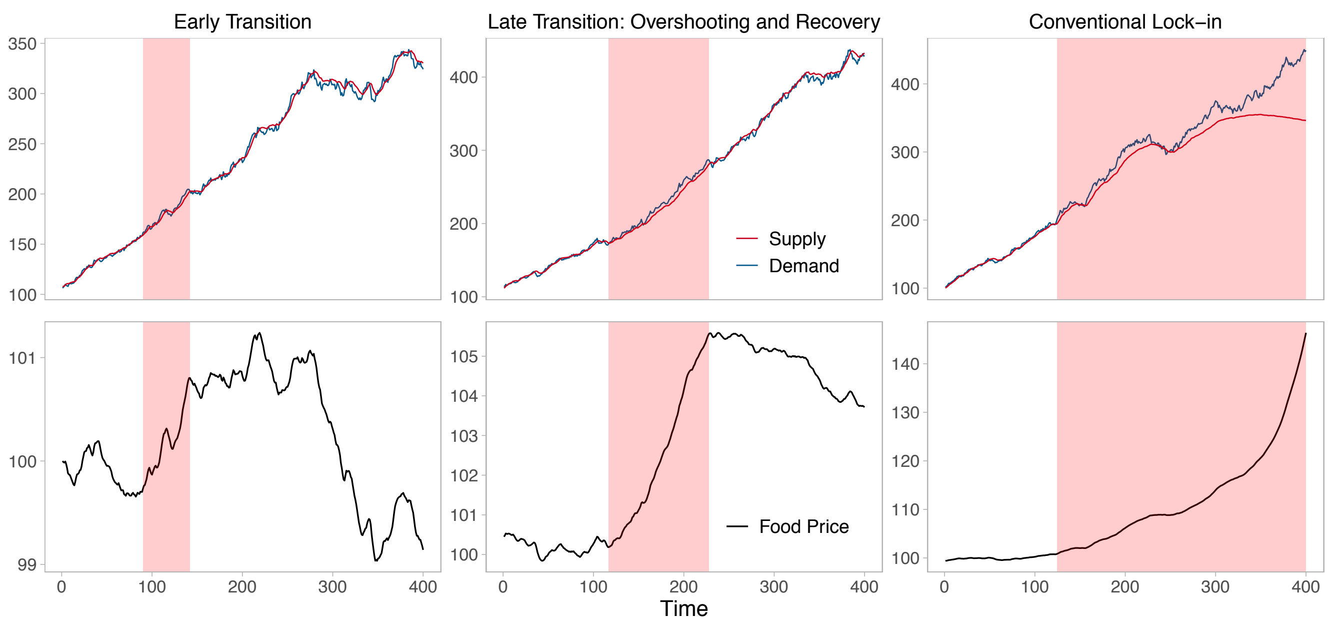
[183] Schrama, M. et el. (2018). Crop Yield Gap and Stability in Organic and Conventional Farming Systems. Agriculture, Ecosystems & Environment 256: 123-130.

[184] Gomiero, T. et al. (2011). Environmental Impact of Different Agricultural Management Practices: Conventional Vs. Organic Agriculture. Critical Reviews In Plant Sciences, 30(1-2): 95-124

[185] Rockström, J. et al. (2017). Sustainable Intensification of Agriculture for Human Prosperity and Global Sustainability. Ambio, 46(1): 4-17.

Current technological choices of agents influence not only contemporaneous food prices and food security, but dynamically shape the trajectories of development of distinct technical paradigms within the agriculture sector, through feedback loops in innovation expenditures and imitation/diffusion patterns. As such, the system can evolve toward a sustainable transition, a conventional lock-in (with sudden collapse of yields and food security) or a delayed transition (over-shooting), as conventional farmers resort to augmented labour force or deforestation to contrast stagnating yields (Figure 58). Both lock-ins and delayed transition are highly harmful in terms of food security, food prices and depletion of natural resources. The probability of realisation of these endogenous scenarios crucially depends on several factors.

Figure 58: Three different single runs of the model, exemplifying the main types of dynamics observed in the model: rapid transition to sustainable farming, overshooting (or late transition) and conventional lock-in. For each run, the distance between total demand and supply and the food price dynamics are shown. X-axis represents time steps in model simulation, y-axis represents changes with respect to initial values (set equal to 100). Red areas correspond to periods of insufficient food.



Results

Overall, our analysis shows that the agricultural system, if left unsupported by appropriate policies, has a small capacity of favouring sustainable transition, because of mis-aligned incentives and coordination failures. For instance, short-run approaches to increasing productivity, such as the depletion of natural resources or soil over-exploitation – which create long-run problems – typically grant a competitive advantage to the farms that use them. This, via path dependence, leads to higher market shares for farms employing conventional techniques, which in turn further delays the collective learning needed for the sustainable trajectory. Figure 59 shows that the likelihood of transition rapidly deteriorates along with switching intensity (a measure of the willingness of farms to rapidly change their technology) and with available information, indicating a fragile and precarious market position of sustainable farmers.

Figure 59: Heat maps for different values of switching intensity (how much agents weigh perceived differences in performance between conventional and sustainable when choosing their agricultural regime) and radius of observation (see Figure 57A). Transition likelihood is defined as the share of Monte Carlo model runs with the final share of sustainable farms greater than 90 per cent. Transition end date indicates the percentage of simulation length at which the transition ends, thus providing a measure of transition speed. Food scarcity is defined as the share of time steps in which the food supply falls short of food demand by more than 5 per cent. Remaining forests are expressed as percentage of the initial stock of forestry. Food scarcity and remaining forests are Monte Carlo means. 50 Monte Carlo replications.

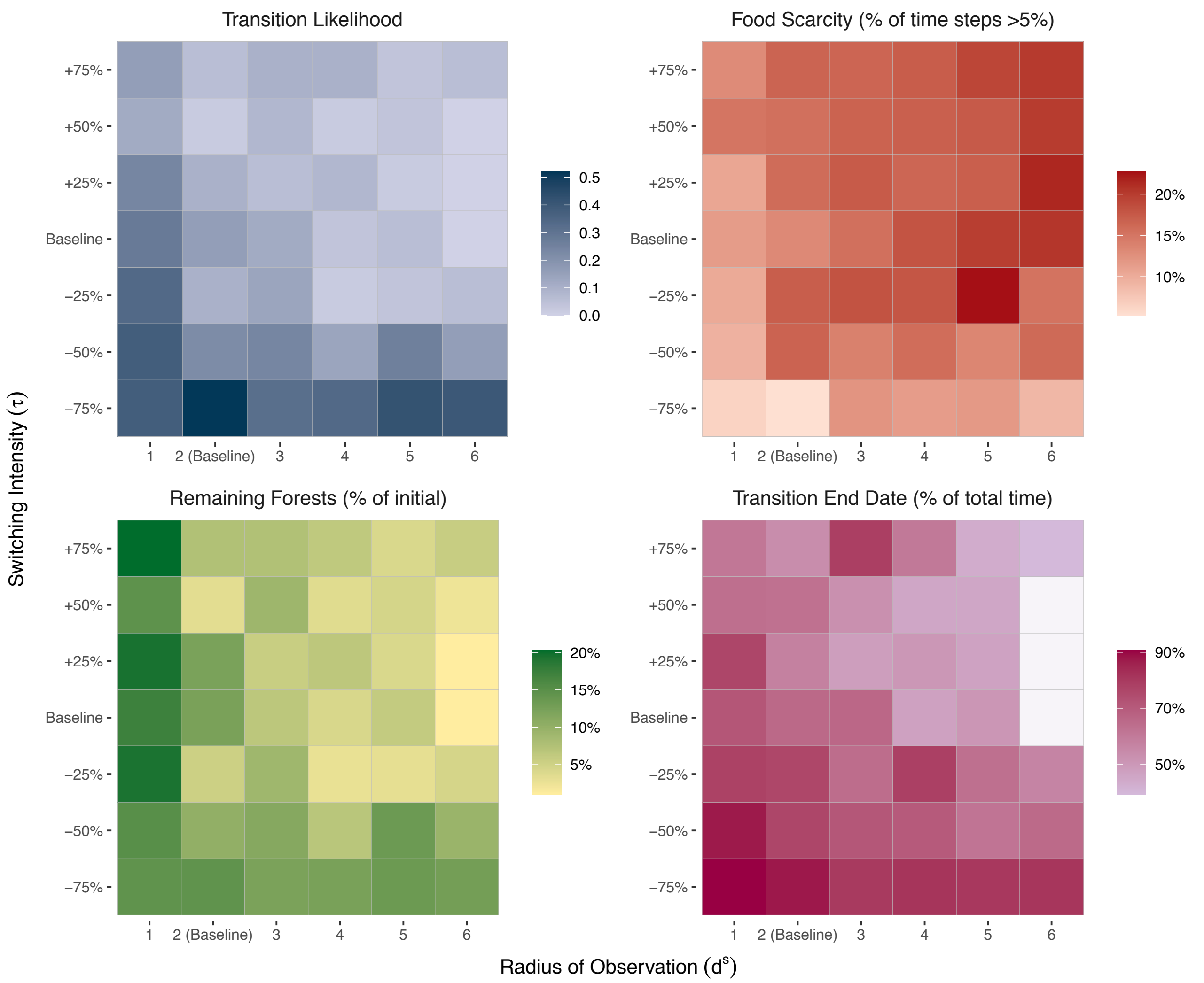
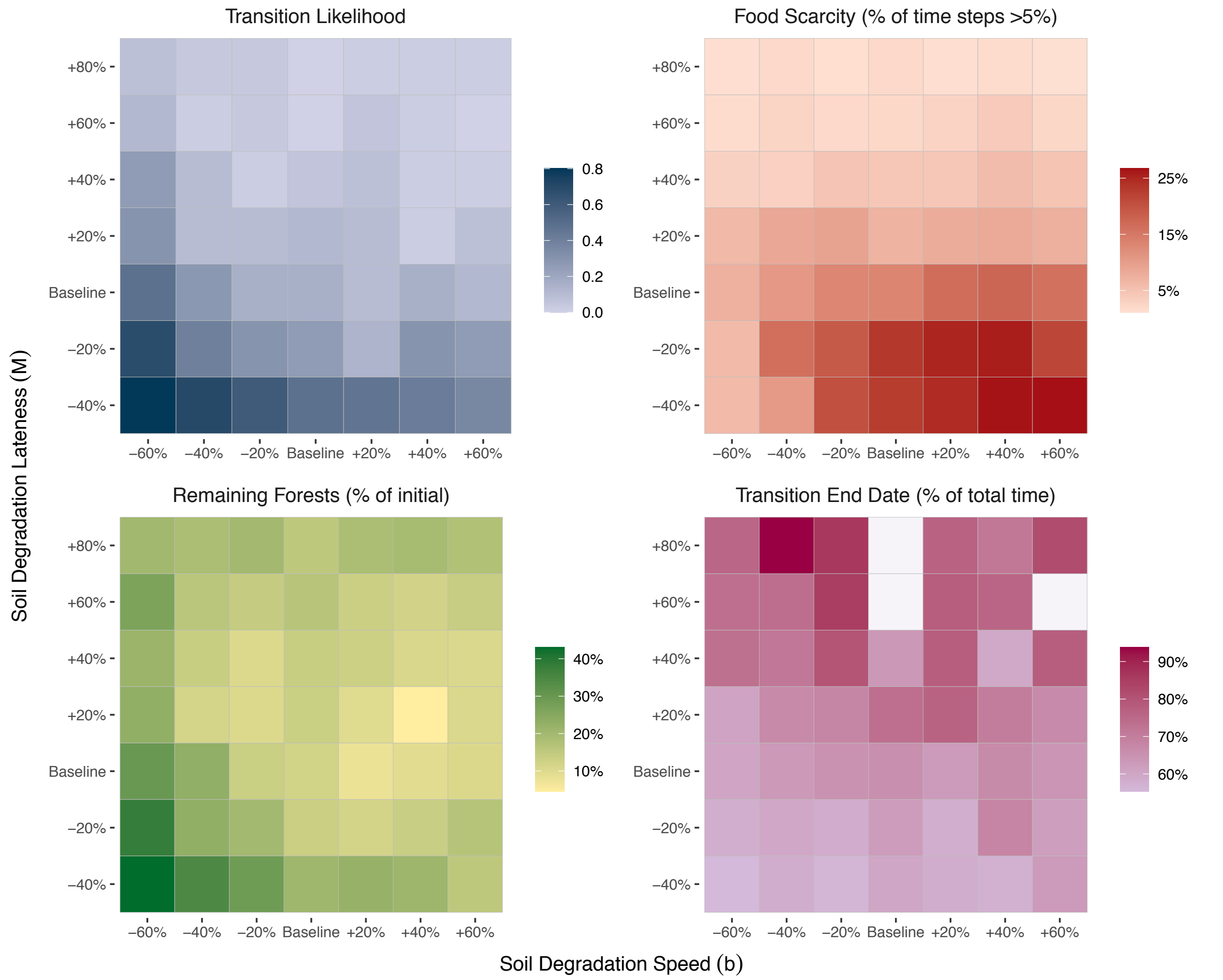


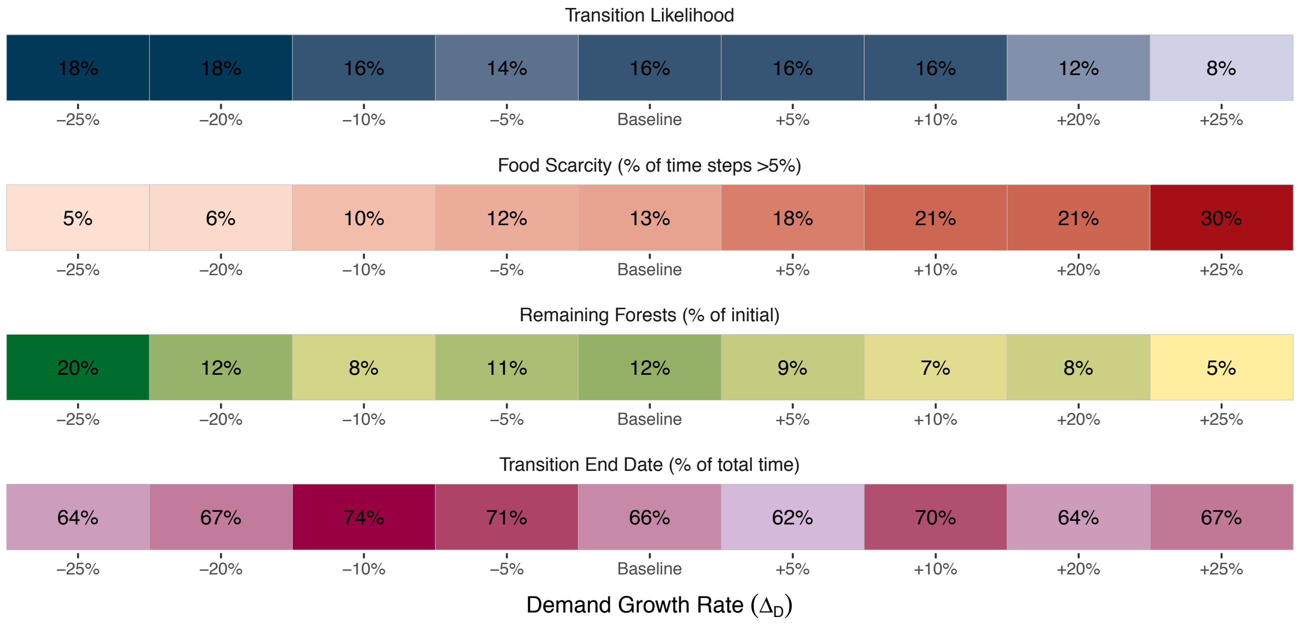
Figure 60 instead shows that agricultural systems perform particularly poorly in terms of favouring sustainable transition when facing rapid and delayed soil degradation phenomena.

Figure 60: Heat-maps for different values of soil degradation speed (how fast maximum soil damage is reached once the first signs of slowing productivity appear) and lateness (how late in time the first signs of damaging effects appear with prolonged usage). Transition likelihood is defined as the share of Monte Carlo model runs with the final share of sustainable farms greater than 90 per cent. Transition end date indicates the percentage of simulation length at which the likelihood ends, thus providing a measure of transition speed. Food scarcity is defined as the share od time steps in which the food supply falls short of food demand by more than 5 per cent. Remaining forests are expressed as percentage of the initial stock of forestry. Food scarcity and remaining forests are Monte Carlo means. 50 Monte Carlo replications.



This finding underlines that market's feedbacks might be insufficient to favour a timely and successful transition when dealing with complex, delayed and not easily measurable environmental feedbacks on productivity and yields. Overall, the probability of transitioning is negatively affected by food demand growth (Figure 61), posing serious concerns about food-security under scenarios of rapid population growth.

Figure 61: Heat maps for different rates of growth of food demand. Transition likelihood is defined as the share of Monte Carlo model runs with the final share of sustainable farms greater than 90 per cent. Transition end date indicates the percentage of simulation length at which the likelihood ends, thus providing a measure of transition speed. Food scarcity is defined as the share od time steps in which the food supply falls short of food demand by more than 5 per cent. Remaining forests are expressed as percentage of the initial stock of forestry. Food scarcity and remaining forests are Monte Carlo means. 50 Monte Carlo replications.



Lastly, the topological structure of sustainable diffusion (and its interplay with available natural resources) matters too. As shown in Figure 62A and 62B, having sustainable farmers clustered (which might favour local imitation but slow down their diffusion via local technology uptake) does not significantly affect transition likelihood. However, clustered natural resources (and thus less easily exploitable) do marginally favour sustainable transition (Figure 62C), by impeding conventional farmers to resort to deforestation as a short-run fix to descending yields.

Figure 62: Heat maps for different initial spatial distributions of conventional and sustainable farms. Transition likelihood is defined as the share of Monte Carlo model runs with the final share of sustainable farms greater than 90 per cent. Transition end date indicates the percentage of simulation length at which the likelihood ends, thus providing a measure of transition speed. Food scarcity is defined as the share of time steps in which the food supply falls short of food demand by more than 5 per cent. Remaining forests are expressed as percentage of the initial stock of forestry. Food scarcity and remaining forests are Monte Carlo means. 50 Monte Carlo replications.

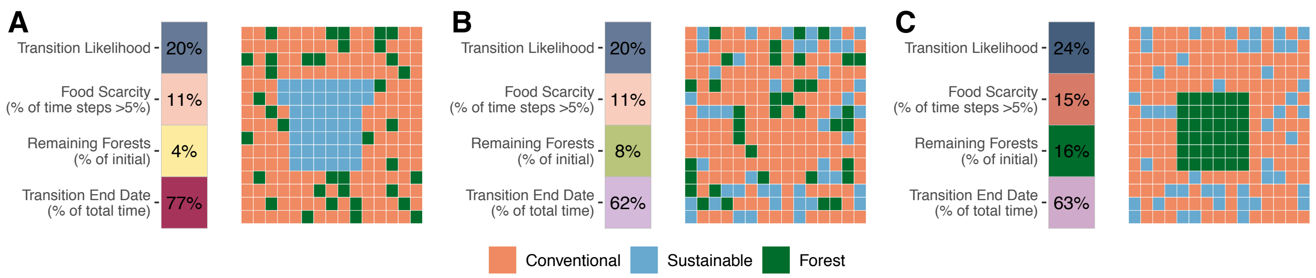
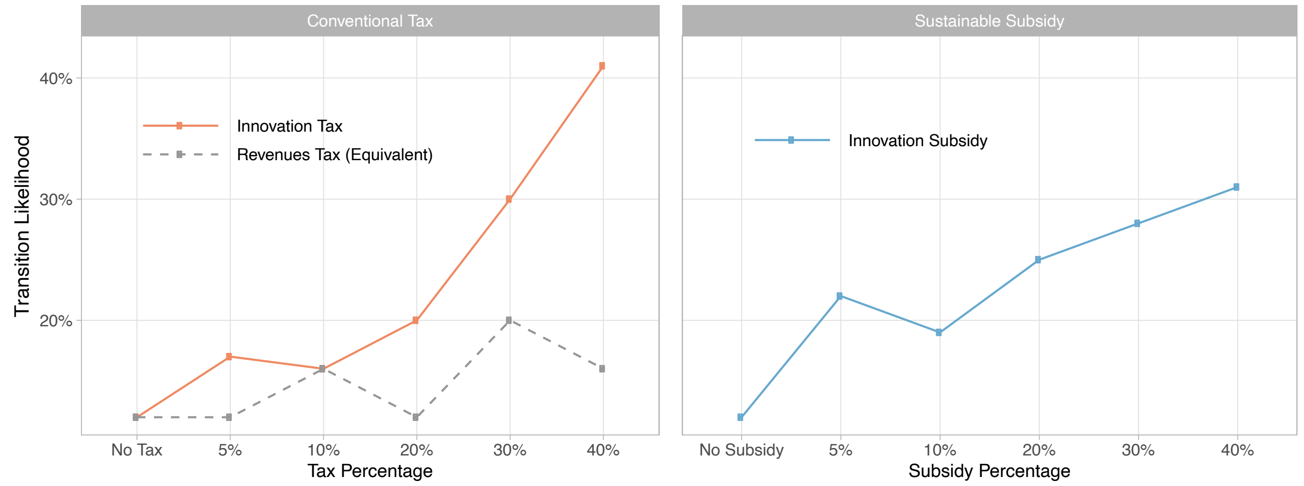


Figure 63: Transition likelihoods for different policies. Innovation subsidies/taxes are percentages of previous period innovation expenditures carried out by sustainable/conventional farms. Revenues tax amount is equal to the monetary equivalent of the innovation tax. Transition likelihood is defined as the share of Monte Carlo model runs with the final share of sustainable farms greater than 90 per cent. Transition end date indicates the percentage of simulation length at which the likelihood ends, thus providing a measure of transition speed. 100 Monte Carlo replications.



Policy implications and conclusion

What emerges from our analysis is that, not only should institutions promote and incentivise sustainable farming, but their protection and nurturing is particularly beneficial when done in the early stages of the simulation. Supporting policies can involve a mixture of tax-based and regulatory instruments.

On the demand side, policies aimed at reducing food waste could certainly play a role in diminishing food scarcity, although they are bound to become progressively less effective for closing the gap between supply and demand in scenarios with high population growth. Spatial dynamics matter too: encouraging clustered communities can help mutual imitation and dynamic learning, but should be accompanied by policies aimed at speeding up the velocity of transition (e.g. by imposing a minimum percentage of terrains to be cultivated with sustainable techniques within a given date).

Regulatory policies can be highly effective (e.g. simply prohibiting deforestation), but would nonetheless result in major short-run food shortages if not coupled with timely policies to reduce the productivity gap between sustainable and conventional techniques. Tax-based policies can be represented by a combination of taxes on conventional farms and incentives toward sustainable ones. To maximise their impact in terms of transition likelihood – and minimise their distortive impact – they should, however, be explicitly targeted at increasing the resources that farms invest in innovation and imitation of sustainable agriculture activities.

Figure 63 shows the effects of these two different policies. Subsidies to sustainable farms are already effective at increasing the probability of transition with relatively low amounts, although their effectiveness increases less than linearly, along with the subsidy amount. This indicates that subsidies can represent a powerful tool to boost sustainable intensification, although with limited effectiveness due to the structural gap between conventional and sustainable techniques (see Figure 57B). On the other hand, when taxing conventional farmers, transition likelihood increases more than linearly with tax severity. Taxes are however highly ineffective if their amount is not substantial, or if they are not directly targeted at innovation expenditures (see Revenues Tax in Figure 63).

In other words, centralised policies aimed at closing the productivity gap between sustainable and conventional techniques are not only needed, but are time-dependent, with rapidly closing windows of opportunity. If supporting policies are introduced too late, the technological gap might become so large that it becomes impossible to avoid a lock-in scenario in unsustainable agricultural practices.

CASE STUDY:

Modelling Labour Market Transitions: The case of productivity shifts in Brazil

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Policy question: How would occupation-level unemployment be affected by growth paths with different drivers and emissions outcomes in Brazil?

Region: Brazil

Methods: A data-driven occupational mobility network combined with an agent-based model.

Key finding(s): The number of occupations facing higher unemployment due to limited mobility is lower in a manufacturing-driven (i.e. lower emissions) growth path (21 per cent of occupations) than in an agriculture-driven (i.e. higher emissions) growth path (49 per cent). So, more effort towards increasing productivity in manufacturing is both better aligned with the country's NDC targets and results in fewer labour market frictions.

Engagement: This case study emerged from a collaboration between the authors and the Brazil office of the World Bank. The data on labour movement, scenarios of interest and the CGE model they were developed with came from the World Bank team. The findings and framing were developed by the authors with input from the World Bank. In future work, this case study will be further developed with the World Bank, both in methodological terms, but also on refining the policy implications. Input from the Brazilian government will also be sought, via the EEIST community of practice in Brazil, to explore additional scenarios that may be of interest.

Summary: The authors combine macro-economic model outputs with a dynamic labour market simulation to study how, within a context of green transitions, productivity shifts in different sectors and regions may affect occupation-level unemployment in Brazil. Specifically, the study combines a data-driven occupational mobility network with an agent-based labour market model to account for limited mobility and second order frictions in the labour market. With this approach, they discuss how changes in labour demand affect occupations depending on how much mobility may be expected to and from other occupations. They find that increased productivity in manufacturing results in fewer labour market frictions than increased productivity in agriculture.

Introduction

Brazil is one of the major greenhouse gas emitters in the world,[186] with most emissions linked to agriculture, directly and indirectly as demand for agricultural land still drives deforestation (Ferreira Filho and Hanusch, 2022).[187] In 2021, emissions from land use change and forests accounted for over 49 per cent of the total, with emissions from agriculture almost 25 per cent.[188]

In 2020, Brazil updated its Nationally Determined Contribution (NDC) with a new intermediate target[189] and, compared to 2005 levels, wants to lower its emissions by 37 per cent in 2025 and by 43 per cent in 2030, with a long-term goal of carbon neutrality by 2060. Gurgel, Paltsev and Breviglieri (2019)[190] argue that the 2030 NDC goal could be achieved mostly through reducing deforestation and changes to agricultural practices. In the long-term, Soterroni et al. (2022)[191] argue that halting deforestation and promoting restoration will be critical to achieving net zero.

While Brazil's Forest Code is a key command-and-control policy for preserving and restoring native vegetation - and, therefore, reducing emissions - its stringency and sustained enforcement are subject to economic pressures. On the one hand, Brazil's highly competitive agriculture is still land-hungry. On the other hand, the restriction of land supply may cause welfare losses from lower agricultural employment and higher food prices (Ferreira Filho and Hanusch, 2022).

Within this context, Ferreira Filho and Hanusch (2022) consider different growth paths and how they would impact deforestation and emissions in Brazil. The authors show that transitioning to a manufacturing or services productivity growth model could reduce emissions and deforestation significantly while sustaining long-term GDP growth, with manufacturing having the biggest emissions savings. Conversely, agricultural productivity growth leads to higher emissions and can lead to both an increase and a decrease in deforestation depending on whether the productivity growth happens in the Amazon or elsewhere respectively (see Ferreira Filho and Hanusch, 2022, for more details).

In both cases, as productivity grows, the relative demand for labour in different occupations would likely shift, potentially requiring workers to switch occupations. Several economic models, including IO and CGE models, estimate the changes in labour demand of different industries during a transition. However, these estimates often do not account for labour market frictions that limit workers' mobility between jobs. Recent studies argue that limited labour mobility needs to be taken into account – generally, and when modelling the post-carbon transition[192] – as in reality some workers may find it harder, or even impossible, to switch into certain occupations and may face higher unemployment rates as a result. Similarly, firms may face more skill shortages and unfilled vacancies in occupations that grow during the transition.

The labour market model

To account for the labour market structure and frictions that can limit worker mobility, in this case-study we model occupation-level labour market dynamics using the data-driven occupational mobility network model developed by Del Rio-Chanona, Mealy, Beguerisse-Díaz, Lafond and Farmer.[193]

We begin by constructing our empirical occupational mobility network[194] (Figure 64) using the RAIS dataset (Relação Anual de Informações Sociais), which contains data on all worker-job-firm combinations of contracts active in Brazil at some point during each year, from 2011 to 2019. The resulting network consists of 2,591 nodes – representing six-digit occupations[195] – and an edge between two nodes reflects the probability that a worker will transition from one occupation to another, as recorded in RAIS.

[186] UNEP, UNEP Copenhagen Climate Centre (UNEP-CCC). Emissions Gap Report 2021. https://www.unep.org/resources/emissions-gap-report-2021.

[187] Ferreira Filho, J. and Hanusch, M. (2022). A Macroeconomic Perspective of Deforestation in Brazil's Legal Amazon. Policy Research Working Papers; 10162. World Bank. https://openknowledge.worldbank.org/handle/10986/38253.

[188] SEEG (Greenhouse Gas Emission and Removal Estimating System). Based on total emissions - CO2e(t) GWP-AR5.

[189] Although with a different baseline, making the target less, rather than more, ambitious in practice (UNEP, UNEP-CCC, Emissions Gap Report 2021).

[190] Gurgel, A. et al. (2019). The Impacts of the Brazilian NDC and their Contribution to the Paris Agreement on Climate Change. Environment and Development Economics, 24(4): 395-412.

[191] Soterroni, A. et al. (2022). Nature-Based Solutions are Critical for Putting Brazil on Track Towards Net Zero. Preprints 2022, 2022110054.

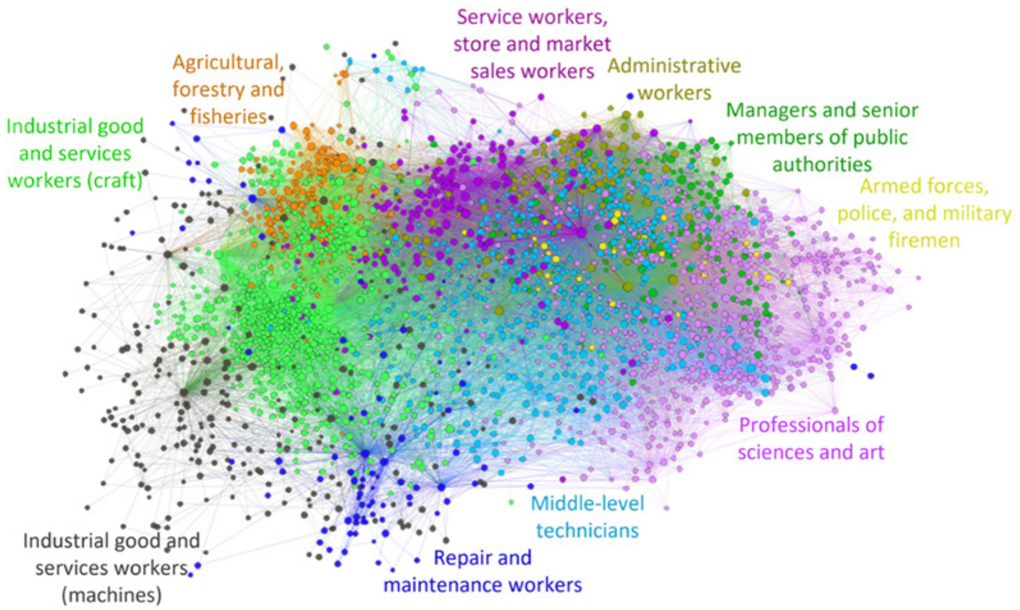
[192] Castellanos, K. and Heutel, G. (2019). Unemployment, Labour Mobility and Climate Policy. National Bureau of Economic Research. https://doi.org/10.3386/w25797

[193] del Rio-Chanona, M.R. et al. (2021). Occupational Mobility and Automation: A Data-Driven Network Model. Journal of the Royal Society Interface. https://doi.org/10.1098/rsif.2020.0898

[194] Mealy, P. et al. (2018). What You Do At Work Matters: New Lenses On Labour. SSRN Electronic Journal, Apr 2018.

[195] Every occupation is classified according to the Brazilian 2002 CBO (Classificação Brasileira de Ocupações) system. This is a nested classification, where each detailed occupation has a six-digit code. Occupations that share the same first digits can be grouped together. In this case study, we also use the three-digit and one-digit occupation codes. There are 2,591 six-digit occupations in our case study, which can be grouped into 196 three-digit occupations, or ten one-digit occupations. For example, six-digit code 913110 refers to Maintenance mechanics for mining equipment; this six-digit occupations is included in the three-digit code 913, which refers to all Maintenance mechanics for heavy machinery and agricultural equipment; the one-digit code 9 refers to all Repair and maintenance workers.

Figure 64: Occupational mobility network. Every node is a six-digit occupation, and wider edges between occupations signify more occupational mobility. Occupations are coloured by their one-digit level occupation (see labels), and sized by the log of total employment of the respective occupation.



Then we turn to an agent-based labour market model that comprises the number of workers employed, unemployed[196] and vacancies open in each occupation at each time step. Workers apply for jobs in accordance with the limitations given by the occupational mobility network; that is, they can only apply to vacancies in occupations that they are linked to in the occupational mobility network (their neighbouring occupations). Workers are fired and vacancies are opened via two processes; a random process and a state-dependent process which responds to the difference between the occupation-specific realised demand (i.e. employment plus vacancies) and the target demand of each scenario. If the realised demand is lower (or higher) than the target demand in the scenario, more vacancies are opened in that occupation and fewer workers fired (or vacancies are closed and more workers are fired).

Brazil's structural change to green growth

We use the product-level labour demand estimates from Ferreira Filho and Hanusch (2022) to simulate occupation-level labour demand and, with our labour market model, study occupation-level unemployment under the mobility frictions given by the occupational mobility network.

Policy scenarios

To investigate how structural change to growth may affect workers in different occupations, we apply two different policy scenarios from Ferreira Filho and Hanusch (2022): a boost to productivity in manufacturing and a boost to productivity in agriculture in Brazil, compared to a baseline that assumes no productivity change. Both of these lead to GDP growth, but agricultural productivity growth would lead to more greenhouse gas emissions.[197] Ferreira Filho and Hanusch (2022) find with their TERM-BR CGE model that a nationwide permanent annual increase of total factor productivity (TFP) of 0.5 per cent in manufacturing leads to a cumulative 3.9 per cent higher GDP over 12 years, 0.8 million hectares less deforestation, and over 67,833 kT less CO2 emissions in Brazil compared to the baseline scenario. Vice versa, an 0.5 per cent permanent annual increase in agricultural TFP in Brazil would lead to a cumulative 1.8 per cent higher GDP, 0.3 million hectares less deforestation, but 18,221 kT more CO2 emissions over the same period.

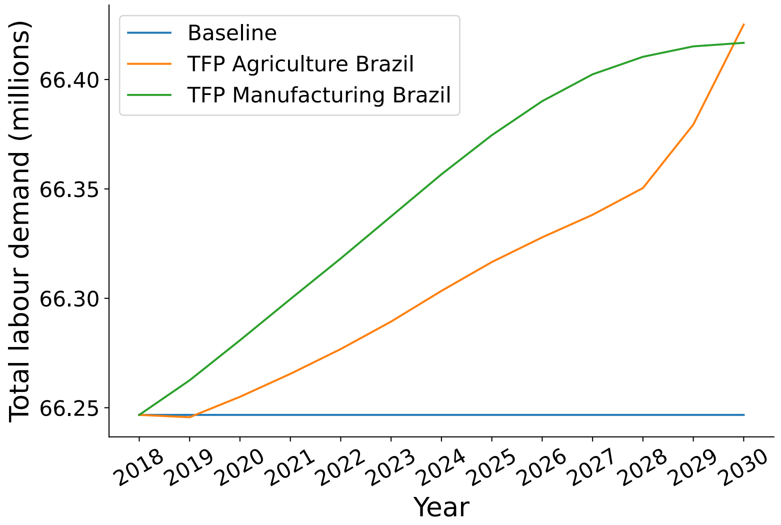
Projected labour demand by occupation

We translate the labour demand changes per commodity to labour demand change per occupation using 2018 RAIS data on industry-occupation composition. As our agent-based labour market does not model population growth, we renormalise the population growth from the labour demand projections by keeping the total labour demand constant in the baseline. We keep the variation in total labour demand for each productivity increase in relation to the baseline. In Figure 65, we show the adjusted total labour demand for the baseline and scenarios.

[196] An unemployed worker counts as unemployed in the occupation in which they were most recently employed.

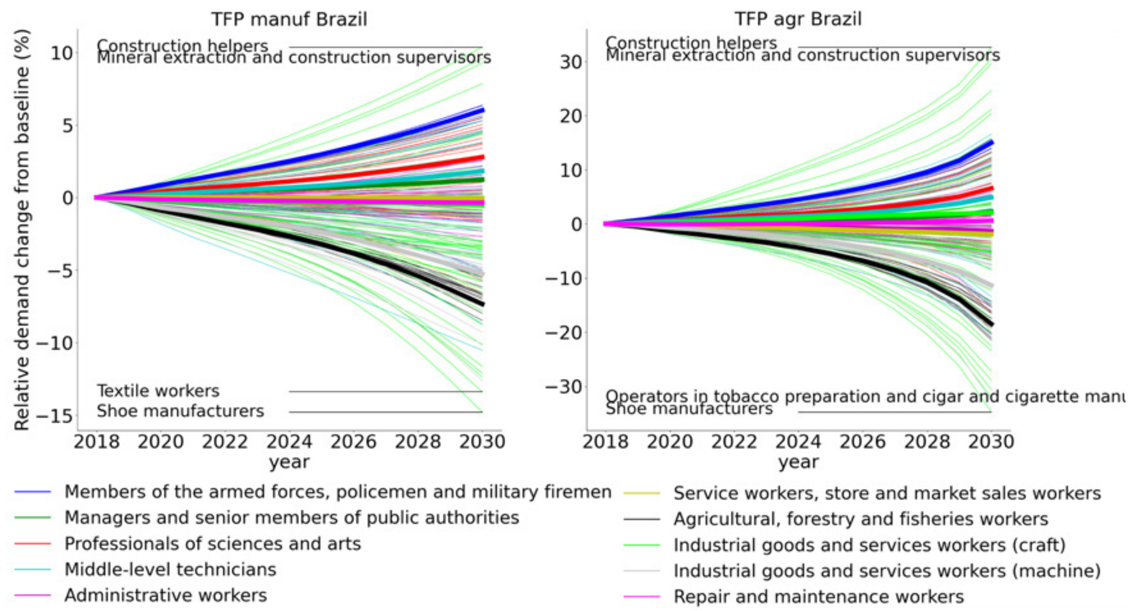
[197] Compared to agriculture, manufacturing is comparably less emissions-intensive due to Brazil's relatively clean power mix (see Ferreira-Filho and Hanusch, 2022).

Figure 65: Total labour demand for each scenario with the total labour demand for the baseline scenario kept constant from 2018 to 2030.



When we disaggregate labour demand by occupation, we find that in both scenarios demand for agricultural workers decreases, and demand for workers in public services and education increases (see Figure 66). The agriculture TFP growth scenario leads to much more occupational relative demand changes with respect to the baseline than the manufacturing TFP growth scenario: at the three-digit level, the groups of occupations with the largest growth (decline) in demand experience a +10 per cent (-15 per cent) change in the manufacturing TFP growth scenario, and +33 per cent (-35 per cent) change in the agriculture TFP growth scenario. Nonetheless, both scenarios see a decline in demand for agricultural workers and some manufacturing occupations compared to the baseline, whereas service workers and construction occupations experience a demand increase.

Figure 66: Employment demand per occupation compared to the baseline for the scenario with TFP growth in manufacturing (left), and with TFP growth in agriculture (right). The bold lines represent the average of occupations grouped by their one-digit level (see legend). The thin lines are occupations grouped at the three-digit level, coloured by their one-digit classification. The top and bottom two three-digit occupations by impact are labelled.



A boost of a sector's TFP implies less labour demand is required for the same output, but general equilibrium effects may cancel this out and increase a sector's labour demand. A productivity increase makes it cheaper to produce a certain product, which can lead to a lower equilibrium price. If demand remains relatively stable despite a lower price, employment needs to decline in order for supply to meet demand. If, however, a lower price increases demand a lot, more workers are required. This may explain part of the difference in the trajectories of demand for occupations in Figure 66.

The demand decline in both scenarios for Agricultural workers may thus be explained as follows. An agriculture productivity increase leads to more output with the same number of workers. This can result in higher wages for its workers and/or lower prices for agricultural products. In this case the demand increase due to lower prices is not enough to counterbalance productivity growth. As a result, demand for workers declines. For the other scenario, an increase in manufacturing productivity may lead to lower prices and higher wages in manufacturing. Wage increases are not restricted to manufacturing but also (partly) affect agriculture due to labour competition pressures. Higher wages in this case are not compensated by more demand as workers receive higher wages, and demand for workers in the agricultural sector declines.

Results

We ran the agent-based labour market model for the agriculture TFP scenario, for the manufacturing TFP scenario, and for the baseline, using the occupational mobility network and, as a comparison, a completely connected frictionless network, in which workers can switch between all occupations without any friction. In Figure 67, for each TFP shock we plot the (percentage) change in labour demand in 2030[198] (in relation to the baseline scenario) against the average (percentage-point) unemployment rate change from 2018 to 2030, also in relation to the baseline scenario. We do so using both the occupational mobility network and the frictionless network.

Using the frictionless network, the changes in labour demand have a similar impact on the unemployment rate for all occupations – around 0.13 percentage points lower than the baseline for the manufacturing TFP scenario and 0.08 percentage points lower for the agriculture scenario. This decrease in the unemployment rate is due to an overall increase in demand for the two TFP scenarios relative to the baseline (see Figure 65); there are more jobs available in the two scenarios and since unemployed workers are free to apply to any open vacancy in any occupation, they would do so until the vacancies opened due to the extra demand are filled. The small variations we see for occupations that have the same demand change in 2030 compared to the baseline are due to the different profiles of this demand change throughout the scenario from 2018 until 2030. This is what would happen if there were no labour market frictions.

When we consider a more realistic labour market structure by using the occupational mobility network, in both scenarios we see a negative correlation between changes in unemployment and worker demand, as we would expect; in general, an increase in labour demand relative to the baseline results in a decrease in the unemployment rate. We can also see that once we allow for mobility frictions, most of the occupations experience a smaller decrease – or even an increase – in the unemployment rate, and occupations that have a similar change in labour demand can see quite different changes to the unemployment rate. That is, the occupational mobility network shows how labour market frictions hinder some of the employment benefits workers would experience in a frictionless network.

In the top panel of Figure 67, we see the results for the TFP agriculture scenario. We can clearly see that network effects impact the unemployment rate of occupations with a similar change in labour demand quite differently. For example, agriculture managers and tree growers see a similar decrease in demand of 20 per cent and 21 per cent respectively, but agriculture managers have an increase in the unemployment rate of 0.24 percentage points, much lower than the increase of over 0.57 percentage points faced by tree growers. One cause of this difference is that the neighbours of tree growers face a greater decrease in demand than agriculture managers, so when the demand shock happens, there are fewer opportunities for tree growers to find employment in neighbouring occupations.

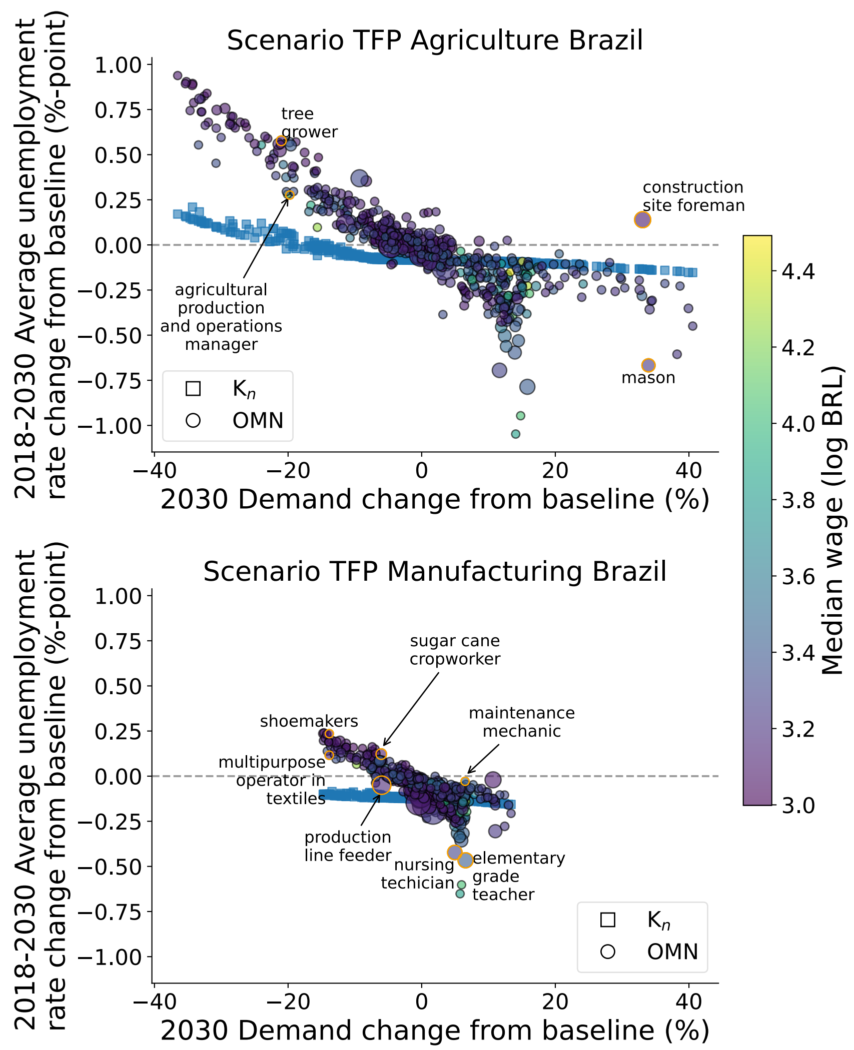
Similarly, both construction site foremen and masons experience an increase in demand relative to the baseline of around 34 per cent. Construction site foremen have more neighbours than masons, but more neighbours can mean that there is more competition for new jobs created by a demand shock, and hence the unemployment rate increases despite an increase in demand, as seen in Figure 67 for construction site foremen but not for masons. These nuanced secondary effects highlight the benefits of considering the occupational mobility network over the frictionless network.

[198] The actual demand change from 2018 to 2030 for each scenario agrees with the demand change in 2030 relative to the baseline almost entirely, with small variations.

Under the TFP manufacturing scenario, we also see the network effects. Shoemakers and multipurpose operators in the textile industry both feel about a 14 per cent decrease in labour demand, but have different unemployment outcomes. Similarly, elementary teachers and maintenance mechanics have an increase in labour demand of around 6 per cent, but elementary teachers see one of the largest declines in the unemployment rate compared to the baseline. In both of these pairs, the occupation that is better off compared to the baseline is the occupation with more neighbours.

We can also identify vulnerable occupations – i.e. those that will experience the greatest increase in the unemployment rate, compared to the baseline in 2030. At the four-digit occupation-level, which contains 621 occupations, vulnerable occupations in both scenarios include civil construction assistants, masonry structural workers, weaving machine operators and agricultural workers in oil-seed crops. Cigarette and tobacco processors are also vulnerable in the agriculture scenario while occupations in the shoe-making sector (handmade shoe and leather goods workers, and shoe-dressing preparatory workers) are at risk of increased unemployment in the manufacturing scenario. These vulnerable occupations would be good targets for re-skilling programmes to mitigate the labour market impacts of a green transition pathway.

Figure 67: Average percentage-point change in the unemployment rate from 2018-2030 for each occupation with at least 1,000 employees in 2018 for TFP Agr Brazil (top), and TFP Manuf Brazil (bottom) compared to the baseline scenario, against percentage change in demand for each scenario in 2030 compared to the baseline. The circles are the model output using the occupational mobility network (OMN) and the squares using the frictionless network (Kn). The size of each circle is proportional to employment in 2018 and the colour represents the log of the median monthly wage in BRL in 2018.



Discussion

Comparing the labour market effects in the TFP manufacturing and TFP agriculture scenarios, we see that the absolute changes in labour demand are lower in the TFP manufacturing shock. More importantly, in the TFP manufacturing scenario the number of occupations facing more unemployment (than in the baseline) due to difficulties in switching between occupations is lower (21 per cent) than in the TFP agriculture scenario (49 per cent). In other words, our results suggest that, overall, the changes in labour demand resulting from a sustained increase in manufacturing productivity allow more negatively affected workers to move from occupations with decreased demand than in the agriculture scenario. This is largely due to the difference in magnitude of the occupation-level labour market demand changes in each scenario, and also influenced by how adaptive workers are. Moreover, as mentioned above, while emissions in the TFP manufacturing scenario are lower than in the baseline, they are higher than the baseline in the TFP agriculture scenario. This indicates that increased attention to manufacturing productivity growth can help align Brazil with its NDC targets and grow the number of jobs, as well as affect fewer occupations negatively.

The network in our model is impacted by several factors such as differences in the skillsets needed or geographical constraints, but it is important to note that we do not address geography explicitly in this case-study. Instead, we assume that there is one job market for all workers to apply to jobs within, and while geographical constraints are implicit in the occupational mobility network (as occupations that are geographically concentrated will be more connected to one another), we cannot consider the role of geography separately from other effects such as skillsets, wage differences, racial and gender biases, etc. As relocation of workers is an important consideration for the CGE scenarios, adding geography into the model is an important direction for future work.

Another consideration for future research is to couple the labour market model with the model we use for demand – in this case the CGE and land-use model. At present, the CGE model is run independently of the labour market model and so the labour market frictions that slow down labour reallocation are not taken into account in subsequent time steps. A coupling of the two models will be able to show how much labour market frictions might slow down, or enable, the transition to net zero. Allowing for more realistic out-of-equilibrium behaviour in the macroeconomic model would be another route for future research.

The set of occupations we use in our analysis is constant; the model only deals with occupations that already exist, specifically within the 2002 CBO occupation classification system. The data we use also works within this classification system and so research into the creation of new jobs is another interesting future research question.

Finally, the RAIS data we use to calculate the occupational mobility network only captures the formal labour force, which in Brazil amounts to around 67 per cent of the total.[199] This should be taken into account when interpreting these results, and in future work we can reconcile the RAIS data with informal labour force data, such as using data from PNAD household survey.

In this case study, we combine scenarios proposed by Ferreira-Filho and Hanusch (2022) to investigate the impacts of total factor productivity increases on Brazil's economy with a more realistic labour market model to show the occupation-level impacts of these scenarios on unemployment. However, this modelling approach could also be used to inform many other aspects of low-carbon transition policies. For example, the occupation-specific labour market implications of increasing the speed of a net zero transition can be investigated. Similarly, our modelling approach could inform policymakers on the labour market implications of different technology choices, and the reskilling required for the different transition options.

[199] Ulyssea, G. (2018). Firms, Informality and Development. The American Economic Review 108.8 https://doi.org/10.1257/aer.20141745

CASE STUDY:

China and the Social Consequences of the Coal Transition

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Policy question: What are the fiscal and employment effects of phasing out coal power in China?

Region: China

Method: Microsimulation.

Key finding(s): Under a baseline scenario consistent with China's carbon neutrality goal, employment supported by coal declines from 2.7 million in 2021 to 1.4 million in 2035, and 94,000 in 2050. The annual rate of tax revenue loss rises to over 10 per cent by the 2040s. However, given the current levels of subsidies, coal is likely to already be a net fiscal drain. China's major coal-producing areas, such as Inner Mongolia, will face significant challenges unless they successfully diversify.

Engagement: The development of this case study benefited from collaboration with the Carbon Tracker Initiative and researchers from the North China Electric Power University, and was completed with the support of the International Institute for Applied Systems Analysis (IIASA). In coordination with the British Embassy in Beijing, it was disseminated widely to an audience in China comprising a number of other embassies, foundations, international organisations, civil society actors and government officials.

Summary: The authors use a dynamic simulation to consider how phasing out coal – a technology choice – can affect employment and tax revenues from the coal sector over time and across space. They use asset-level data in a micro-level dynamic simulation of the coal sector that has higher resolution than that implied by the regional aggregation often needed in macro modelling, while overcoming the lack of high-quality micro data required to run empirically robust network models.

Introduction

China faces an unprecedented structural challenge in phasing out the use of coal in its domestic economy. China's coal consumption, at some four billion tonnes annually, is four times more than that of the second-largest consumer, India, and underpins most of its electricity generation and heavy industrial production. If China achieves its long-term target of carbon neutrality by 2060, coal's role as an energy source will diminish to a fraction of its current level in the coming decades. Achieving this requires widescale deployment of a combination of renewables, electrification, synthetic hydrogen-based fuels, energy efficiency measures, and, most likely, carbon capture and storage coupled with other carbon-removal technologies.

These structural and technological shifts will have profound consequences for the composition of China's economy at all levels. Researchers and policymakers need to be able to analyse in detail how these changes will play out over space and time across the coal value chain as well as the wider economy. In designing policies to manage the socioeconomic and distributive impact of these changes, two key aspects stand out: the effect of coal power phase-out on employment in the coal sector, and the impact on tax revenue from the sector.

In their study Estimating the Employment and Fiscal Consequences of Thermal Coal Phase-Out in China, Clark and Zhang (2022)[200] set out to answer these closely related questions. Due to data limitations at the time of writing, their study focuses on thermal coal (for electricity generation) only, which accounts for roughly half of China's total coal consumption.[201]

Approaches to modelling structural change

Traditionally, a structural economic change of this nature and its effects on jobs and tax revenues would be analysed through the lens of equilibrium-based macroeconomic modelling based on detailed input-output tables describing production-consumption networks.[202] These models are designed to capture substitution effects across industries in response to changes in prices and demand and to incorporate rates of technological change, but do not generally capture the dynamics of specific sectors at a high level of granularity. They rely on a significant degree of regional aggregation and a number of quantitative assumptions that are not necessarily accurate and are hard to validate in data-poor contexts subject to command-and-control policies and heavily regulated markets, like China (e.g. on price elasticities, demand growth, price formation, etc). More recent approaches use network analysis to understand how labour markets adapt to changes at the micro level – but the corresponding models rely on detailed, high-quality micro-level data such as linked employer-employee datasets.[203 204]

In China's case, the data required to run empirically robust network models is largely unavailable to researchers outside the Chinese government. Furthermore, most conventional economic models are incapable of ingesting micro-level data without some form of aggregation, producing relatively low-resolution results. Therefore, macro modelling is not sensible and network modelling is not feasible.

Model design, dynamics and limitations

Given these constraints, rather than predicting what the most likely pathway might be, this study uses a micro-simulation approach to model the dynamics in the coal sector system. The study estimates the magnitude and distribution and of jobs and tax revenues generated by the thermal coal sector (both geographically and across value chains and enterprises), and how these change over time.

Using asset-level datasets of China's coal power plants and coal mines, supplemented by a range of independently sourced data points and assumptions on employment in coal transport, plant utilisation rates, tax rates and productivity improvements, the coal sector is modelled independently from other sectors and taking the final demand for coal as determined exogenously as a function of China's climate policy.

[200] Clark, A. and Zhang, W. (2022). Estimating the Employment and Fiscal Consequences of Thermal Coal Phase-Out in China. Energies (Basel), 15(3): 800. doi:10.3390/en15030800.

[201] Most of China's coal consumption for purposes other than electricity generation is used to generate heat, largely for industrial processes such as steel and cement production, with a small and shrinking proportion still being used for domestic heating. At the time this study was undertaken, data availability limited the scope to thermal power only. The Spatial Finance Initiative at Oxford University has since published asset-level datasets for the steel and cement sectors that may facilitate an expansion of this model to cover a much greater share of China's total coal consumption.

[202] Mercure, J-F. et al. (2018). Macroeconomic Impact of Stranded Fossil Fuel Assets. Nature Climate Change, 8(7): 588-593. doi:10.1038/s41558-018-0182-1.

[203] del Rio-Chanona, R. M. et al. (2020). Supply and Demand Shocks in the COVID-19 Pandemic: An Industry and Occupation Perspective. Oxford Review of Economic Policy. doi:10.1093/oxrep/graa033.

[204] Mealy, P. (2018). Know What? New Lenses on Productive Knowledge Shed Light on Long Run Development, Structural Change, Job Switching and the Transition to the Green Economy. In J. D. Farmer & C. Hepburn (Eds.).

The demand-driven model is built from the bottom up, incorporating location-specific data on individual thermal coal plants in China, and linking these to provincial coal-mining capacity. Employment and tax revenue calculations are overlaid on this network and evolve over time, based on changes in the activity of coal plants. Differences in coal type, and the physical distance between mines and plants, is also accounted for, allowing a coal transportation layer to be added to the analysis. For aforementioned data quality reasons, plants are not linked to specific mines in this iteration of the model, although as researchers develop a greater understanding of the determinants of mine-plant relationships (e.g. distance, transportation cost, shared mine and plant ownership), this could be incorporated in a straightforward manner.

Consistent with the risk-opportunity analysis framework developed in Mercure et al. (2020),[205] the model is designed to handle non-marginal changes, while remaining – in this iteration – agnostic on substitution and price effects resulting from changes in demand. This is not to say that these effects are not relevant to the Chinese case, but rather to reserve judgement in the face of the reality of heavily regulated markets, as well as fundamental uncertainty on price formation, elasticities and the details of coal supply contracts. As information availability improves, this model can certainly be improved to reflect greater knowledge on these critically important dynamics.

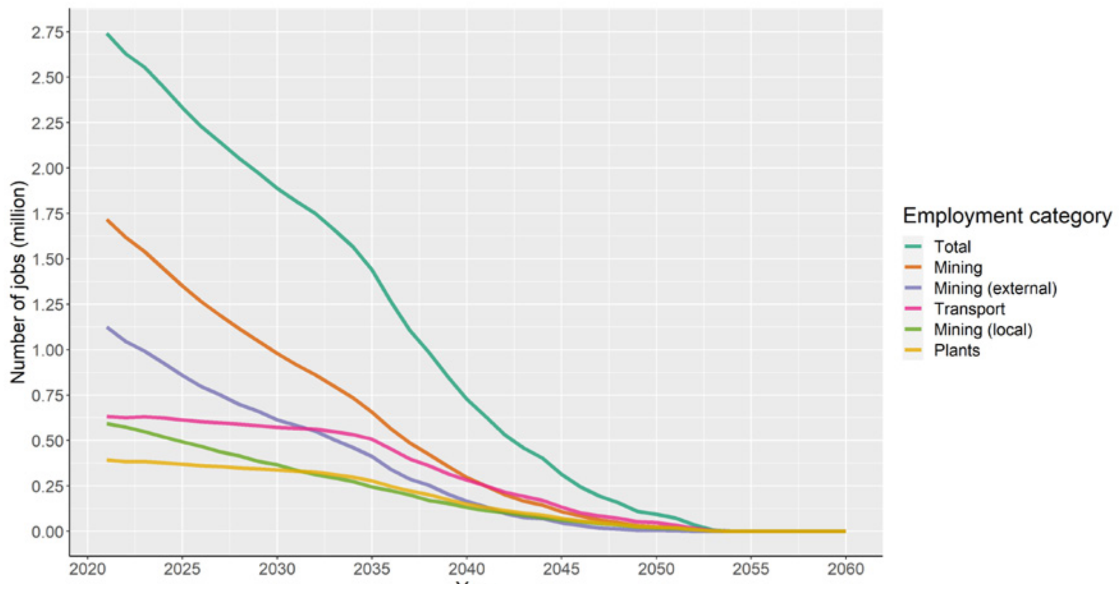
Results

We model a baseline scenario as one in which existing plants operate as planned for their 30-year lifetimes and are then retired; all currently approved plants are built (while those which are currently planned but not approved are not built); and the mining industry does not have an alternative source of demand for thermal coal.[206] These conditions result in a phase-out of coal power by the mid-2050s. Any retiring coal plants are replaced not with new coal power but with lower-cost sources of clean power.

The model is run for four other scenarios: a No Transition (NT) scenario (in which all planned plants are built and operate for their full lifetimes, regardless of approval status); and three additional scenarios reflecting more ambitious climate policies, calibrated to approximately match the coal capacity trajectories modelled by He et al. (2020).[207] The R scenario reflects greater competition from low-cost renewables, and the C50 and C80 scenarios require 50 per cent and 80 per cent reductions in emissions from coal-fired power by 2030 relative to 2015, respectively. Progressively stricter scenarios entail a greater short-term drop in coal capacity and a more rapid phase-out of the remaining fleet.

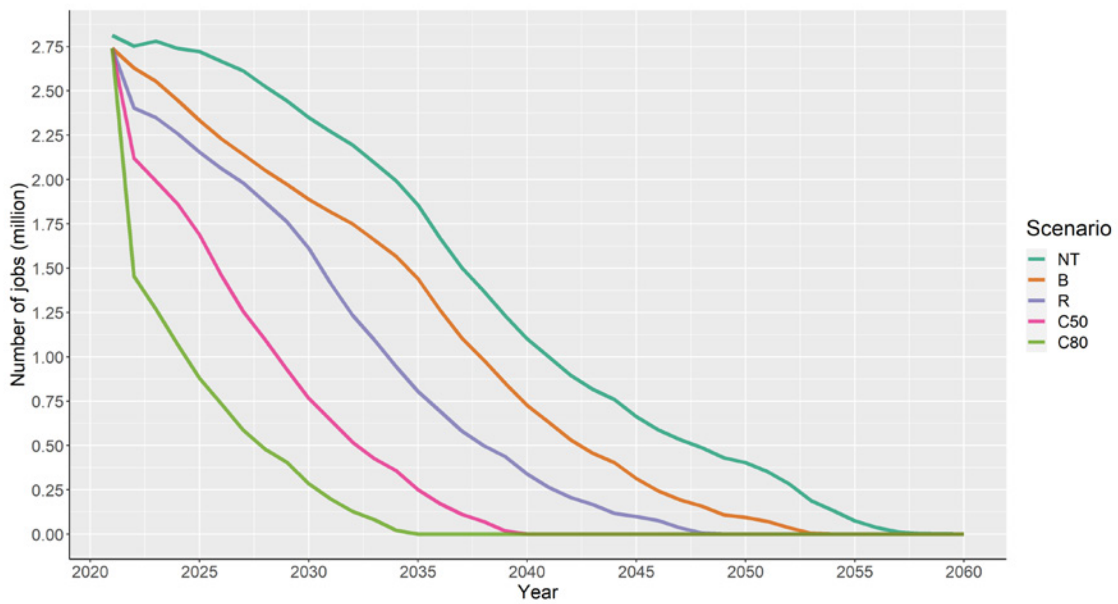
In the baseline scenario, a continuation of historical labour productivity growth trends in the coal mining sector implies jobs will be lost to efficiency in the medium term. Employment supported by thermal coal consumption declines from 2.7 million in 2021, to 1.4 million in 2035 and 94,000 in 2050. Total mining jobs are separated into those generated by coal consumption in the same province where the coal is mined ('local') and coal consumption in other provinces ('external'). Across both categories, the number of coal miners alone facing redundancy even without any changes to the existing policy baseline is projected to exceed 1.1 million by 2025 (see Figure 68).

Figure 68: Employment in thermal coal mining, power, and transport sectors under baseline scenario, 2021–2060.



As Figure 69 shows, the R scenario's impact on total employment is limited until the late 2020s, but its marginal impact over the baseline widens to 630,000 jobs in 2035, before narrowing again – with much larger gaps for C50 and C80. Conversely, a NT scenario would only protect 500,000 employees from redundancy by 2030 and employment would still fall 40 per cent by 2040, and 85 per cent by 2050.

Figure 69: Employment in the thermal coal mining, power and transport sectors under five coal phase-out scenarios, 2021-2060.



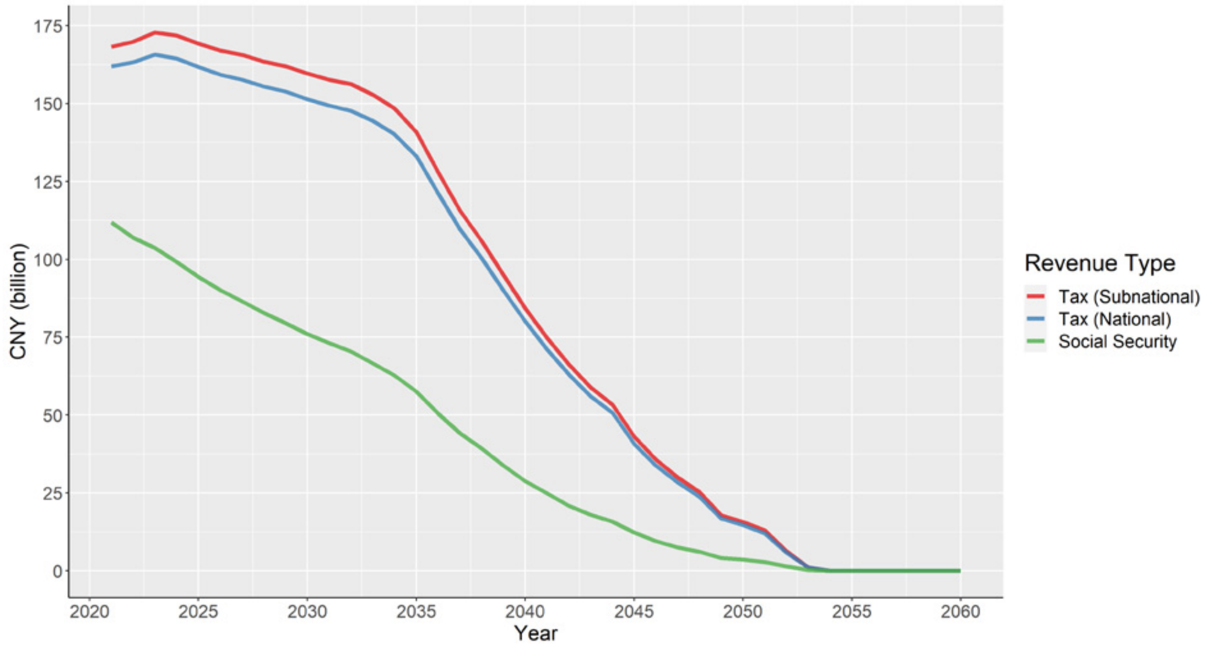
[205] Mercure, J-F. et al. (2020). Risk-Opportunity Analysis for Transformative Policy Design and Appraisal. Global Environmental Change 70: 102359.

[206] It is possible but unlikely that large-scale alternative uses for thermal coal will be found within China, assuming it continues to export only a modest share of its total coal production. This may lead to the outright closure of mines producing thermal coal exclusively, particularly those supplying specific plants. However, while many coal mines produce either thermal or coking (metallurgical) coal, some mines produce both types and may be less affected by a phase-out of thermal coal only. It remains to be seen whether China's demand for coking coal will decline at a similar rate to thermal coal or whether decarbonisation of industrial coal use will be delayed in comparison.

[207] He, G. et al. (2020). Rapid Cost Decrease of Renewables and Storage Accelerates the Decarbonization of China's power system. Nature Communications, 11(1): 1-9.

The contribution of thermal coal to tax revenues in the same scenario totals approximately CNY 300 billion annually from 2021-2030 (with an additional CNY 110 billion in social security contributions), peaking in 2023 at CNY 340 billion (see Figure 3). With total subsidies, not including greenhouse gas externalities or fully including local pollution externalities, likely to be at around CNY 480 billion annually (based on a detailed survey of the available literature on direct and indirect subsidies across the value chain modelled in the study), the thermal coal sector considered on its own is likely to already be a net fiscal drain on China's public finances.

Figure 70: Breakdown of tax (national and subnational) and social security revenues generated by thermal coal sector, 2021-2060, baseline scenario.



As coal plants begin to retire in larger numbers in the mid-2030s, fiscal revenues fall rapidly, with the annual rate of tax revenue loss rising from 1 per cent through the 2020s, to over 10 per cent by the 2040s. As assumptions for China's future policy on coal becomes stricter, losses in jobs and tax revenues are brought forward in time. Under an admittedly unlikely policy of no transition at all, in which all currently planned coal plants are built, these losses are delayed but not ultimately prevented.

Tax revenues track total coal consumption, such that the B and NT scenario see revenues peak in 2023 (CNY 339 billion) and 2027 (CYN 399 billion) respectively. The tax base remains stable up to 2030 even under the R scenario, falling by just 17 per cent through the 2020s and declining rapidly thereafter. The C50 and C80 scenarios see a similar rate of decline but brought forward 10-11 years and 15-16 years compared to the baseline, respectively. This reflects the capital intensity of the tax base: tax revenue declines are driven almost entirely by capacity retirement.

Assessing these results at the provincial level suggests that the coal-producing areas responsible for the vast majority of production, namely Inner Mongolia, Shanxi, Shaanxi and Xinjiang, will face significant challenges in managing the localised effects of expected job losses and redirecting labour supply to other productive uses. With industries dependent on coal exports, these provinces are relatively labour-efficient, but their high level of exposure to declining coal demand implies a rapid collapse in tax revenues to their respective provincial government in the 2030s unless they successfully diversify.

At the company level, coal demand from the 'Big Five' state-owned power companies supports 40 per cent of national jobs and tax revenues from thermal coal in 2021. The jobs supported by the 10 largest firms' activities nationwide – with one exception – will fall by roughly 70-85 per cent by the early 2040s, while tax revenue generated by each firm's coal consumption will fall by roughly 45-70 per cent.

Policy conclusions

This work yields at least two major policy conclusions, to be refined and tested in future research. First, millions of jobs in China's thermal coal sector are at risk in the coming decades, but failing to adopt decarbonisation policies will likely have a limited impact on the magnitude and distribution of jobs lost because most of these losses are driven by consolidation and automation. Only the most aggressive decarbonisation policy scenarios (C50 and C80) result in a significant increase in job losses, particularly in the 2020s. The prospect of large-scale job losses in the coal sector is therefore an important policy consideration, but not in itself a reason to delay low-carbon transition measures, especially in the context of expanded employment in other sectors, and cost savings resulting from a rapid transition.[208] The case study Unstoppable renewables and marginal pricing in China, India and Brazil finds that a scenario in which the transition to clean power is accelerated has more positive outcomes for employment and GDP in China than a scenario in which the transition to clean power is delayed.

Second, losses in tax revenues from declining coal sector activities are not a reason to delay the transition either, because they are very likely to be more than offset by the savings made by reducing subsidies paid to the sector, even without considering greenhouse gas externalities. However, wide variations in the net short- and long-term net fiscal impact on individual provinces make a strong case for redistributive measures to be taken by the national government. Any net fiscal savings from phasing out coal in less-exposed provinces could be used to temporarily replace losses felt by more-exposed provinces as they reposition and/or diversify their tax base, easing their path through the transition.

Looking ahead: the usefulness of a bottom-up lens

The plant-specific analysis allows the user to identify the ultimate (demand-side) drivers of employment and tax revenues from the coal sector at a high level of granularity both in terms of location and asset ownership. Accounting for flows of coal across provincial borders also allows for analysis of how demand in one province can support employment and tax revenue in another.

The model also allows for many different types of demand-side and supply-side policy to be evaluated, based on their impact on demand from individual plants or supply from individual mines. Scenarios for future coal demand can be calibrated in a number of ways, either by adjusting the lifetime of each coal plant/mine and its utilisation/production rate directly, or by simulating the effect of provincial or national policies to control emissions from the coal power sector or coal production (which, for example, may target less-efficient plants first). Similarly, the underlying assumptions and calculations for estimating employment and tax revenues associated with coal mining, transportation and use can be easily adjusted in response to new or updated information on various aspects of the coal sector value chain.

While the existing model covers only coal use in the power sector, it can also be expanded to include coal use in heavy industry (primarily for steel and cement manufacturing) and the underlying modelling approach can also be expanded to other parts of the energy sector, including non-coal power generation, and to oil and gas extraction and use (although in the latter case, there is a much greater international dimension).

This model is relatively simple in its construction and logic, and does not examine how declines in employment and tax revenues in the coal sector might be offset by gains due to substitution away from coal towards other energy sources. These questions are perhaps better answered by other modelling approaches using network analysis and input-output tables, but the microsimulation approach employed here can either be integrated into these complementary approaches or used as a means of comparing results and calibrating the dynamics of responses to external stimuli.

For example, this modelling approach can be used to identify how 'optimal' pathways for coal phase-out identified through macroeconomic modelling (e.g. based on least-cost power generation) might diverge from the results of the top-down policies that continue to play a major role in determining coal demand in China. It could also be used in dialogue with results from other models to identify where results might be unrealistic or imply unprecedented changes to the composition of the coal sector in different provinces and regions across China. Last but not least, the high-resolution nature of the analysis can also help to anticipate sources of political, economic or other resistance to change, based on vulnerable locations, entrenched interests, political-economic incentives or other factors.

[208] See Way, R. et al. (2022). Empirically Grounded Technology Forecasts and the Energy Transition. Joule, 6(9): 2057-2082. doi.https://doi.org/10.1016/j.joule.2022.08.009.

CASE STUDY:

Economic Impacts of Net Zero in India by 2070

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Policy question: What are the macro-economic impacts of achieving net zero in India by 2070?

Region: India

Method: E3ME-FTT:Power

Key finding(s): (1) Solar energy becomes a dominant technology by 2070, covering a 57 per cent share of primary energy demand, which is enabled by the electrification of many end-use technologies, (2) a transition to a net-zero economy likely leads to net-positive macroeconomic impacts for India, where the GDP could grow by an additional US$ 840bn by 2070 compared to the baseline scenario, (3) the transition towards net zero will likely lead to a decimation of jobs in the fossil fuel-related sectors, with more than 2 million jobs at risk, and (4) will support job creation in other sectors such as the power generation, construction and services sectors.

Engagement: This case-study emerged and evolved from multiple engagement activities with Indian stakeholders organised by The Energy Research Institute (TERI) over the course of the EEIST timeline.

Summary: The authors use the E3ME-FTT:Power model to explore likely future power system configurations in India, with a special interest on the combination of policies in key energy intensive sectors to achieve net zero. The model uses self-reinforcing mechanisms of technology uptake and explores the combined impacts of a range of policies, including: (i) carbon price, (ii) energy efficiency investments, (iii) biofuel blending mandates, (iv) vehicles taxes and subsidies, (v) road tax, (vi) fuel tax, (vii) EV mandates, (viii) phase-out regulations on carbon-intensive processes, (ix) investment subsidies on low-carbon processes, (x) strategic power investments, and (xi) feed-in-tariffs.

Introduction

With a growing population,[209] economy and living standards,[210] and a high dependency both on coal and on energy imports,[211] India faces many challenges to achieve its pledge of achieving net-zero emissions by 2070. Substantial emissions could be released if future demand is met via today's supply chains using today's energy systems. Reducing these emissions would be necessary to limit global warming to well below 2°C. However, climate change mitigation does not have to be a net cost and can provide opportunities for some regions, and risks to others.[212] India is a net importer of fossil fuels and in a net-zero setting its energy trade balance is likely to improve. Furthermore, a transition to net zero invokes economic activity and leads to additional jobs, replacing jobs in the fossil fuel sectors (mainly coal supply). Models can provide insights on how India could potentially achieve net zero by 2070, either from a perspective of what a good combination of technologies might be or from a perspective of what the expected outcomes of policies are. A large-scale change such as this will prove a risk to some economic agents and an opportunity to others. Those employed in fossil fuel-related industries will likely lose their jobs (e.g. coal mining) or see the nature of their employment change (e.g. vehicle manufacturing).

In this case study, we investigate a decarbonisation scenario and compare the results to the baseline using E3ME-FTT. The baseline is aligned with a 'current policies scenario'. The net zero scenario that will be presented here is but one of virtually infinite pathways India's economy can potentially undergo to achieve net zero by 2070. A key feature of E3ME-FTT is that it is not an optimisation model that assumes that economies operate at (near) equilibrium with perfect allocation of resources. Often, spare capacity can be called upon to invoke change. This can come in the form of underutilised labour force, or additional investments being made available without crowding out investments elsewhere (e.g. through loans), among others. In addition, E3ME-FTT allows for a multitude of policies beyond carbon pricing. This makes it possible to test the effects of different combinations of policies, and see which approaches are most effective in reducing emissions and contributing to positive economic outcomes.

Table 11 shows an overview of the policies implemented to achieve net zero by 2070 in India, and similar policy packages are simulated for all other regions in the world. It is unlikely that any one country will commit to such a stringent policy package without other large economies also committing to similar targets. The policy package consists of carbon-penalising policies, such as carbon prices or phase-out regulations on energy-intensive technologies, and of low-carbon promotion policies, such as subsidies. This policy package has been developed on a trial-and-error basis, since E3ME-FTT is a simulation tool. Simulation does not guarantee the desired outcome; it only presents the likely outcome. An initial version of this policy package was developed to investigate stranded fossil fuel assets due to decarbonisation and extraction strategies.[213] While numerous variations of the presented policy package are possible, past endeavours have shown that essentially all policy levers need to be used to achieve a strict target such as net zero.

[209] United Nations Department of Economic and Social Affairs, Population Division. (2022). World Population Prospects 2022: Summary of Results.
[210] OECD. (2023). Real GDP long-term forecast (indicator). doi: 10.1787/d927bc18-en (Accessed on 06 January 2023)
[211] IEA. (2020). India 2020 Energy Policy Review. IEA Energy Policy Reviews. OECD Publishing. https://doi.org/10.1787/9faa9816-en.
[212] Mercure, J. F., et al. (2021). Reframing Incentives For Climate Policy Action. Nature Energy, 6(12): 1133-1143.
[213] Mercure, J. F., et al. (2021). Reframing Incentives for Climate Policy Action. Nature Energy, 6(12): 1133-1143.

Table 11: List of policies implemented to simulate net zero by 2070 in India.

Sector(s)	Policy	Policy details
Multiple	Carbon price	Starts at US$40/tCO2 in 2024 and increases to US$325 $/tCO2 in 2070 (2022 values).
	Energy efficiency investments	Sector-specific reduction in final energy demand.
	Biofuel blending mandate	Blending e.g. bioethanol with petrol. Affects all oil-based transport applications.
Road transport	Vehicle tax	Increased registration tax on ICE vehicles from 2024 onwards.
	Vehicle subsidy	Subsidies on the purchase price of EVs from 2024 onwards.
	Road tax	Increased road tax on ICE vehicles from 2024 onwards.
	Fuel tax	Increased fuel tax on oil products from 2024 onwards.
	Phase-out regulation	Ban of ICE vehicle sales. Inefficient (older) ICE models are banned in 2024. More efficient ICE models are banned in 2040.
	EV mandate	Force manufacturers to offer a certain minimum number of EVs in their portfolio.
Power generation	Investment subsidy	From 2024 onwards, a 20 per cent subsidy on nuclear power, a 50 per cent subsidy on CCS applications and a 60 per cent subsidy on BECCS is applied.
	Phase-out regulation	Coal power is gradually phased out by 2060. Other unabated fossil-fuelled power generation is not allowed to increase from 2028 onwards.
	Strategic public investment	Strategic investments in BECCS between 2024 and 2026 to seed the system.
	Feed-in tariff	Feed-in-tariffs on wind power from 2024 to 2036 with a full phase-out by 2046.
Residential heating	Phase-out regulation	Ban on sales of fossil-fuelled domestic heating systems from 2024 onwards.
	Fuel tax	A fuel tax in line with carbon taxes.
	Investment subsidies	Subsidies on heat pumps and solar thermal from 2024 onwards.
Steelmaking	Investment subsidies	From 2024 onwards, a 10 per cent subsidy on upfront investment of CCS applications and a 50 per cent subsidy on other primary low-carbon technologies is applied.
	Energy subsidies	Hydrogen (50 per cent) and electricity (25 per cent) use are subsidised from 2024 to 2046, followed by a gradual phase-out by 2057.
	Strategic public investment	Strategic investments in hydrogen-based steelmaking from 2024 to 2032, and in electrolysis methods from 2035 to 2039 to seed the system.
Land use	Mitigation of land-use emissions (assumption-based)	Mitigation of land-use emissions include reduced emissions from agriculture, reforestation, afforestation and other land-use based measures.

Description of E3ME-FTT

Description of E3ME

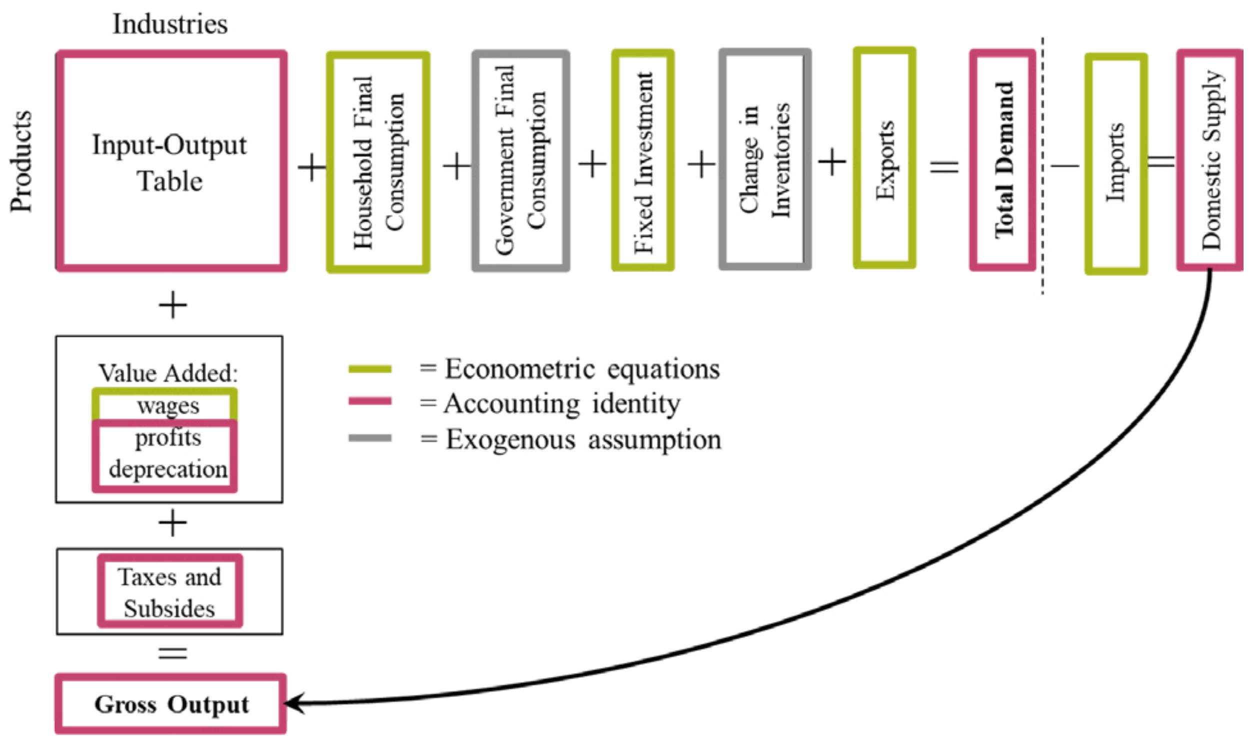
E3ME is a computer-based model of the world's economic and energy systems and the environment. Economic activity undertaken by persons, households, businesses and other groups in society has effects on other groups (possibly after a time lag) and these effects may persist into future generations. But there are many actors and the effects, both beneficial and damaging, accumulate in economic and physical stocks. A detailed description can be found on the Cambridge Econometrics website.[214]

The effects of economic transactions by economic agents are transmitted through the environment, the economy and the price and money system (via the markets for labour and commodities), as well as through global transport and information networks. The markets transmit effects in three main ways: 1) through the level of activity creating demand for inputs of materials, fuels and labour; 2) through wages and prices affecting incomes; and 3) through incomes, leading in turn to further demands for goods and services. These interdependencies suggest that an E3 model should be comprehensive and include many linkages between different parts of the economic and energy systems. Hence why E3ME was designed with a high geographical and sectoral resolution.

E3ME-FTT is a global model of 71 regions, with major economies represented individually, and distinguishes 70 economic sectors in European countries and 44 in non-European countries. E3ME is a demand-led macro-econometric model. It determines the components of demand using time-series econometrics to solve components of final demand and various other indicators. See Figure 71. The econometric parameters represent past and current behaviour in response to shocks.

The energy domain is also determined by econometric relationships and builds on some of the accounting identities displayed above, but also includes responses to endogenous innovation and energy prices. The wholesale part of non-renewable energy prices is formed via a cost-supply curve approach, which integrates an uncertainty parameter. Tax brackets are then added on top.

Figure 71: National accounts structure of E3ME.



[214] Cambridge Econometrics (2022). E3ME Model Manual. Available at: https://www.e3me.com/what/e3me/

The role of technology in the E3ME-FTT model
Understanding why and how economic agents pick technologies is important in questions surrounding decarbonisation of the economy. Time series econometric equations require a long track of history in order to simulate the future. For novel technologies, such history does not exist and therefore econometric equations are not entirely suitable to address technology-induced transitions. This is where Future Technology Transformations (FTT) comes into play. FTT is a suite of models integrated with E3ME that describes technology decision making in the most emission and energy-intensive industries, such as power generation,[215] iron and steel,[216] household heating[217] and passenger vehicles.[218] It is based on the understanding of evolutionary economics that socio-technical regimes (why something is done the way it is done) change due to internal (e.g. innovation) and external (e.g. shortages or policies) pressures, and such change is often irreversible and non-marginal. FTT incorporates uncertainty in its input parameters which represents the heterogeneous character of economic agents as well as fundamental uncertainty.

FTT determines the technology configuration to meet the demand, which is determined elsewhere in E3ME-FTT. The core builds on the Lotka-Volterra replicator function, which compares all technologies on a pair-wise basis and takes investor preferences (determined as a binary logit), technology substitution frequencies and market shares of the previous year as inputs to determine market shares of the current year.[219] It includes positive feedbacks such as learning-by-doing based on global cumulative technology capacity additions, and negative feedbacks due to sectoral constraints, such as VRE deployment in the power sector leading to supply-demand mismatches or scrap availability being limited for recycling in the iron and steel sector.

How does E3ME differ from other models?
E3ME is often compared to Computable General Equilibrium (CGE) or Discrete Stochastic General Equilibrium (DSGE) models.[220 221] In many ways the modelling approaches are similar; they are used to answer similar questions and use similar inputs and outputs. However, underlying this are important theoretical differences between the modelling approaches. Models like E3ME build upon data and try to infer economic relationships from that. Most other macro-economic or integrated assessment models (IAMs) try to build upon micro foundations and theory.

In a typical CGE or DSGE framework, optimising behaviour is assumed, output is determined by supply-side constraints and prices adjust fully so that all the available capacity is used. In E3ME the determination of output comes from the demand side of the economy and it is possible to have spare economic capacity. It is not assumed that prices always adjust to market-clearing levels.

The differences have important practical implications because they mean that, in E3ME, regulation and other policies could potentially lead to increases in output, if they are able to draw upon the available spare economic capacity. The role of the financial sector is key.

The role of finance
E3ME is a Post-Keynesian model and within this school of thought money is endogenous – i.e. it can be created by banks through, for example, lending. This approach differs from that in many other models where the supply of money is fixed.[222] A fixed supply of money implies full crowding out, whereas an endogenous supply of money does not per se imply full crowding out. E3ME is agnostic on finance. The model tracks the investment needs of a given sector as a result of the econometric relationships or the FTT outcomes, but it does not provide information on whether the demanded finance is accessible.

[215] Mercure, J. F. (2012). FTT:Power: A Global Model of the Power Sector with Induced Technological Change and Natural Resource Depletion. Energy Policy 48: 799-811.

[216] Vercoulen, P., et al. (2018). Decarbonizing the East Asian steel industry in 2050. Meijo University Discussion Paper #0008.

[217] Knobloch, F. et al. (2021). FTT: Heat – A Simulation Model for Technological Change in the European Residential Heating Sector. Energy Policy 153: 112249.

[218] Lam, A and Mercure, J-F. (2015). The Effectiveness of Policy on Consumer Choices for Private Road Passenger Transport Emissions Reductions in Six Major Economies. Environmental Research Letters, 10(6): 064008.

[219] Mercure, J. F. (2015). An Age Structured Demographic Theory of Technological Change. Journal of Evolutionary Economics, 25(4): 787-820.

[220] Mercure, J. F., et al. (2019). Modelling Innovation and The Macroeconomics of Low-Carbon Transitions: Theory, Perspectives and Practical Use. Climate Policy, 19(8): 1019-1037.

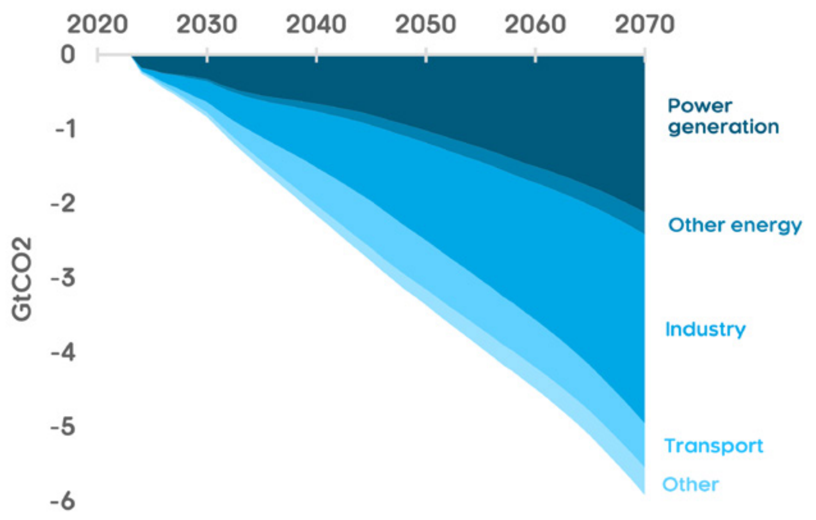
[221] Lefevre, J., et al. (2022). Global Socio-Economic and Climate Change Mitigation Scenarios Through the Lens of Structural Change. Global Environmental Change 74: 102510.

[222] Mercure, J-F and Pollitt, H. (2018). The Role of Money and the Financial Sector in Energy-Economy Models Used for Assessing Climate and Energy Policy. Climate Policy, 18(2): 184-197.

Results

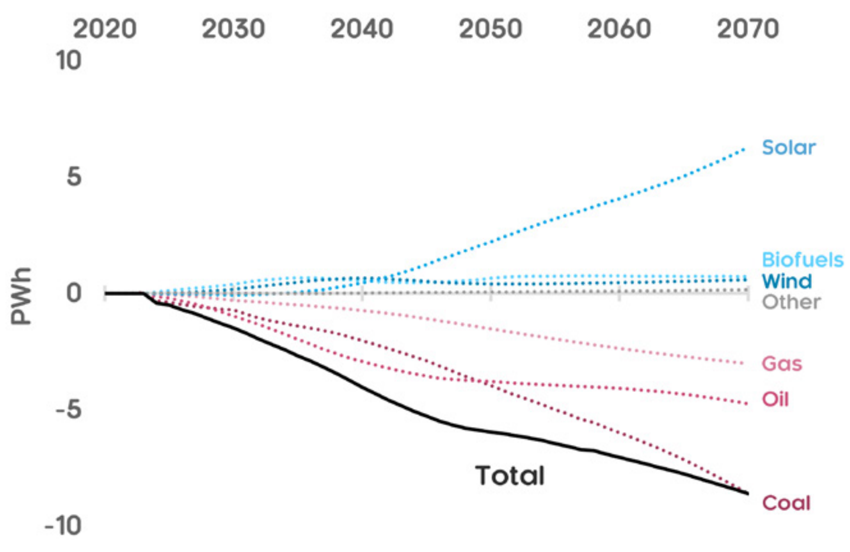
CO2 emissions
Comparing the net zero scenario to the reference scenario (in line with current policies), a reduction of 5.9 Gt CO2 of energy and process-related emissions was found by 2070, amounting to a cumulative reduction in emissions of 141 Gt CO2 between 2020 and 2070. In percentage terms, this is a reduction of 91 per cent compared to the baseline, which leaves a residual of 0.5 Gt CO2 annual emissions by 2070, which is assumed to be offset via mitigation of land-use emissions (see Figure 72). Most of the reductions are achieved in power generation and industry, with smaller contributions from the transport and household sectors. The former two sectors rely on to a substantial degree on fossil fuels in the baseline scenario, which is removed due to technology switching as a result of the policy package. While the net zero scenario features an almost complete decarbonisation of the road transport sector by 2050, the baseline also features a more partial decarbonisation, particularly from 2045. The differences in CO2 outcomes between the net zero scenario and the base case are therefore somewhat limited in the transport sector. The household sector is almost completely decarbonised in the net zero scenario by 2070. But household emission levels are low in the baseline as well, as the majority of households switch from biofuel-based heating to low-carbon alternatives. In the net zero scenario, a portion of heating based on liquid petroleum gas (LPG) is replaced by clean technologies, contributing a small reduction in CO2 emissions.

Figure 72: Energy and process-related CO_2 emissions, absolute differences from baseline, 2020-2070, $GtCO_2$.



Primary energy demand
The policy package removes most of the reliance on fossil fuels and this is illustrated by the changes in primary energy demand between the net zero scenario and the baseline (see Figure 73). Total primary energy demand falls by 8.6 PWh relative to the baseline by 2070 (a 24 per cent decrease), as businesses and consumers invest in energy efficiency measures, and switch to more energy-efficient technologies (such as electric vehicles). Coal- and oil-based primary energy production is replaced mostly by solar power, which is enabled by the electrification of many end-use technologies. This includes electrification of the road transport sector, with oil use from internal combustion engine vehicles mostly disappearing by 2050. Strong declines in oil use are also seen in the power generation and industrial sectors. Coal use sees strong declines across a range of heavy industries, including power generation, steelmaking and non-metallic minerals. Declines in gas demand are driven through reduced uptake of LPG as an energy source in households, as well as lower use of natural gas in industrial applications. Solar energy becomes a dominant technology by 2070, with a 57 per cent share of primary energy demand. Much remaining fossil fuel demand is for non-energy use, or for applications with carbon capture technology built in.

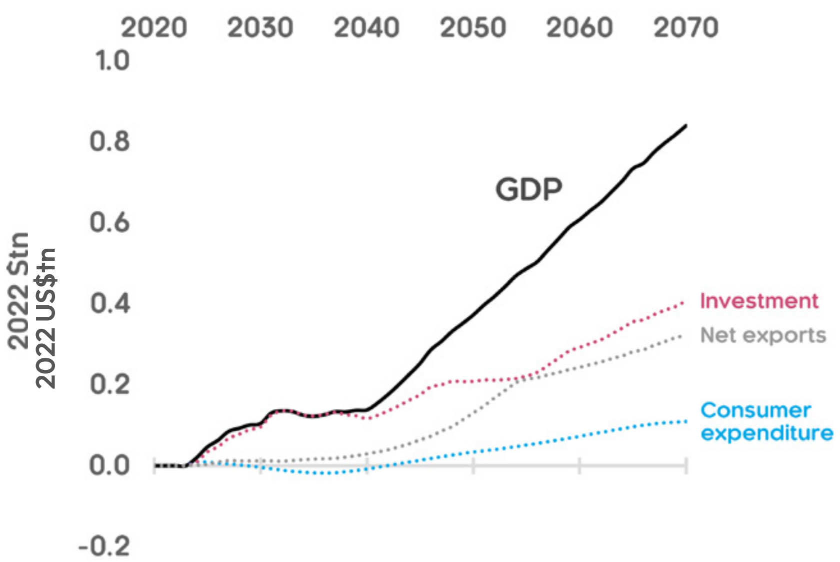
Figure 73: Primary energy demand by carrier, absolute differences from baseline, 2020-2070, PWh.



GDP and components

Our modelling suggests that a transition to a net-zero economy likely leads to net-positive macroeconomic impacts for India. GDP could grow by an additional US$840bn by 2070 compared to the baseline (see Figure 74). This represents a 2.5 per cent increase. Much of this additional demand is driven by investments in low-carbon technologies and energy-efficiency measures, which creates economic activity in construction and electrical engineering, and which dominates between 2024 and 2040. Afterwards, there is also a substantial gain from the reshoring of energy production. As various energy users switch to electrical technologies, output in the domestic power-generation sector increases substantially, leading to a lower reliance on imported fossil fuels, which improves the trade balance. A smaller impact can be seen from the effect of the transition on consumer expenditure. Employment gains from increased output in a number of sectors (see below) contribute to an increase in real incomes and consumption. Similarly, households apply more efficient technologies, which reduces energy bills and unlocks spending in other goods and services.

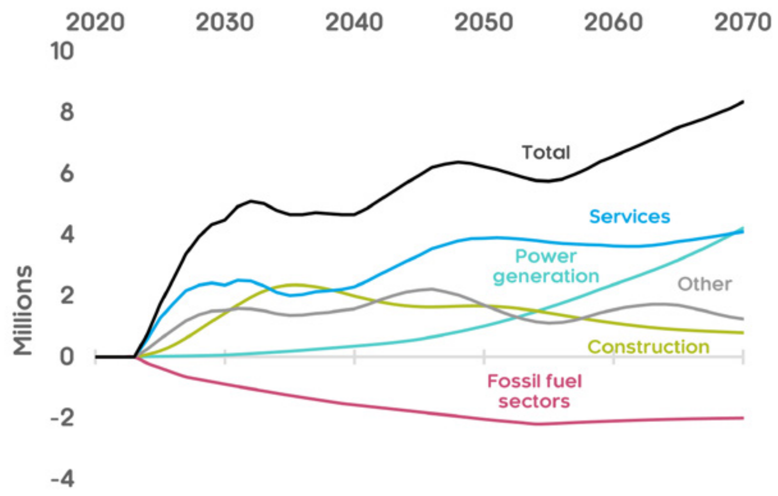
Figure 74: GDP and components, absolute differences from baseline, 2020-2070, 2022 US$tn.



Employment

While the GDP results indicate mostly positive impacts, the simulations do show that not everyone stands to gain. A transition away from fossil fuels – particularly coal – will likely lead to a decimation of jobs in the fossil fuel-related sectors, including extractive and refining sectors. More than 2 million jobs are at risk. These jobs could be at risk due to automation regardless of mitigation policies, as might be the case for China.[223] However, these job losses are compensated by job creation in other sectors. Much of this employment would be concentrated in the power-generation sector, as energy production is reshored into India's economy. There is also a strong boost to employment in construction, particularly in the early and middle part of the scenario period, as the building and renovation work required to deliver the transition gets underway. Increasing employment in these sectors boosts incomes of consumers, and their additional consumption is concentrated on services sectors, which then also see output and employment increase. Overall, our modelling results suggest that India's aggregate employment would see an 8.4m boost by 2070 as a result of the clean energy transition – a 1.6 per cent increase on baseline levels.

Figure 75: Job, absolute differences from baseline, 2022-2070, millions.



Discussion and conclusion

First and foremost, no single model tells a complete picture. A few important aspects are missing in these simulations. First, skills are not tracked and therefore it is implied that jobs are interchangeable. This will unlikely be the case, and reskilling of those that lose their job in fossil fuel-related jobs would be necessary. Second, the supply of money is endogenous in E3ME-FTT. However, it is agnostic on the source of investments (e.g. loans, foreign investment, accumulated savings or wealth, etc). Here, the investments to facilitate this transition are assumed to be available. Therefore, the additional investments shown in the net zero scenario should be interpreted as the investments needed to achieve the transition described above. Third, increased carbon sequestration or reduced emissions from land use is assumed. At the moment, the model does not include a representation of land use. Fourth, climate and pollution damages are not accounted for in any scenario. The likely reduction in climate and pollution damages provide another benefit to decarbonisation that is often overlooked, and – admittedly – difficult to estimate.

Despite these model limitations, we deem it to be likely that many opportunities lie ahead for India on the road to net zero by 2070. The transition provides opportunities of improving India's energy security position, a more efficient energy supply system overall, large-scale net job creation, and – most importantly – large-scale reduction in emissions. It is important to note that the rest of the world also enacts policies to decarbonise, which contributes to making low-carbon technologies more accessible due to a global push.

In this representation of net zero, we found that important technology transitions are found in the power sector towards solar PV, onshore wind power and some bio-based power generation. Road transportation transitions to electric power trains, and domestic heating switches away from biobased and LPG-consuming units to solar thermal and various electric forms of heating. In the iron and steel industry, we find a large-scale transition to steel recycling and hydrogen-based steelmaking. All these transitions lead to supply-side efficiency gains, leading to a reduction in primary energy demand.

[223] Clark, A. and Zhang, W. (2022). Estimating the Employment and Fiscal Consequences of Thermal Coal Phase-Out in China. Energies 15(3): 800. https://doi.org/10.3390/en15030800 (Note, this work is presented in this report in the case study on the coal transition in China).

CASE STUDY:

Decarbonising the Indian Economy: Policies and impacts

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Policy question: What are the most impactful policy combinations to decarbonise the Indian economy over the next three decades? What are the likely implications of enacting these policies on economic growth and employment?

Region: India

Method: System dynamics model

Key finding(s): Decarbonisation of the Indian economy is possible by focusing a range of policies on decarbonising the power, transport and industrial sectors, while creating net savings in costs and achieving better economic growth and employment outcomes.

Engagement: The decarbonisation scenario underlying this case study has been developed and refined in consultation with sectoral experts from industry, think tanks, academia, funding partners and a few members of the policymaking community. Key findings and insights from the analysis have been presented and discussed at platforms including the research collaborative for a proposed Global Climate Alliance (GCA)[224] and working groups set up by the Indian Ministry of Road Transport and Highways and the National Insititute for Transforming India (NITI Aayog) under the India Climate and Energy Modelling Forum (ICEMF).[225]

Summary: The authors use a system dynamics model to consider what policy combinations might be needed to decarbonise the Indian economy, and what the impacts of these might be on growth and employment. The authors suggest the model allows a more realistic representation of the interaction between policies and the economy, and they find that decarbonisation of the Indian economy is possible while creating net savings in costs and achieving better economic growth and employment outcomes.

[224] The Global Climate Alliance (GCA) Collaborative is an independent research effort to evaluate how Global South countries can best secure the support of Global North countries to address the economy-wide impacts of climate change, including both adaptation and mitigation measures. Over the past two years, several academic institutions and think tanks have been collaborating on these issues and pooling their individual research efforts.

[225] India Climate and Energy Modelling Forum (ICEMF) is a platform for leading energy experts, think tanks, researchers, modellers and policymakers to collaborate and examine important climate, energy and environment-related issues, including their economic linkages, through integrated modelling exercises.

Introduction

India announced its goal to reach net zero emissions by 2070 at the 26th Conference of Parties (COP-26) in November 2021.[226] Charting a low-carbon development pathway for the country that meets the aspirations of its people, such as reliable access to adequate energy, will require a deep structural transformation of the Indian economy, which relies on fossil fuels for around three-fourths of its total energy needs at present.[227]

To design effective policy packages that meet India's decarbonisation and development objectives, an evaluation of the different policy options in isolation is not sufficient; it also requires policymakers to understand the potential relationships between policy options across different sectors and the economy, and how such interactions affect the achievement of policy objectives.

Analytical framework

The India Energy Policy Simulator (EPS),[228] an open-source, systems dynamics (SD) model, can provide such insight to inform policymaking by enabling an integrated assessment of cross-sectoral climate policy packages for India through 2050, along with their macroeconomic implications.

The policy options in the EPS span the main sectors of the economy: transportation, buildings, electricity supply, industry (including agriculture, waste, and wastewater), land use and hydrogen. Policy options included cover both pricing policies (e.g. taxes and subsidies) as well as mandates (e.g. for technology adoption or retirement). The structure, modelling approach, underlying data sources and assumptions of the India EPS are explained in a technical note available online.[229]

The main strengths of the modelling approach of the EPS, compared to those that have been used for climate policy analysis in India so far, include the following:

- The SD approach of the EPS can offer a more realistic representation of the dynamic interaction between policies and the economy compared to existing modelling approaches (most use a computational general equilibrium or partial equilibrium approach), giving rise to overall effects that are different from the sum of the effects of enacting individual policies. For example, the EPS calculates technology costs based on a combination of projected global prices and endogenous learning to account for the effects of local technology diffusion. This means a mandate or a subsidy to promote the uptake of a technology can create a reinforcing loop, whereby increased uptake of a technology due to a policy further brings down technology prices, which in turn accelerates its uptake.
- The cross-sectoral policy analysis enabled by the economy-wide coverage of the EPS can enable users to discover synergies and trade-offs in policy implementation across different sectors. For example, policies to decarbonise electricity supply failing to keep pace with end-use electrification policies preclude the latter from achieving their mitigation potential, and in extreme cases can result in an emissions penalty.
- The EPS includes an integrated input-output model, which calculates the impact of climate policies enacted in a scenario on macroeconomic parameters, such as GDP, employment and government accounts, considering direct, indirect and induced economic effects of the enacted policies. These are not outputs typically available in models presently used for climate policy analysis in India, and literature on the potential macroeconomic implications of climate action in India is limited. However, this is a particularly relevant component of analysis for Indian policymakers, for whom economic development is a key policy objective.

Some of the main limitations of the EPS are as follows:

- It simulates policies at an aggregate spatial (national) and temporal (annual) scale. Model outputs are available at an aggregate level and do not allow for the assessment of how effects of enacted policies – for example impacts on jobs and GDP – are distributed across regions or population groups, such as by income, gender or age.
- Indirect and induced economic impacts in the model are calculated based on transaction relationships between industries in the economy per India's input-output (I/O) tables as of 2015, which are assumed to hold over time.
- It is presently not possible to quantify the uncertainty in the model.

[226] https://pib.gov.in/PressReleasePage.aspx?PRID=1768712

[227] https://www.iea.org/reports/india-energy-outlook-2021/energy-in-india-today

[228] https://india.energypolicy.solutions/scenarios/home

[229] https://www.wri.org/research/tool-designing-policy-packages-indias-climate-targets

Our analysis

We used the India EPS to analyse a policy package focusing on the power, industry and transport sectors, which would put India on course to reach net-zero CO2 emissions by 2070. Our policy package, henceforth referred to as the Long-term Decarbonisation (LTD) Scenario, builds upon existing policy targets for renewable energy, energy efficiency and electric mobility in the short term and considers the policy-supported phase-in of currently nascent technologies, such as hydrogen and battery storage, in the medium-term, to reach ambitious levels of implementation by 2050. The choice of the policies modelled in this scenario is guided by three main criteria: a) their alignment with current policies and targets in India and the emerging conversation around policies to support new green technologies like hydrogen, b) the relative effectiveness of a policy (when compared to other policy options available in the model) in contributing to greenhouse gas emissions abatement, and c) their impact on macroeconomic indicators – i.e., government accounts, GDP and jobs.

We present our results relative to a Reference Scenario, which incorporates the impact of existing policies, as of 2019.

The level of ambition for the policy settings and the rate of policy implementation in the LTD scenario is decided based on a combination of factors, including the existing level of achievement in the Reference Scenario, review of literature to identify the technical potential achievable for the technologies modelled within the policies, and preliminary consultations with sectoral experts on policy feasibility, given on-the-ground implementation challenges in India.

Our approach is to construct a forward-looking, or 'what-if', scenario aimed at evaluating the plausible outcomes of a given set of policy actions, rather than providing a set of 'optimal' policy actions. There are several alternative combinations of actions that may reach the same level of emissions in future, each with their own implications for other outputs such as costs, social benefits and economic impacts.

The specific questions of policy interest for our analysis were the following:

- What are the most impactful policies/policy combinations to decarbonise the Indian economy over the next three decades?
- What are the likely implications of enacting these policies for investment, economic growth and employment?

Results

The Reference Scenario sees India's total emissions approximately double over the next three decades – emissions rise from just over 3 billion tonnes of carbon dioxide equivalent (BtCO2e) in 2022 to around 6 BtCO2e in 2050. Emissions rise despite a 61 per cent improvement in emissions per unit of GDP over this period, driven by economic growth and urbanisation.

The fastest growth in emissions is seen in the industrial and transport sectors – emissions approximately triple by 2050 compared to the present in both sectors. Power sector emissions, in contrast, do not increase significantly from present levels, owing to India's renewable energy targets and falling technology costs, which are considered within the Reference Scenario. In 2050, the industrial sector comprises almost 50 per cent of the total emissions, followed by power (18 per cent) and transport (16 per cent).

Key policy levers for decarbonisation

Policies in the LTD scenario are primarily focused on decarbonising three sectors – namely, the industry and transport sectors, because of the rapid growth in emissions in the Reference Scenario, and the power sector, because green electricity is a prerequisite for the success of end-use electrification policies and green hydrogen production.

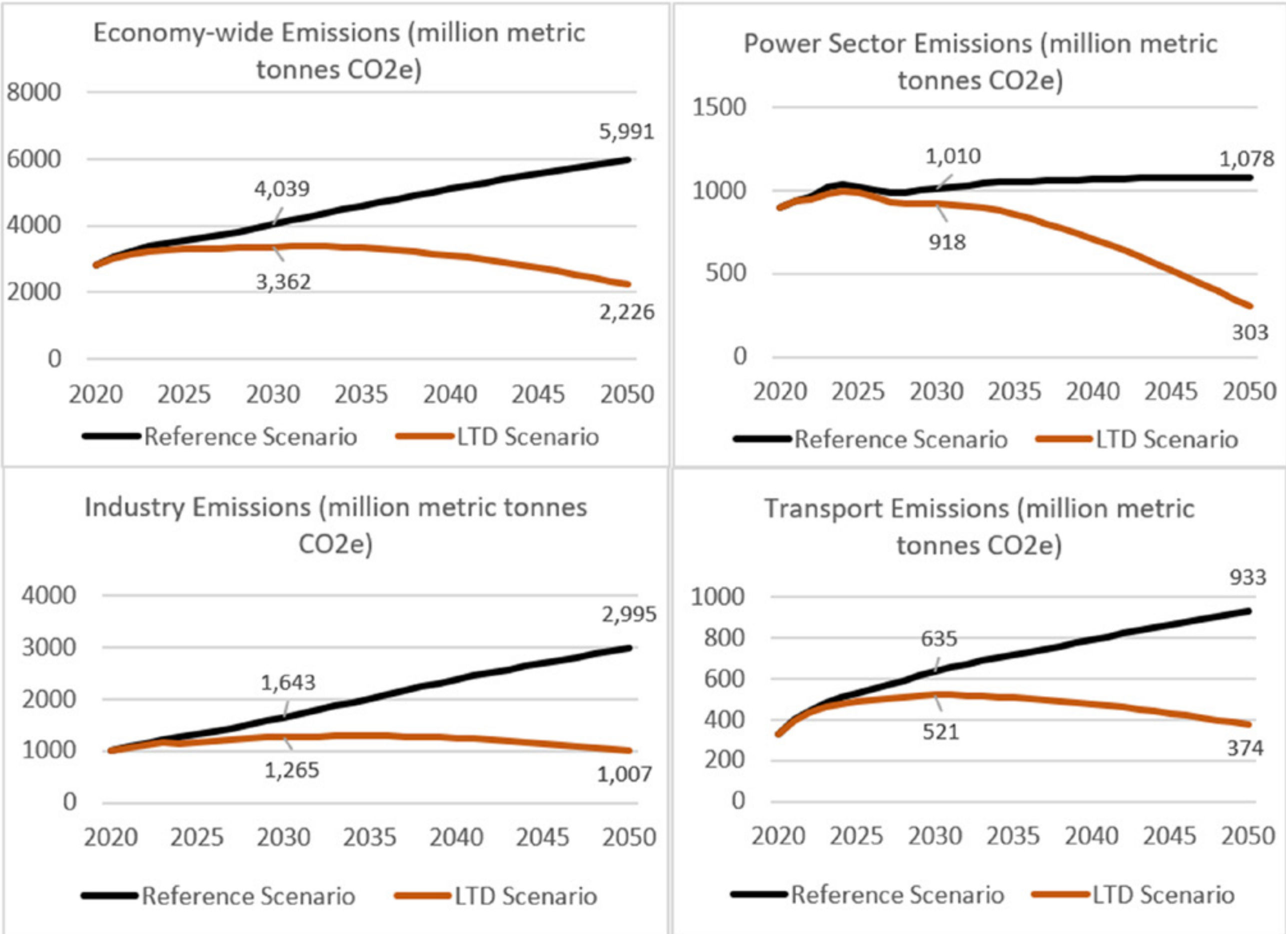
Policies (and their level of ambition) are chosen by applying the criteria mentioned in the previous section. For example, the mandates for clean electricity generation and electric vehicle adoption build on existing policy targets for renewable energy and electric mobility. Mandates for electrification and hydrogen adoption in the industry are chosen due to the high emissions abatement potential of underlying technologies, based on preliminary consultations with sectoral experts. A carbon tax is primarily chosen as a means to raise public revenue during the transition, although it also plays a complementary role in supporting decarbonisation mandates. The key policy assumptions of the LTD scenario are summarised in Table 12.

Table 12: Key policy levers in the LTD Scenario. *Unless otherwise noted, the policy is linearly implemented starting from 2020 to reach the full policy setting in 2050.

Policy	Reference Scenario (2050)	LTD Scenario (2050)*
Industrial electrification & hydrogen mandate (% Substitution of fossil fuels in industrial sector. Linearly increasing from 0 in 2030)	0	50%
Hydrogen production via electrolysis mandate (Linearly increasing from 0 in 2025)	0	100%
Carbon tax (per tonne of CO2e) (In the power and industry sectors)	0	INR 3500 (USD 50)
EV/hydrogen sales mandate (% of new vehicle sales) Passenger LDV, Passenger HDV Freight LDV, Freight HDV 2W, 3W (H2V sales mandate starting from 2030)	 35%, 23% 14%, 4% 38%, 30%	 80%, 50% (+25% H2V) 70%, 25% (+45% H2V) 100%, 100%
Material efficiency mandate (Demand reduction for emissions intensive goods w.r.t. Reference Scenario)	-	Cement: 15% Iron & steel: 20%
Carbon-free electricity generation mandate (mandated minimum %)	68%	93% (75%)
Early retirement mandate for coal power (linearly increasing from 300MW/year in 2027)	-	7 GW/year

The policies in the LTD scenario reduce Reference Scenario emissions by about a fifth in 2030 and two-thirds in 2050. In cumulative terms, the emissions reduced over the period 2020-2050 relative to the Reference Scenario amount to just over 46 $BtCO_2e$. Figure 76 shows the economy-wide and sectoral emissions trajectories for the two scenarios over this period.

Figure 76: Comparison of greenhouse gas emissions in Reference and LTD scenarios.



In the power sector, the proportion of carbon-free electricity generation reaches close to 50 per cent by 2030 and over 90 per cent by 2050 (compared to slightly less than 25 per cent at present) because of mandates for carbon-free electricity generation and early retirement of coal power. The reduction in the cost of renewable energy (RE) due to technology diffusion, initially a result of these mandates, in turn drives further RE capacity addition, which further reduces costs. Thus, a positive reinforcing effect is created for RE technology uptake, and the carbon-free electricity generation exceeds the policy mandated requirement over time. This is complemented by a carbon tax, which makes fossil-fuel based electricity more expensive at the same time. Coupled with the increasing cost-competitiveness of RE relative to fossil fuels, power sector policies together result in no new coal capacity additions after 2024.

The rapid decarbonisation of the power sector supports mandates for fossil fuel substitution with electricity and/or green hydrogen in the industry and transport sectors in achieving their emissions mitigation potential. These fuel-switching mandates, phased in from 2025 or 2030, serve as the main policy levers for decarbonising the industry and transport sectors in the long term, while energy-efficiency policies play a role in the short term. These mandates are complemented by the carbon tax, like in the power sector. However, unlike in the power sector, this policy combination does not achieve a cost tipping point in the industry and transport sectors due to a more gradual implementation of the mandates and a greater difference in brown and green technology costs in these sectors. Nevertheless, significantly higher shares of electricity and hydrogen are achieved in the overall industrial and transport energy mix as a result of these policies, compared to the Reference Scenario (see Table 13).

Table 13: Share of electricity and hydrogen in industrial and transport energy mix over time.

	Industrial Energy Mix				Transport Energy Mix			
	Share of Electricity		Share of Hydrogen		Share of Electricity		Share of Hydrogen	
Year	Reference Scenario	LTD Scenario	Reference Scenario	LTD Scenario	Reference Scenario	LTD Scenario	Reference Scenario	LTD Scenario
Present	13%		0%		1.5%		0%	
2030	16%	20%	0%	2%	3%	6%	0%	0%
2050	16%	40%	0%	18%	9%	29%	0%	7%

Economic outcomes

We find that long-term decarbonisation of the Indian economy is possible while creating net cost savings across the economy over time, and achieving better economic growth and employment outcomes, relative to the Reference Scenario.

The transition to green technologies requires additional capital expenditure over the Reference Scenario. The additional annual capital expenditure amounts to around US$28bn (2018) (~0.5 per cent of GDP) in 2030, and rises constantly thereafter as RE infrastructure, EVs, battery storage and green hydrogen production is ramped up, to reach US$247bn (~1.5 per cent of GDP) in 2050. While the scale of upfront capital investments can present challenges in terms of financing, we see that the reduction in fuel and operations and maintenance costs across the economy from the uptake of green technologies outweighs the upfront capital costs over time, creating net savings in the long run starting in the decade of the 2040s.

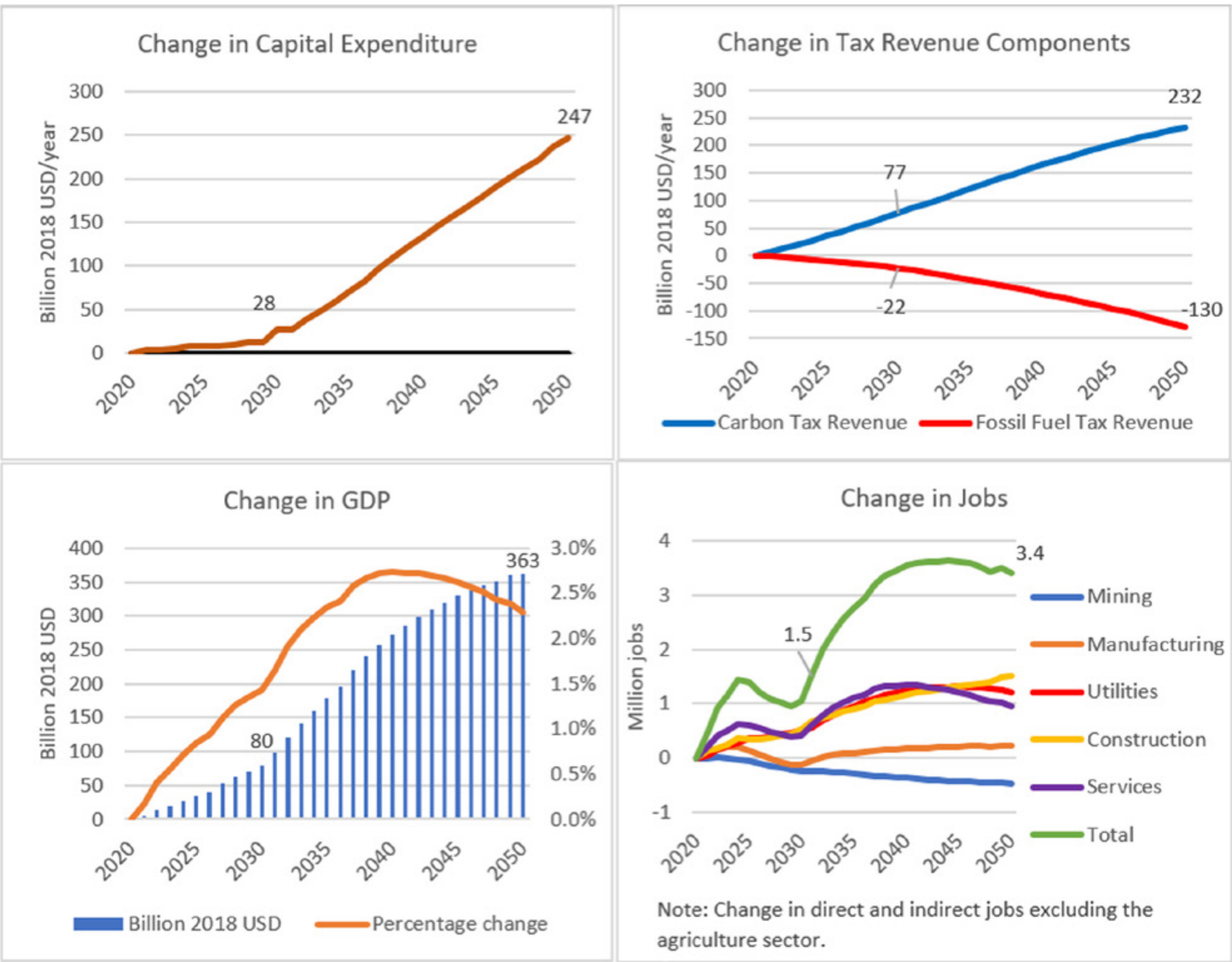
The transition away from fossil fuels results in a contraction of brown sectors such as coal mining, petroleum refining and manufacturing for internal combustion engine vehicles. Moreover, a reduction in the use of petroleum products, which contribute over 25 per cent of the central government's total tax revenue at present, can significantly dent overall tax collection and aggravate the economic contraction by constraining government spending. Government spending on basic services such as education and healthcare has a multiplier effect on economic growth by improving productivity. However, we find a carbon tax (increased in a phased manner over time) has the potential to offset the loss in petroleum taxes during the transition by widening the tax base to all emissions-causing uses of fossil fuels, including industrial process emissions.

Productive public expenditure sustained by carbon tax revenues, together with growth in industries like clean electricity generation and hydrogen production, more than compensates for the contraction in brown sectors in the LTD scenario. Overall, the policy package in the LTD scenario delivers a GDP that is 2.3 per cent higher and generates 3.4 million more jobs by 2050, relative to the Reference Scenario.[230] The drivers for economic growth and employment are supply-side effects – while the overall demand for energy and materials reduces as a result of efficiency improvements, investments to decarbonise supply (along with associated indirect and induced effects) drive growth.[231] Figure 2 shows the macroeconomic outcomes of the LTD scenario relative to the Reference Scenario.

[230] These include direct jobs (created due to enacted climate policies) and indirect jobs (created within industries that supply to directly affected industries). The agriculture sector is excluded from the jobs estimates presented here.

[231] Indirect effects refer to changes in output or employment of sectors that supply the sector directly affected by a policy. Induced effects are created by changes in re-spending of money by workers or government in the economy as a result of direct and indirect effects.

Figure 77: Macroeconomic outcomes in the LTD Scenario, relative to the Reference Scenario.



Conclusion

Our policy package in the LTD Scenario primarily relies on early policy signals (e.g. mandates for renewable energy, electric mobility, and industrial fuels) to spur private investment in green technologies and, in turn, the reinforcing effect of falling technology costs from their uptake to accelerate further green technology adoption. A carbon tax serves as a complementary policy in this context by further reducing the cost of using green technologies relative to brown ones. In our policy package, the carbon tax also serves to offset the loss in public revenue from declining petroleum tax collections, thereby mitigating the negative impact on economic activity due to a cut in productive government spending. However, a carbon pricing policy can have a significant effect on essential commodity prices in the short run and be ineffective as a tool to raise public revenue in the long run, as fossil fuel use is eliminated from the economy. This underscores the need for careful design, including an evaluation of alternative sources of public revenue.

There are several policy types which we have not explored or have not been able to explore in our policy package, which can be critical for policymakers to evaluate and consider as India moves towards a low-carbon future. While we do not rely on subsidies in our policy package due to their implication for government accounts, technology-specific subsidies can serve as an important complementary policy in accelerating the adoption of nascent green technologies, such as offshore wind, hydrogen and battery storage, by creating cost tipping points for these technologies, in combination with other policies. A similar complementary policy, which is outside the purview of our policy package, is the creation of public infrastructure, such as EV charging stations and hydrogen distribution networks, to encourage the adoption of green technologies by consumers and industry.

Finally, to ensure that the low-carbon transition is also one that is sustainable and just, redistributive policies are a must to evaluate and include in any policy package to ensure that the costs and benefits of the transition are equitably distributed across all sections of society.

CASE STUDY:

Data-Driven Systems Mapping of SDGs and Energy Transition Interactions

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Policy question: What risks and opportunities for sustainable development goals (SDGs) will the energy transition create, and how might we manage these?

Region: Brazil

Method: A data-driven approach to systems mapping.

Key finding: Wind energy is relatively well-connected with Brazil's SDG and economic indicators, interacting with outcomes in the health, water and sanitation sectors, as well as having more intuitive connections to emissions and access to electricity. There is also some evidence of an underexplored connection between wind energy and biofuels. Conversely, solar energy production has a more distant connection with SDG and economic indicators, suggesting there is less evidence of strong synergies or trade-offs between solar and other objectives. Future work will look more closely at these relationships.

Engagement: This work has been presented to the EEIST Brazilian community of practice, but full engagement has not begun yet. The modelling work is ongoing and the core engagement work is planned for the next stage of development. This will involve presenting the full maps and analysis, focused on trade-offs and synergies between the transition and SDGs, to policy stakeholders as a basis for discussion of how more tailored analysis could be developed and used.

Summary: The authors use a data model to consider more general development implications of increasing the role of renewables in Brazil's energy sector. The main objective of the study is to explore synergies and trade-offs between diversifying renewable energy and other dimensions of sustainable development so that policymakers can consider how to leverage synergies and tackle bottlenecks to achieve the country's SDGs. The study uses a data-driven systems mapping approach that combines data-based network estimation methods, standard network analysis and subjective map analysis, allowing for quantitative and qualitative representations of the broader systems in which renewable energy policies are embedded, which in turn can inform high-level decision making and cross-sectoral policy coordination.

Introduction

What risks and opportunities for the SDGs will the energy transition create, and how might we manage these? In this case study, we take a step back from narrowly focused simulation models and consider how the energy transition might be interacting with a broader set of objectives, represented by the SDGs. We use a data-driven systems mapping approach to explore the interactions between SDG, economic and energy transition indicators in Brazil. Specifically, we use country-level, time-series data to estimate networks of SDG, economic and energy transition indicators (our maps) and then analyse the resulting maps using subjective map and sub-map analysis to complement standard network metrics.

We focus on the interactions between the SDGs and the expansion of wind energy; and motivated by an initial set of results that suggests a link between wind energy and biofuels, we iterate to study further biofuels, with a focus on sugarcane. Nonetheless, the analysis using these types of maps is flexible, so more focused policy analysis, or contextualisation of other modelling results or advice, is also possible, as demonstrated in the ongoing EEIST sub-project on which this case study is based.[232]

The Sustainable Development Goals: a systems approach to policy

The 2030 Agenda for Sustainable Development, with 17 SDGs, was adopted by the United Nations General Assembly in 2015. For each goal, there are between five and 19 targets, and between six and 28 indicators. The 2030 Agenda envisioned the integration of economic, social and environmental development goals as components of an interlinked system, rather than individual targets. Applied academic work has reflected this systems approach to policy, and there is a fast-emerging literature on SDG interactions,[233] with many approaches conceptualising the interactions as networks of SDG indicators, as we do here. Moreover, with the 2030 deadline approaching and many countries falling behind on several goals, better understanding SDG interactions has become a key policy issue as synergies need to be leveraged and trade-offs tackled.

Interactions between the energy transition and SDGs have been considered. Nerini et al (2017)[234] summarise synergies and trade-offs between SDG7 (Energy) and non-energy SDGs based on expert elicitation. Similarly, McCollum et al. (2018)[235] map synergies and trade-offs between energy and other SDGs, but based on a large-scale, systematic review of the energy literature. The most recent IPCC Working Group III report summarises an assessment of the literature on the interaction between the SDGs and climate change mitigation options, including the energy transition.[236]

Energy transition and the SDGs in Brazil

In Brazil, the share of renewables in the energy supply matrix has been historically high (between 39 per cent and 58 per cent since 1970) and significantly higher than the world average (46 per cent versus 14 per cent in 2019).[237] However, given the environmental costs and climate exposure associated with further expanding hydropower from its current levels, wind and solar energy have gained relevance in the last 10 years as a means to diversify the production of renewable energy.

Within this context, currently, affordable and clean energy (SDG 7) is the only SDG achieved and maintained in Brazil. Others on track for achievement, but with challenges remaining, are Climate Action, Clean Water and Sanitation, and Quality Education.[238] In all other dimensions, the performance is less promising, so better understanding how Brazil's advantage in clean energy and the recent diversification of renewables in the energy matrix interact with other dimensions of sustainable development could inform key policies aiming at SDG achievement.

[232] Barbrook-Johnson, P. and Senra de Moura, F. (2022) Using Data-Driven Systems Mapping to Contextualise Complexity Economics Insights. INET Oxford working paper, https://www.inet.ox.ac.uk/publications.

[233] Breuer, A. et al. (2019). Translating Sustainable Development Goal (SDG) Interdependencies into Policy Advice. Sustainability 11(7); Bennich, T. et al. (2020). Deciphering the Scientific Literature on SDG Interactions: A Review and Reading Guide. Science of The Total Environment 728, 138405.

[234] Fuso Nerini, F. et al. (2018). Mapping Synergies and Trade-Offs Between Energy and the Sustainable Development Goals. Nature Energy 3, 10-15.

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[227] Empresa de Pesquisa Energética. (2022). Brazilian Energy Balance 2022: Year 2021. Empresa de Pesquisa Energética, Rio de Janeiro; Empresa de Pesquisa Energética (Brasil) (2022) Power matrix and electrical matrix. ABCDEnergia Blog. Available at: https://www.epe.gov.br/sites-pt/abcdenergia/Paginas/MATRIZ-ENERGETICA.aspx.

[238] Sachs, J. et al. (2022). Sustainable Development Report 2022, Cambridge University Press, Cambridge.iopscience.iop.org/article/10.1088/1748-9326/aaafe3.

The data-driven systems mapping approach

Bringing data into systems mapping

We use a novel data-driven systems mapping approach designed to allow us to explore broad interactions across different domains in a system, and to contextualise, communicate and embed the insights of new economic thinking in real-world policy questions. In a typical systems mapping exercise the main goal is to determine, often in a participatory fashion, the system's key factors and the links between them.[239] The core outputs are a mapping process and a corresponding map representing a comprehensive and shared vision of the forces at work, which in turn can be used as a framing and discussion tool in policy design, appraisal and evaluation.

Our key methodological contribution is to provide an approach for bringing data into the mapping process, and for building system maps directly from data. This approach allows us to build networks representing empirical regularities between a broad range of factors and analyse these networks in policy-relevant ways.

Network estimation: methods

We demonstrate the use of two data-driven network estimation techniques – correlation networks and the PC algorithm. These are just two of a longer list of methods we hope to combine in ongoing work.

Correlation thresholding is one of the most common network estimation techniques, largely because it is easy to implement and interpret, and does not impose restrictive assumptions on the relationships between the variables. The method consists of two main steps: first, given a set of nodes (i.e. the variables we bring into the analysis), we estimate a full correlation matrix. Then, starting with an empty network, for each pair of nodes we populate our network with an edge (i.e. a connection between them) if the estimated correlation between them is higher than the chosen threshold and/or if the probability of the observed test statistics, in case there was no real link between the variables (p-value), is lower than the chosen threshold.

Correlation thresholding is a good baseline, but as it focuses on pairwise relationships only, it cannot address issues caused by confounders or, more generally, map relationships between nodes of the system while accounting for the other nodes of the system (conditional dependence). One alternative is to think of the system as a network of conditional dependencies that can be modelled as a graph and use conditional independence tests to learn the structure of the graph. In other words, when assessing whether there is an edge between two nodes, all variables in the system are taken into account.

To implement such an approach, here we use the PC algorithm,[240] one of the main algorithms for causal structure learning. This works in three steps: 1) it determines the 'skeleton' of the network – that is, it estimates all network edges, without considering the direction of relationships; 2) it determines the edge orientation for v-structures $x \rightarrow z \leftarrow y$, that is, a structure where two variables x and y have a common effect z; and 3) based on the results from steps 1 and 2, determines further edge orientations.[241]

Network estimation: data

We use country-level, time-series of SDGs, macroeconomic and energy sector indicators. Data on the SDG indicators were obtained from the United Nations SDGs database, which we complemented with data from the World Bank, Climate Watch Data, the Economic Commission for Latin America and the Caribbean, the World Inequality Database and the Brazilian Integrated System of Disaster Information (S2ID). Data on the energy sector, including energy transition indicators, and on macroeconomic factors are from the Brazilian Ministry of Mines and Energy, the Brazilian Institute for Applied Economic Research, the World Bank, the Brazilian Institute of Geography and Statistics, and the Brazilian Sugarcane Observatory.

Using and analysing system maps

Once a network has been estimated, different approaches can be used to analyse the system and interpret the results. We recommend following Barbrook-Johnson and Penn (2021, 2022)[242] and considering three broad types of use and analysis: (i) observing the structure of the full maps, i.e. using different layouts and visualisations to explore the overall map structure, looking for clusters, bottlenecks and disconnected factors, for example (ii) network analysis, i.e. using formal network measures to look for well-connected and influential factors, and (iii) submap analysis, i.e. looking at bespoke sub-sections of the map to consider specific questions – for example, what is influencing key outcomes, or what paths are between sets of activities or inputs, and outcomes.

[239] Barbrook-Johnson, P. and Penn, A. (2022). Systems Mapping: how to build and use causal models of systems. Palgrave.

[240] Spirtes, P. et al. (1993). Causation, Prediction, and Search – Lecture Notes in Statistics 81. Glymour, C., Scheines, R and Spirtes, P. (2001), Causation, Prediction, and Search, 2nd edn, MIT Press, Cambridge..

[241] Heinze-Deml, C. et al. (2018). Causal Structure Learning. Annual Review of Statistics and Its Application 5: 371-391.

[242] Barbrook-Johnson, P. and Penn, A. (2021). Participatory Systems Mapping for Complex Energy Policy Evaluation. Evaluation 27(1): 57-79. Barbrook-Johnson, P. and Penn, A. (2022), Participatory Systems Mapping, Systems Mapping, Palgrave Macmillan.

Limitations

This case study is based on work in progress and here we only implement two network estimation methods, using a dataset that is still under construction. More generally, the key limitations of any data-driven systems mapping exercise will likely revolve around difficulties in merging it into participatory processes, communicating the richness of the maps and findings to others in an accessible way, and in obtaining usable and comprehensive data on all factors of interest.

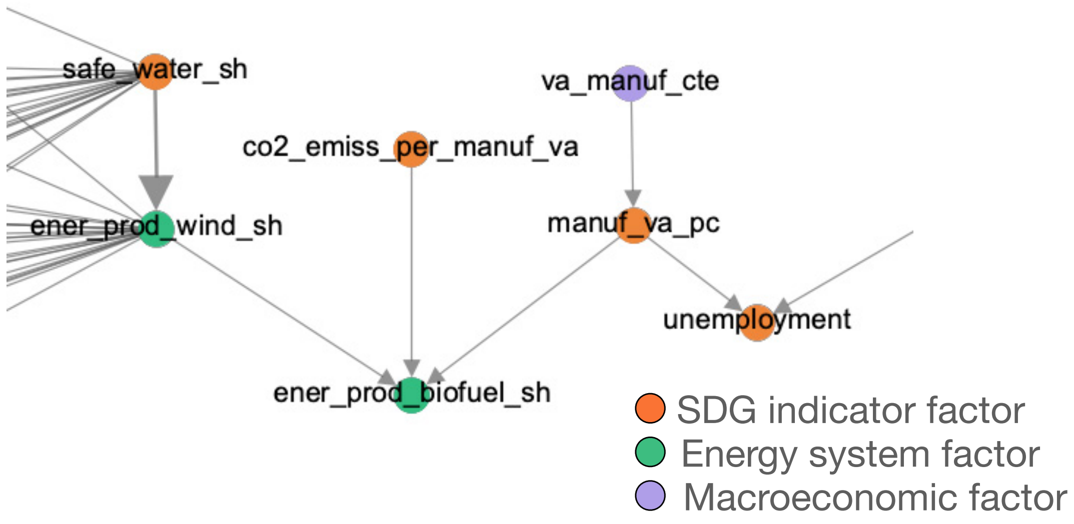
Example findings: Wind energy and biofuels

To illustrate our approach, in this section we present our preliminary findings on how wind energy interacts with other dimensions of sustainable development in Brazil and demonstrate how we iterate on a first set of results to further investigate the role of biofuels in the Brazilian SDG-energy system.

Our full map (not shown here) suggests wind energy is connected to several nodes in the correlation network and, as a result, wind energy is the most well-connected among the energy transition-related factors and one of the top five nodes in three standard network measures: betweenness (which captures if the node is a 'bridge' or 'bottleneck'), closeness (which captures if a node is 'in the thick of it') and degree (number of connections). Specifically, our preliminary findings suggest that wind energy is associated to total greenhouse gas emissions (SDG 13) and access to electricity (SDG 7), but they also indicate other somewhat less intuitive interactions with outcomes in the health sector[243] (SDG 3), with access to water (SDG 6) and to sanitation (SDG 6), with protected areas (SDGs 14 and 15) and with material consumption (SDG 12).

Besides being connected to several nodes in the correlation network, in the PC algorithm network the wind energy share is associated with the share of biofuels, a major source of energy in Brazil. Motivated by this connection, we further investigate the influence of biofuels in the SDG-energy system. Looking upstream from biofuels (Figure 78), we can see that manufacturing value added and CO2 emissions per unit of value added in manufacturing (both SDG 9 indicators) have a relationship with it. Since biofuels include sugarcane products, firewood, vegetable oils and waste energy sources, which in turn can be transformed into thermal, mechanical and light energy, the plausibility of these associations and any mechanisms behind them would be interesting topics for further research, as would discussions with stakeholders in the energy and manufacturing sectors, especially considering that industrialisation is an important dimension of the SDGs.

Figure 78: Ego network[244] of biofuels. This shows the two-step ego network (i.e. all nodes connected directly or via one step) of biofuel production, but cuts out many of the nodes connected via wind energy production.



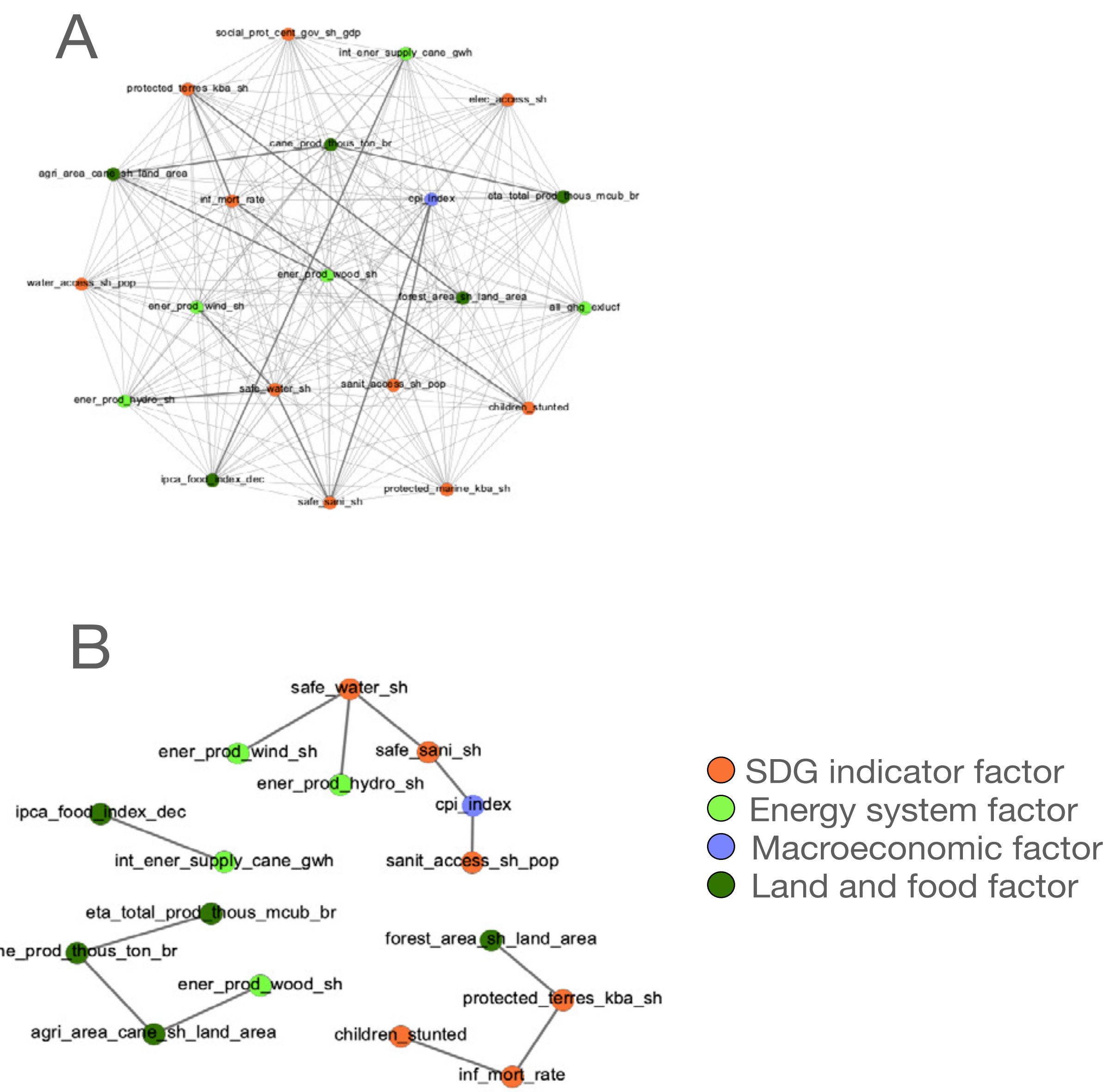
[243] Share of women with anaemia, infant and neonatal mortality, children stunted.

[244] An ego network is a subset of a network focused on one particular node and its neighbours.

To demonstrate how submaps exploration can inspire further literature reviews, data collection and mapping, we iterated again, this time with an extra focus on the role of biofuels and land use as the starting point. The idea is to explore the interdependencies between biofuels, land use and food prices in Brazil, in light of a strand of literature that considers co-movements in oil and agricultural output prices, as the latter is increasingly used as input for energy production.[245]

We collected additional data to disaggregate biofuels, with a focus on sugarcane. Specifically, we included sugarcane and ethanol production, as well as data on the supply of electricity from sugarcane. Other sources of renewable energy included are woodfire, solar, wind and hydro. We also include data on the sugarcane and forest shares of Brazil's land area, and a food price index. The resulting submaps are shown in Figure 79. This iteration shows the biofuel factors much more tightly connected into the map, with all of them holding a central position.

Figure 79: Ego networks of biofuels 2. A) The two-step ego network of the biofuel-related factors. B) The same network, but with only the edges appearing in both correlation and PC algorithm networks shown.



[245] Hassler, J. and Sinn, H. (2016). The Fossil Episode. Journal of Monetary Economics 83: 14-26. Peersman, G. et al. (2021). The Interplay between Oil and Food Commodity Prices: Has it changed over time? Journal of International Economics 133: 103540.

When we thin the map by only including connections which appear in both PC algorithm and correlation networks, we see a different picture. Firstly, we see an intuitive chain from land area producing sugarcane, to sugarcane production, to ethanol production. While the PC algorithm was not able to direct these edges, for policy purposes, expert knowledge and/or further data collection could be used to complete this section of the map. We also see a relationship between electricity supply from sugarcane and food prices, but electricity supply from sugarcane is not linked to the rest of the chain – an issue that could be discussed with sector specialists.

Similarly, the link between land area producing sugarcane and the share of energy production from wood could be further investigated, as well as the lack of a link between forest area (SDG 15) and sugarcane production, especially considering that the extent to which sugarcane production may influence deforestation is an important issue to be considered in both energy (SDG 7) and forest conservation policies (SDG 15).

In sum, our data-driven maps show wind energy well-connected to other nodes in the SDG-energy system, potentially interacting with outcomes in the health, water and sanitation sectors (SDGs 3 and 6) besides being linked to emissions (SDGs 9 and 13) and access to electricity (SDG 7). Wind energy may also be connected to biofuels, which, when further disaggregated with a focus on sugarcane energy and land use, are also well-connected in the correlation network. Finally, the PC algorithm network of biofuels offers interesting suggestions for further investigations on interactions among sugarcane production, forest area and emissions.

Conclusion

This preliminary data-driven systems mapping exercise has shown how wind and biofuels appear to be more connected into the SDG and economic indicators in Brazil than solar. This suggest efforts to seek out synergies and opportunities, or address trade-offs and risks between the transition and SDGs, may be best focused on wind and biofuels. In future work, we will explore these relationships in greater detail and present them to policy stakeholders tasked with supporting Brazilian progress on SDGs, to inspire further rounds of analysis driven by stakeholder questions.

We believe this approach to data-driven systems mapping is a useful tool to complement more narrowly focused models and to combine with qualitative systems mapping approaches (as seen in the case study What is the most cost-effective form of carbon pricing?). Systems mapping has proved useful and popular among analysts working in policymaking, from policy design through appraisal to evaluation,7 and we believe we should make more use of the different types of systems mapping, including more data-driven approaches. Specifically, within a new economic thinking and modelling framework, systems mapping is a key early step in Risk-Opportunity Analysis[246] and is a useful method for opening up economics, making its insights more accessible and encouraging pluralism.

[246] Mercure, J-F. et al. (2021) Risk-Opportunity Analysis for Transformative Policy Design and Appraisal, Global Environmental Change, 70: 102359.

CASE STUDY:

The Green Complexity and Competitiveness of China's Exports

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Policy question: How is the comparative advantage of nations likely to be affected by the energy transition? What policies are best deployed to help countries navigate changing comparative advantage and position themselves for future prosperity?

Region: China

Method: Green complexity index based on economic complexity literature.

Key findings: (i) Understanding a country's existing green complexity index, and its green complexity potential, provides an indication of directions of likely future comparative advantage; (ii) Strategic long-term policies can drive a nation towards areas of potential comparative advantage; (iii) China has succeeded in doing this over the last two decades, with its rise as a green product exporter proving even more powerful than its position as the leading global manufacturer.

Engagement: The methods in this case study have been developed in an academic context as a general framework on capabilities. Much of the data and results for most countries globally has been made publicly available on the Green Transition Navigator (https://green-transition-navigator.org/). This resource has been used for multiple reports on green export capabilities of various countries. This particular case study on China emerged as part of a collaboration between the Oxford team and Lombard Odier, a Swiss private bank, and a version of it was presented at a side-event of COP26 in Glasgow, among other places.

Summary: The authors use a data analysis approach to explore global trade data and the comparative advantage different countries have in green products. The study presents the Green Complexity Index approach, which builds on the economic complexity literature. This literature has had a huge influence on how we think about countries' development; here it is applied to China's green competitiveness and shows China's rise as a green product exporter is even stronger than its rise as the leading global manufacturer.

Introduction

This case study presents the application of economic complexity-based measures to understand green competitiveness in China. The transition to a low-carbon economy will require switching to greener technologies in many sectors, implying that countries with high production of green technologies stand to be likely beneficiaries of the green transition. Acquiring the capabilities to export sophisticated green products can be part of a green growth strategy, but may not be easy everywhere. Here, we assess 25 years of global trade in green products to understand recent trends in China's green competitiveness and product complexity, and consider what might lie ahead. This type of analysis can give insight into the industrial dynamics and impacts we might expect in different countries as the green transition unfolds. This case study is a summary of the application of the approach by Mealy and Teytelboym (2020)[247] to China and other countries by Andres et al. (2021).[248]

Measuring green competitiveness

The 'green' products we track are a list of 295 products as defined by Mealy and Teytelboym, who amalgamate environmental goods lists compiled by the WTO, the OECD and APEC. The sub-categories within this include renewable energy products, efficient consumption of energy technologies, carbon capture and storage products, and wastewater management and potable water treatment. The countries potentially well-placed to gain from the low-carbon transition are those who manufacture and export sophisticated equipment to make the transition happen, such as solar panels, wind turbines, electrolysers, and batteries and their components.

Our methodology also identifies countries that have the export capabilities that may allow them to move into exporting green products in the future. This is based on the idea that industrial development is often path-dependent.[249] Empirical evidence has shown that countries and regions are significantly more likely to develop competitiveness in products and services which require similar capabilities to those they already possess.[250] There is further evidence to suggest that countries which specialise in more technologically sophisticated products tend to enjoy greater income and GDP growth.[251]

To capture these phenomena, we employ an approach first introduced by Hidalgo et al[252] and extended by Mealy and Teytelboym to measure competitiveness in exporting green products. The proximity of a product to a country's current capabilities is strongly associated with the probability that this country will develop relative competitiveness in this product in the future (if it does not already export it competitively).[253]

We use the algorithm developed by Hidalgo and Hausmann to calculate the Product Complexity Index (PCI), which is a proxy for technological sophistication. We will occasionally refer to the Economic Complexity Index (ECI), which measures the overall complexity of a country's export basket. A country's ECI has been shown to be a significant predictor of that country's future GDP growth.[254]

We apply the approach of Mealy and Teytelboym here and combine these measures of complexity with the combined WTO, OECD and APEC list of traded green products to develop indices of green complexity or green competitiveness. We use two key metrics to assess countries' progress in capitalising on the growing green product market.

1. **The Green Complexity Index (GCI)** measures the number and complexity of green products that a country has exported competitively. It constitutes a composite measure of green competitiveness and allows us to compare countries directly on their current green export strengths.

[247] Mealy, P and Teytelboym, A. (2020). Economic Complexity and the Green Economy. Research Policy: 103948.

[248] https://www.inet.ox.ac.uk/publications/predictors-of-success-in-a-greening-world/

[249] Grubb, M. et al. (2014). Planetary Economics: Energy, Climate Change and the Three Domains of Sustainable Development. Planetary Economics.

[250] Hidalgo, C. et al. (2007). The Product Space Conditions the Development of Nations. Science, 317: 5837; Neffke, F. et al. (2011). How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions. Economic Geography, 87.3.

[251] Hidalgo, C. et al. (2007). The Product Space Conditions the Development of Nations. Science 317: 5837; Hausmann, R. et al. (2007). What You Export Matters. Journal of Economic Growth, 12.1.

[252] Hausmann, R. and Hidalgo, C. A. (2009). The Building Blocks of Economic Complexity. Proceedings of the National Academy of Sciences, 106(26): 10570-10575.

[253] Hidalgo, C. et al. (2007). The Product Space Conditions the Development of Nations. Science, 317: 5837; Neffke, F. et al. (2011). How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions. Economic Geography, 87.3.

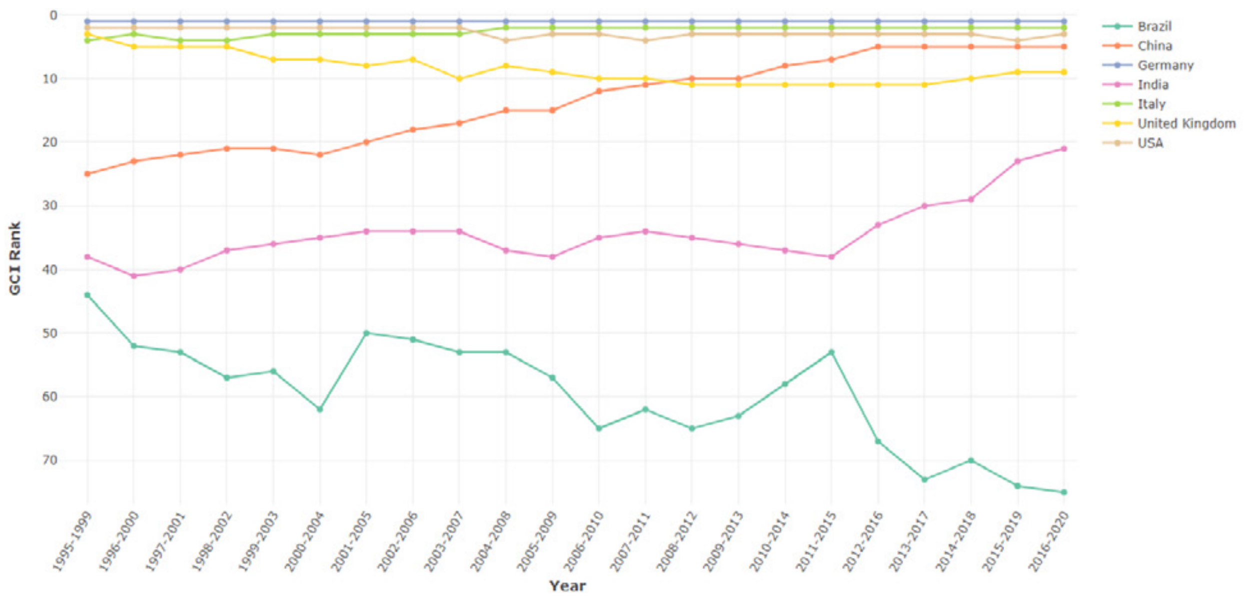
[254] Hidalgo, C. et al. (2007). The Product Space Conditions the Development of Nations. Science 317: 5837; Hausmann, R. et al. (2007). What You Export Matters. Journal of Economic Growth, 12.1.

2. **The Green Complexity Potential (GCP)** measures each country's proximity to complex green products that it does not yet export competitively. We use a measure of proximity between products that is based on how often two products are co-exported. Proximity between a product and a country indicates how similar a product is to a country's current export capabilities. Identifying products that are closely related to a country's capabilities allows us a glimpse of what those future paths might look like, due to the path dependency often observed in industrial development. GCP has been shown to be a significant predictor of a country's future GCI.[255]

To prevent our analysis from being skewed by short-term fluctuations in trade, we use annual average values over rolling five-year periods (1995-1999, 1996-2000, etc). For more details on the methodology, please refer to the report [256] this case study is based on and Mealy and Teytelboym (2020).[257]

Germany and Italy have consistently scored high on GCI between 1995 and 2020 (see Figure 80), and Germany currently holds top rank. The UK has stayed consistently in the top 10. India has risen close to the top 20, whereas Brazil has dropped into the 70s. However, arguably the most striking positive trend is the rise of China.

Figure 80: GCI through time for selected countries.



China's green complexity trends and opportunities

Over the past decade, China has become the world's largest manufacturing economy. It is also the world's largest emitter of greenhouse gases. However, its global dominance in manufacturing is mirrored by its clean technology production capabilities. China currently ranks 42nd in economic complexity overall (ECI), but fifth in green complexity (GCI).

China's national industrial strategy is aimed at progressing the technological frontier. 'Made in China 2025'[258] announced in 2015 as a major piece of industrial policy, identified 10 industries in which China aims to become the world leader by 2025. These included both green vehicles and rail transport technology. Its focus on high-tech industries may raise both its economic and green complexity ranking. China's 14th five-year plan (for 2021-2025) emphasises a similar set of industries. It also outlines plans for more scientific and technological self-reliance and stronger collaboration between industry and research institutions.[259] More recently, the 2022 government Central Economic Work Conference again outlined technological priorities considered key in forging
China's outward industrial competitiveness, with energy technologies central; however, there was more emphasis on self-reliance than previously.

Next, we will discuss past trends in China's green product categories, then highlight detailed products that form strengths and potential diversification options, and finish with an analysis of China's EV industry.

[255] Mealy, P and Teytelboym, A. (2020). Economic Complexity and the Green Economy. Research Policy: 103948.
[256] https://www.inet.ox.ac.uk/publications/predictors-of-success-in-a-greening-world/
[257] Mealy, P and Teytelboym, A. (2020). Economic Complexity and the Green Economy. Research Policy: 103948.
[258] State Council of The People's Republic of China. (2015). Made in China 2025. <http://english.www.gov.cn/policies/latest_releases/2015/05/19/content_281475110703534.htm>
[259] Mallapaty, S. (2021). China's Five-Year Plan Focuses on Scientific Self-Reliance. Nature: 353-54. <https://doi.org/10.1038/d41586-021-00638-3>.5.

Trends in China's green competitiveness

China's share in global green exports increased from 3 per cent in 1995-1999 to 19 per cent in 2015-2019. Its share of green imports increased as well, but to a lesser extent: from 2.87 per cent at the start of the period to 8 per cent during the most recent period. China is a net exporter of green goods (reflecting its dominance in global manufacturing exports more broadly).

China's GCI rank increased from 25th in the 1995-1999 period to fifth in the latest 2015-2019 period, while its GCP rank increased from seventh to first. This indicates that China not only increased its green export share, but also moved into relatively complex green technologies. Its high GCP in particular indicates that China is well-positioned to further increase its global green competitiveness in the future. Renewable energy products are China's most important green export, as well as import.

Export values increased in many categories over the course of the study period, but especially in more complex ones (Figure 81). The top three categories are renewable energy products, followed by products in efficient consumption of energy technologies and carbon capture and storage, then wastewater management and potable water treatment. As Figure 82 shows, China's average proximity to green products has increased for all environmental categories. This indicates that China's productive capabilities are increasingly aligning to those required to competitively produce green technologies. This is also captured by its high rank in GCP.

Figure 81: Export value through time by environmental product category.

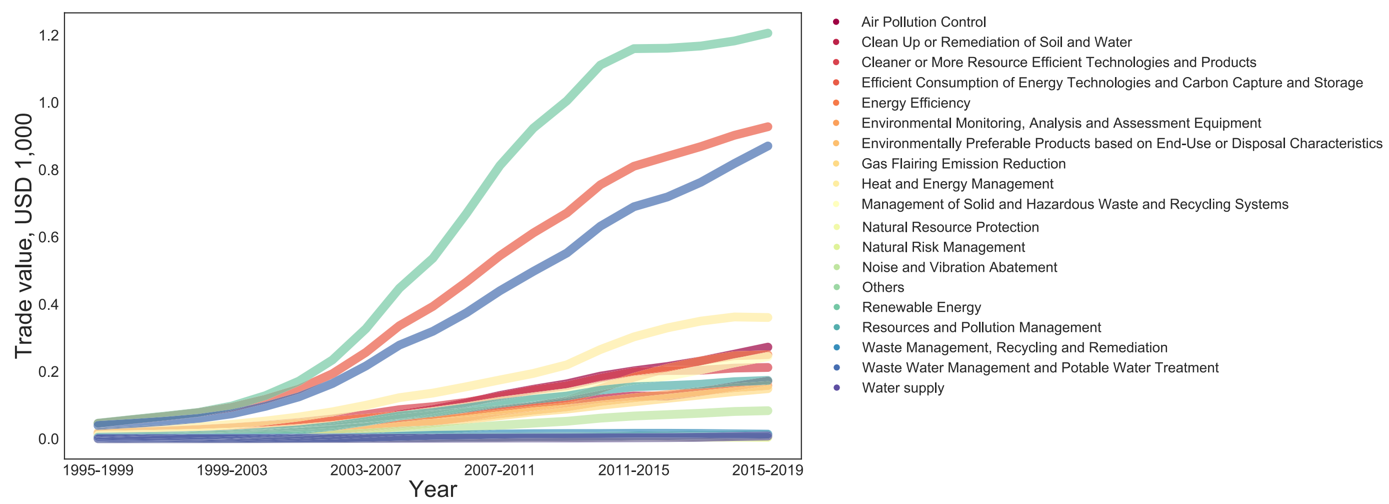
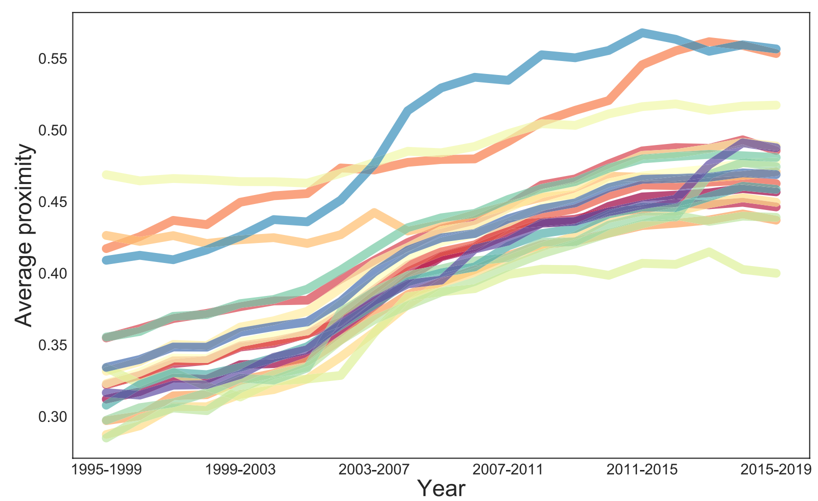


Figure 82: Average proximity to products by environmental product category.



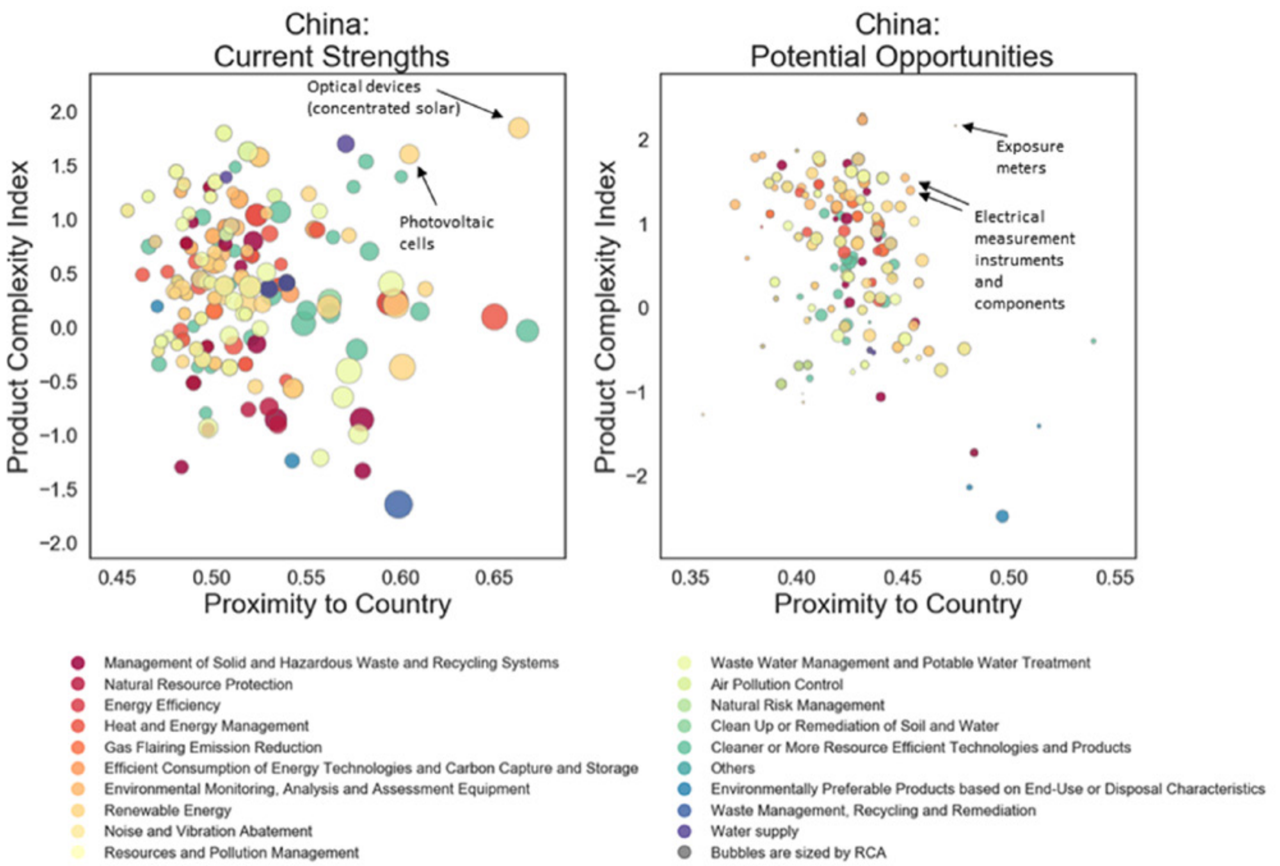
China's green strengths and opportunities

China's first NDC submission called for further R&D spending in renewable energy and related technologies, including desalination and climate change risk assessment methodology.[260] Some environmental monitoring technology is highly complex and close to China's current strengths, such as exposure meters or electrical measurement instruments and their components, both of which can be used in environmental monitoring.

Figure 83 divides all green products into those which China exports competitively (based on Revealed Comparative Advantage,[261] and labelled 'Current Strengths') and those which it currently does not (labelled 'Potential Opportunities'). The horizontal axis shows the products' proximity to China's current productive capabilities, which is an indication of how quickly China could develop competitiveness in those products in the future where it does not already have it.

Figure 83 shows that, for China, the most proximate products tend to have a lower PCI score, indicating that there is a trade-off between transitioning into 'proximate' versus 'complex' new products. High-complexity products are more likely to add value and open up greater diversification opportunities, but if products high in complexity tend to be relatively further away from existing capabilities, transitioning into those will be riskier.

Figure 83: China's green export products divided into current strengths (left) and potential opportunities (right). Size of product circle indicates China's current RCA; colours represent product categories.



[260] NDRC. (2015). China's Intended Nationally Determined Contribution: Enhanced Actions on Climate Change.

[261] Revealed Comparative Advantage is a measure of the relative advantage of a certain country in exporting a certain product. An RCA of a country-product pair of 0.5 means that country exports half of what is expected given the global average exports of that product and the country's total export value. A country exports a product with competitive advantage or capabilities if it has an RCA of >1 for that product.[247] Mallapaty, S. (2021). China's Five-Year Plan Focuses on Scientific Self-Reliance. Nature: 353-54. <https://doi.org/10.1038/d41586-021-00638-3>.5.

Low-emission vehicles

One of China's 'Made in China 2025' target industries is green vehicles. There have been policies in place for Chinese consumers to buy hybrid and electric cars since 2009, and in 2035 all new vehicles sold must be electric, hybrid or fuel-cell driven, according to a Ministry of Industry and Information Technology guided report.[262] Electric and hybrid vehicles represent about 5 per cent of new car sales in 2020 and perhaps 20 per cent in 2025, making it the world's largest EV market in absolute numbers.[263]

In our analysis, China's share of global export of new energy vehicles (which includes natural gas-powered vehicles besides electric, hybrid and hydrogen-powered ones), is only about 1 per cent for 2015-2019, compared to 12-25 per cent for Germany, Japan and the US – all three countries with large automotive sectors. China had not yet developed competitive export capabilities in this area in 2015-2019, with an RCA of 0.06 and proximity to productive export capabilities comparatively low at about 0.4.

However, since 2017 EVs have their own export code (separated from other 'new energy' vehicles), but this is not included in our longitudinal data covering the period of 1995-2019. Tracking this new export code, it can be found that China was the third-largest net exporter of EVs in 2021, with exports up fourfold from 2020, capturing 13.7 per cent of the global export markets for EVs,[264] which means that China had only gained export capabilities (RCA = 1.02 > 1) in EVs in 2021.[265]

Separately, we can find in the dataset that China already had export capabilities (RCA = 1.1 > 1) in the 2015-2019 period in buses that are non-diesel-powered and thus often less polluting[266] and is a major player in that export market. But those are a different product with a lower complexity (PCI of 0.43) from new energy vehicles (PCI of 1.87).

Conclusion

This case study presented two relatively new measures of economic complexity – the Green Complexity Index and Green Complexity Potential – that can be used by policymakers to understand fine-grained areas of current and future comparative advantage as the transition to net zero plays out. These measures were applied to China, with a view to understanding China's evolution over time and where China stands in the race to benefit from the energy transition. It was found that China has achieved a dramatic transformation of its economy in the form of world-leading increases in green complexity over recent decades, and in the final period of the study (2015-2019) China ranked fifth in green complexity and first in green complexity potential.

From earlier research it is clear that this success did not happen by accident and is driven by China's targeted industrial policy, which included industry-specific subsidies, preferential credit and measures which aggressively target technology transfer. We discussed the 'Made in China 2025' strategy, which targets sustainability and some key green technologies such as electric vehicles, where China has gained export capabilities in 2021, as well as digitalisation and high-tech industries. But not every country will find adopting such interventionist industrial policy feasible or desirable. China's experience demonstrates what is possible, and other countries will observe that leaving the evolution of the economy exclusively up to market forces can mean that opportunities to exploit increasing returns are missed.

Looking forward, policymakers can use their country's green complexity index and green complexity potential to signal areas of likely future comparative advantage. Strategic long-term policies – whether heavily or lightly interventionist – can help steer nations towards areas of potential comparative advantage. In China's case, our analysis suggests that it is already strong in such a large number of areas that doubling down and maintaining comparative advantage in many of those areas is likely to make sense. For instance, given the disruption underway in the automotive sector and the scale of the value at stake, it may be sensible for China to continue to strengthen their investment in EVs. Policymakers in other countries may draw different conclusions from the analysis of their own economy's green complexity potential.

[262] Tabeta, S. (2020). China Plans to Phase out Conventional Gas-Burning Cars by 2035. Nikkei Asia. < https://asia.nikkei.com/Business/Automobiles/China-plans-to-phase-out-conventional-gas-burning-cars-by-2035>

[263] IEA. (2020). Reports: Electric Vehicles.

[264] Workman, D. (2021). Electric Cars Exports by Country. World's Top Exports. < https://www.worldstopexports.com/electric-cars-exports-by-country/?utm_content=cmp-true>

[265] Taking China's percentage of world trade at 13.5% using 2020 data from https://wits.worldbank.org/CountryProfile/en/WLD

[266] This category includes electric and hydrogen buses, but also those that run on non-diesel fossil fuels such as natural gas or petrol.

CASE STUDY:

Closing the Green Financial Gap in the UK: Low-carbon electricity transition and economic implications

SARAH HAFNER (ANGLIA RUSKIN UNIVERSITY), ALED JONES (ANGLIA RUSKIN UNIVERSITY)

Policy question: What are the macroeconomic implications of a UK low-carbon electricity transition implemented in conjunction with and without a policy designed to close the green finance gap?

Region: UK

Method: System Dynamics model

Key findings: Closing the green finance gap policy scenario alongside a low-carbon power scenario leads to the co-benefits of lower power system costs and lower unemployment, as well as increases in GDP.

Engagement: This case study analysed 31 policy reports from multi-stakeholder groups or organisations that represent wider stakeholders within the finance community, alongside 17 structured interviews with private investors, asset owners and managers, banks and pension fund representatives, and actuaries. Roundtable discussions also fed into this work through events hosted by the Aldersgate Group, World Bank, the Institute and Faculty of Actuaries and the Observer Research Foundation (India). This work builds on previous engagement through the Capital Markets Climate Initiative (CMCI) led by the then Minister for Climate Change at the Department for Energy & Climate Change.

Summary: The authors use a System Dynamics model to consider whether policies are aimed at the energy sector enough to support a low-carbon transition in the UK. Specifically, the study presents the Green Investment Barrier Model, which focuses on the modelling of the financial sector, including variables such interest rates and exchange rates, and links this to investment in the energy sector to model the interplay between the two sectors passing through the real economy. Unlike traditional models that focus solely on the energy sector, we find that energy policies alone are not enough to achieve net zero ambitions in energy and that financial regulation is needed alongside energy policies to increase the available capital from institutional and private investors.

Introduction

Meeting its climate policy objectives requires the UK to rapidly decarbonise its energy sector. This demands high levels of investments into low-carbon energy infrastructure. For example, DECC[267] estimated the required investments into low-emission energy infrastructure, including transmission and generation, is £130bn by 2030. Other sources, such as the Committee on Climate Change (CCC)[268] and Vivid Economics[269] estimated the required investment to be higher, ranging up to £300bn by 2030. Traditional sources of capital (e.g. project finance) will not be enough to cover the required energy infrastructure investments. Therefore, additional funding sources, such as finance from institutional or private investors (e.g. mainstream investors or high-net-worth individuals) are required to cover the green finance gap.[270] However, currently private and institutional investors are not investing sufficiently into green energy infrastructure, for example due to lack of confidence given the technology risks, unstable policies, high up-front capital requirements of renewables or lack of information.[271 272]

While current energy-economy models reveal a variety of different aspects/implications of low-carbon energy transitions (and apply a large range of different focuses), to date none of them – with the possible exception of the extended EIRIN model[273] – demonstrate how policies contribute to scale up the green investment necessary to finance the low-carbon energy infrastructure and show what the related macroeconomic implications are. Our study aims to fill this gap and thus extend the current existing energy-economy modelling landscape. We focus on the following question:

- What are the macroeconomic implications of a UK low-carbon electricity transition implemented in conjunction with and without a policy designed to close the green finance gap?

To address this question, we apply the extended Green Investment Barrier Model (GIBM)[274] which includes key results from the qualitative investigation on the green finance gap by Hafner et al.[275]

Current energy policies, such as feed-in-tariffs, contract-for-difference or subsidies, focus primarily on energy firms' investment decisions. However, the policy scenarios presented in this case study additionally aim to influence the finance decisions of private and institutional investors required to provide finance to energy firms or invest directly into energy infrastructure.

Modelling approach

The model presented in this study is a descriptive simulation model as opposed to the more common equilibrium and optimisation models. SD is a suitable tool to investigate key mechanisms of complex systems that are characterised by feedback loops, uncertainty and path-dependency, and to manage and/or improve these systems by intervening at leverage points that either strengthen desirable or weaken undesired feedback loops.

GIBM is calibrated to the UK context and allows for the simulation of different low-carbon electricity transition scenarios.[276] The model includes the endogenous simulation of key macroeconomic variables such as GDP or unemployment, emissions (as key environmental indicators) emitted by the electricity supply sector, and electricity system costs. The economic model sectors of GIBM can be said to be embedded in a post-Keynesian/ ecological macroeconomic framework. Specific model equations build generally on different non-equilibrium modelling approaches, including post-Keynesian economics, ecological economics or system dynamics, but also equilibrium approaches (e.g. Constant Elasticity of Substitution – CES – production function). The model has a narrower scope than large-scale models, such as, for example,

[267] UK Department of Energy & Climate Change. (2014). Energy Investment Report, April 2014. https://www.gov.uk/government/publications/energyinvestment-report-april-2014 (Accessed April 19, 2019)

[268] Committee on Climate Change. (2013). Next Steps on Electricity Market Reform – Securing the Benefits of Low-Carbon Investment. Committee on Climate Change. https://www.theccc.org.uk/wp-content/uploads/2013/05/1720_EMR_report_web.pdf. (Accessed May 1, 2019).

[269] Vivid Economics. (2012). Energy and the Economy - The 2030 outlook for UK Businesses. A London School of Economics Report Commissioned by RWE NPower. Available at: www.vivideconomics.com/publications/energy-and-the-economy-the-2030-outlook-for-uk-businesses (Accessed May 4, 2019)

[270] OECD. (2016). Fragmentation in Clear Energy Investment and Financing. Available at: http://www.oecd. org/investment/investment-policy/BFO-2016-Ch5-Green-Energy.pdf (Accessed July 4, 2018).

[271] Hafner, S. et al. (2019). A Scoping Review of Barriers to Investment in Climate Change Solutions. Sustainability, 11(11), 3201.

[272] Hafner, S. et al. (2020). Closing the Green Finance Gap – A Systems Perspective. Environmental Innovation and Societal Transitions, 34: 26-60.

[273] Dunz, N. et al. (2019). Climate Transition Risk, Climate Sentiments and Financial Stability in a Stock-Flow Consistent Approach. Journal of Financial Stability 54: 100872.

[274] Hafner, S. et al. (2021). Modelling the Macroeconomics of a 'Closing the Green Finance Gap' Scenario for an Energy Transition. Environmental Innovation and Societal Transitions, 40: 536-568.

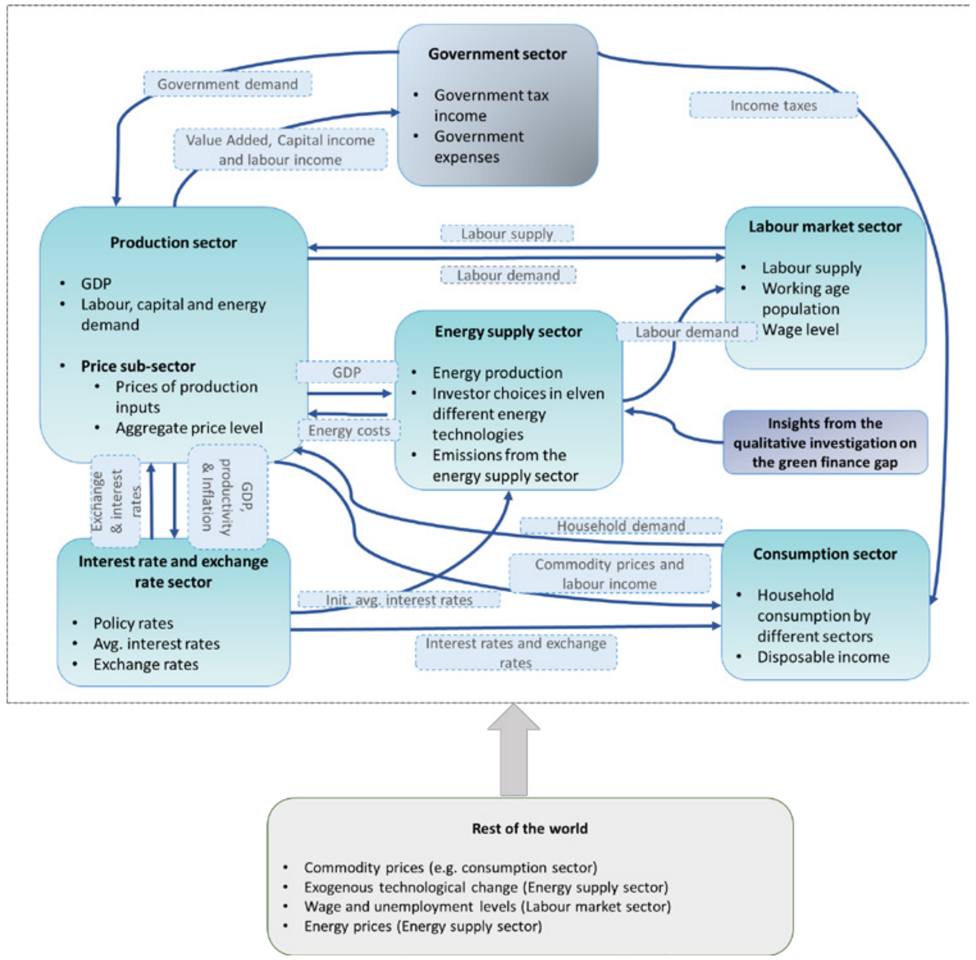
[275] Hafner, S. et al. (2020). Closing the Green Finance Gap – A Systems Perspective. Environmental Innovation and Societal Transitions, 34: 26-60.

[276] Hafner, S. et al. (2021). Economic Impacts of Achieving a Net-Zero Emissions Target in the Power Sector. Cleaner Production, 312: 127610.

the Cambridge Econometrics E3ME model, but is wider in scope than a stylised mathematical model. Specifically, GIBM includes 313 stock variables and more than 3,000 variables in total. The simulation horizon for this study included the period from 2016 to 2050, with time steps of 0.25 years.

Figure 84 gives an overview on GIBM and its key macroeconomic sectors (e.g. production, consumption and labour market), the public sector and electricity supply sector. The model allows us to understand what the macroeconomics implications and electricity system costs of different electricity transition scenarios are.

Figure 84: Overview of GIBM. The main causal relationships between model sectors. GIBM is visualised in the dashed box, i.e. the rest of the world is outside the GIBM. The model sectors in the parenthesis in the 'Rest of the world' box indicate that additional exogenous inputs from the rest of the world enter the model. The production process at the macroeconomic level is represented with a demand-led CES production function – that is, the production inputs, labour, capital, energy and intermediate inputs are not (necessarily) fully utilised. The production sector also includes the simulation of prices; the consumption sector simulates household consumption per industry; the labour market sector determines employment and simulates unemployment as the difference between labour demand coming from the production sector and the available labour force. In addition, the labour market represents the wage level and includes a sub-sector that simulates the UK working population endogenously; the exchange and interest rate sector includes the exchange rate between the UK and its main trading partners, and the average interest rate for credits of UK firms; the public or government sector tracks state income and expenditure. Finally, the electricity supply sector includes a detailed representation of the electricity production capacity and determines annual energy produced in the UK. The power supply sector is differentiated by 12 electricity production technologies, including biomass, hydro, marine, onshore wind, offshore wind, solar, other thermal and other renewable energies as renewable technologies, nuclear and CCS gas as other low-carbon technologies and finally coal and gas as brown technologies.[277 278]



[277] Hafner, S. et al. (2021). Modelling the Macroeconomics of a 'Closing the Green Finance Gap' Scenario for an Energy Transition. Environmental Innovation and Societal Transitions, 40: 536-568.

[278] Hafner, S. et al. (2021). Economic Impacts of Achieving a Net-Zero Emissions Target in the Power Sector. Journal of Cleaner Production, 312: 127610.

Description of the GIBM complexity features

The following provides a list of complexity features captured by the GIBM in line with the Risk-Opportunity Analysis framework:[279 280]

- Complexity & multiple equilibria/non-equilibrium: In GIBM, the different economic sectors are also interconnected, as well as the economy with the energy sectors. Also, due to the complexity, agents cannot take 'rational' decisions and a long-term equilibrium outcome is not given.
- Deep uncertainty: SD modelling acknowledges uncertainty at the level of model construction; system complexity means that future system behaviours are not predictable based on past system structure and behaviours.
- Non-linearity: The consumption sector includes changes in the parameter of elasticities once certain consumption levels are reached.
- Feedback-loops, path-dependency and lock-in: The power sector includes cost-decreases of renewable technologies due to learning-by-doing and the economic sector includes the Keynesian GDP-multiplier effects.
- Actor behaviour and decision making: SD aims to represent how model agents take decisions, considering both relevant economic and socio-psychological factors (e.g. agents' values or preferences). In GIBM, the decisions of financial investors are mimicked by using the results of a qualitative study[281] (which includes interviews with these investors) to also include 'soft parameters' about which there is currently no quantitative data.

Description of the scenarios and results

We simulate and compare the following policy scenarios (key macroeconomic dynamics, induced by the introduced scenarios are described in detail Hafner et al., 2021a):

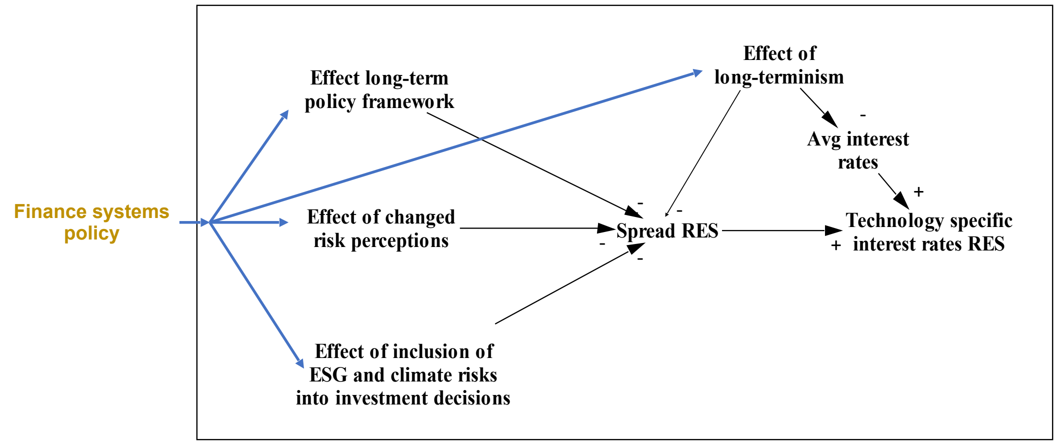
- The low-carbon energy transition scenario (LETS) influences variables in the energy sector of the model as it implies that only renewable energy sources are chosen for new installations. In addition, it implies linear decrease of installed brown energy capacity from 2020 onwards, leading to zero emissions by 2050 in the energy sector. The LETS is introduced by assumption and the required policies are not specified. Within LETS no specific policies are directed towards investors which address current perceived barriers in investment (as reported by mainstream investors and institutions) towards green infrastructure and therefore there is a limit on the availability of capital for such projects.
- The finance system's policy scenario (FSPS) influences variables in the finance sector of the model. This policy scenario is assumed to tackle key green investment barriers in an effective and holistic way, drawing on a systems perspective. Importantly, we note that while the details of this systems policy developed are not specified in this study, we assume that the systems policy involves amendments in current regulations, investment advice, risk assessment requirements (e.g. ESG criteria and climate related risks disclosure), metrics reported and tools applied, drawing on empirical evidence stated in Hafner et al. (2020a). The introduction of this systems policy therefore closes the green finance gap (the availability of capital matches the projected requirements under the future scenarios such that all investable projects are able to attract enough capital). This means that green investment flows to renewable energy infrastructure are no longer restricted by the availability of finance as compared to the base-run that represents the current situation of a green finance gap. That is, in GIBM, without the introduction of an adequate policy available, green finance is below the amount of finance required to finance a green energy transition. Furthermore, the introduction of a systems policy reduces the mark-up on interest rates of renewable energy projects in particular, while also reducing the average interest rate in general (see Figure 85).
- Finally, the scenarios introduced above were tested in combination.

[279] Mercure, J-F. et al. (2021). Risk-Opportunity Analysis for Transformative Policy Design and Appraisal. Global Environmental Change, 70: 102359.

[280] Grubb, M. et al. (2021). The New Economics of Innovation and Transition: Evaluating Opportunities and Risks.

[281] Hafner, S. et al. (2019). A Scoping Review of Barriers to Investment in Climate Change Solutions. Sustainability, 11(11): 3201.

Figure 85: Impacts of a finance system's policy: A finance system's policy tackles key green investment barriers from a system's perspective. It (i) lowers average interest rates, (ii) lowers the interest rate spread on renewable energy technology investment and (iii) closes the green finance gap.[282 283]



In the following, we present the simulation results for the following key policy indicators:[284]

- Greenhouse gas emissions of the energy supply system
- Unemployed workers plus inactive working-age population
- GDP
- Energy system costs
- Direct generated employment by the energy transition

We choose to define 'unemployed' in this study as the sum of unemployed and inactive workers.[285]

Table 14 shows the results of the simulated energy policy scenarios in terms of the chosen policy indicators as percentages against the base-run simulation results of the same policy indicator (always in accumulated numbers, if not indicated differently). Importantly, although the UK has implemented a CFD scheme, a stylised CFD scenario is not used as a base-run, as the interest lies in understanding the additional costs of different policy scenarios compared with the base-run where no major scheme (but a -price) is introduced.

Table 14: Overview on policy outcomes of the tested scenarios – orange highlights the worst achieved results and blue the best achieved one of all tested low-carbon policy scenarios; impacts on accumulated variables from 2016 to 2050.

	Emissions (%)	GDP (%)	Unemployment (%)	Direct employment (%)	System costs (%)
Finance system's policy (FSPS)	-7.09	3.05	-1.47	15.12	-2.58
Low-carbon energy transition scenario (LETS)	-44.90	0.50	0.20	-6.90	12.44
FSPS and LETS combined	-44.90	3.46	-1.4053	40.15	3.66

[282] Hafner, S. et al. (2021). Modelling the Macroeconomics of a 'Closing the Green Finance Gap' Scenario for an Energy Transition. Environmental Innovation and Societal Transitions, 40: 536-568.

[283] Hafner, S. et al. (2021). Economic Impacts of Achieving a Net-Zero Emissions Target in the Power Sector. Journal of Cleaner Production, 312: 127610.

[284] Results are presented in 'accumulated' terms, which means that the annual amount of each of the chosen policy variables is added up/accumulated over the simulation time horizon from 2016 to 2050.

[285] In GIBM, the number of people outside the labour force is dependent on the percentage of unemployment due to the so-called 'discouraged workers effect'. Therefore, individuals who although would desire to work, may decide to stay outside the labour force due to discouragement and are therefore a part of the inactive labour force. In our study, we decided to consider these otherwise 'hidden' individuals in our policy evaluation.

Model results demonstrate that the 'closing the green finance gap' policy scenario alongside a low-carbon power scenario leads to the co-benefits of lower power system costs and unemployment, and increases in GDP. Importantly, the results show that focusing on closing the green finance gap alone would not be enough to reach net-zero emissions of low-carbon electricity production by 2050 – policies in the electricity sector itself are needed to complement it.

Conclusion

Given these results, we recommend the implementation of a low-carbon energy transition scenario in combination with policies aiming to close the green finance gap that are based on a systems approach.

Moreover, the simulation results demonstrate that while there exists no clear win-win solution, the implementation of a long-term finance system's policy, designed to contribute to close the green finance gap, brings various co-benefits both introduced in isolation as well as in combination with a low-carbon energy transition:

- When a finance system's policy is introduced in isolation it reduces the average market interest rates and leads to a lower spread on the interest rates of renewable energy technologies. These effects lead further (i) to an increase in GDP due to lower average interest rates and therefore (ii) also a decrease in unemployment, (iii) to an increase in direct employment due to lower financing costs of renewable energy sources and (iv) to lower energy systems costs due to lower market interest rates. The only disadvantage caused by this scenario introduced in isolation are the higher emissions due to the increase in GDP, which implies a higher production and use of energy.
- A finance systems policy combined with a low-carbon energy scenario leads to various co-benefits. That is, the LETS and FSPS introduced in combination lead to higher GDP and direct employment, and at the same time to lower unemployment and energy system costs – and importantly to zero emissions in the energy system costs in the UK by 2050.

The effects from a finance system's policy stem on one hand from its effect on lower interest rates and on the other hand because it closes the green finance gap, which subsequently avoids energy imports from abroad. Given the above, we recommend the implementation of a low-carbon energy transition scenario in combination with a finance system's policy. The key insights, policy implications and conclusions presented are robust under the sensitivity analysis performed.

CASE STUDY:

Exit Options for Renewable Energy Investments in Brazil

ANNA CAROLINA MARTINS (UNICAMP, BRAZIL), MARCELO PEREIRA (UNICAMP, BRAZIL)

Policy question: How might ‘exit options’ analysis support private financing of renewables projects?

Region: Brazil

Method: Financial modelling

Key finding(s): The uncertainty in the financial evaluation of individual renewable energy projects is a key driver for the application of exit options by creditors and, despite being relatively unknown in the country, this project valuation method is relevant for pushing forward the Brazilian renewables sector.

Engagement: This work has been presented and discussed across a range of meetings and engagement activities in 2021 and 2022, with representatives of the Brazilian National Development Bank (BNDES), the Brazilian Photovoltaic Solar Energy Association (ABSOLAR), the UN Economic Commission for Latin America and the Caribbean (ECLAC), and the Brazilian Energy Research Office (EPE). The work is ongoing and further engagement is planned.

Summary: The authors use a financial modelling approach to consider the feasibility and impacts of an alternative approach – exit options – to private financing of renewable projects. Their modelling suggests this approach has potential and that detailed exploration of implementing and adopting it should be conducted.

Introduction

Despite the consensus that a quick energy transition is needed, the current levels of private funding for green energy are still insufficient[286 287 288] and, given the huge investments required, it is unlikely that public investments alone will reach the necessary levels.[289] In Brazil, the situation is no exception. Public banks such as the BNDES and the Bank of Brazil (BB) are the largest funders of renewable energy [290 291] and another substantial part of investments are made by international development banks such as the European Investment Bank (EIB) and the Agence Française de Développement (AFD). But investments made by the private sector take place in smaller proportions and, according to CEPAL (2020), [292] are reliant on public policies and incentives. So, evaluating alternatives to stimulate the private sector to increase the financial support of renewable energy projects is an important part of the green transition agenda.

Green energy financing

Historically, infrastructural investment in Brazil has relied mainly on public sources of capital (EPGE, 2023).[293 294] Even if precise figures are not available, anecdotal evidence indicates that the role of private creditors in renewable energy finance is mainly as a mediator of public institutions’ programs, like BNDES Fundo Clima or Finem ‘indirect support’ modality,[295] or BNDES Garantia and FGI credit guarantee instruments.[296] However, such modalities and instruments assume a traditional financial evaluation of projects, where the (direct or indirect) creditor requires financial guarantees for the entire project, without effectively considering the ‘added value’ of an early exit option. This is particularly critical for very long-term projects, like energy generation, where the uncertainty about energy prices and generation costs, prone to substantial volatility over time, is significant.

The risk aversion of public entities, like BNDES, in requiring substantial credit guarantees from candidate projects may be justified by the Brazilian regulatory framework. But such constraints may not apply to private creditors when supplying their own funds. Understanding under which conditions (real) private finance of renewable energy may change their current behaviour, and increase their support to the green transition, seems to be a key issue for policy analysts and decision makers to address. Supporting a regulatory framework that enables new financing agents and models is crucial for a successful green transition, in particular in developing countries like Brazil, where credit for investment has been historically scarce and expensive.[297]

One major bottleneck on private green energy finance is the scarcity of risk-adjusted renewable energy (RE) investments.[298] The most common project evaluation practice is based on a project’s discounted cashflow, also known as net present value (NPV), and considers funds required for both CapEx and OpEx. However, this type of project evaluation and financing does not consider that the parties involved may change their investment strategies as the project develops. This means, once agreed in contract, they must keep their resources dedicated to the project.

Given that green energy projects may require large amounts of financial resources, over long time periods, such rigidity may easily discourage private-sector investment,[299] in particular because of the significant uncertainty about some key assumptions required by the NPV calculation. It can be trivially demonstrated that energy prices demonstrate

[286] IEA. (2017). Perspectives for the Energy Transition: Investment needs for a low-carbon energy system.

[287] Wüstenhagen, R.A.E.M. (2012). Strategic Choices for Renewable Energy Investment: Conceptual framework and opportunities for further research. Energy Policy.

[288] Bloomberg New Energy Finance. (2010). Global Trends in Sustainable Energy Investment 2010: Analysis of Trends and Issues in the Financing.

[289] Fadly, D. (2019). Low-carbon transition: Private sector investment in renewable energy projects in developing countries. World Development, 122, 552-569.

[290] BNDS. (2022). Fundo Clima – Subprograma Energias Renováveis. Available at <https://www.bndes.gov.br/wps/portal/site/home/financiamento/produto/fundo-clima-energias-renovaveis>. Accessed on December 20, 2022.

[291] Banco do Brasil - BB (2022). Estimulo à Energia Renovável. Available at <https://www.bb.com.br/pbb/pagina-inicial/sobre-nos/sustentabilidade/energias-renovaveis/solucoes-para-voce#/>. Accessed on December 20, 2022.

[292] CEPAL, Energia. (2022). Available at < https://www.cepal.org/pt-br/subtopicos/energia#> . Accessed on December 20 2022.

[293] EPGE. (1999). Investimentos, Fontes de Financiamento e Evolução do Setor de Infra-Estrutura no Brasil: 1950-1996, Available at < https://bibliotecadigital.fgv.br/dspace/bitstream/handle/10438/575/1199.pdf>, Accessed on January 12, 2023.

[294] Albanez, T. and Ribeiro do Valle, M. (2012). High Interest Rates, Capital Sources and Capital Structure: The Debt Of Brazilian Companies In The Period 1997-2006, Available at <https://www.revistas.usp.br/rco/article/download/52667/56551>. Accessed on January 12, 2023.

[295] BNDES Finem. Geração de Energia. Available at < https://www.bndes.gov.br/wps/portal/site/home/financiamento/produto/bndes-finem-energia> . Accessed on January 12, 2023.

[296] BNDES, Guia do Financiamento. Available at < https://www.bndes.gov.br/wps/portal/site/home/financiamento/guia> . Accessed on January 12, 2023.

[297] BNDES, Guia do Financiamento. Available at < https://www.bndes.gov.br/wps/portal/site/home/financiamento/guia> . Accessed on January 12, 2023.

[298] Nelson, D.and Pierpont, B. (2013). The Challenge of Institutional Investment in Renewable Energy. Climate Policy Initiative, San Francisco.

[299] DWIH São Paulo. (2022). 10th German-Brazilian Innovation and Sustainability Congress. Available at < https://www.dwih-saopaulo.org/en/event/10th-german-brazilian-innovation-and-sustainability-congress/> Accessed on September 29 and 30, 2022.

significant volatility in the long run, and in turn, so does the expected project's revenues. Even on the cost side, volatility of essential factors, like wages, (imported) equipment prices and exchange rates, has been historically high, particularly in developing countries. Adding up all this uncertainty leads to creditors requiring high (internal) rates of return for the projects to be financed, discarding in the process many projects that would prove perfectly viable ex post.

Real option analysis

To address this issue, Real Option (RO) analysis has been increasingly used in the evaluation of renewable energy projects in places like California, Norway and Turkey (see Table 15) and has long been used in financial-feasibility studies for power-generation projects in China.[300] Unlike usual financial options, where the underlying assets are liquid assets (easily traded), real options are applied to real assets such as investment projects. The key idea is that the parties involved (i.e. creditor and developer) may change their decisions about the financing and development of a project after it has started, without incurring a breach of contract or litigation.

There are distinct types of Real Options. Gazheli (2018)[301] highlights three:

- Postponement: Option to wait to invest in the project. Thus, the irreversible investment may happen only when more information of future market and production conditions is available.
- Alteration: Flexibility to change the project, through the possibility of altering the form of production, given future market and production conditions.
- Exit: Opportunity to exit the project before the expected term and take back any residual value.

When receiving finance requests, and where the economic environment or the future context is uncertain, the creditor may wish to wait a while to decide on whether or not to invest in a given renewable energy project. In such cases, the postponement option offers the chance to participate in such projects at some point in the future. The alteration option, on the other hand, would enable the agents to switch to technologies or business models that prove to be better over time. Or, if a project offers different ramifications such as wind, solar or hydro, the investing agent can acquire the right to switch between technologies according to the market feasibility.

The exit option, the focus of this work, allows both agents (creditor and developer) the right, but not the obligation, to leave the project before the fixed term. That is, if for any reason the project's financial performance is affected negatively, both the creditor and the developer may (within an agreed period) opt to exit the credit operation, therefore allowing opportunities to change investment decisions.[302] In such cases, the creditor may abstain from the obligation to finance other stages previously established in the contract, as will be detailed below, and both agents must agree on the period(s) in which they can exit. Furthermore, the exit option does not exempt the developer from paying off the amount already borrowed.

Therefore, the exit option provides an alternative instrument to reduce the risk taken by the creditor, and the increase of the project's NPV due to this reduction is indeed a valuation of such option. Put simply, if the traditional valuation (i.e. no exit option) is NPV1 = X, then the valuation considering the exit option value is NPV2 = X + Y. The option value is thus, NPV2 - NPV1 = X + Y - X = Y. Consequently, projects that are not viable under the usual criterion (i.e. have a negative NPV), but presenting a positive-valued exit option, may become feasible.

Exit options for green energy investments in Brazil

Now, we focus on the potential for the application of exit options for renewable energy projects in developing countries like Brazil. The RO approach has been applied in wind, solar and hydro energy projects in various countries (see Table 15). However, we have no information about its application in the case of Brazil, likely due to the absence of this kind of instrument in the standard credit models proposed by BNDES, by far the largest primary source of investment finance for renewable energy [ibid.]. In any case and considering the increased uncertainty in a developing country, it seems that further exploring this alternative can enable financing a group of projects that otherwise would not be viable.

[300] Kim, K. H. P. A. H. K. (2017). Real Options Analysis for Renewable Energy Investment Decisions in Developing Countries. Renewable and Sustainable Energy Reviews.

[301] Gazheli, A. A. J. V. D. B. (2018). Real Options Analysis of Investment In Solar Vs. Wind Energy: Diversification strategies under uncertain prices and costs. Renewable and Sustainable Energy Reviews.

[302] Kim, K. H. P. A. H. K. (2017). Real Options Analysis for Renewable Energy Investment Decisions in Developing Countries. Renewable and Sustainable Energy Reviews.

There are different methods for estimating the value of an option, as exemplified in Table 15. Here, we apply the RO analysis framework proposed in Kim[303] and briefly discuss the potential of exit options to boost Renewable Electrical Energy (REE) financing. We focus on Brazil, where between 2012 and 2021 almost 7,000 publicly funded infrastructure projects, including renewable energy projects, were suspended (i.e. begun but then paused for some reason, such as insufficient funding or changes in expected outcomes) with a total contract value of BRL 9.32 billion. This highlights the need to review the way projects are evaluated and approved.[304]

Our contribution is to propose a simple model to evaluate projects by considering critical variables that can broadly reflect the economic volatility of an infrastructure project NPV. We focus on two variables – wages and labour productivity – therefore incorporating in the valuation model volatility arising from the labour market. The idea is that higher labour productivity can reduce the costs and make the project NPV (more) positive, but if wages grow faster than labour productivity, the reverse happens. We use wages and labour productivity to exemplify typical sources of project volatility and, from there, define the implicit 'cost' of this volatility through an exit option value. For completeness, we also consider two additional variables, service (energy) tariffs and capital utilisation (service/energy demand) in our model.

We proceed in three steps:

1. Define three future context scenarios for the four test variables, namely, moderate, best, and worst cases;
2. Apply a binomial tree model,[305 306] which estimates the expected probability (q) of a project becoming more profitable, and calculate the model's single exit option value;
3. Combine the expected NPV with the exit option value to obtain a more realistic project evaluation.

In a demonstration of the concept, we apply the proposed evaluation model to provide a sense of the magnitude of the effects in a real renewable energy project. In future work we will explore it further, by integrating the model as a behavioural rule to be (potentially) adopted by creditors and developers in an agent-based model, like the Dystopian Schumpeter Meeting Keynes model by Lamperti et al.[307] and presented in the case study 'Policy Options for Rapid, Smooth Decarbonisation and Sustainable Growth'. This will allow us to study how ROs in a macro-integrated, RE-financing set-up could affect the energy transition over time in a complexity-informed integrated assessment model.

Simulation and preliminary findings

As a demonstration for the analysis, we consider the Itumbiara hydroelectric plant, part of the Furnas System.[308] The total investment of the project (construction) was US$187.5m. Importantly, the first seven years of the project were dedicated to construction and the remaining 40 years to operation (concession period). As such, we calculate the exit option value on the seventh year. In practice, this gives the option holder, the project creditor, the right to exit the project at the end of the first stage (construction) of the project, on year seven.

Based on a range of technical and market parameters relevant to the Itumbiara project, we build the best, moderate and worst-case scenarios, assuming historically consistent maximum and minimum evolution trajectories for the four considered variables: wages, labour productivity, energy tariff and energy demand. The corresponding Binomial Tree is presented in Figure 86.

[303] Kim, K. H. P. A. H. K. (2017). Real Options Analysis for Renewable Energy Investment Decisions in Developing Countries. Renewable and Sustainable Energy Reviews.

[304] National Confederation of Municipalities-CNM (2022). Estudo técnico- Obras Paradas. Available in < https://www.cnm.org.br/biblioteca/exibe/15354>. Accessed 2022.

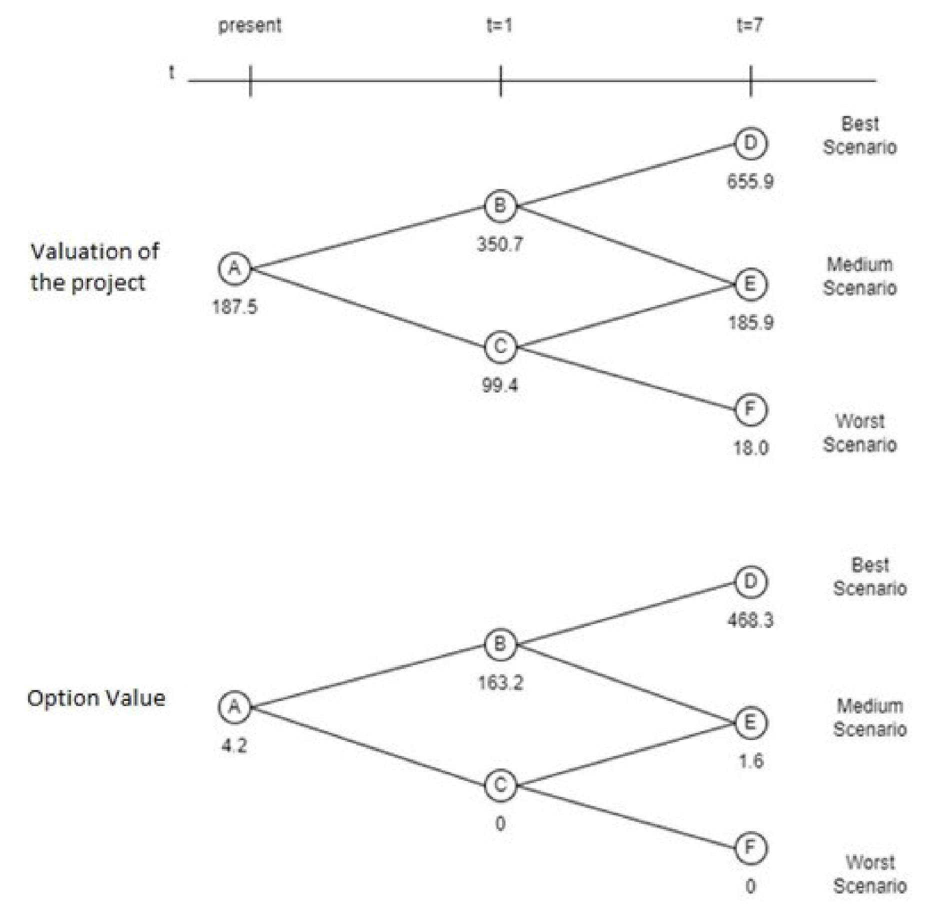
[305] Valuation of the exit option can be computed using different methods: Binomial Tree, Partial Differential Equations, Simulation; Dynamic Programming, Empirical Analysis, Monte Carlo Least Squares Approach, Game Theory, or Probabilistic Model (Extension of the table in Kim, 2014).

[306] Kim, K.t. et al. (2014). Evaluation of R&D Investments in Wind Power in Korea Using Real Option. Renewable and Sustainable Energy Reviews 40: 335-347.

[307] Lamperti, F. et al. (2018). Faraway, So Close: Coupled Climate and Economic Dynamics in an Agent-Based Integrated Assessment Model. Ecological Economics 150: 315-339.

[308] Brazilian hydroelectric power plant systems with facilities in the states of São Paulo, Minas Gerais, Rio de Janeiro, Espírito Santo, Paraná, Goiás, Mato Grosso, Mato Grosso do Sul, Pará, Tocantins, Rondônia, Rio Grande do Sul, Santa Catarina, Ceará, Bahia and the Federal District.

Figure 86: Project and option valuation lattices (in US$ million). Note: Nodes D,E,F represent the project value and the option value at t=7 in the different scenarios. Node A in both trees are the values brought in at t=0. That is, at the present time. The Node A in Option Value tree is the value that should be considered at the time of project evaluation.



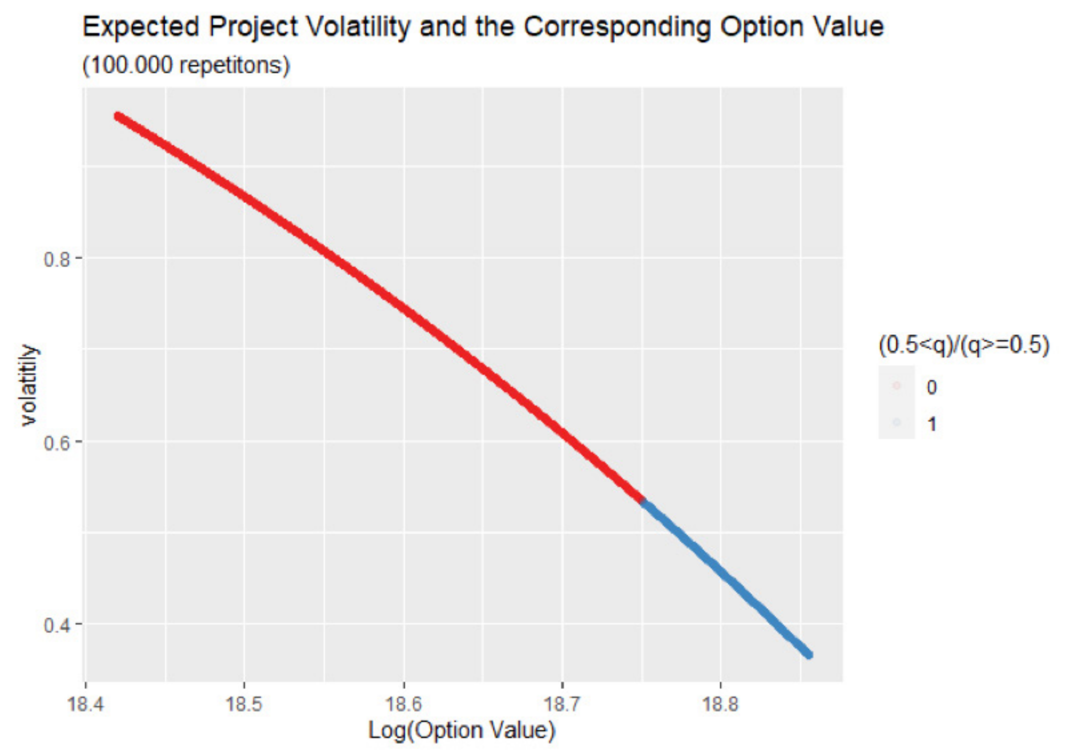
As shown in Figure 86, the creditor agent, if considering this mechanism, 'acquires' the right to exit the project at the end of the construction step (after seven years) by increasing the traditional moderate-scenario NPV by US$4.2m. Therefore, the creditor would be no longer required to finance the next project stage (OpEx) if the option is exercised, while preserving the full rights to receive back the outstanding loans (CapEx). Since the NPV without option value for this project was calculated to be approximately US$3.7m, the option value consists of 53 per cent of the new present value. This significant difference means that similar projects with a slight lower NPV may have been refused, while the consideration of the exit option would have proved them as creditworthy as the Itumbiara case.

Starting with the Itumbiara benchmark project, we simulate 100,000 similar potentially viable projects[309] to investigate how the exit option value relates to project variables' volatility. In our model, the difference between the worst and best-case scenarios is given by different assumptions for the wages, energy tariff, capital utilisation and labour productivity, based on the historical volatility. It is worth noting that these variables are fundamentally driven by the respective markets, but how they affect project performance also depends on the developer's skills, another type of uncertainty we seek to deal with in the model. Therefore, the exit option value will reflect both market and project-specific uncertainty.

For the set of simulated projects, Figure 87 shows the modelled total project volatility, the corresponding exit-option value, and the probability q that the project becomes more profitable. Projects with q lower than 0.5 are shown in red, and those with q greater or equal to 0.5, in blue.

[309] We focus our analysis on financially viable projects – that is, those with a positive net present value.

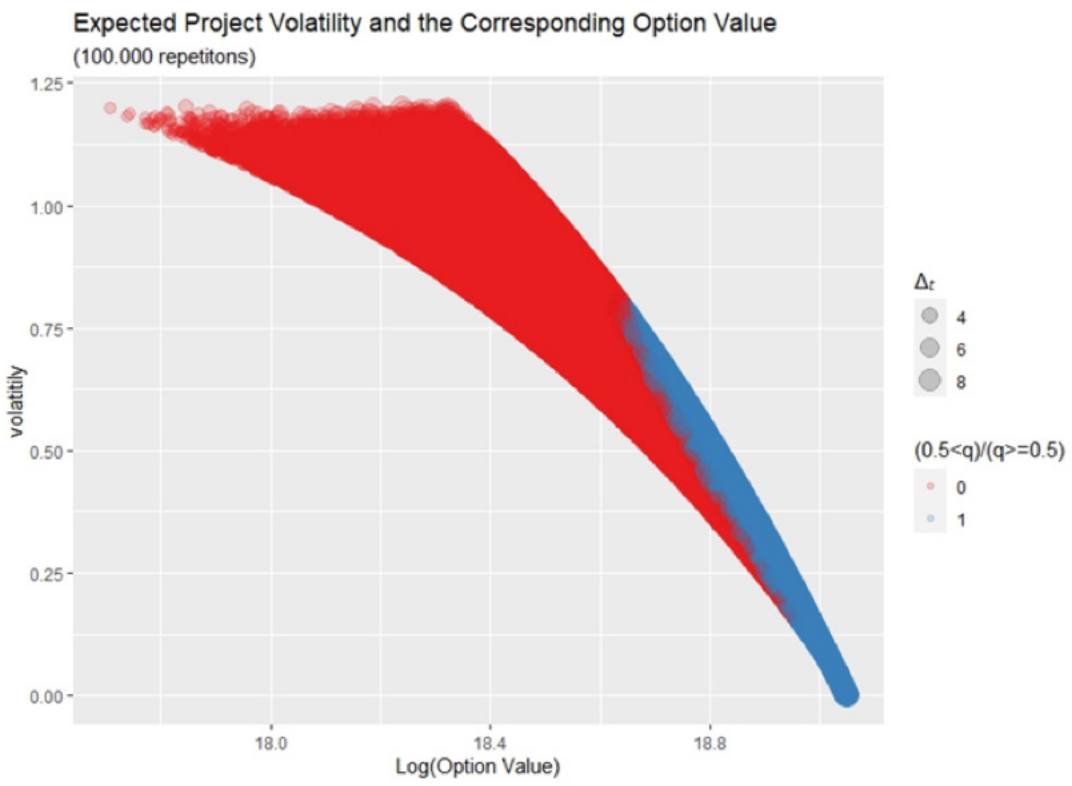
Figure 87: Expected Project Volatility and the Corresponding Option Value with =7 (US$ million/100M repetitions). Source: Elaborated by the author.



Overall, we find that the higher the project volatility, the lower the exit option value. At lower levels of volatility, the share of projects with higher probability of becoming more profitable is higher – and among the projects with very low volatility, all are more likely to increase in value than to devaluate (those in blue). These are low-risk projects and, as such, have the highest exit option value. In turn, higher volatility implies a lower probability of project value appreciation, and lower option value, which can be interpreted as the risk premium incurred by financing the project.

In Figure 88 we present a further exercise, allowing for some flexibility on the time the exit option can be exercised ( ) in each simulated project, from the second until the ninth year. In this case, we can see that there are projects with the same volatility but different option values, and this is because the probability of an undesirable NPV trajectory for some is higher than for others. In this case, adding the exit option to the financial operation would allow creditors to exit the project without incurring unplanned costs (e.g. litigation) as more information about the project performance is realised over time, and so allowing for an increased 'appetite' for risk.

Figure 88: Expected Project Volatility and the Corresponding Option Value, with ranging between 2 and 9 (US$ million/100M repetitions). Source: Elaborated by the author.



Finally, within the ranges of our simulations, most projects have a probability of becoming more profitable lower than 0.5 (areas in red), suggesting that plants like Itumbiara hydro plant, ex ante, have lower probability of being economically viable, even if the main driver for this assessment is exclusively connected to the historical volatility embedded in the main variables. In many cases, perfectly feasible projects, ex post, are discarded because of valuation methodology constraints on dealing with the uncertainty associated with long-term projects.

Conclusion

These experimental results seem consistent with the low levels of private investment in the infrastructure sector in Brazil and many developing countries. The documented higher volatility of domestic markets in these economies, plus the limited ability of the usual valuation methods – developed for advanced countries – to deal with such level of uncertainty, seem to indicate new approaches are required if engagement of private finance is desired.

It is worth emphasising that the simulation above was based on a hydropower plant, so carrying out similar exercises for wind and solar energy projects would be important next steps to better understand the potential of exit options to strengthen private financing for green energy in Brazil. Other than its potential, a better understanding of the reasons for the lower adoption of RO in Brazil, as well understanding the regulatory changes that may be required to make it more viable to financing agents, is the natural direction of our future research.

Table 15: Real Options applications with different valuation methods.

Legend: PDE = Partial Differential Equations; AB = Binomial Tree; SIM = Simulation; PD = Dynamic Programming; AE = Empirical Analysis; AMMQ = Monte Carlo Least Squares Approach; GT = Game Theory; MP = Probabilistic Model

Source: Extension of the table in Kim (2017).[310]

Authors	Country	Type ER	Methodology
HOFF (2003)	California	Photovoltaic	AB
ZHANG X (2005)	Non-Regional	Hydraulics	SIM
KJAERLAND (2007)	Norway	Hydraulics	EDP
KUMBAROĞLU (2008)	Turkey	Wind	EDP
LEE (2010)	Taiwan	Wind	AB
YANG (2010)	China	Wind	SIM
BATISTA (2011)	Brazil	Hydraulics	SIM
LEE (2011)	Taiwan	Wind	AE
ZAVODOV (2012)	China	Hydraulics	AE
REUTER (2012)	England	Wind	EDP
BOOMSMA (2012)	R. Nordic	Wind	AMMQ
LEE (2013)	Indonesia	Hydraulics	GT + SIM
CESEÑA (2013)	UK	Photovoltaic	SIM
KRONIGER (2014)	England	Wind	EDP + SIM
KIM (2014)	Korea	Wind	AB
ABADIE (2014)	UK	Wind	EDP
WEIBEL (2015)	England	Wind (onshore and offshore)	AMMQ
JEON (2015)	Korea	Photovoltaic	MP
ZHANG (2016)	China	Photovoltaic	EDP
KIM (2017)	Korea	Hydraulics	EDP
AGATON (2018)	Philippines	ER	EDP + AMMQ
GAZHELI, (2018)	Non-Regional	Solar and Wind	EDP

[310] Kim, K. H. P. A. H. K. (2017). Real Options Analysis for Renewable Energy Investment Decisions in Developing Countries. Renewable and Sustainable Energy Reviews.

EEIST

Conclusion

This report represents a major effort to demonstrate and evidence the value of a range of new economic modelling on specific topics and policy questions, in partnership with policy stakeholders in key countries in the global energy transition. It has presented an overview of the types of approaches described as 'new economic modelling', considering how they fit into different types of policy questions, and how to start using them.

It has presented 15 applied and policy-led case studies of these approaches being used on live policy questions and creating insights and value for real decision makers. As such, we believe this report delivers on the promise of new economic modelling, taking us past critiques of existing approaches and abstract ideas, and providing the specific insights to take us further in energy and climate policy analysis.

Summary of case study findings

From the case studies, a set of key findings emerge on the four types of policy questions we focus on, Table 16 summarises these.

Table 16: Policy questions addressed and key findings in this report.

Policy questions	Key findings
Development direction: Should we decarbonise? How much will it cost? What will be the macroeconomic impacts?	• Multiple case studies, for different countries and using multiple methods, all find that decarbonisation is likely to provide net job creation and, depending on the specific economic structures of the geographies of interest, may lead to economic growth overall. • A faster transition than currently envisaged is preferable. • There may be negative impacts or costs under certain transition scenarios and we can identify the specific periods, sectors or occupations where these might be, as well as connections to other development objectives.
Technology choices: Which technologies should we focus on? What will be the sectoral impacts?	• Policymakers should minimise barriers to zero-emission technologies, whose performance improves and costs reduce with greater deployment. These include solar, wind, electrolysers and batteries. Policymakers should shape markets to be conducive to faster innovation and growth in these technologies. • Different countries will have different technologies to focus on, depending on their current situation. • Transitioning away from fossil fuel technologies can have predictable and manageable impacts, depending on the nature of the transition.
Policy choices: Which policies are best to support our goals?	• Investing in zero-emission technologies tends to be more effective than putting a price on fossil fuels for achieving emissions reductions and innovation in key energy technologies. • Regulation can be highly effective as a means to reallocate investment towards zero-emission technologies, accelerating their improvement and cost reduction. • Technology mandates or government procurement are effective policies to kickstart an industry, and can make other policies more effective. • Carbon pricing can be helpful when used as part of a package of policies (more so when implemented as a tax than when implemented as a cap-and-trade scheme). • Timing of policy support is key, with late support increasing the chances of unwanted lock-in. • Policy support can often be revenue or fiscal-neutral.
Policy design: How should we design this policy?	• Subsidies or taxes may be particularly effective when they are set at a level that makes a zero-emission technology cost-competitive with fossil fuels. • Regulations may be more effective when they mandate uptake of a zero-emission technology than when they require increasing efficiency of fossil fuels (though both together may be best). • Emissions trading schemes need to be designed to avoid introducing a brake on emissions reductions when quick progress outstrips adjustments in permit supply.

Themes and lessons

The case studies are individually rich and varied, but there are some key overarching themes and lessons:

1. **Primacy of co-produced analysis with stakeholders and partners.** A common theme is the use of co-production to develop insights, with policy teams and modellers working closely together to define the analysis questions and approach, and iterating through rounds of analysis and discussion. This mode of working is not universal, and is not essential, but it is the primary way in which insights are delivered alongside improvements in capacity and capabilities for both users and producers of modelling. We recommend viewing co-production of modelling insights as a default option.

2. **Value of detailed policy appraisal.** Many of the case studies provide detailed policy analysis, or use modelling which has the capability to provide this. Here, we are referring to models that have enough structural realism and model parameters that we can meaningfully represent the details of policy implementation, not just use a carbon price as a proxy. Using models that cannot capture detailed representations of policies, or running scenarios which do not include realistic policy scenarios, is rarely likely to be of value to policymakers. Policy should appear in a model, but should be set exogenously, allowing modellers and policy clients to use the model to run policy scenarios easily.

3. **A new generation of bottom-up, structurally realistic, empirically validated economic simulation models.** Whether they be agent-based models, system dynamic models, or E3ME and its extensions, all of the simulation models in this report aim to represent economic and energy systems in structurally realistic ways, which capture bottom-up relationships rather than observed relationships between macro-variables. Vitally, they hold themselves to high standards on empirical validation – only producing results we can have confidence in, because of their past performance. This is a common and important theme, and a significant improvement on earlier generations of these types of models. What is new is the availability of both computing power and fine-scale data to improve the quality, sophistication and reliability of the models.

4. **Agent-based models are important, but not everything is an agent-based model.** Agent-based models are synonymous with complexity economics, and sometimes with new economic modelling. However, the breadth of case studies here shows there are other approaches too – both simulation and data analysis approaches. This is important, because new economic modelling is pluralist in nature and this is reflected in the fact it encompasses a range of modelling approaches. This plurality allows new economic modelling to respond to different stakeholder needs and policy contexts.

5. **We need to consider the maturity of different modelling approaches when using them.** To manage expectations and ensure different approaches are used appropriately, it is vital that we understand the maturity of different models. CGE and DSGE models,[311] for example, are very mature. They have been widely used in academic and policy contexts, and so have well-developed norms, frameworks and institutions to support their use. This means they can often be used quickly and in a familiar way, but are more 'set in their ways', where it is difficult to take a step back and question certain assumptions. In contrast, many new economic approaches are less mature and there is less orthodoxy around their use. This means they may be slower to use, and there may be many decisions which need to be made in each application, which can be skipped in more established approaches. On the other hand, they are more flexible to each application. The one exception to this is E3ME, which in the last 23 years has developed an institutional support and operational framework to allow it to be used in a similar way to more established modelling approaches. This provides one blueprint for other new economic approaches.

[311] Computable General Equilibrium and Dynamic Stochastic General Equilibrium models.

The future for new economic modelling

This report documents just the beginning of applying new economic modelling for climate and energy policy. The policy influence is only just beginning to be felt. As the value of these approaches is more widely appreciated, as they improve and as these efforts expand, we see the following key trends for the next five years:

1. **Knowing what works in practice.** Both within and beyond EEIST, we are already aware of a large range of national and regional governments, multilateral organisations, private-sector actors and funders that are using or planning to use the types of modelling we have presented here. The application of these types of analysis is set to expand significantly in the coming few years. This is important for two reasons. First, the learning that will be generated, beyond individual policy insights, on what works for the application of these methods, will be vital in improving their use. Second, it will expand the examples and blueprints for policymakers to use to articulate more clearly the types of policy analysis they want. We often hear policy teams complain about the drawbacks of different types of models, but are not sure what the solution looks like. Now they have a positive story and vision to explain more fully what they want.

2. **Broader dissemination of applied systems thinking.** As the models are applied more widely, so too will be the systems thinking concepts behind them. Our previous report, Ten Principles for Policy Making in the Energy Transition,[312] outlined the broader policy implications of new economic modelling and approaches. This is one part of a wider conceptual framework. Beyond this are concepts such as feedback loops, tipping points and disequilibrium. As the applications expand, we expect the sophistication and 'literacy' of policymakers in applying systems thinking to increase markedly. This is an exciting avenue in its own right.

3. **Methodological innovation and transparency.** Alongside the application of methods and ideas, we expect to see a surge in innovation of new methods, reflecting their growing success and demand for their use. These innovations are most likely to be around: (i) ever-improving calibration and validation of models; (ii) use of more and better data and new types of data; (iii) use of machine learning techniques to build better data-derived models; and (iv) communication and visualisation of model design and insights. There are also likely to be big opportunities in building capacity in different institutions to produce and use these types of modelling, as well as a broader push for more transparency and clarity around models, reflecting their more intuitive and structurally realistic leanings. If the capacity building and training can be delivered around these methods, we expect more policy teams to engage with models critically, understanding their assumptions, design and why they are giving certain results, rather than accepting modelling insights passively.

This future for new economic modelling is an opportunity rather than an inevitability. We need to learn from and use current policy insights, and then continue to invest in applying these methods to real-world policy and decision. Vitally, we need to do more to build capacity and expertise in the institutions that can make use of these approaches.

[300] https://eeist.co.uk/eeist-reports/

Appendix

Example data requirements for new economic models

This appendix provides a summary of the data collected and used in a selection of the models presented in this report. This is presented in a spreadsheet form following this short introduction.

This summary was developed in part to provide members of the EEIST consortium with an understanding of the data requirements associated with applying a modelling capability to a given context. Hence, the data is broken down by major model components (and thus the types of data and the models which use them) – scenarios, production, labour, energy and SDGs. The data is also split into data that is a 'minimum requirement', and 'important but not required'. The former are required for the model to provide reliable results; the latter are important but can be replaced with estimates or substituted with data from other contexts.

As discussed in the main body of the report, the data collected for each model provides them with measurements from real-world indicators, anchoring them in the real-world phenomena, and the context of the specific case studies. The ability of a model to predict or forecast the future is heavily dependent on the quality and quantity of data used. It is worth noting that the quality of the data used in each of the case studies presented in this report varies between contexts. However, no one country or context has the best quality of data for each application. All case studies are therefore compromised to some extent by the quality of the data they use. For this reason, the models will generally employ stochastic approaches to explore the uncertainty associated with their data and provide range estimates of their outputs. Aggregated global studies are the most likely to provide the best predictions, but are limited in that they can only provide outputs at a global scale.

The data requirements spreadsheet can be found at [https://eeist.co.uk/eeist-reports/new-economic-models-of-energy-innovation-and-transition/.](https://eeist.co.uk/eeist-reports/new-economic-models-of-energy-innovation-and-transition/)

Appendix for case study: What is the most cost-effective form of carbon pricing?

This is an annex to part three of the case study. The annex was written by Huaiyu Wang, Jia Liu, Tianyi Wu, Zheng Kang, and Zhangang Han.

A: levelised cost of energy infrastructure

Levelised Cost Of Electricity (LCOE) for each technology is used to guide the technology choice when a new plant is going to be established.[313] For a newly built power plant, its LCOE could be calculated as:

$$\mathrm{LCOE_i} = \sum_{y=y_b}^{y_{b+d}} \frac{\mathrm{LC}(y) * (\delta * \mathrm{IC} + \mathrm{MC} + \mathrm{FC})}{(1+r)^{y-y_b}}$$

LC = The percentage influenced by the learning rate of total cost at year y.

MC = The maintenance cost at year y.

FC = The fuel cost of the power plant at year y.

y = The certain year in which overall cost is estimated.

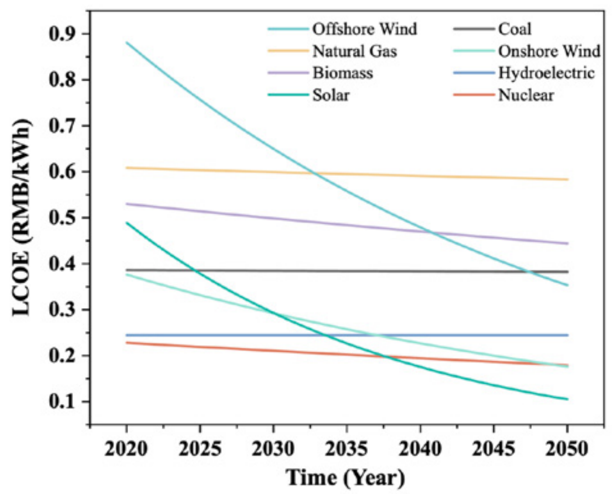
R = The discount rate of capital. We assume it to be constant all the time.

The summation symbol represents the LCOE is a variable of lifetime which works from the year of construction to its design year, assuming the plant not being shut down or dismantled. The numerator represents all costs in a given year of the lifetime and the denominator represents the factor required to discount the costs from this year to the year of construction according to the compound interest formula, with the discount rate chosen to be the annualised rate of return of the CMB-GD from 2001 to date, which is 1.25 per cent. In the ETS scenario the future carbon cost here is not a specified value but an estimated one (last year's quota) because a power plant cannot know how much carbon quota it can get. And the factor that identifies the build year, equals 1 at the build year but 0 anytime else.

[313] Branker, K. et al. (2011). A Review of Solar Photovoltaic Levelised Cost of Electricity. Renewable and Sustainable Energy Reviews 15(9): 4470-4482.

The final LCOE used in the model is illustrated in Figure A-1. As showing in the figure, the technology progress of conventional technologies – coal, natural gas, hydro, nuclear – is very limited. In contrast, significant progress is assumed for wind and solar power.

Figure A-1 : Cost evolution of traditional and innovative technologies.



B: Bounded rationality and partition function

The principle of finite rationality in the decision-making mechanism is reflected in the final choice of energy source for the new power plant. A stochastic decision-making mechanism similar to the Partition Function (PF) in statistical physics is introduced, linking the probability of a thermodynamic system being in a certain state to the probability of choosing a power plant for a certain energy source. The higher the energy, the lower the probability of instability in a thermodynamic system, and similarly the higher the LCOE, the lower the probability of choosing to build a power plant. In this mechanism, the probability of choosing a certain power plant i Pi is given by the following equation:

$$\begin{cases} E_i = \mathrm{LCOE_i} \\ Z = \sum_{E_i} e^{-\beta E_i} \\ P_i = \dfrac{e^{-\beta E_i}}{Z} \end{cases}$$

Where ß is the rationality index, the larger ß is, the more sensitive Ei is to probability and the more rational the decision is; the smaller ß is, the less sensitive probability is to Ei and the less rational the decision is. Z is the PF which works as the normalisation parameter, which sums. Using a uniform random number generator to generate random numbers between 0 and 1 and the above formula to calculate each Pi, the axis is then divided in a determined order for each energy plant Pi. The interval in which the random number falls is the interval in which the plant is selected for construction. The process is repeated until the condition that no new plants are needed is met, and the process of building new plants for the year is completed.

C: Decommission rule of existing plants

The decision to decommission a power plant is not an easy one, given the huge labour cost involved in building a plant, the cost of equipment, the cost of construction and demolition, and the considerable jobs and energy supply that the plant can provide. It is clearly not realistic to be too sensitive to the profitability of a power plant (intolerable losses and rapid dismantling) or too insensitive (always working and running regardless of operating conditions). Therefore, in our model we introduce a dismantling probability Pdown to simplify this decision process. The power plant shall check the profit of the latest Tthreshold years, in which the number of loss years ndeficit divided by Tthreshold is the power plant dismantling probability, that is:

$$P_{\mathrm{down}} = \frac{1}{T_{\mathrm{theshold}}} * n_{\mathrm{deficit}}$$

using a uniform random number generator to generate a random number between 0 and 1. If it is greater than or equal to Pdown, then the plant is not dismantled, and vice versa.

D: Carbon price in ETS with soft cap and free allocation

In this scenario, we use the empirical formula to calculate the annual carbon price, citing from existing reference:[314]

$$p_{CO_2} = 10 + 40 \times \left(\frac{\sum_{j=1}^{n} e_j}{t} \right)$$

Where: pCO2 : the price of CO2 permits in Yuan/ton

ej : emission of power plant j

n : the number of power plants

t : the total cap in ton/year.

In order to validate the formula, the permit price is computed for the base year with 877gCO2/kWh as the benchmark for the majority of producing units. The outcome reveals that the average price is approximately CNY 54.2/tCO2 (with a soft cap around 4,280MtCO2), accurately representing China's reality. This gives the team assurance that the formula, which was initially developed for EU ETS, is applicable.

E: Clearinghouse double auction mechanism.

The carbon trading mechanism we used is a unified state auction of carbon quotas for all thermal power plants, where the state directly auctions carbon quotas at the first level, obtains auction bids from each power plant for its own quota, and then matches them from highest to lowest price until the quota is issued. The learning mechanism for the power plant auction bids is based on the Roth-Erev multi-agent reinforcement learning algorithm,[315 316] where the probability of choosing the next action is adjusted according to the benefit of the previous action. The auction mechanism flows as follows.

Auction

1. Each year, the state determines the total number of allowances based on the carbon emission targets given by the foreign investors, equates them to the number of auctions in the year and issues the allowances in batches for purchase by coal and electricity companies.

2. Coal and electricity companies give their purchase volumes and bid according to the bid probabilities obtained from their studies, rank the coal and electricity companies' bids from highest to lowest, add up their purchase quotas until they reach the quota volume issued by the state, and use the price at that point as the quota price for this year.

Note: Each coal-fired factory can only emit CO2 of the amount of allowances purchased, and the allowances are only used to generate electricity, without taking into account that the factory then sells the allowances.

Bidding and learning

1. A certain number of values are taken as bid points at equal intervals between the reserve price and the maximum acceptable carbon allowance price for the power plant, and each bid will be selected from the bid points based on the probability of the bid points corresponding to the learned bid points.

The minimum allowed bid is 0, and the maximum bid is designed, in the model, as the break-even point for each agent, which means the bidding price equals the revenue from electricity sales minus fuel cost.

2. This study adopts the Roth Erev reinforcement learning model with forgetting factor, based on two basic assumptions of multiple traders in the market:

- Successful and similar choices in the past will be more likely to be used in the future.
- Recent experience will be more useful for current decision making than long-term experience.

The basic settings of the model are as follows:

$$q_{jk}(1) = \frac{s(1)X}{K}$$

$$p_{jk}(1) = 1/K$$

$$r^* = \frac{r-e}{K-1}$$

$$q_{jk}(n+1) = (1-r)q_{jk}(n) + ME(j,k,k',n,K,e)$$

$$ME(j,k,k',n,K,e) = \begin{cases} R(j,k,n)(1-e), k = k' \\ q_{jk}(n)\dfrac{e}{K-1}, k \neq k' \end{cases}$$

$$p_{jk}(n+1) = \frac{q_{jk}(n+1)}{\sum_{m=1}^{k} q_{jm}(n+1)}$$

[314] Chappin, E. (2011). Simulating Energy Transitions. Mother Pelican. Delft University of Technology. Retrieved from http://www.chappin.com/thesis.

[315] Roth, A. E. and Erev I. (1995). Learning in Extensive-Form Games: Experimental data and simple dynamic models in the intermediate term. Games and Economic Behavior 8(1): 164-212.

[316] Nicolaisen, J. et al. (2001). Market Power And Efficiency in a Computational Electricity Market with Discriminatory Double-Auction Pricing. IEEE transactions on Evolutionary Computation, 5(5): 504-523.

Where qjk(n),pjk(n), is the 'preference' and probability for the j th individual to choose the k th bid in the n th auction, e is the experimental parameter, which reflects the speed of learning. The preference is the accumulation of historical income (profits generated by purchasing carbon quotas) in the carbon quota auction, and the probability is the normalisation of the 'preference' of all bid choices. At initialisation, the 'preference' and probability of each choice are equal, where K is the number of bid choices and X is the estimated initial average return. r is the recency parameter, representing the forgetting ratio of the 'preference' of the last auction of the same strategy. ME(j, k, k', n, K, e) is a preference update item. If the auction is successful, the bid will choose to linearly increase a positive 'preference' according to the learning speed e, and the proportion of the proceeds from the remaining bids will be distributed to the unused strategy 'preference'. The current policy and specific parameters expected from using this mechanism are as follows:

Table E-1: Parameter settings for the machine-learning bidding.

parameters	symbol	value
recency parameter	r	0.1
experimental parameter	e	0.5
the number of bid choices	K	50
estimated initial average return	X	4,000,000
scaling parameter	S(1)	1

The reason for letting r be 0.1 is that r is the recency parameter, and it is reasonable to take a smaller value. e is 0.5 because it has a range of values from 0 to 1, so the median value of 0.5 was taken. K=50 was chosen because, after experiments, it was found that if K was small, the bids would be too discrete, and too large would make the agent learn too slowly. X only related to the initialisation after experiments found that, due to the existence of forgetting factor, as long as the value is large to a certain extent, the model is insensitive to the value of X, and finally 4,000,000 is selected. s(1) is the scaling parameter, s(1) is set to 1 means no additional scaling.

Coal power plant construction restrictions

Is new coal power plant construction allowed when the quota is full? If it is not allowed, extra regulation and administrative intervention is introduced. Although a policy that the authors of the current paper do not appreciate, we still simulate such a policy, to provide a deeper understanding of the auction mechanism for decision support.

F: The capacity, power generation and CO2 emission distribution in the base year

Figure F-1: Capacity distribution in the base year.

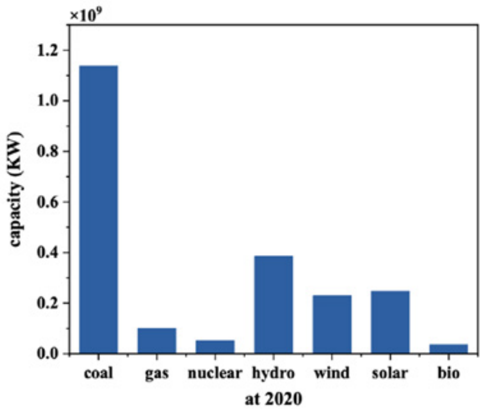


Figure F-2: Power generation distribution in the base year.

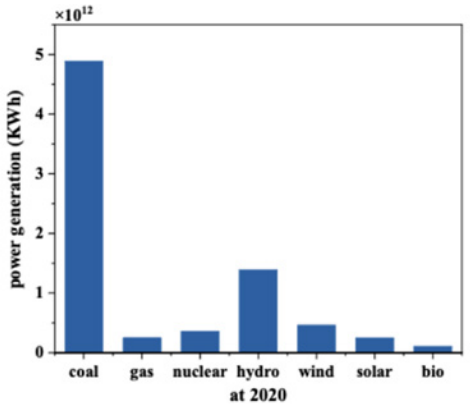
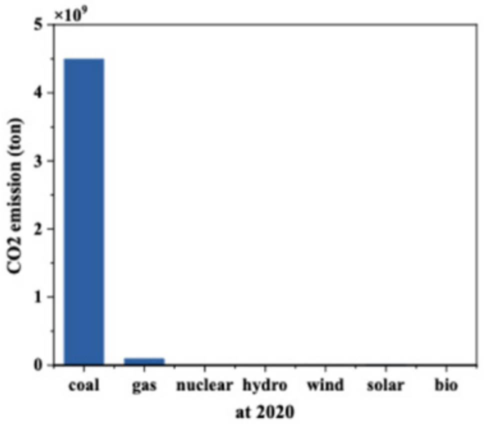


Figure F-3: CO2 emission distribution in the base year.



EEIST

Economics of Energy Innovation and System Transition

The Economics of Energy Innovation and System Transition (EEIST) project develops cutting-edge energy innovation analysis to support government decision making around low-carbon innovation and technological change. By engaging with policymakers and stakeholders in Brazil, China, India, the UK and the EU, the project aims to contribute to the economic development of emerging nations and support sustainable development globally.

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