A new perspective on decarbonising the global energy system

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About this report

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Foreign, Commonwealth & Development Office

University of Oxford — Institute for New Economic Thinking at the Oxford Martin School

Baillie Gifford

Abstract

An analysis of historical cost trends of energy technologies shows that the decades-long increase in the deployment of renewable energy technologies has consistently coincided with steep declines in their costs. For example, the cost of solar photovoltaics has declined by three orders of magnitude over the last 50 years. Similar trends are to be found with wind, energy storage, and electrolysers (hydrogen-based energy). Such declines are set to continue and will take several of these renewable technologies well below the cost base for current fossil fuel power generation. Most major climate mitigation models produced for the IPCC and the International Energy Agency have continually underestimated such trends despite these trends being quite consistent and predictable. By incorporating such trends into a simple, transparent energy system model we produce new climate mitigation scenarios that provide a contrasting perspective to those of the standard models. These new scenarios provide an opportunity to reassess the common narrative that a Paris-compliant emissions pathway will be expensive, will require reduced energy reliability or economic growth, and will need to rely on technologies that are currently expensive or unproven as scale. This research provides encouraging evidence for governments that are looking for greater ambition on decarbonising their economies while providing economic growth opportunities and affordable energy.

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Summary for Policymakers

A rigorous analysis of the historical cost trends of energy technologies shows that the decades-long increase in the deployment of key renewable energy and storage technologies (e.g., solar, wind, batteries, and hydrogen) has gone hand-in-hand with consistent steep declines in their costs. For example, the cost of solar PV has declined by three orders of magnitude (more than 1000-fold decrease) as it has become more widely deployed over the last 50 years – declining so much that the International Energy Agency recently declared solar PV in certain regions “the cheapest source of electricity in history” (IEA, 2020). Such cost reductions are the consequence of experience gained in design, manufacture, finance, installation, and maintenance – and the overall pattern of development is hence known as the ‘experience curve’.

In contrast, non-renewable energy technologies have seen no significant deployment-related cost declines over the last 50 years. The cost of electricity from coal and gas has largely remained steady, fluctuating by less than an order of magnitude. The average cost of nuclear electricity has even increased over this same period, partly in response to safety concerns.

These long-term technology cost trends appear to be consistent and predictable (Farmer & Lafond, 2016; McNerney et al., 2011). Alongside advances in the technologies themselves, we have seen advances in our understanding of how technological change unfolds in the economy more broadly and of the characteristics that fast-progressing technologies have in common with each other (Wilson et al., 2020). Several new methods that are statistically validated and firmly grounded in data have been developed for forecasting technological progress (Nagy et al., 2013; Way et al., 2019).

Incorporating technology cost trends into a simple, transparent energy system model has produced new climate mitigation scenarios that starkly contrast to those currently produced for the IPCC and the International Energy Agency (IEA). It may come as a surprise that in most major climate mitigation models, such as the IPCC’s Integrated Assessment Models (IAMs), the costs of energy technologies are not handled very transparently. They assume unsubstantiated limits to cost declines and often contain out-of-date data (Jaxa-Rozen & Trutnevyte, 2021; Krey et al., 2019). We use an alternative approach to explore the implications of these discrepancies and have found an exciting new decarbonisation scenario we have named the Decisive Transition in recognition of the commitment to a clean energy system that this scenario represents.

A new perspective on decarbonising the global energy system

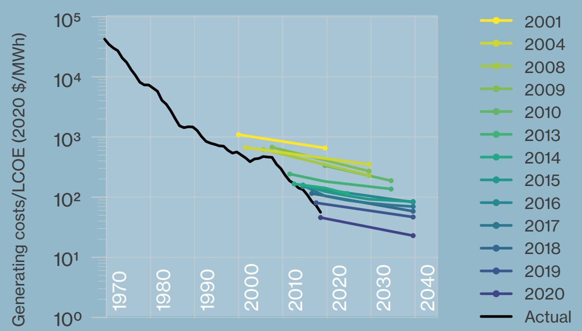
A novel approach to energy systems modelling – accounting transparently for the real-world, historical cost trends of renewable energy technologies – indicates that the decarbonisation of the global energy system:

- Is likely to be cheaper than commonly assumed
- May not require any declines in economic growth
- Can be achieved without large investments in unproven and potentially expensive technologies

The problem

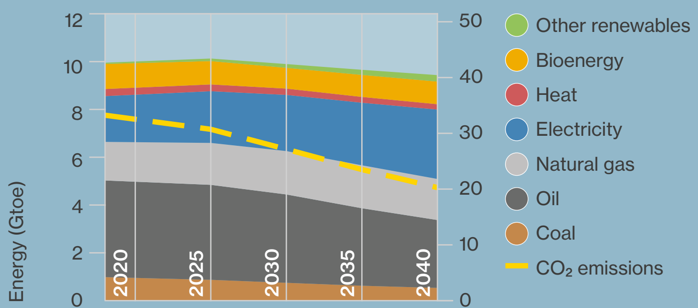
Existing energy system models have consistently underestimated the cost reductions and growth potential of key renewable and energy storage technologies.

Average global solar photovoltaic costs



(IEA World Energy Outlook 2001-2020, Nemet 2006, and IRENA 2020)

Global final energy mix



Sustainable Development Scenario

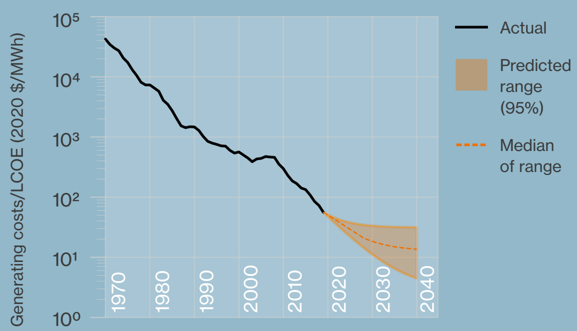
The IEA's Sustainable Development Scenario (IEA World Energy Outlook 2019):

- 3.4% p.a. economic growth
- Requires expensive large-scale carbon capture & storage (CCS)
- Keeps coal through CCS retrofits
- Some electrification benefits
- Electricity prices unlikely to fall
- Emissions are less aligned with Paris goals

Our response

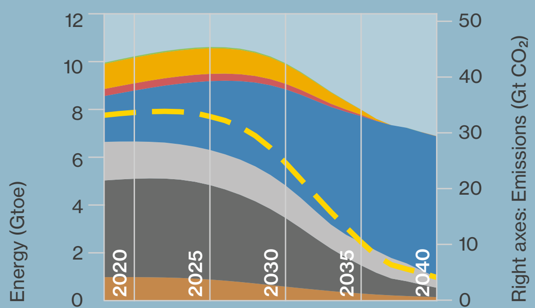
Our energy systems model is built on observed trends in the relationship between the rate of deployment and the cost of energy technologies such as **solar**, **wind**, **batteries** and **hydrogen**.

Average global solar photovoltaic costs



(Based on Way et al. 2020)

Global final energy mix



Decisive Transition scenario

Our Decisive Transition scenario:

- 2% p.a. useful energy growth (>3.4% p.a. economic growth)
- No expensive large-scale CCS required
- Rapid phase-out of all fossil fuels
- Large efficiency gains from electrification
- Electricity prices are *very likely* to fall
- Emissions are more aligned with Paris goals

This scenario is created by selecting deployment rates for new energy technologies, based on their historical trends, and allowing such trends to continue for around a decade before tapering off. Technology costs are then simulated hundreds of thousands of times to generate probabilistic forecasts based on the methodology published by Farmer & Lafond (2016). These probabilistic cost forecasts are generated for the various key technologies to model a lower cost evolution of the energy system that has yet to be explored by the major mitigation models of the IPCC and IEA.

This new perspective suggests a reassessment is due regarding the potential cost and pace of the global energy system's transition. At present, policymakers usually assume that the transition of the energy system to a Paris-compliant emissions pathway will be expensive; that it will require a net reduction in the provision of energy services or economic growth; and that it will rely critically on technologies that are currently expensive, unproven, or potentially controversial – such as carbon capture and storage (CCS), second-generation biofuels, and new nuclear energy designs (e.g., small modular reactors).

In this report, we present two contrasting scenarios that illustrate how properly accounting for technological cost trends can challenge common perceptions regarding the costs and benefits of a Decisive Transition to clean energy technologies. The modelling presented in this report contrasts two very different scenarios: a **Stalled Transition**, in which total demand for energy services continues to grow at its historical average of 2% per year, but with the ratios of the different energy technologies frozen at their current values. This scenario provides a useful 'worst-case' baseline and a counterfactual for estimating relative costs. The second scenario is a **Decisive Transition** in which current exponential growth rates in clean energy technologies continue for the next decade, then gradually relax back to the low system-wide rate. Here we see that within 25 years, fossil fuels are displaced from the energy sector, with all essential liquid fuel use replaced by "green" hydrogen-based fuels. Solar and wind provide most of the energy; transport and heat are mostly electrified; and reliable electricity is maintained using batteries and chemical-based energy storage technologies. To provide a like-for-like comparison with the Stalled Transition, useful energy also grows at 2% per year, a rate much higher than in other deep decarbonisation scenarios.

Our Decisive Transition achieves almost all the reductions in greenhouse gas emissions necessary to match the most ambitious IPCC scenarios. Figure 1 presents the global warming associated with the Stalled (orange) and Decisive Transition (purple) scenarios compared to three key IPCC warming scenarios. Our Stalled Transition scenario is most closely aligned with what is regarded as the 'worst-case' IPCC scenario (SSP5 RCP8.5). The Decisive Transition is most comparable to the SSP1 RCP2.6 high mitigation ambition "Taking the Green Road" scenario. This is a remarkable outcome because, in contrast to the high ambition IPPC scenarios (SSP1 RCP1.9 and SSP1 RCP2.6), the Decisive Transition scenario achieves this result without reducing non-energy-based emissions; without any significant deployment of nuclear, carbon capture and storage, or energy-saving technologies; and without requiring a reduction in energy demand or economic growth. It is merely a result of extending the current high growth rates in deployment of clean energy technologies for another decade.

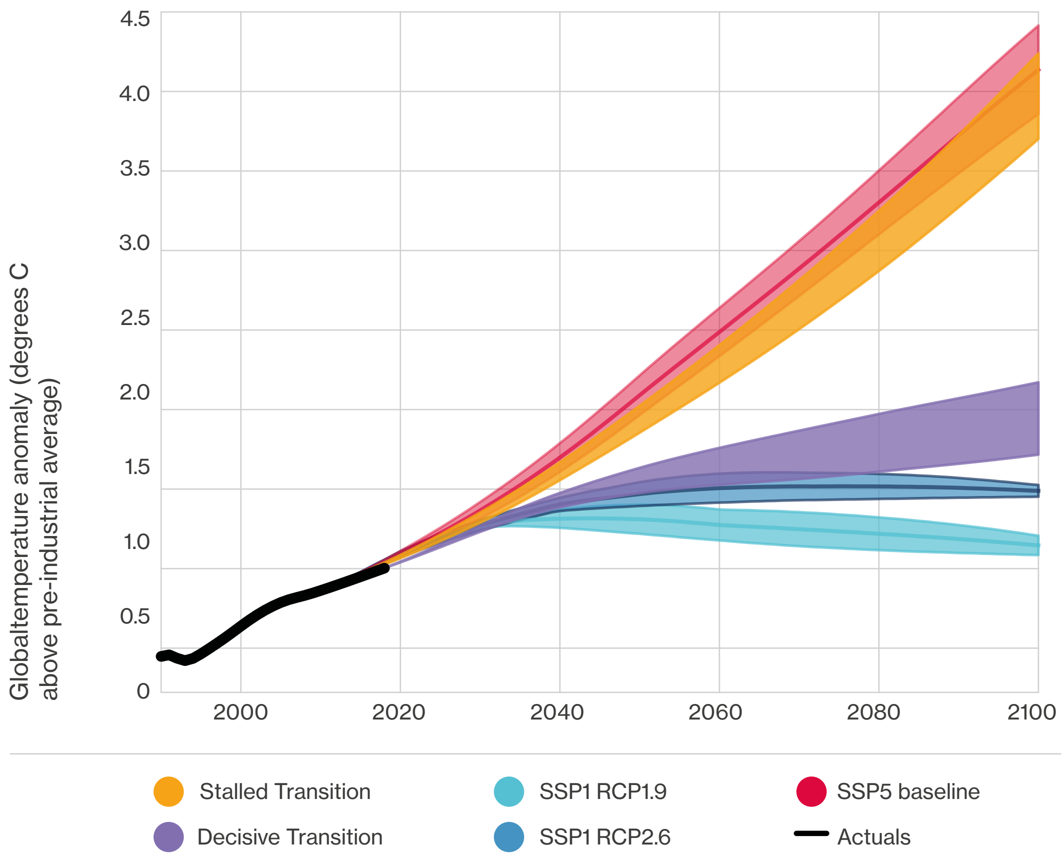


Figure 1: Comparisons of Temperature Anomalies from the estimated global emissions of two PTEC scenarios Stalled and Decisive Transition and three IPCC scenarios SSP5-RCP8.5 baseline, SSP1-RCP1.9 and SSP1-RCP2.6.

The Decisive Transition is significantly cheaper than the Stalled Transition. The modelling show-cased in this report suggests that a clean energy system could be trillions of dollars less expensive to engineer than continuing with the current system based on fossil fuels (Way et al., 2020). This is even without factoring in pollution and associated morbidity and mortality (Vohra et al., 2021), or the multitude of additional physical climate costs likely to result from higher levels of global warming (Arnell et al., 2019).

In the short- and medium-term, situations may arise where renewables cannot cheaply meet the energy demands of certain regions. In these situations, arguments might be made for investment in interim fossil-fuel-based solutions, such as natural gas. However, it should be kept in mind that such investments may not contribute to the final transition and can instead lead to carbon lock-in and create additional transition risk. Foreign aid should be aligned to enable developing states to instead “leapfrog” to electrification and new clean electricity generation, load balancing, and storage technologies.

Unlike most other ambitious scenarios, the Decisive Transition scenario does not rely on underdeveloped technologies, such as carbon capture and storage (CCS) and Bioenergy with CCS (BECCS). This raises questions about whether we should continue channelling investment towards technologies like CCS and nuclear fusion for energy provision. Neither may mix particularly well with renewables and will detract investment away from driving down costs in renewables and storage technologies.

It is still vital that we counter institutional and social barriers to a Decisive Transition, that financial stability is maintained, that gender and social equality is maintained or improved, and that job losses in the fossil fuel industries are addressed. The IEA has shown the potential for renewables to provide far more jobs than other energy-related investments (IEA, 2020), but these jobs may not be created in the areas where coal mines are being closed. Industrial strategies will therefore need to be developed to counter such transition risks. Efforts to maintain or improve gender and social equality should be prioritised now to avoid perpetuating existing gender inequalities (Pearl-Martinez & Stephens, 2016). Social equity concerns also go well beyond the implications for coal miners and include communities tied to coal-fired power stations and communities linked to oil extraction and refinement (Carley & Konisky, 2020). Countries with high reliance on coal-fired energy will also require international support in establishing grid balancing, storage, and efficient power markets to enable higher renewable penetration.

Transition risks are real and likely, given how rapidly technological trends are moving, but it must be remembered that, unlike physical climate risks, stranded assets are only a one-off cost. If we do not end climate change, the more frequent and damaging extreme hurricanes, floods, droughts, and wildfires are likely to cause far greater economic costs that will be constant, long-term, and potentially permanent. Our estimates show the costs of climate damages up to the end of the century from a Stalled Transition are at least ten times greater than any transition risk associated with the Decisive Transition.

In summary, the Decisive Transition scenario indicates that the decarbonisation of the global energy system:

- Is likely to be cheaper than commonly assumed.
- May not require any declines in economic growth.
- Can be achieved without large investments in unproven and potentially expensive technologies.
- Has the potential to save hundreds of trillions of dollars in physical climate damages.

This new perspective also suggests that renewable technologies like solar and wind can provide a steady and secure energy supply, rebutting common beliefs regarding the intermittency problems with renewables. There is a belief that the large-scale deployment of renewables in the global energy system will lead to energy supply failures and high grid integration costs in the future. Our model challenges these perceptions by coupling solar and wind deployment with the deployment of sufficient short-term storage (e.g., batteries) and long-term storage (e.g., hydrogen and ammonia) technologies to ensure high levels of energy security.

This feature allows these storage technologies to also "ride" down experience curves of their own, reaching far higher deployment levels than are commonly anticipated. In doing so, the model demonstrates that it is economically feasible to create a carbon-neutral energy system which:

- Deals with the intermittency problem of renewables through the use of energy storage technologies.
- Allows key storage technologies, such as batteries and electrolysers, to continue their cost decline trends.
- Provides for high levels of energy security while enabling large-scale integration of renewables.

This research offers the opportunity to revisit thinking around the most financially effective speed to transition to a Paris-compliant world. We have found strong evidence to suggest renewable and energy storage technologies will continue their current decreasing cost trends. Most, if not all, of the major climate mitigation models informing decision makers, have continually underestimated these trends. For instance, most major climate mitigation models have minimal electric vehicle take-up in the next few decades. However, if electric vehicle costs continue on current trends, they could be cheaper to buy and run than internal combustion vehicles in less than a decade (Sharpe & Lenton, 2021). Somewhat counter-intuitively, this increased electricity demand from electric vehicles might actually drive down electricity costs (Lafond et al., 2020). This is due to the positive feedback dynamics that our model is designed to capture and that standard economic models do not. Increased adoption of electric vehicles will lead to more demand for electricity. If this increased demand is met with the deployment of more renewables, renewables will get cheaper, electricity generation will get cheaper, electric vehicles will become cheaper and more desirable... and the feedback repeats – provided that this new electricity demand is met with more deployment of renewables.

This research can act as a catalyst for governments to reassess their NDCs at COP26. This is especially true for nations looking to enact a "green recovery" programme or expects significant future energy demand growth and, therefore, are already considering new investment in energy infrastructure (Hepburn et al., 2020). We need a better understanding among national policymakers on what drives these renewable cost reduction trends and how a Paris-style collaboration on investment in renewables and storage for national targets could benefit all countries. COP26 offers a ripe opportunity for a Glasgow Accord on action. Renewables are clear "runners" in the technology race, and early investment will allow countries to capture more of the prosperity this green industrial revolution offers (Farmer et al., 2019).

After the turmoil and horrible cost of the Covid-19 pandemic, we cannot afford business-as-usual – it is too risky and too expensive. When coupled with storage, expanded transmission networks, and smart grids, renewable energy potentially provides a solution to the *energy trilemma* that a fossil fuel-based system simply cannot replicate – an energy system that is affordable, secure, and sustainable.

Introduction

In this report, we propose a novel approach to energy systems modelling and examine the new perspectives such an approach offers on the assumed cost of climate mitigation.

We focus on the experience curves of technologies – historical trends in the relationship between the rate of deployment and the cost of specific technologies – and what they can tell us about the cost and feasibility of the global energy system's transition to net-zero emissions.

A rigorous analysis of the historical cost trends of energy technologies shows that the decades-long increase in the deployment of renewable energy technologies (e.g., solar, wind, batteries, and hydrogen) has gone hand-in-hand with steep declines in their cost. For example, the cost of solar PV has declined by three orders of magnitude over the last 50 years as it has become more widely deployed. These cost reductions are the consequence of experience gained in production, finance, installation, and maintenance – hence the term 'experience curve'. By contrast, non-renewable energy technologies have seen no significant deployment-related cost declines over the last 50 years. The cost of electricity from coal and gas has remained mostly steady, fluctuating by less than an order of magnitude. The average cost of nuclear electricity has even increased over this same period.

Based on these historical cost trends, we developed a novel forecasting method in which renewable technologies' costs stochastically relate to their deployment rate. We estimate the parameters of this relationship using historical data. This probabilistic cost forecasting method is used to construct the Probabilistic Technological Change (PTEC) global energy system model. PTEC comprises four energy-use sectors (electricity, industry, transport, and buildings) and includes 13 different energy technologies: non-renewable energy sources like oil, coal, gas, and nuclear; renewable technologies like solar and wind; and energy storage technologies like batteries for short-term storage and hydrogen and ammonia for long-term storage.

The observed historical correlation between deployment rates and cost reductions does not imply causation and is, in reality, a two-way process: increasing experience with a technology drives down its cost, which then causes further deployment. By using deployment as the driver of cost in our model we are produce contrasting future energy transition scenarios based on actual trends. These scenarios are created by selecting different deployment rates for the various energy technologies in the model. Technology costs are then simulated hundreds of thousands of times using the probabilistic forecasting method. A key result of interest is how the resulting cost distributions of specific energy technologies and total energy system costs evolve.

In this report, we will present the results for two very different transition scenarios: a **Stalled Transition**, in which total demand for energy services continues to grow at its historical average of 2% per year, but with the ratios of the different energy technologies frozen at their current values. This scenario is not necessarily realistic since it is hard to imagine solar PV or wind's recent growth to stop this abruptly. Still, it provides a useful 'worst-case' scenario to act as a baseline and a counterfactual to examine relative costs. The second scenario is a **Decisive Transition**. Here useful energy also grows by 2% per year overall, as with the stalled transition. However, in this scenario resolute policy and investment action maintain the deployment of renewable technologies near their current rates for another decade before they relax to the system-wide growth rate of 2% per year. Solar and wind provide most of the energy, transport is mostly electrified, and reliable electricity is maintained using energy storage.

Changing the 'policy mood music'

As we will demonstrate, the contrast between these two scenarios offers a new perspective to decision-makers about the benefits of pushing decisively for a transition towards renewable energy technologies.

This new perspective creates an opportunity to shift the 'policy mood music' around the global energy system's transition. At present, the 'mood music' policymakers often hear is that the transition of the energy system to a Paris-compliant emissions pathway will be expensive; it will require a net reduction in the provision of energy services; and it will rely critically on technologies that are currently expensive, unproven, or potentially controversial – such as carbon capture and storage (CCS), second-generation biofuels, and new nuclear energy designs.

Additionally, it is commonly assumed that, since renewable energy technologies like solar and wind only provide energy intermittently, they cannot provide energy security. Thus, some believe that the large-scale deployment of renewables in the global energy system will lead to high grid integration costs in the future. The PTEC model challenges these perceptions by coupling solar and wind deployment to the deployment of both short-term storage (i.e., batteries) and long-term storage (i.e., hydrogen and ammonia) technologies. This feature allows these storage technologies to simultaneously "ride" experience curves of their own, to far higher deployment levels than are commonly assumed possible. In doing so, the model demonstrates that it is economically feasible to create a carbon-neutral energy system which deals with the intermittency problem of renewables, provides high levels of energy security both in terms of meeting peak demand and reducing the need for importing fuels, and can accommodates the cost of large-scale integration of renewables into the energy system.

As with any model, PTEC has its limitations (which we discuss later in the report). However, these limitations do not undermine the model's ability to offer a glimpse of a broader range of possible energy futures and climate mitigation solutions than those captured in the current energy and climate mitigation models used to inform policymaking.

We do not claim that the results presented for the decisive transition scenario are set in stone. What the results show, however, is that if a model transparently accounts for the real-world, historical cost trends of renewable technologies, then a much broader range of possible futures becomes visible. It may come as a surprise that in most Integrated Assessment Models (IAMs), the costs of energy technologies are not handled transparently. They assume unsubstantiated limits to cost declines and are usually using data that is years out-of-date. This is important because these models currently set the policy mood music around the overall cost and feasibility of climate mitigation efforts. The contrast between the inputs and results of the different models are sufficient to suggest that reassessing the policies and investment decisions currently pursued by decision-makers is a good idea. At the very least, the future envisaged by the decisive transition scenario shows that resolute action through investment and deployment could deliver big wins in both the future cost of energy and the world's ability to tackle climate change.

How to read this report – a roadmap

The remaining sections of the report explain *why* this research calls for a new perspective on the decarbonisation of the global energy system, and how it affects the policy mood music.

Section 1 deals with how information on energy transitions is currently provided to decision-makers and how this sets the current policy mood music. What models are being used to inform decision-makers on climate mitigation pathways? How are they constructed? What was their intended purpose, and how are they used in practice?

Section 2 describes the limitations of these existing climate mitigation models. What assumptions and data do they use for assessing mitigation options and their costs? What information are they not providing to decision-makers? How do they narrow the perspective on possible transition pathways for policymakers?

Section 3 introduces our alternative perspective: an energy model built around the empirically observed correlations between deployment rates and the cost of various energy technologies. We discuss how using aggregate technology levels leads to a class of models with lower complexity than current energy systems models. This feature offers a level of transparency that many models do not provide.

Section 4 shows the results of using our methodology. We introduce two sample energy transition scenarios (the 'stalled' and 'decisive' transition scenarios) and cover how we calibrated them to scenarios used by the IEA and IPCC. We then provide a detailed comparison with those major mitigation scenarios on, for example, overall costs of the transition, final energy mix, and future emission levels.

Section 5 explains how our model's limitations might affect the results we present. We consider what kind of additional analysis we might need for understanding the full effects of a more decisive and therefore faster energy transition. For example, we discuss the impacts of a decisive energy transition on institutions, labour markets, financial markets, the risk of stranded assets etc.

Finally, in Section 6, we return to how our research can shift the policy mood music away from a reliance of far-off expensive solutions and toward existing clean technologies with a track record of consistent cost declines and successful deployment.

Section 1: How models inform decision-making on climate

Understanding the costs and consequences of climate change

Decision-makers in government and industry have relied for decades upon the guidance provided by various models to provide information on future climate change scenarios and how global development might evolve under varying levels of ambition to stop climate change (Krey et al., 2019).

The current pandemic has only emphasised the value of using models for decision-makers in high-stake situations, where non-linear dynamics and large uncertainty are evident. The management of the COVID pandemic has also demonstrated how models are not just about generating predictions but serve more broadly as a way for scientists to inform policymakers about a system's dynamics and allow them to contrast the implications of different strategies. We have seen how even elementary models played an invaluable role in illustrating key messages, such as simple SIR models being used to demonstrate what "flattening the curve" looks like. It is often not just the results of a model that matter – it is the transparency and clarity of the model as a whole.

Yet any trust that the scientific community may have gained in the pandemic is far from unconditional. Covid-19 has also highlighted the dangers of misinterpreting models. When failing to communicate assumptions and uncertainties, models only add to the uncertainty that decision-makers face. This failure can often lead to recommendations being put in the wrong context or worse. Initial confusion around "herd immunity" in countries such as the UK and Sweden served to highlight this point.

Some of the factors that made models so critical for Covid-19 also apply to climate change. They are both highly complex issues, which will require decision-makers to rely heavily on experts and the scientific community. Now more than ever, we believe it is crucial that for people to understand better any explicit biases found in models and how such models inform decisions.

This section provides some background on how climate change scenarios are developed, what are the most used scenarios, and how they inform policymaking. This section intends to give the reader a background understanding of some of the major organisations and their research, which is key to understanding this report's focus and relevance.

How climate mitigation scenarios are developed

Climate mitigation scenarios are developed using a series of connected models, each of which is intended to produce an internally consistent representation of some part of the full energy-economy-climate system. Such coupled or integrated models often include i) a socio-economic model, which makes future projections of human development like population growth and economic growth; ii) an energy system model, which provides energy services to the modelled economy using various technologies, some of which produce greenhouse gas (GHG) emissions; and iii) an earth system model, which calculates the impact that GHG emissions might have on the earth's climate.

Table 1 provides a brief overview of each of these models with a summary of how they are used to provide decision-makers with information on climate mitigation pathways. Appendix A provides more detail on each of these model types. A scenario typically sets initial values for crucial factors; a model then determines how these interact and change. Note that each model may be used to evaluate various scenarios. The same scenario can produce different results using different models; the same model can produce different results running different scenarios.

This report mostly draws comparisons to the models developed by and for two key authorities: the International Energy Agency (IEA) and the Intergovernmental Panel on Climate Change (IPCC). These organisations publish a range of climate mitigation scenarios using "energy system models" and the generally more complex 'process-driven' Integrated Assessment Models (IAMs). Further information on these organisations and other providers of climate mitigation scenarios is provided in Appendix A.

As shown in Table 1, there are many different types of models that provide decision-makers with information regarding the consequence of climate change and potential mitigation pathways. These span across various disciplines and sectors, including physical science, economics, social science, energy systems, biodiversity, and land use. To create a more comprehensive assessment of climate change, we can link several specific models together in what is known as an Integrated Assessment Models (IAM). Such IAMs can vary significantly in their complexity (e.g., depending on how many separate models are linked) and the policy questions they are designed to elucidate (see Appendix A for more information).

This report focuses specifically on models, including energy system models and 'process-driven' IAMs or *policy evaluation models*,[1] that provide information to decision-makers on feasible climate mitigation pathways and scenarios. For convenience, we refer to this collection of models as "**climate mitigation models**" or simply "mitigation models". Mitigation policies are generally applied in the form of a social cost on carbon emissions with the climate mitigation models optimising social welfare and reducing emissions in response to this price on carbon emissions. Adaptation and vulnerability models are also used to inform individuals, groups, and governments' adjustments to climate impacts.

1 The 3rd Assessment Report of the IPCC divides IAMs into two broad categories: policy optimisation models (POMs) and policy evaluation models (PEMs) (IPCC, 2001).

Table 1: Models relevant to providing decision-makers with information regarding climate mitigation pathways. Note that the categorisations of models we present here are not mutually exclusive, and there are many examples of crossovers.[2]

Models	Examples	Applications
Climate Models: (ESMs, GCMs, EMICs and emulators)	HadCM3, EdGCM, GFDL CM2.X, ARPEGE-Climat, MOM-3, MAGICC, FAIR GENIE, MIROC-lite, IGSM	• understanding impact of emissions on the climate system • production of radiative forcing and warming pathways • establishing climate targets • understanding physical risks • climate attribution • inputs to impact models (IAMs)
Energy System Models	MARKAL, MESSAGE, TIMES, IEA World Energy Model, Shell World Energy Model, PRIMES	• constructing mitigation pathways in energy systems • energy strategy development for policy
Land Use Models	GLOBIOM, GAINS	• analyse the competition for land use between agriculture, forestry, and bioenergy • land use emissions
'Simple' IAMs	CETA, DICE, MERGE, PAGE, FUND	• assess the costs and benefits of avoiding different levels of warming • calculate the Social Cost of Carbon
'Complex' or 'process-driven' IAMs	IMAGE, WITCH, TIAM, MESSAGE-GLOBIOM, AIM, GCAM, REMIND, MAgPIE, C3IAM	• constructing mitigation pathways • constructing alternative future socio-economic scenarios • building the scenarios matrix to explore multiple socio-economic and mitigation options • transition risk
Climate Impact, Adaptation and Vulnerability Models (IAVs)	CLIMPACTS, CALVIN (Dickinson, 2007a)	

There is thus a vast range of modelling approaches that the climate community has employed to understand climate change and the cost of policies to mitigate that change. The models used are all mathematical but use theoretical underpinning from different branches of physical and social science for their calculations.

2 For example, land use mitigation, modules of IAMs or impact models are likely also to have elements of adaptation within them. (Dickinson, 2007).

As all models are simplifications of the systems they model, they must rely on a range of assumptions about how such systems function, and how they might change into the future. There is much debate around how key processes are modelled (the methodologies), how they are parameterised and sources of data (the inputs), what is, or is not included, and how uncertainty is represented. Compounding these sources of contention is the fact that the major mitigation models are quite large and generally lack transparency around their inner workings (Gambhir et al., 2019). The mitigation models used by the IEA and IPCC do have important common elements. These similarities include viewing climate change as an inter-temporal optimisation problem and reliance on general or partial equilibrium economic models to resolve questions around the cost of investing capital in mitigation solutions (Farmer et al., 2015). This common approach is also not without its controversy, including an under-representation of non-linear dynamics (Farmer et al., 2015), and tendency to focus on unproven solutions such as carbon dioxide removal technologies (untested in use, reliance, effectiveness and costs),[3] rather than renewables, despite the latter's recent dramatic decline in costs (Gambhir et al., 2019; Pietzcker et al., 2017).

The increasing complexity and size of models have also made them more challenging to compare and evaluate, motivating several "model intercomparison projects" (MIPs). Most prominently, the Coupled Model Intercomparison Projects (CMIP) (1-3. 5 and current CMIP6) efforts to facilitate evaluations and improvements across climate models (GCMs, AOGCMs and ESMs) have informed the IPCC Assessment Reports (mostly WGI) (O'Neill et al., 2016).

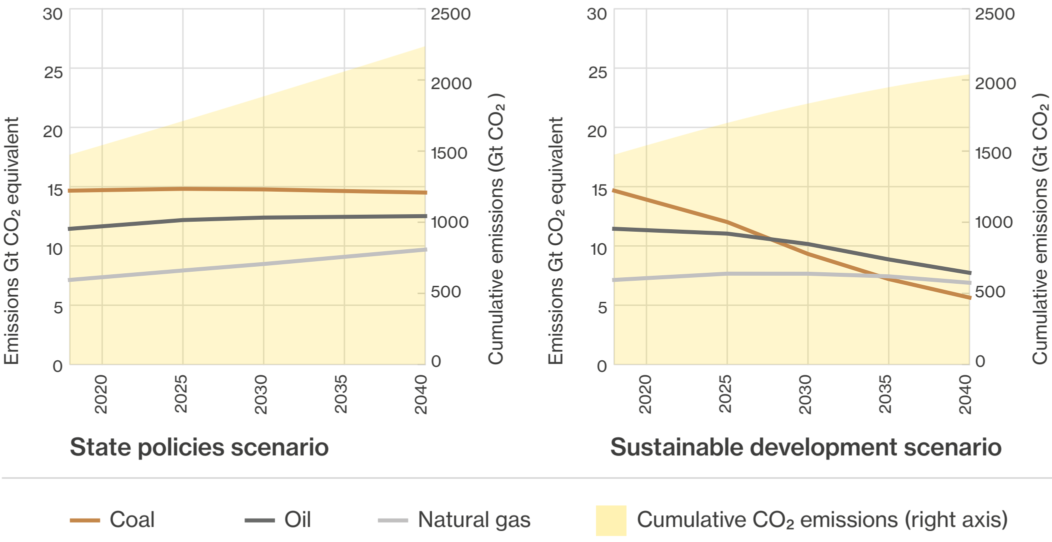
The range of scenarios modelled

All climate mitigation models are run against an underlying socio-economic scenario – a plausible set of assumptions about how our social, economic, and political systems might evolve over the coming century. The IEA only model the energy system and calculate energy demand based on a consistent set of socio-economic drivers across each of their scenarios which include a 3.4% annual global GDP growth and an additional 1.6 billion people on the planet by 2040 (Figure 1).

In contrast, the IPCC models include the emissions of the entire global economic systems and make use of shared socio-economic pathways (SSPs) to produce a range of different possible futures around the key drivers of change, including population and GDP. These are used in the IPCC models to provide estimates of future global energy requirements, demand for emissions-intensive products such as steel and cement, land-use changes, and associated emissions. They give a consistent 'baseline' storyline of future population, economic growth, societal attitudes, technology costs and the arena of international policy, that are independent of mitigation possibilities.

3 Greenpeace reject the use of negative emissions technologies (see Appendix A), while others, including the IPCC's net zero scenarios, are heavily reliant on bioenergy with carbon capture and storage with between 8-18 Gt CO_2 being removed per annum when net zero is achieved (Greenpeace, 2018).

Each is based on a different narrative, with qualitative ‘low’, ‘medium’, or ‘high’ capabilities to mitigate or adapt (Figure 2).[4]



● **Figure 1**: IEA annual global energy system emissions forecasts by fossil fuel type (left axis) and total cumulative emissions (yellow shading – right axis) to 2040. Source: IEA 2019.

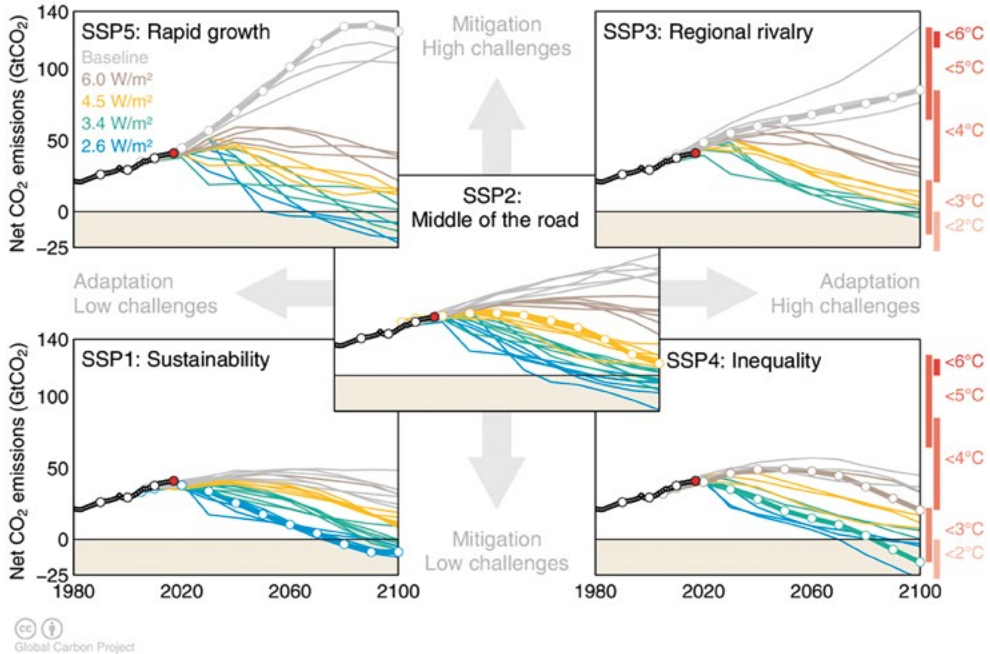
To achieve standardisation the IPCC focus on a limited number of global warming scenarios know as Representative Concentration Pathways (RCPs), which have become the standard reference to classify different warming limits. Since CMIP5 and AR5 these RCPs have been matched with the Shared Socioeconomic Pathways (SSPs). They combine to provide projections of cumulative greenhouse gas concentrations with associated estimates for radiative forcing and global warming. The SSP-RCPs combinations produce a range of emissions scenarios from the lowest total emissions pathways SSP1-RCP1.9 (introduced following the Paris Agreement and captures pathways that achieve the 1.5°C target), to the ‘worst-case’ pathways SSP5-RCP8.5 (Figure 2).[5] This range corresponds to an increase in global mean temperatures above pre-industrial levels of around 1.5°C to 4.3°C in 2100.

The resultant climate scenarios (also known as ‘emissions scenarios’) generated by these models given their underlying socio-economic drivers, are then used to understand the potential impacts of those emission scenarios on the global climate. However, and very importantly, most major climate mitigation models do not include this feedback dynamic.

4 SSP1 is the Sustainability scenario: a world in which the global population peaks mid-century, and there are strong and flexible global, regional and national institutions; SSP2 is the Middle of the Road scenario: a continuation of economic and technological trends with slow process to achieving the SDGs; SSP3 is a Resurgent Nationalism scenario: regional rivalry and conflicts with weak global institutions, and fossil fuel dependence; SSP4 is an ever-increasing Inequality scenario: modelling a growing divide between prosperous and well educated societies and the global poor; and lastly SSP5 is the rapid growth scenario: a world in which economic output and fossil fuel energy use are unconstrained by environmental consequences (van Vuuren et al., 2014).

5 The numbers associated with the RCPs represent the total radiative forcing in the year 2100 relative to 1750 (from 1.9 W/m² to 8.5 W/m²)

In most mitigation models, emissions and the climate risks they might generate do not impact the economic growth (Kolstad et al., 2014). The socio-economic drivers in the IEA scenarios and the SSPs of the IPCC have their future population and GDP set exogenously. Therefore, the purpose of the climate mitigation models is to understand how the changes in society and the economy represented by the socio-economic drivers might impact global emissions and the potential costs of policies to mitigate emissions to meet a future goal, such as achieving 1.5 degrees by 2100.



- **Figure 2**: Global CO_2 emissions ($GtCO_2$) for all IAM runs in the SSP database, separated by SSP. Thick grey lines represent the Baseline scenario for each SSP where no carbon price is applied. Source: Carbon Brief, 2018.

Opportunities for improvement

As the IEA and IPCC scenarios are all generated using different models with different socio-economic drivers it is not surprising that they produce the array of contrasting scenarios shown in Figures 1 and 2. It should be made clear that there are no probabilities associated with any of these scenarios. In other words, each scenario is equally as likely as all others. These scenarios are merely projections of possible futures and the model developers are quite clear on this point. This poses an obvious challenge to decision makers trying to address the climate risks that such scenarios present, given that risk is defined as likelihood multiplied by consequence and although these scenarios inform us of their consequences, we do not know the likelihood associated with any of them.

A good portion of this uncertainty is inherent in the pure complexity of the problem and providing a range of modelled scenarios is one approach that informs decision makers about the scale of this uncertainty. However, there are some sources of uncertainty that if addressed by the major mitigation models might offer decision-makers some more palatable solutions to this climate change conundrum.

Inputs and methodologies: In general, the differences in model scenarios and the costs of mitigation can be attributed to different methodologies (e.g. general equilibrium vs. post-Keynesian), different model structures (e.g. production function with elasticities, logit sharing for fuel swaps), representations of different technology options, and the parameterisation of those technologies ("techno-economic assumptions") (Krey et al., 2019). Key differences include the assumptions implicitly coded into each model and those decided by the user (external assumptions); as well as which variables are endogenous (determined by the model) or exogenous (determined by factors outside the model). The IEA scenarios each use a consistent set of socioeconomic drivers and are produced by a single model. In contrast the SSPs represent very different socioeconomic themes and each of the IAM teams interprets the themes of the SSPs differently (e.g., rivalries between countries or sustainability ambitions). However, each share the same external assumptions about GDP, population and the policies or socio-economic storylines of the relevant SSP. The main drivers of future exogenous change within the SSPs are arguably those long-term population and economic development, and urbanisation pathways (Riahi et al., 2017). Other factors that can differ between models include income elasticities, representations of tax systems, and technology costs. They each also contain a nexus of internal processes such as model calibration, optimisation, applications of a price on carbon, and mechanisms of delivering supply capacity and allowing technological development. Importantly, each of these assumptions influence the estimated costs of mitigation that result from these models – information which is presented to decision-makers that are being asked to support these mitigation efforts.

Keeping up-to-date: Only modellers that regularly update their base-year calibration, such as the IEA's Energy Technology Perspectives (ETP) model, appear to be able to keep up with clean energy technology progress and changes. For example, the increasing gap between the low levels of actual CCS deployment and the high CCS deployment required in ambitious temperature stabilisation scenarios; as well as the low levels of solar PV deployment in the Paris-compliant IPCC scenarios and the high levels of actual deployment (Minx et al., 2020). Updating of parameters such as technology costs can have dramatic effects. For example, the influential DICE model (see Appendix A) is known for its original unusually high 'optimal' warming levels of 3.5°C. However updating its parameters results in the DICE model recommending economically 'optimal' climate policies and emissions pathways that are in line with the UN Paris climate targets (Hänsel et al., 2020).

Uncertainty: Much of the uncertainty inherent in modelling the complex interactions between our climate system and the global economy reflects the lack of complete understanding of these systems (Weyant, 2017). An additional source of uncertainty is inherent in each system's complex dynamics, which allow for the possibility of large scale, non-linear shifts in the Earth system (Oppenheimer et al., 2014), along with the ensuing economic catastrophes (Wagner & Weitzman, 2018). Significant discrepancies exist between current understanding of climate tipping points and their representation in the leading 'simple' IAMs DICE, FUND and PAGE (Lenton & Ciscar, 2013; Lontzek et al., 2015), undermining accurate estimates of the costs of climate change (Revesz et al., 2014). Such amplification mechanisms are also not necessarily negative, with positive tipping elements likely to exist in socioeconomic, technological, and political systems that might deliver, for example, accelerated climate mitigation (Farmer et al., 2019; Sharpe & Lenton, 2021; S. R. Smith et al., 2020).

One key positive tipping element is a result of the learning-by-doing feedbacks that have led to consistent long-term cost declines for certain key clean energy technologies – which are poorly reflected in the IPCC and IEA scenarios (Minx et al., 2020).

This report explores the implications of addressing some of these key opportunities for improvement. Specifically, we focus on the application of an alternative methodology for forecasting technology costs, the implications for using up-to-date empirical evidence, and incorporating a probabilistic technological change forecast method that enables the feedback dynamics associated with technology experience curves to be incorporated in an energy systems model.

Before we address these issues in the subsequent sections of this report, we will first provide here an overview of how such climate mitigation scenarios are being used by decision-makers around the world to provide some context as to how important such modelled scenarios are to our climate mitigation efforts.

How are decision-makers currently using climate mitigation scenarios?

Climate scenario modelling is vital for policymaking on the international, national, and local scale as well as increasingly within the private sector (Fiedler et al., 2021). By 2015, over 100 Energy System Models were being used in academic papers and policy in the UK alone (Hall & Buckley, 2016). Since then, the construction and evaluation of accessible models have proliferated even more.[6] While it should be remembered that models deliver insights instead of answers (Huntington et al., 1982), these insights have been indispensable for creating awareness of the risks of climate change, inspiring over 1,800 climate change laws worldwide (Eskander & Fankhauser, 2020), and other forms of climate action.[7] In general climate mitigation models are used for the following:

- To set quantitative targets (international and national) and to review and assess progress towards those targets,
- To develop sector strategies and assess possible pathways to mitigation,
- To test policy under various scenarios and model its impact,
- To determine risk and potential liabilities, and the flipside: to uncover potential opportunities,
- To develop regulation and recommendations for industry,

6 For example, in CMIP6 there are 49 different modelling groups participating, compared to 35 in CMIP5 (Hausfather, 2019).

7 For example, The IPCC SR1.5 2018 is explicit about the need for scaling up of the NDCs, and, that without additional mitigation efforts, warming is more likely than not to exceed 4ºC: a temperature associated with risks of substantial species extinction, global and regional food insecurity, the consequential constraints on common human activities, and limited potential for adaptation. (IPCC, 2014).

- To determine adaptation requirements to physical changes,
- To support attribution claims and to litigate against irresponsible actors,
- To identify potential barriers to, or issues arising from, mitigation,[8]
- To calculate costs, and balance climate needs with benefits and co-benefits.

Setting climate targets, plans, policies, and strategies

Target settings are a major application of climate scenarios, most prominently through guiding binding legislation on the international and national levels. By 2012, 67% of global GHG emissions were subject to national legislation or strategies (Lucon et al., 2014). Sub-national actors also have similar commitments, including cities (C40; Arup, 2016), regions,[9] and private companies.

Most prominently, emissions modelling has been central to international agreements. The Paris Accord, adopted in 2015 by the parties to the UNFCCC (UN Framework Convention on Climate Change) aims to limit warming to well below 2°C and pursue efforts to limit it to 1.5°C, a goal informed by the IPCC AR5 and IEA 2014 ETP scenarios.[10] Countries will need to report and reduce emissions in line with their Nationally Determined Contributions (NDCs), practical national pathways towards low-carbon and zero-carbon economies. Determining NDCs relied on a "stocktaking" process with the 'fair' allocation of emissions allowances from a 'global carbon budget', and regional assessment models using emissions scenarios for achievable pathways of various national strategies (van den Berg et al., 2020).

In conjunction with the NDCs, many countries have also introduced national legislation drawing on climate modelling or a scenario-based approach. The first legally binding national climate change mitigation target was the UK's 2008 Climate Change Act (The UK government, 2008), which committed the UK to reduce its GHG emissions by 80% by 2050, under a carbon budgeting system. In 2019, it was updated to a net-zero target, taking into consideration ten new research projects, three expert advisory groups, and reviews of IPCC work and others. This included the 2018 IPCC SR1.5 and used models such as MAGICC and AIM/CGE 2.0 to address the likelihood of achieving the Paris Agreement goal (Committe on Climate Change, 2019). Table 2 provides a list of further examples of how climate scenarios and modelling has been utilised for the development of national and sub-national policy.

8 The IPCC AR5 WGIII is explicit that for buildings, barriers could include split incentives, fragmented markets and inadequate access to information. For industry, investment costs and a lack of information are the main obstacles. For AFOLU, it warns that bioenergy systems are not necessarily sustainable and efficient, instead recommending which bioenergy technologies should be used.

9 For Example, Victoria's Climate Change Act 2017 (Climate Change Act, 2017).

10 This included presentations of climate modelling such as from the IPCC AR5, the IAMC (Integrated Assessment Modelling Consortium), as well as the IEA 2014 ETP 2 °C (SED, 2015).

Table 2: Examples of utilisation of climate scenarios and modelling for national and sub-national policy

Name of Policy	Use	Year	Model(s) Used	How model (s) are used
US				
Social Cost of Carbon (US EPA)	Calculating costs	2016	DICE, FUND, PAGE	• Monetisation of the threat of climate change into SCC figures
EU				
2020 Climate & Energy Package (European Commission, 2009), Fit for 55 Package	Target setting, testing policies, sector-specific strategies	2008, 2020	PRIMES, POLES, GEM-E3, GAINS, GLOBIUM-G4M, CAPRI, and models from other organisations incl. IRENA, Global Renewables Outlook, 2020	• The PRIMES model simulates a market equilibrium solution for EU energy supply and demand, including consistent EU carbon price trajectories. It provided a decomposition analysis of the changes in emissions drivers 2000-2005 per sector and EU member state. It explored three cases to understand the effects of key policies; namely the ACEA agreement on car manufactures, the Biofuels Directive, and the RES-E Directive for renewable energy. • GLOBIOM-G4M integrates the agricultural, bioenergy and forestry sectors, to project emissions from LULUCF
UK				
Climate Change Act 2008 and "Building a Low-Carbon Economy" (Committee on Climate Change, 2008). Revised Net Zero goal 2019	Target setting, Trading schemes, risk assessments and adaptations	2008	PAGE, MAGICC, IPCC AR4, WGI, WGIII, AgMIP, WaterMIP, CMIP3, CMIP5, Ackerman & Stanton (2008), Stern Review (2007)	• Uses standard PAGE model but then augment this to reflect more recent developments. This covers sulphate, equilibrium warning, damage function, low-cost control measures and abatement potential, and additional abatement costs. • Uses MAGICC to project GHG concentrations and GMT for different emissions trajectories • The 2017 Risk Assessment uses (Chp2 p5): PESETA II, and the sector modelling intercomparisons as well as major syntheses

Name of Policy	Use	Year	Model(s) Used	How model (s) are used
Singapore				
National Climate Change Strategy (National Climate Change Secretariat, 2012)	Adapting to physical risks, Sector-specific strategies	2012	ICRM's (Institute for Catastrophe Risk Management) modelling; IEA WEO (IEA, 2011); IPCC AR4	• how people respond to temperature, humidity, pollution, and ventilation. • update the national strategy • design ways to increase renewables, encourage efficiency improvements, change transport systems, etc • address flood risks using a flood forecasting system; explore mangrove restoration • establish several research institutes and centres
Ireland				
National Energy & Climate Plan	Sector-specific strategies, Target setting, R&D investment	2020	PLEXOS (electricity system model) SEAI BioHeat model, ESRI I3E CGE model	• Considers multiple scenarios (WAM and WEM) and projections, detailed technology analysis of energy/low carbon technology to assist with the targeting of energy research & innovation investment and to fill the gaps in mass deployment of technologies
Chile				
Chile's Nationally Determined Contribution and Chilean NDC mitigation proposal (Mitigation and Energy Working Group, 2020)	Identification of challenges & opportunities for Chilean mitigation pathways.	2020	LEAP, AMEBA, PELP, 2006 IPCC Guidelines	• Sectoral models were used for Energy, IPPU, Agriculture, LULUCF and Waste. Activity data used for the GHG estimate was projected according to national guidelines and methodologies applied as per the 2006 IPCC Guidelines. For energy demand LEAP was used as a simulation model; for Power Systems AMEBA. Fuel price trajectories are obtained from the Long-Term Energy Planning Process.
Hong Kong				
The People's Republic of China Third National Communication on Climate Change (Melillo, 2015)	Target Setting	2015	MARKAL-MACRO	• The setting of scenarios was mainly based on the fuel structure, considering other factors including the energy efficiency of various components

Name of Policy	Use	Year	Model(s) Used	How model (s) are used
Tonga				
Tonga Strategic Development Framework 2015-2025 (Tonga 2015)	Determining risk and uncovering opportunities	2015	2013 World risk Index	• establish the risk of natural hazards and the country's exposure and vulnerability • establish the growing vulnerability given sea-level rise and rising temperatures
Local Council of Victoria				
Victoria Coastal Council 2008 and 2014 Strategy (Victorian Coastal Council, 2008)	Adapting to physical risks, sector-specific strategy	2008, 2014	IPCC Report	• Sea level rise and flood management strategy planning

It should be noted that new policy targets can, in turn, influence the direction of scenario analysis. For example, political ambitions around the Paris Accords 1.5°C target have encouraged mitigation research to develop pathways that limit warming to 1.5°C such as the IPCC's 2018 Special Report on Global Warming of 1.5°C (IPCC 2018 SR1.5).

Additionally, a rare area of consensus among IAMs is that the current national pledges to reduce emissions by 2030 are insufficient to achieve a trajectory in line with the stated Paris target of 1.5°C (Pan et al., 2017). The multi-model study ADVANCE[11] tests an NDC scenario which focuses on the aggregate effect of the NDCs and explores the 'decarbonisation bottlenecks' arising from not updating to more ambitious targets. This makes uncontroversial the acute need to scale up the ambition of the NDCs and new scenarios analyses to accompany them.

Given the 'ratcheting' requirement (Paris Agreement, Article 4) for countries to communicate enhanced NDCs every five years, each country will need to report its progress and update its commitment at the upcoming Conference of Parties (COP26) in Glasgow. This requires monitoring and assessing the status of and opportunities for further national mitigation efforts, including updating models with technological and other parameter developments (Skelton et al., 2019). Despite this, only 40 countries submitted new NDC targets by the end of 2020, ahead of when COP26 was initially scheduled in Glasgow. Climate Action Tracker reports that only eight countries that they analysed submitted stronger NDC targets. These include the EU (who raised its 2030 target from 40% below 1990 levels to 55%) and the UK (who increased it from 57% to 68%). Notably, China, the largest emitting country, has recently said they will achieve carbon neutrality by 2060. In contrast, another eight countries have explicitly not increased their ambition in their new NDCs.[12] These include Australia, who set the same target as before, and Brazil, who actively weakened their already insufficient targets.

11 Using the POLES, MESSAGE, GEM-E3-ICS, IMACLIM, REMIND, IMAGE, WITCH and AIM/CGE models. (Vrontisi et al., 2016).

12 Climate Action tracker, accessed 9th February 2021.

Potentially, in response to inaction by the previous US administration, there has been some recent momentum in more ambitious climate targets by sub-state and non-state actors. Examples of this include the “Race to Zero” campaign, which aims to achieve net-zero carbon emissions amongst “real economy” actors by 2050. As a new report states, the number of net-zero pledges amongst local governments and businesses has roughly doubled in less than a year, with many prioritising climate actions in their recovery from Covid-19 (Data-Driven EnviroLab & New Climate Institute, 2020). This trend may help put pressure on governments to catch-up when revising their NDCs.

Given the targets developed regarding climate projections/emissions scenarios, IAM and sectoral systems models explore the potential for policy-led mitigation and test policy under various scenarios. Sector-specific policies (e.g. for energy, land-use and buildings strategies) have been more widely used than economy-wide policies (mainly due to administrative and political barriers preventing the (more optimal) economy-wide strategies) (Lucon et al., 2014). Energy Systems modelling has been especially essential for national energy strategy development towards decarbonising the energy sector and ensuring energy security. In a meta-analysis of UK energy scenarios (Energy Research Partnership, 2010), the role of modelling tools was deemed essential to understanding key uncertainties in future energy systems transitions and the broader energy system impacts, influencing numerous policy papers.[13]

Other uses of climate mitigation scenarios

Climate mitigation scenarios have several important applications beyond setting climate targets, government plans, policies, and strategies. They are featuring more prominently in evaluating business risk and meeting climate risk disclosure requirements (Fiedler et al., 2021). They also have an application to legal cases, enabling litigators to translate the science into legal arguments (Stuart-Smith et al., 2021). Lastly, they are being used to help understand the needs of vulnerable regions for climate adaptation (Australian Government, 2011) and incorporate climate risk in the evaluation of proposed government projects costs-benefit analysis (IWGSCC, 2010). Such additional applications are explored in more detail in Appendix A and demonstrate the degree to which climate mitigation scenarios have infiltrated decision-making processes across much of society.

13 Notably, the White Paper on Nuclear Power (BERR, 2008), the Renewable Energy Strategy (Department of Energy and Climate Change, 2009), Electricity Market Reform (EMR) Impact assessment, the Fourth Carbon Budget (Climate Change Committee, 2011a), the Renewable Energy Review (Climate Change Committee, 2011b), the Energy White paper (Department of Energy & Climate Change, 2011), the Bioenergy Strategy paper (Department of Energy and Climate Change, 2019), the Gas Generation strategy (Department of Energy & Climate Change, 2012) and the Heating Strategy (Department of Energy & Climate Change, 2013).

Section 2: Empirical technological progress trends and the need for a fresh look at the future

New clean energy opportunities

Over the last few decades, the costs of several important clean energy technologies have fallen steeply and consistently. Since 2010 the costs of solar PV energy, wind energy, batteries and electrolyzers fell by around 85%, 47%, 65% and 51% respectively (Way et al., 2020), in line with their historical trajectories. The exact reduction rates depend on how costs are measured, but these headline figures summarise well the radical nature of the progress observed. In contrast, fossil-fuel-based technologies have seen no such progress, costs have remained approximately flat.

As clean energy costs have fallen, various tipping points have been crossed (Farmer et al., 2019; Sharpe & Lenton, 2021), and the scale of the markets within which they compete has gradually expanded, from niche applications to mass market. PV and wind are now on average the cheapest forms of new-build electricity generation on the planet (IEA, 2020c), and some electric vehicles (EVs) are getting close to parity with their internal combustion engine vehicle (ICEV) counterparts on a total-cost-of-ownership (TCO) basis (Hagman et al., 2016) (with some even predicting their sticker prices will be cheaper within around 2-3 years (Henze, 2020). It is difficult to understand exactly why these technologies have steeper experience curves, although it has become increasingly clear that characteristics inherent to certain technologies, such as simplicity, modularity, and standardisation, are a large part of why policy has been so successful in these cases, while it has failed in others (Huenteler et al., 2016; Malhotra & Schmidt, 2020). But few successes were by accident, as they are generally the result of decades-long policy support (albeit erratic and weak) that led, as anticipated, to increased innovation and experience with technology deployment, in both the public and private sectors.

Faced with such unrelentingly positive trends, it is important to consider why all large climate mitigation models still conclude, as they always have done, that any transition to a climate-safe energy system would be an arduous, speculative, and expensive task. This question is especially salient because when using up-to-date data, empirical trends show that future costs of key energy technologies will almost certainly be much lower than these models assume or predict (Krey et al., 2019).

Alongside advances in the technologies themselves, there have also been advances in understanding how technological change proceeds in the economy more broadly, and of the characteristics that fast-progressing technologies have in common (Wilson et al., 2020).

Methods that are statistically validated and firmly grounded in data have been developed for forecasting technological progress (Farmer & Lafond, 2016; Lafond et al., 2018). As a result of extensive data collection and analysis, it is now apparent that the striking cost reductions described above are just part of much longer technological trends that are expected to continue into the future.

Such progress trends, which have been widely observed and studied since at least the 1960s (Arrow, 1962), were originally assimilated into energy models in the late 1990s (Mattsson & Wene, 1997), and by the year 2000 the benefits of targeted support for low carbon technologies were widely acknowledged (Grübler et al., 1999; IEA, 2020c). Modelling at the time suggested that in the long run, total energy system costs would be approximately equivalent, regardless of whether a high- or low-carbon scenario was pursued, it was simply a matter of making learning investments in key low-carbon technologies early enough to bring their costs down and enable widespread adoption (Gritsevskyi & Nakićenovi, 2000; Mattsson & Wene, 1997).

Since these promising early results though, energy models have ballooned in size and complexity. The technologies, geographies, and socio-economic mechanisms they include have been disaggregated in to smaller and smaller pieces, with the intended aim of making the models more realistic. However, increasing model complexity inevitably leads to reduced transparency, making it harder to understand precisely what is driving the results (Farmer et al., 2015).

Large models face two serious problems. First, they are exceedingly hard to calibrate, initialise, and keep up to date using real world data. This is partly because there are so many parameters that it is practically difficult to obtain and update the relevant inputs as new data becomes available; but it is also partly because the required data simply does not exist. At best this could be because nobody has collected the data (e.g., for a specific technology in a specific region), but often it is because the data is fundamentally difficult or impossible to know, as is the case with parameters regarding consumer preferences, firm investment decisions or the "damage function" (the extent to which climate change damages the economy) (Pindyck, 2013).

Second, it is difficult and time consuming to validate, or "back-test", large models against real world data.[14] The scientific method entails observing data, proposing a model for the underlying process, then carefully testing the model's ability to make predictions using the observed data. Failing to adequately perform the validation step means the model's predictive power is unknown, and so results should be considered merely speculative. Yet, no large energy models have been comprehensively back-tested, while only a few have been partially back-tested, despite many studies highlighting performance failures in specific cases (e.g., Wilson et al., 2013). Again, this is partly because the data required for validation is very hard or impossible to obtain (especially the historical data required for back-testing), and partly also because it is very time consuming.

14 Back-testing involves calibrating a model to a given point in the past, then running the model from that point, and comparing its forecasts to observed data in the past. This allows for rigorous, quantitative assessment of its ability to accurately forecast the behaviour of the underlying system.

In hindsight, the increase in model complexity appears to have had two important effects. First, it made the models more opaque and harder to validate; and second, it involved the addition of many new model components, which appear to have had the cumulatively effect of artificially constraining the development of PV, wind, and energy storage (whether grid-scale storage or EVs). These constraints prevented model users from exploring scenarios in which these technologies developed along anything other than very low growth and low progress paths (as compared to the realised path). In other words, the path these technologies would follow was evaluated prior to the model's formulation and considered so expensive and technically infeasible that a renewables-based system could never happen. Presumably, it was also viewed by the modellers to be too unrealistic and improbable to even consider testing these underlying assumptions. Modellers' beliefs about the limitations of certain technologies were encoded in the models, which then produced results that simply confirmed and presumably further shaped the modellers' beliefs.

The fact is that (to the best of our knowledge) not one single large energy model has considered any scenario in which global average PV costs would fall to around 50$/MWh in 2020, yet this is what has happened. This astounding failure suggests a lack of regard for model validation in general, and a lack of understanding of the need to pay special attention to fast progressing technologies, for example by only using technology cost forecasts that are supported by substantial empirical evidence. Instead, modelling teams have focused on extending, expanding, and complicating their models in other areas. By focusing on smaller and smaller pieces of the puzzle however, the significance of the larger, more important trends has been neglected – and still is, as evidenced by the lack of PV and EVs in most recent IPCC scenarios.

This lack of attention paid to empirical trends is surprising for several reasons. First, recent costs are a clear reminder that for some technologies (but not all), sustained policy support works, and can help shape far preferable sets of technology options than would be arrived at through myopic market processes alone (and any ensuing market distortions that may result, of course). Second, the science of technology forecasting has advanced dramatically in the last ten years, with ever more reliable, evidence-based forecasts being produced. Third, it is well known that choices around how to model technological change in energy-climate models have a dramatic effect on the results produced (Creutzig et al., 2017). Finally, recent developments put a handful of clean energy technologies on the cusp of having a truly enormous impact on the global energy-climate system, so the observed trends and dynamics that brought these technologies to this point should rightly be centre stage in any modelling of their future development.

With all of this is mind, in particular the need to *ensure future energy scenarios are consistent with observed historical trends*, now is a good time to reassess future prospects both for specific technologies and for the wider energy system, to see how these compare with empirical trends, and to examine the assumptions underlying the large energy models that are central in shaping our common understanding of which future energy scenarios are possible.

Historical development of energy system reporting

To understand the context of energy scenarios produced by different modelling approaches, it is important to understand how the energy system developed up to this point. Ever since modern energy accounting methods were introduced well over a century ago, *primary energy* (the energy contained in energy sources as they exist in nature) has been the dominant metric used to describe energy stocks and flows. This is because historically most energy used was in the form of coal, oil, gas, or biomass, which are naturally described in terms of their physical mass and volume.

However, this characterisation of energy supply is not well suited for electricity generated from non-combustible sources, such as hydro, solar and wind. If not used with care, primary energy can give a distorted picture of the energy system, as it does not account for the large differences in efficiency with which different energy sources are converted into useful energy services in the economy. *Energy services*, such as mobility, lighting, heating, and cooling etc. are the end-use services that consumers care about on a practical basis, and it makes no difference to them how much primary energy was lost in conversion processes along the way.

In fact, only around 20-70% of the primary energy contained in fossil fuels typically ends up providing useful energy services (20-30% for mobility, up to around 70% for heating), the rest is lost mostly as waste heat. In contrast, around 95% of the energy produced by solar and wind electricity generators is put towards useful work, with only a small fraction being lost as heat during electricity transmission and distribution.[15] Clearly, when comparing energy sources with such diverse characteristics, it makes sense to use a metric that somehow normalises energy quantities in terms of the useful services they provide to society. For this we use the *useful energy* metric, which is defined as the last measurable flow of energy before the delivery of energy services (Grubler et al., 2012).

Useful energy accounts for all conversion losses up to the point of use, and so captures most of the largest efficiency differences between the various primary energy sources and energy carriers in use in the economy.[16] However, there are further efficiency differences in end-use technologies that are not captured by this metric alone. For example, even though electric heat pumps are far more energy efficient than gas boilers, requiring only around one fifth of the useful energy to provide equivalent levels of heating service, the total quantity of useful energy required will also depend on the quality of insulation present in the building being heated.

15 Note that the primary-to-useful energy conversion efficiency concept described here is distinct from both the efficiency with which renewable electricity technologies extract energy from their energy sources (e.g., PV panels are currently around 20-25% efficient at converting solar energy to electricity), and the utilisation rate of the technology (e.g., PV panels produce power for around 18% of the time (IRENA 2020). Note further that neither of these apparently "low" values for PV are problematic, all that matters is the cost of the resulting energy, which, as stated above, is on average the cheapest electricity on the planet.

16 *Energy carriers* (or *intermediate* or *secondary energy*) are substances or phenomena used in end-use energy applications (such as cars, furnaces, computers). Gasoline, coal, and electricity are examples of energy carriers. Primary energy resources are often converted to different energy carriers to facilitate transport, storage, or market transactions of energy. For example, crude oil is converted to gasoline for use in vehicles and coal is converted to electricity for use in electric appliances.

While useful energy is a much better metric than primary energy for comparing the practical usefulness of different energy sources, it still only gives a rough guide. In many cases it is an approximate lower bound on the efficiency gains available from using modern, electricity-based technologies instead of old, fossil-fuel-based technologies. Therefore, with the caveat that the concept is intrinsically hard to quantify and does not represent the full picture, we use a simple useful energy metric here that captures the most important differences: we scale primary energy from each source by a constant factor that roughly represents its "average" conversion efficiency. Though these conversion efficiencies may vary with time as technological progress occurs, on the whole they have remained roughly constant for at least the last half century, so this simple approach is a good first-order approximation.

Figure 3 shows the amount of *useful energy* used to provide energy services in the economy for the last century, from all major energy sources. We use the following efficiency factors to convert energy carriers to useful energy: biomass: 25%; oil: 25%; coal: 60%; gas: 60%; and electricity: 90%. These are roughly the values observed historically (De Stercke, 2014).

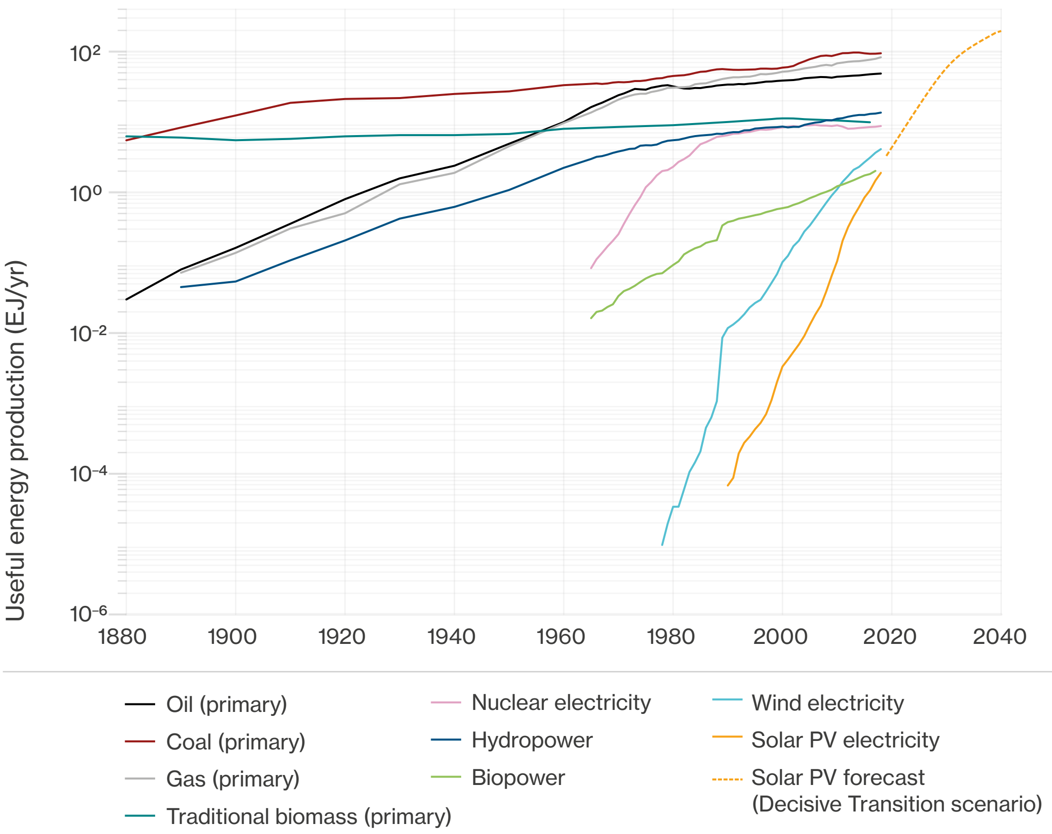


Figure 3: Historic trends in useful energy supply from all major energy sources. The dashed yellow line shows one possible trajectory for the future development of solar PV, called the Decisive Transition scenario in this report.

Note that data is plotted on a logarithmic scale. This is a useful perspective for natural systems whose ability to grow is largely determined by their present size (for example, this applies to many systems related to economic growth). In other words, it is not so important how big any given component is, what matters is its growth rate.

On a logarithmic scale, constant growth rates are manifested as straight lines. The plot shows that while fossil fuels had fairly high constant growth rates historically, since around 1970 they have been much lower. It also shows that solar PV is the fastest growing energy supply technology ever seen, and that wind is also growing quickly. In contrast to all other major energy sources, solar and wind electricity generation have on average grown at over 40% per year and 20% per year, respectively, for the last 30 years.

High growth rates cannot continue forever, but the *exact points at which they switch to lower growth trajectories are of great importance, as these are key determinants of how quickly emissions will be removed from the system*, as clean, modern technologies replace old, dirty technologies. If PV and wind continue to grow at roughly their current rates for just one more decade, they will provide almost as much electricity as the entire power generation system produces today. While this is very significant in itself, decarbonising transport would require extra electricity as compared to that used today, so there would still be room for much more growth after this.

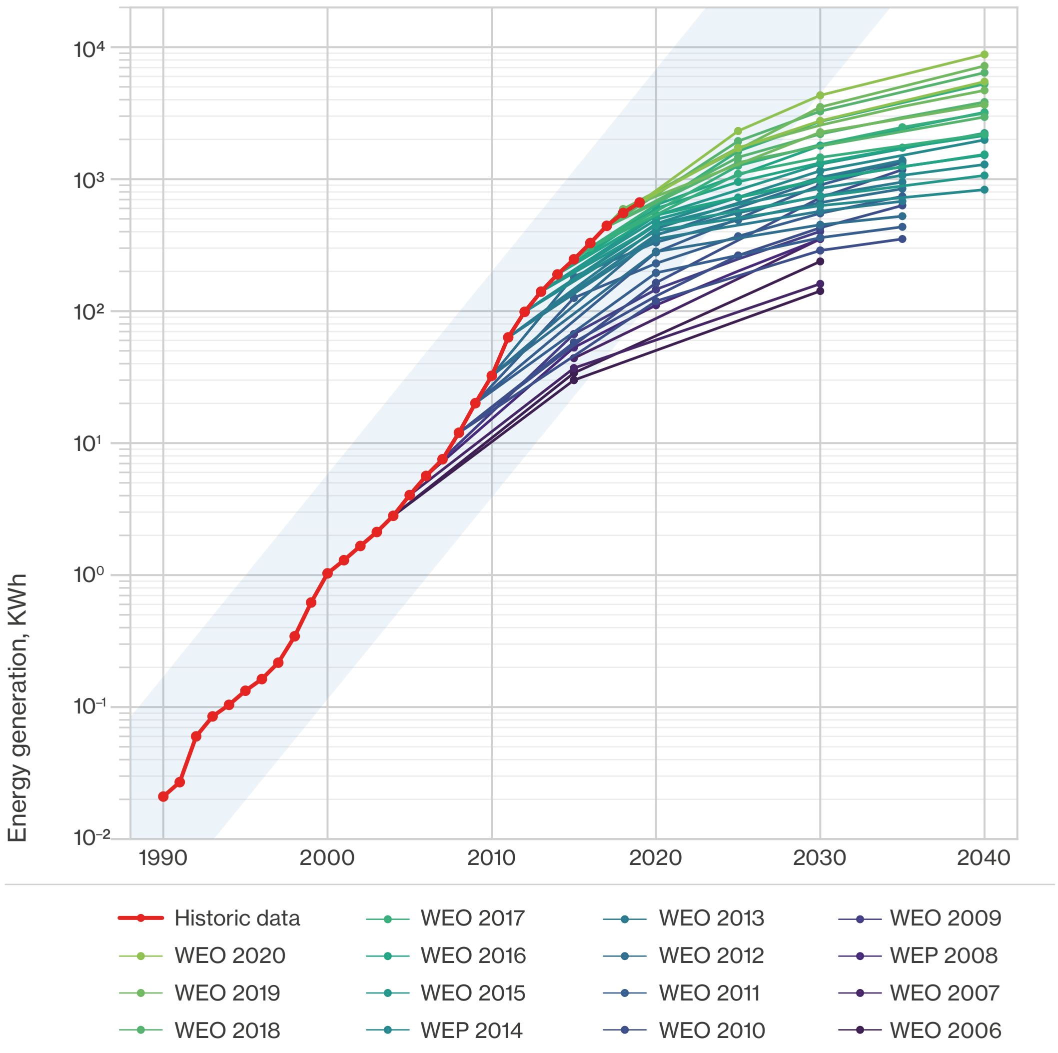
Faced with these clear and apparently optimistic trends, which echo the cost reduction trends already mentioned, it is important to consider what might cause these growth trends to slow. Quite simply, it is the relative costs of different technologies, and the effect that policy may have on these. Hence it is necessary to explore possible technology cost trajectories, but before moving on to this it is worth first considering how energy models have in the past imagined the energy system may evolve: what kind of scenarios have previously been constructed, presented, and analysed by modellers and policy makers?

How have scenarios changed over time?

Modelling large, slow-moving objects is relatively easy, it is the modelling of small, dynamic objects that is often more difficult, and may therefore serve as a better barometer of a model's reliability and veracity, and potentially help uncover systematic biases. Instead of observing historical projections of, say, global oil or gas consumption, it is more enlightening to observe how smaller system components such as solar PV and wind have been projected to develop in various scenarios over the years.

The most frequent and standardised data available for observing such trends are the future technology deployment data contained in the IEA's annual World Energy Outlook (WEO) reports. These give levels of future technology deployment that were, as a result of a vast collection of modelling and data assumptions, considered to be consistent with some given scenario of how the global energy system may evolve. Figure 4 shows the development of solar PV deployment scenarios over time.

It is important to highlight that these projections do not represent simple, unconditional forecasts of how deployment was predicted to evolve, so should not be interpreted in this way. Having said that, each data point was the product of a long, detailed process of technology and economic modelling, so observing the overall trend is a good starting point for further analysis. At the very least, the observed data illustrates the kind of scenarios that have been available to policy makers for analysis and, importantly, how these scenarios have changed over time.



- **Figure 4**: IEA projections of future installed generation from solar PV in various scenarios from successive publications. The historic data is the same as that shown on Figure 3. Source: IEA, World Energy Outlook 2006-2020. The light blue band shows the approximate long run trend.

While the plot uses data from the IEA (because it is the longest, most consistent, and highest quality data available), other models produce comparable scenario data that could also be used. However, other models' data is much harder to obtain, less frequent, and generally less consistent in terms of methodologies employed. As far as we are aware, the trend shown here is entirely consistent with other models' output, though this is hard to verify in detail due to their poor record in producing regular updates to allow cross-validation by the wider scientific community.

The plot shows that deployment levels observed in reality have been consistently much higher than levels in scenarios presented to policy makers and industry in the WEO reports. While the details of how this happened – and what the implications have been – are complex (Hoekstra et al., 2017; Johnsen, 2016), the key point to note is that the development of the energy system as it actually occurred has consistently not been presented to policy makers as a plausible, realistic scenario. EVs, grid batteries and electrolysers are all on growth curves similar to PV, yet barely feature in the wide array of scenarios available to policy makers today.

This raises the obvious question: in hindsight, will the scenarios currently being considered adhere to the same systematic trend? To answer this question, we need to know how scenarios are constructed, in particular how future technology costs are modelled.

Historical technology cost trends

Technologies that eventually reach mass commercialisation typically start out very expensive, and through innovation and learning over many years, decline in cost. In some cases, once a technology reaches cost levels similar to its direct competitors, cost reductions stop, and stable market shares are established. This happened for both nuclear power and combined-cycle gas turbines (CCGTs): costs fell sharply during their initial commercialisation phases in the 1960s and 1980s, respectively, but then plateaued as stable market shares were reached (or even began rising in the case of nuclear power) (Way, Mealy & Farmer 2020). The precise shares eventually reached are determined by a whole range of characteristics of both the technologies themselves and the wider system within which they are embedded.

In other cases, though, a technology's cost continues falling to levels lower than its direct competitors, in which case market dominance is achieved. An example of this is the eventual domination of combined-cycle gas turbines over open-cycle gas turbines (OCGTs) for electricity generation (though as noted above once CCGT costs undercut their OCGT competitor, they stopped falling). A key question then when considering technology deployment patterns is – how far will a technology's cost continue to fall due to ongoing R&D, innovation and learning processes? To provide background context, Figure 5 shows long-run useful energy costs and prices of key energy technologies (using the same efficiency conversion factors as in Figure 5)

Note that again the data in Figure 5 is plotted on a logarithmic scale, as this makes the relevant long-run trends easy to see. A cost reduction of a fixed percentage per year is manifested here as a straight line. Hence it is clear that the cost of solar electricity has fallen at around 10% each year for at least the last half century. In contrast, oil, coal, and gas prices have been approximately constant for over a century.

Coal-fired electricity improved consistently over the first half of the twentieth century but then progress stopped. This is because initially, innovation and learning processes generated significant design improvements in all aspects of this relatively unexplored technology. In addition, the range of tools and knowledge available for discovering and implementing improvements themselves expanded significantly during this period. As time wore on though, it became harder and harder to discover novel improvements for most of the equipment used, as design and efficiency limits inherent to the underlying physical processes were approached. Eventually no significant further cost reductions were found, and costs have approximately tracked the underlying fuel price ever since (in fact rising slightly due to system-wide regulations attempting to internalise a small fraction of the significant external pollution damages caused by the technology).

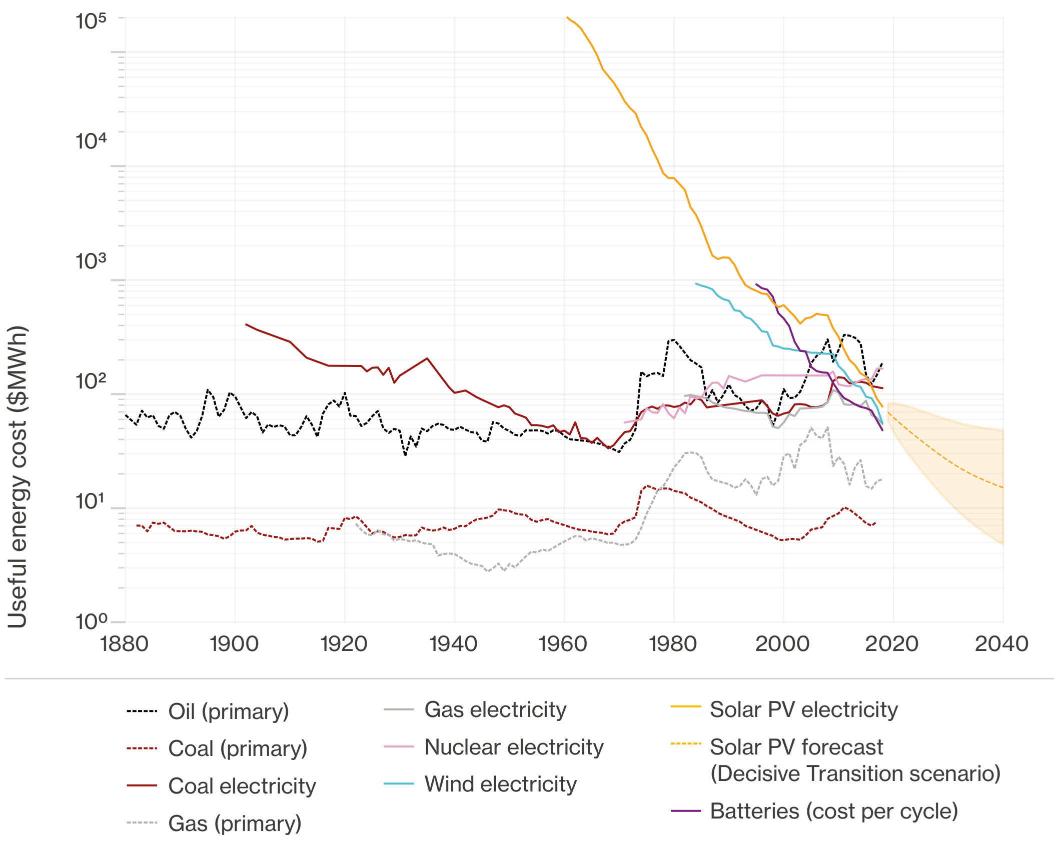


Figure 5: Long-run useful energy costs and prices of major energy supply technologies. Primary oil, coal and gas paths are based on price data; all other technology paths are based on cost data. Costs and prices are scaled by technology-specific useful energy conversion factors. The dashed yellow line and shaded area show the cost forecast for the LCOE of solar PV in the Decisive Transition scenario (median and 95% confidence interval).

Solar, wind and batteries are knowledge intensive technologies that require no fuel inputs and are not expected to follow this simple trend. Instead, their continued progress depends on factors such as materials science, R&D applied to manufacturing, deployment and control processes, and manufacturing scale. Because these are such knowledge intensive technologies, and the stock of knowledge can just keep expanding as long as resources continue to be invested, there is no clear reason why cost reductions cannot continue on their current trajectories for quite some time. For example, improvements in computers and algorithms will likely allow the discovery of better materials, which will in turn translate into better performing technologies (e.g., higher PV module efficiency and longevity, lower manufacturing costs) (Schmidt et al., 2019). Knowledge intensive processes build upon past knowledge (which is not easily forgotten) and diffuse rapidly among the community. As long as there are discoveries to be made, investing more effort will be a productive activity. While it is possible to break down cost progress into various components such as financing, manufacturing, installation, maintenance, decommissioning, recycling etc. (Kavlak et al., 2018) these are all highly knowledge intensive activities and the distinctions between them are likely negligible relative to the large, constant fuel input costs required by any fossil fuel alternative.

In contrast, long-run fossil fuel costs are determined by two factors: the availability of physical resources and the costs involved in acquiring and using these resources. On the one hand, innovation, and technological progress act to make the extraction, transport, and usage of fossil fuels cheaper (i.e., these are knowledge intensive activities), but on the other hand, resource depletion acts to make them all more expensive. The result is that continued innovation and learning appear to be required just to keep price levels approximately constant – there is no long-run progress (see Figure 5).

Technology cost forecasting

With this historical picture in mind, it is important to consider whether these trends will continue in future: how well can technology costs be forecast? This question has been studied in detail over many years, and various mathematical models have been proposed to forecast technology costs based on observed data of factors such as time, annual production, cumulative production, R&D investment, and combinations thereof.

Two well-known patterns observed in technology data are Moore's law, which refers to a regularity in the relationship between cost and time, and Wright's law (also known as the learning curve, or experience curve), which refers to a regularity in the relationship between cost and experience (where experience means the sum total of humanity's "experience" with the technology). The concept of experience is hard to define or quantify though, so is often proxied by the cumulative production of a technology. This still leaves room for interpretation though, for example, the "production" of electricity generation technologies can be measured either in terms of nameplate capacity installed (or produced), electricity generated or number of generating units produced. While it is good to be aware of this nuance, for most applications the choice of variable does not make a big difference.

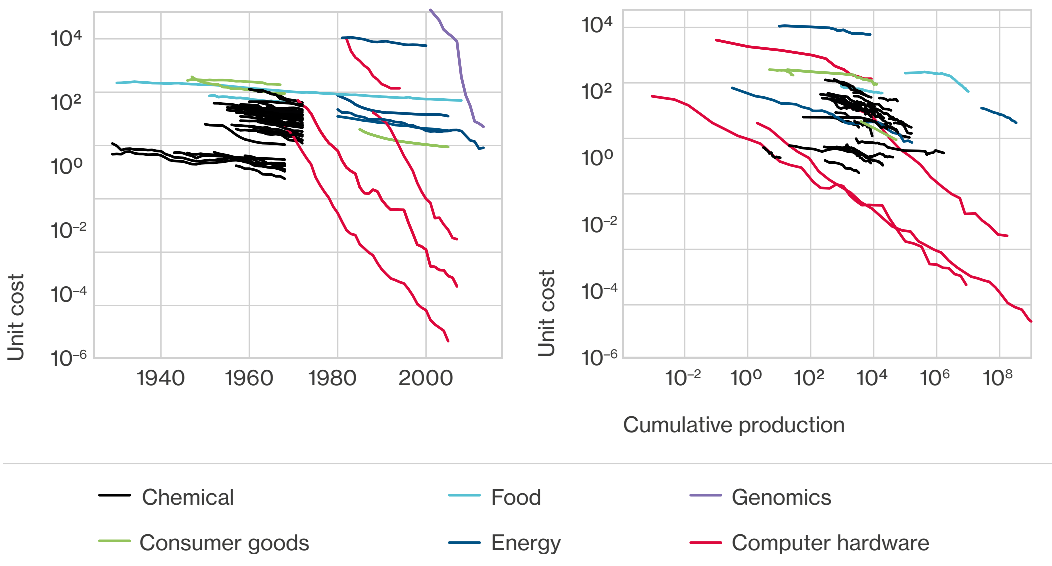


Figure 6: The relationship between unit costs and time (left) and cumulative production (right) for various technologies.

To quantitatively test the various mathematical relationships proposed in the literature, Nagy et al. 2013 collected data on over 50 technologies spanning many decades. This dataset was later expanded by Farmer & Lafond 2016 and Lafond et al. 2018. The data is shown in Figure 6, where the left panel shows costs plotted against time, and the right panel shows costs plotted against experience.

There are two important observations to make. First, there are high levels of regularity in the cost trends observed. Second, different technologies improve at very different rates. Together these two facts will have important consequences for updating our understanding of various technologies' likely roles in climate change mitigation.

Nagy et al. 2013 performed a set of hindcasting (or back-testing) experiments that tested the ability of six different models to make simple point forecasts (including the Moore's and Wright's law models). For each technology, at each year in the past, data observed prior to that year was used to calibrate each model and make forecasts for "future" years (i.e., years after the year in which the forecast was made, but which are nevertheless in the past relative to now). These forecasts were then compared with the realised "future" values, and the performance of each model was statistically quantified. Moore's law and Wright's law forecasts were found to produce the best forecasts (i.e., the smallest forecast errors), and so subsequent statistical analysis focused on these.

As a first extension of this work, Farmer & Lafond 2016 used the same dataset to test a more advanced forecasting method based on Moore's law, which uses both the observed trend and the volatility of historical data to produce probabilistic forecasts. The basic idea is that in addition to a stable, underlying Moore's law cost reduction trend, there are also random fluctuations that occur annually, which may cause costs to depart from the stable trend. The intuition for this model is that technological progress and innovation act in reliable, methodical ways to reduce costs, but external factors from other parts of the economy may also have an impact, in a periodic but random way. These random shocks, which may be positive or negative, are independent of innovation within the field of the technology itself. For example, there could be a shortage of materials due to activity elsewhere in the economy; or a new, better machine may be developed in another field that happens to bring costs down significantly. These random shocks accumulate over time, potentially dragging the technology's cost far away from the underlying trend and forming a probability distribution of possible future technology costs. Historical data is used to calibrate both the stable trend component and the periodic shocks, and hence produce technology-specific probabilistic forecasts that are consistent with past data.

The same rigorous hindcasting procedure described earlier was implemented, and this verified that the probabilistic forecasts made using this method were highly consistent with observed data. Therefore, to the best of our knowledge this forecasting method should perform just as well when making real, out-of-sample forecasts of the future. The work was extended further by Lafond et al. 2018, where instead of applying Moore's law to the stable, underlying cost reduction trend, they used the Wright's law relationship, so that increases in experience are assumed to cause cost reductions. As before, the hindcasting procedure was implemented, and it was found that the probabilistic forecasts generated by this method are of approximately equally high quality as those produced by the probabilistic Moore's law method.

However, there is a significant difference between the two approaches. Moore's law methods suppose that technology costs are best predicted based purely on the passage of time; hence, these forecasts are independent of everything else going on in the economy. This may be a reasonable assumption in some limited cases, but it is incompatible with the notion that exerting more effort on a given technology – throughout the entire global economy, from R&D through to end-users – will have an impact on the speed of innovation and improvements that occur.

As an example of why it makes sense for technology cost forecasts to depend on experience, note that much of the very recent progress in PV modules is the result of the technology reaching a scale at which high volume manufacturing processes are used. But if government deployment incentives had been lower than they were for the last two decades, production volumes would likely be much smaller, so economies of scale due to manufacturing process optimisation would not yet have been achieved. Conversely, if deployment incentives had been higher or earlier (within reason) then it is likely that costs would have fallen earlier too. After all, the techniques required to scale up production were not ground-breaking, requiring no fundamental innovations. That said, there are clearly some important relationships with other sectors and technologies, for example, progress in computer chip manufacturing likely improved the availability of silicon wafers used in PV module manufacturing. However, the multiple factors associated with progress are hard to tease apart and it is unwise to rely on ex-post, technology-specific narratives, rather than quantitative, empirically tested models (Kavlak et al., 2018; Nemet, 2006).

Many authors have highlighted the fact that the experience curve correlation does not imply causation, and that while deployment may cause costs to drop due to technological progress, decreasing costs may also cause greater deployment, so care must be taken with any forecasts made using experience curves (Nordhaus, 2009; Witajewski-Baltvilks et al., 2015). In order to address this issue, (Lafond et al., 2020) studied technologies produced in the US for use in World War II, as this is a case in which it is clear that production was caused by government policy, as opposed to falling prices. It was found that for this large data set, increasing experience did indeed cause costs to fall, to some extent, though costs also fell as a result of background progress elsewhere in the economy. The latter part is not surprising since there was so much technological progress occurring throughout society in this period, but overall, the results still provide solid empirical evidence for the argument that increased experience and innovation do, to some extent, cause technological progress and should be modelled as such.

The end result of these long, detailed investigations completed over the last decade is that the probabilistic Wright's law forecasting method developed by Lafond et al. (2018) is an empirically validated method that is also consistent with the intuition that the more effort is directed towards improving a technology, the greater the chance there is of improvement occurring. This is the model we use in this report.

Modelling technological change

The purpose of describing the above developments in such detail is to underscore the fact that forecasting technological change is incredibly difficult, and that there is great variation in the quality of forecasting methods available. Because of this, it is essential to use the most empirically and theoretically justified methods possible, and to regularly produce forecasts that can be compared with observed data, in order to continually assess their performance.

Furthermore, energy-climate models are often very sensitive to future technology costs, so it is essential that they use the most trustworthy forecasts possible. Since this is such a critical element of energy-climate models, one would expect that both the cost forecasting methodology and the forecasts themselves would be described prominently in documentation and results, but unfortunately this is not the case. In most cases the forecasting method is described only briefly at best, and specific cost forecasts are not documented at all.

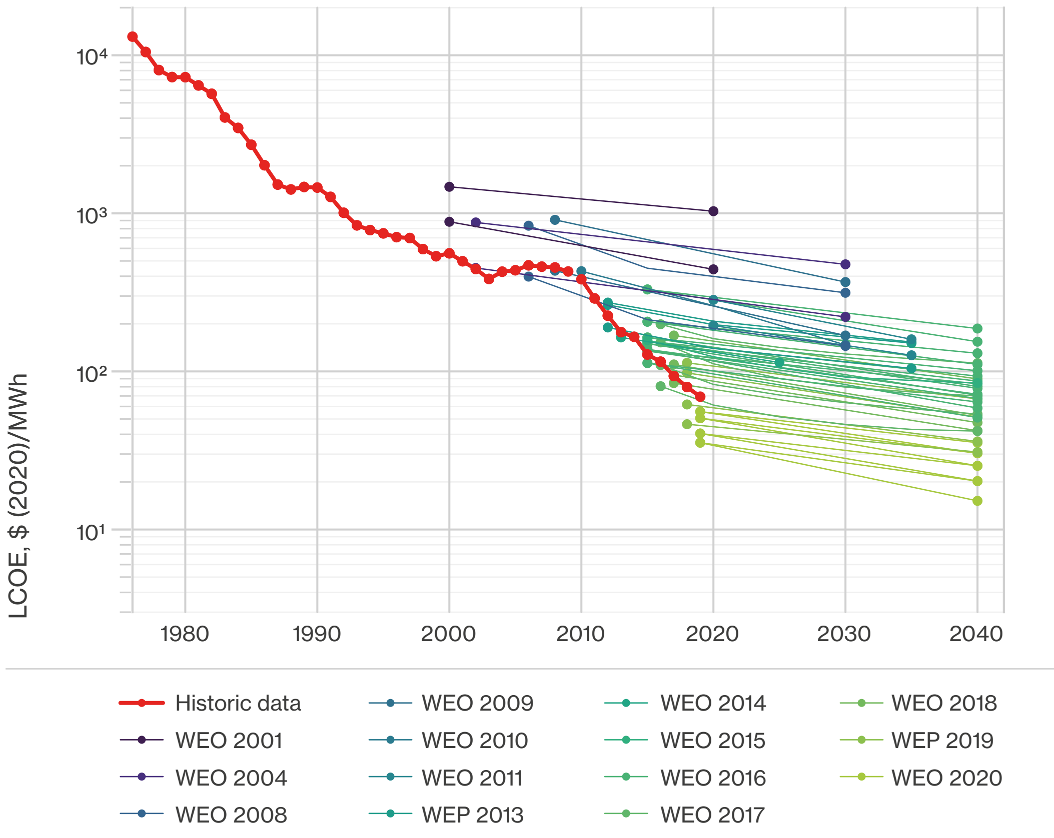
The way technological change (TC) is modelled in energy-climate models can be divided in to two categories: exogenous TC or endogenous TC. In exogenous TC, technology costs are defined by a model, such as Moore's law, and remain permanently fixed throughout the scenario construction process, independent of any market or deployment models being used. In endogenous TC, however, technology costs depend on the scenario construction process itself, and a model, such as Wright's law, is used to relate costs to deployment, and vice versa.

Assessing model cost forecasts and projections

Comprehensive testing and validation of large energy models is infeasible by anyone except the model developers themselves. In addition, the technology cost forecasting methods, assumptions, and constraints used in the models are often poorly documented, opaque, and hence impossible to scrutinise outside of the full modelling environment. Therefore, researchers attempting to understand how reasonable and reliable the models' characterisation of future technology developments are likely to be, are left with few options.

One simple approach is to examine publicly available model outputs, for selected model components only, and compare them with known, realised data points. One would reasonably ask what historical data can tell us about modelled technology costs in future. Indeed, the only way this could yield any insight would be if there was a stable, erroneous correlation between past and future costs. This is precisely what we observe. Since it is well known that there have been consistent discrepancies between the IEA's PV capacity projections and reality (Figure 4), this is a good place to start in attempting to understand technology cost projections too.

We examined the IEA's WEO reports for all available years and recorded all solar PV cost values found in each – both the current costs and the projected future costs. The reporting is not consistent over the reports, with different years providing either capital cost or levelised cost of electricity (called "generating costs" in early reports) in various years, or sometimes no data at all.



● **Figure 7**: Actual versus IEA projected LCOE of Solar PV. Sources: IEA World Energy Outlook 2001-2020, Nemet (2006) and IRENA (2020). The dots show data points provided for different scenarios and regions in successive WEO reports. Connecting lines are provided to emphasise the underlying trend.

Each projected cost value is associated with a specific scenario, and in most years three scenarios are provided. In recent reports, scenario- and region- specific costs are given, but in general the differences are small. Figure 7 shows the IEA's PV LCOE projections over the years, plus a long time series of actual LCOE values for PV in the US (which is a good approximation for the global average).

Since 2001, the IEA consistently projected a much more gradual decline in costs than actually occurred. Projections for decades ahead became outdated within just a few years. For example, in 2010 the IEA projected that PV LCOE would be around \$180/MWh in 2035; only three years later it was already below \$170/MWh (all in constant 2020 USD).

The plot shows that there has been a systematic bias in the projected future costs of PV reported in the WEOs. This suggests that either there is a fundamental flaw in the way these costs have been modelled, or, implausibly, that every single year, only high-cost PV scenarios have been reported. The former is clearly more likely, but it is impossible to know for sure since the model has not been tested (or made available for testing). If the errors were simply due to the inherent uncertainty of the future and random events in the world, then we would expect some cost projections to be high and some low (as is commonly observed in oil price forecasts). The systematic nature of the errors here implies a systematic error source.

Whatever the cause, the fact is that modellers, policy makers, investors and analysts reading the WEOs have, for the last two decades, consistently been given the impression that PV is and will always be a very expensive technology. This is a serious failing. The IEA states that cost projections are internally consistent with the scenario being modelled, i.e., they are conditional upon all scenario assumptions, and so if the scenario assumptions are not realised, then the cost projections should also not be expected to be realised. While this is a valid point, due to the inevitable conditionality of any sophisticated forecast methodology, it does not explain why, since the projections have clearly been at odds with the data since around 2010, suitable adjustments were not made to the scenario assumptions, to explore scenarios that produced projections more in line with the historical trend. It is striking how, when plotted against time in this way, all the projections have almost exactly the same exponentially decreasing trend, and how this is clearly at odds with the long run trend.

That WEO projections are overly pessimistic in both cost and deployment of renewables suggests that the modelling approach used is systematically failing to account properly for endogenous TC. These two factors are inherently linked. If the broader deployment of technology reduces its cost through learning, then too little growth also implies too little cost reduction. Conversely, if the technology becomes cheaper, it makes sense that it becomes more widely used.

It should be noted that, as detailed in Krey et al. (2019), all major IAMs also use PV cost projections that are significantly higher than the data suggests is likely. In fact, all IAMs considered in that study use PV capital costs in 2050 that are higher than current PV capital costs in the US. The problem of inadequate representation of endogenous TC in energy models is therefore a widespread phenomenon. Furthermore, the reason why attempts to assess the reliability of large models has so far focused on PV is simply because it is the technology for which most data is available, since it has been relatively well documented and included in models for several years now. Other clean energy technologies such as grid battery storage, EVs and electrolyzers are likely to be similarly poorly represented.

What causes the projections to go so wrong?

It is difficult to say precisely why large models have consistently considered some realised technology trends to be unviable scenarios, but the most likely reasons are:

1. Initialising models with out-of-date, unrealistically high-cost data. Even just a few years can make a lot of difference for fast progressing technologies like PV and batteries.
2. Using technology progress rates that are lower than historical data suggest are justified.
3. Imposing an upper limit on the percentage of variable renewable energy (VRE) allowed in the power grid.
4. Requiring VRE sources to be backed up with energy storage technologies (e.g., batteries, hydrogen) whose costs are themselves badly calibrated (too high) and not consistent with observed progress trends.
5. Imposing an unrealistically high mark-up on the cost of VRE in the power grid, to account for system integration costs.

6. Imposing growth rate constraints on technologies.
7. Imposing floor costs on technologies, designed to prevent their costs falling below some exogenously defined levels.
8. Not accounting for technology-specific characteristics that alter the value of technologies in different regions or markets (for example, the correlation between PV and air-conditioner demand increases the relative value of PV in some markets).

Different models appear to include different combinations of these factors, all of which may contribute to preventing experience curve trends being accurately portrayed in model outputs. In models that use endogenous TC, assumptions that directly constrain technology deployment (3, 4, 5, 6, 8) cause cost reductions to be constrained, because less learning occurs. Conversely, assumptions that directly constrain cost reductions (1, 2, 7) cause deployment to be constrained, because cheaper technologies are generally deployed in largest quantities. These constraints thus cause the cost-deployment feedback loop observed empirically from being accurately replicated in models.

As well as observing how PV cost projections have changed over time, we can also observe how one internal feature of the cost modelling process has changed over time: PV floor costs. Floor costs are often imposed in models that use endogenous TC, as a way of preventing technology costs from becoming lower, and installations becoming higher, than modellers consider realistic. However, there is no empirical evidence to suggest that floor costs are a sensible modelling choice in the long run. After all, computer processing power costs have fallen by around seven orders of magnitude since the 1970s, while PV module costs have only fallen by around four, so far. Using modellers' guesses to determine lower bounds on technology costs in future is not a reliable strategy. Table 3 shows some floor costs that have been used in IAMs over the years.

Table 3: Solar PV floor costs in various IAMs compared with realised PV system prices. Floor costs were collected directly from the relevant papers, building upon existing literature reviews by Baker et al. (2013), DeCian et al. (2016), and Carrara (2018). PV system price data is for US systems, collected from IEA PVPS Trends reports.

Year	Paper	Model	PV system price in US, \$(2020)/kW	Model floor cost, \$(2020)/kW	Year model floor cost falsified
2000	Kouvaritkakis et al. 2000	POLES	13465	2400	2013
2000	Barreto & Kypreos, 2000	ERIS	13465	757	
2002	Feber et al., 2002	MARKAL	10926	1055	2019
2004	Anderson & Winne, 2004	E3MG	9975	1691	2016

Year	Paper	Model	PV system price in US, $(2020)/kW	Model floor cost, $(2020)/kW	Year model floor cost falsified
2006	Bosetti et al., 2006	WITCH	8881	636	
2007	Bosetti et al., 2007	WITCH	8031	618	
2009	Bosetti et al., 2009	WITCH	5112	597	
2009	Rout et al., 2009	TIMES	5112	2800	2013
2010	Edenhofer et al., 2010	IMAGE	6004	1485	2017
2011	Luderer et al., 2011	REMIND	4891	758	
2012	Bibas et al., 2012	IMACLIM	4628	1121	2017
2012	Bibas et al., 2012	IMACLIM	4628	1958	2014
2014	Criqui et al., 2014	POLES	1952	1212	2017
2015	Luderer et al., 2015	REMIND	1567	545	
2016	Witch, 2016	WITCH	1610	541	
2017	Creutzig et al., 2017	REMIND	1040	238	

Improving the estimation of technology costs

It is vitally important that energy models undergo rigorous testing and validation to ensure their outputs can be relied upon. As described here, even basic attempts to assess the historical veracity of major energy models and IAMs reveal that they have consistently provided output at odds with empirical trends. This is a serious problem as it implies potentially critical areas of scenario space have simply not been explored (e.g., those with very high deployment of solar, wind, EVs and green fuels such as hydrogen and ammonia). This in turn is problematic because it means that policy makers and investors seeking to develop strategies to combat climate change are consistently told that certain types of future scenario are expensive or impossible, when in fact they may not be.

The problem is now obvious, as technology costs repeatedly fall through floor cost limits set by modellers, and the real energy system continues to develop clean energy technologies faster than any of the models thought was plausible.

The inconsistency is well known by now for PV, but there is a real risk that current model outputs regarding grid battery storage, EVs, electrolyzers, and potentially other hi-tech, clean, fast progressing technologies, will be proven similarly flawed in future, and worse, may be holding back their progress now, by unnecessarily lowering expectations.

Much greater attention must be paid to using empirically grounded approaches for technology forecasting, such as those described in Lafond et al. 2018. There is clearly a balance between model realism, which results in increased model complexity, and model reliability, which demands lower complexity. Evidence suggests that large energy models have been, and perhaps still are, putting too much weight on aiming for realism, but in doing so are unable to capture basic technological trends – trends that may well end up rendering all their scenarios obsolete. We now proceed to consider how to build an energy model, from the bottom up, around empirically grounded technology forecasts.

Section 3: A probabilistic technological change model for estimating the cost of the global energy transition

Introduction

Given the difficulties the major mitigation models have experienced with incorporating the pace of clean energy technological change into their scenarios, the question is, what might climate mitigation scenarios look like if they did not suffer such difficulties? This report provides a first pass at answering this question.

To do so, we develop two contrasting scenarios that allow us to quantify the relative impact that technological change could have on climate mitigation efforts. The scenarios are identical in underlying energy service demand, but very different in the direction taken by the global energy system. In one scenario, the current expansion of clean technologies already underway is stalled, and there is very little change in the energy mix going forward. In the second scenario, decisive action is taken to maintain current technological trends, continuing the currently high deployment rates and subsequent learning-by-doing in renewable technologies. Each scenario is named based on this narrative and can be summarised as follows:

Stalled Transition scenario:[17] The transition to clean technologies is stalled, and the current energy mix prevails long term, meaning that the relative size of all energy sources is maintained approximately constant at their current values. Total useful energy increases at 2% per year, be that through economic growth or population growth or other drivers of demand. Final energy remains high because only a limited proportion of the global system is electrified. This is designed to be counterfactual to the second scenario and is a viable scenario in its own right, given that it matches particularly well to the IPCC scenario with the highest economic growth and the highest emissions (SSP5-RCP8.5 Baseline).

Decisive Transition scenario:[18] Current growth rates in clean energy renewable technologies continue for the next decade, then gradually relax back to the low system-wide rate. Within 25 years fossil fuels are displaced from the energy sector, with all essential fuel use replaced by "green" hydrogen-based fuels.

17 This scenario is named the No Transition scenario in (Way et al., 2020).

18 This scenario is named the Fast Transition scenario in (Way et al., 2020).

Solar and wind provide most of the energy, transport is mostly electrified, and reliable electricity is maintained using energy storage based on batteries and hydrogen-based fuels. To provide a like-for-like comparison with the Stalled Transition counterfactual, useful energy also grows at 2% per year.

These scenarios are not generated using least-cost optimisation methods (as this is computationally intractable) but are instead manually configured to match their narratives. They are, however, both physically feasible within the solution space of our empirically grounded model. It is difficult to imagine a higher emission scenario than the Stalled Transition, given the renewables deployment rates that have been observed historically.

This section of the report provides an overview of the Probabilistic Technological Change (PTEC) forecast model used to generate these scenarios. The layout of this section is as follows. First, a non-technical overview summarises the modelling approach and outlines the critical areas of departure from other major energy system models (described in Sections 1 & 2). Second, we provide a more technical description of each model component and the assumptions they embody. This includes discussing key dynamics, such as the representation of endogenous technological change and managing the intermittency problem associated with renewables. Third, we present more detail on how the above two scenarios were constructed using PTEC.

The main design principles of the PTEC model are simplicity and transparency, so we are keen to ensure readers can engage with the model's construction and its implications. When technical terms arise, we attempt to provide intuitive examples, for clarity. Readers are also invited to consult the Glossary at the end of the report. Despite its simplicity, there is still a great deal of detail to the model and the assumptions underpinning its development, which cannot be fully covered in this report. Our aim here is to provide sufficient detail to convey the legitimacy of the approach, and to give an overview of how the scenarios used for this analysis are constructed. Those interested in a more substantive description of PTEC are directed to (Way et al., 2020), which provides a thorough account of how the model was developed.

The PTEC Energy System Model

A simple and transparent model for forecasting technological change in the global energy sector

As outlined in Section 2, the PTEC model seeks to distinguish itself by offering a simple and transparent methodology for forecasting technological progress in the energy sector. This contrasts with the "crowded landscape of model-based analyses that can overwhelm decision-makers with their complexity" (DeCarolis et al. 2017, pp. 185). To achieve this, several simplifying assumptions are necessary, but care is taken to ensure all such assumptions are empirically grounded. When a deliberate choice is required, the model generally takes a conservative approach (i.e., on the pessimistic side, regarding costs and progress of new clean technologies compared to fossil fuels). Hence, the results likely understate the true cost-saving potential of a 'green' technology transition.

The model consists of 22 components that directly cover 83% of all final energy use and 82% of energy CO_2 emissions. This includes the most common fossil fuels (oil, coal, gas), renewables (solar, wind, hydrogen, hydropower, biopower), and nuclear power. It does not include several potential but currently still nascent technologies, such as carbon capture and storage (CCS), second-generation bioenergy, small modular nuclear reactors, or new geothermal energy, because these technologies are all unnecessary to prove our main results. It also does not assume any conversion efficiency improvements, or how efficiently energy gets transferred from its production source into its end-use consumption.

Whilst we do not explicitly allow conversion efficiency improvements for individual technologies in our scenarios, we still allow for total system efficiency gains via switching between technologies. For example, fossil fuels generally contain a high energy density, however converting fossil fuels to electricity involves a significant loss of energy in power stations, mostly as heat. In a few circumstances some of this lost energy can be utilised, such as in combined heat and power systems, or district heating, or industrial heat usage, but most often it merely radiates away. On the other hand, renewables have relatively low efficiency in converting natural irradiance or wind energy to electricity. But once the electricity is generated, there is little energy lost from its generation to consumption. This simple but substantial gain is extensively exploited in our most ambitious Decisive Transition scenario.

Assuming useful energy grows at the same rate in both our scenarios is advantageous for two reasons. Firstly, it allows for easier comparison across scenarios because we compare like-for-like on a "level playing field". Secondly, this assumption allows us to contrast our ambitious scenario with the high ambition scenarios of other major mitigation models which assume considerable energy demand reductions. This is not to say we do not agree with demand management approaches. There are many possibilities for innovation, efficiency increases, and improvements on the demand-side. For example, new technologies might allow us to achieve more economic growth from the same amount of useful energy or at a much cheaper rate than the solutions we provide in the Decisive Transition. However, we do not require such demand reductions in this report for our headline results.

To ensure that the scenarios are sufficiently realistic, the model includes some additional constraints and adjustments. This involves verifying that any predicted growth rates of technologies are in line with current trends and do not have any unreasonably sharp increases, which could be the case when applying a consistent 2% annual growth in useful energy. Indeed, the technology growth rates in the two scenarios presented are less than or equal to their most recent observed rates. Thus, even in our most ambitious scenario, there is no reliance on an increase in renewable energy deployment above current trends. In fact, it is gas electricity (the slack variable) that needs to temporarily grow above historical trends to meet our 2% growth in useful energy demand. For renewable technologies, we only make the simple assumption that they continue to grow at or below their current exponential rates for roughly the next decade and then taper off once they become the dominant energy source.

To ensure the feasibility of the renewable transition, an additional requirement for storage capacity availability is put in place, reflecting the most up to date scientific evidence available.

This is enacted to manage the intermittency of solar and wind energy generation, which can fluctuate significantly depending on location, time of day, season, and year. For example, Solar PV installations can produce a surplus of energy during the day but a deficit during the night. To overcome this "intermittency problem", large amounts of electricity must be curtailed (over-build) or excess energy stored and dispatched when needed. Therefore, the Decisive Transition scenario requires a clearly defined scale-up of storage technologies to match any increase in variable renewables. This storage is added in several forms including short-term batteries, multi-day battery storage, and long-term power-to-X (P2X) fuels (where X stands for chemical storage such as hydrogen, ammonia, or methanol).

Outside of these constraints, there are no other requirements that the PTEC scenarios must fulfil, such as real-world obstacles like political opposition, the pace of decision-making processes, or land use concerns. PTEC also examines the global energy system overall, not looking at differences between individual regions or the availability of suitable sites. However, these factors are all modelled implicitly, via choices of variables that accurately reflect historical technology trajectories. These are clear limitation of the PTEC model, some of which we address in Section 5, but they enable the model to be kept much simpler and more transparent – addressing one of the clear limitations and criticisms of the major mitigation models. The purpose of the PTEC scenarios is to examine what is technically possible. Ultimately, the choice to achieve a decisive transition to a clean energy future will rest with our global decision-makers and their ambition for change and not just in the technologies they have available to them.

Components of the PTEC model

As discussed previously, a key distinguishing feature of the PTEC model is that it is designed to be simple and transparent. Simplification does, however, come at a cost. Most of the global energy system is covered in as accurate a form as possible in the model, encompassing around 83% of final energy.

The aggregated components that are included are as follows:

- 3 direct-use primary energy resources: oil, coal, and gas
- 7 electricity generation technologies: coal, gas, nuclear, hydropower, biopower, wind and solar PV
- 5 energy carriers: oil, coal, gas, electricity, P2X fuels
- 3 storage and conversion technologies: daily-cycling batteries, multi-day storage, electrolysers
- 3 end-use sectors of the economy: transport, industry, and buildings

Energy is supplied by three direct-use resources and seven electricity generation technologies. Note that coal and gas can be used directly or to generate electricity. Energy from these ten sources flows into the intermediate energy sector, via one of the five carriers, where conversion and storage happen.

Finally, the energy is used on demand in three economic sectors: transport, industry, and buildings (including residential). This simple specification currently accounts for 97% of electricity generation, 83% of all final energy, and 82% of final energy CO_2 emissions. Making the reasonable assumption that traditional biomass will remain close to carbon-neutral over its lifetime, the amount of final energy CO_2 covered even increases to 93%.

Energy system omissions

Note that this model does not cover the non-energy sector. However, in developing emissions scenarios to match those presented for the IEA and IPCC scenarios, we have added non-energy sector emissions estimates to allow like-for-like comparison. This is explained further in Appendix C and the results presented in Section 4.

Some energy sources and carriers were omitted from the model to maintain its simplicity. In general, components were either omitted because (i) the component is small and thus negligible or (ii) there is little verifiable data to suggest that this component will grow significantly in the future. Details are provided in Appendix C and Way et al. (2020) but in short they include examples such as biomass for cooking and biofuels in building energy use. These components are added on to the modelling results in post-processing (see Appendix C for details) to equilibrate our results with those of the IEA and IPCC, but for simplicity they are not explicitly included in the model. It is important to note that these simplifying assumptions are generally conservative, providing a cost/emissions advantage to fossil fuels. For example, the largest omission (9.9% of useful energy) is intermediate fossil fuel usage – whereby fossil fuels are needed to generate even more fossil fuels (e.g., powering coal mines). By excluding this, fossil fuels are modelled here as more efficient than they are in reality. Hence, fewer CO_2 emissions will be attributed to them for any given amount of useful energy produced.

Primary, final, and useful energy

The concepts of *primary*, *final*, and *useful energy* are helpful in energy system modelling, but they can also be a source of confusion. The general idea is that as *primary* energy (e.g., embodied in crude oil, coal, and wind) is extracted from nature and delivered to consumers, some of it is lost before reaching this end-use sector as a *final* energy source (gasoline, electricity). Moreover, energy gets lost when consumers try to use it in the end-use sector (e.g., powering transport, heating buildings, communications). That is, not all the *final* energy supplied becomes *useful* energy.

To give an example, consider a consumer wanting to power their car. To fuel an internal combustion engine vehicle (ICEV), crude oil (*primary* energy) must be refined into gasoline (*final* energy) which is then supplied to the car fuel tank. There is an energy loss associated with the production, refinement, and distribution of crude oil as gasoline (Brandt, 2011) but the *primary* energy associated with the gasoline is by convention the energy embodied in the crude oil required to make it. The ICEV converts only around 20-40% of this embodied energy from the gasoline in the tank (*final* energy) into the motion for the vehicle (*useful* energy). The remainder is mostly lost as heat. By contrast, electric vehicles (EVs) convert the energy in their batteries (*final* energy) into vehicle motion (*useful* energy) at closer to 80% efficient.

What matters in terms of calculating CO_2 emissions for these two types of cars is the *primary* energy used to supply the *useful* energy of the vehicle, and the carbon intensity of that *primary* energy. For this reason, it is important to know the source for the electricity used to charge the EV battery. If the EV is powered by electricity generated from a coal-fired power station, then only around 35% of the total coal used (*primary* energy) will get converted to electricity (*final* energy), resulting in the EV potentially producing more emissions than an efficient ICEV. If the EV is powered by electricity sourced from renewables (*primary* energy), the only losses are some line losses in the electricity grid, and the CO_2 emissions are minimal.

In calculating emissions, the concept of *primary* energy is therefore helpful. However, the concept of *primary* energy is a somewhat non-sensical for technologies like solar PV, as the *primary* energy is not defined as the sun's radiant energy. The *primary* energy reported for renewables like wind and solar is by convention calculated using a 100% conversion factor between *final* energy and *useful* energy. The conversion rates used in this report match this convention and those of the IEA (2019).

In calculating costs of the energy system, what is most relevant is the *final-to-useful* energy efficiencies and how much investment in energy generation infrastructure is required to reliably supply the final energy needed to deliver the useful energy that is demanded by the global economy. If the cost of delivering this *final* energy for the whole system is the same for a renewables-plus-storage-based energy system as a fossil-fuel-based energy system, then the system that requires less *final* energy to deliver that *useful* will be cheaper (ignoring discounting). A significant portion of the Decisive Transition's cost savings can be attributed to such efficiency savings brought about by widespread electrification.

Deploying technologies in the PTEC Model

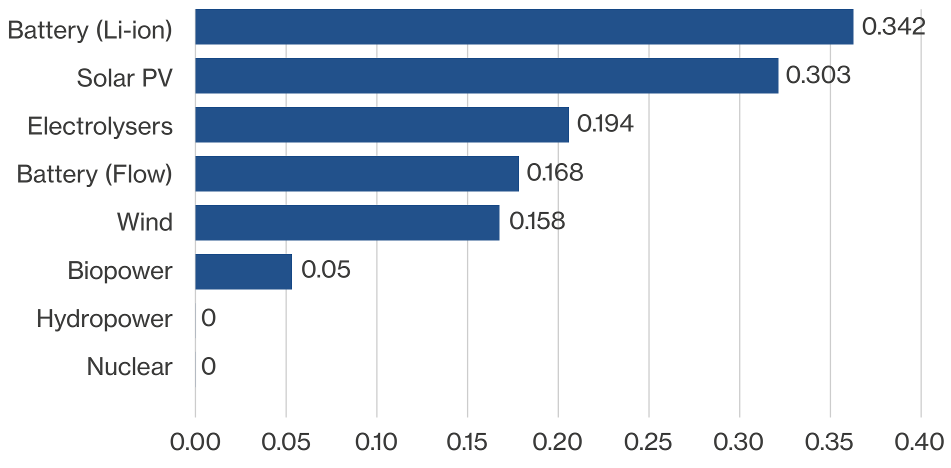
Experience exponents across technologies

Renewable energy sources, particularly solar PV, have the potential to become a cheaper source of electricity generation than fossil fuels. In many places, they already are (IEA, 2020c). In Section 2, we outlined how endogenous technological change suggests the potential for cost-saving from renewable energy is most significant when it is widely deployed globally. Yet, many existing models of the global energy system do not incorporate this critical dynamic. Some insert explicit constraints on new technologies, such as price floors, below which their prices cannot fall (Cian et al., 2016).

PTEC instead classifies technologies depending on whether their costs have remained approximately flat or declined over recent decades as they have become more widely deployed. This indicates where we can expect cost-savings in the future. As Section 2 showed, fossil fuel costs (direct-use oil, coal and gas; plus, coal- and gas-fired electricity) have remained relatively flat and are thus put in the first category. All other technologies are placed in the second category, where we apply the probabilistic forecasting approach developed by Lafond et al. (2018) to identify their historical "experience exponents". This is shown in Figure 3.

Note that the trend for nuclear power is somewhat less clear, varying a lot by country and might even have increasing costs through time due to safety concerns and public acceptability issues. Hence, in PTEC, we simply set its experience exponent to 0%, noting that nuclear energy does not become a dominant component in either of our two scenarios.

By applying historical trends in deployment rates, the PTEC model opens up a solution space in the climate mitigation story currently not well explored. For scenarios where there is a continuation of the transition towards renewable energy, the vast room for deployment still available means that a lot of 'experience' can be acquired with the potential for continuing cost reductions.



- **Figure 8**: Experience exponent parameters of key technologies used in PTEC. Source: (Way et al., 2020).

The uncertainty of future costs

To forecast future costs, it is critical to incorporate elements of the uncertainty inherent in such forecasts. In terms of the technology costs presented in PTEC, we differentiate between two sources of uncertainty. The first source of uncertainty is unanticipated future shocks, which remain inherently unknowable. For example, a sudden shortage in the raw materials needed to produce PV cells. Secondly, there is uncertainty around the "true" functional form of the experience curve relationship – that is how much each unit of cumulative production affects costs for a specific technology. Our historical estimates in Figure 3 may rely on imperfect data or change going forward. Thus, the model takes a stochastic approach, whereby we estimate our equations using historical data and include these two sources of randomness. Repeating this hundreds of thousands of times for each scenario, we have a range of different possible outcomes that can then be used to construct confidence intervals. Technical details of this are described in Appendix B and in Way et al. (2020).

Managing the intermittency problem

To make extensive use of variable renewable energy (VRE), it is critical that storage capacity also grows to insure against fluctuations in output (Barron & McJeon, 2015). Apart from cost considerations, this has been seen as the main obstacle to a large-scale 'green' transition. It is most pertinent for overcoming the daily solar cycle (Shaner et al., 2018) and to a lesser extent, wind. Measures are required to overcome these daily fluctuations and more extended periods of change that may be caused by natural weather patterns, seasonal changes, and inter-annual variability.

To address this issue, PTEC uses three modelled storage technologies, all of which have sufficient historical data from which to infer trends: lithium-ion batteries for short timescales, redox flow batteries for intermediate timescales, and P2X fuels for long timescales. We have seen in Figure 8 how these appear to follow Wright's Law and have favourable learning rates – like the renewable technologies that they are meant to complement. These three technologies are not necessarily the cheapest solution to store energy; we propose that they merely are a solution. This follows our conservative approach, acting as a possible upper bound on costs.

For each storage technology and each end-use sector, a constraint is placed so that at least a set fraction of energy can be stored. Under the Decisive Transition scenario, we require that short-term and multi-day batteries respectively hold 20% and 10% of average daily electricity generated by wind and solar in the power grid and transportation sectors. Additionally, we require that there be enough P2X fuel stored to cover one month's worth of end-use electricity each year. Since none of these storage technologies is yet widely used, it would be unrealistic to allow them to jump up straight to this fraction. Instead, the installed storage capacity first grows at a gradual rate, determined using existing historical data, until the constraint is met.

To make use of this storage capacity, we also need to have the ability to store a portion of the energy produced in excess of demand. Under the Decisive Transition, we build up an overcapacity in solar PV and wind to be able to generate 100% of aggregate annual final electricity by 2040, whilst still only accounting for 82% of the generation mix. This creates a large amount of surplus energy that can be stored.

We believe that this combination of high storage capacity and over-supply of dispatchable energy allows the Decisive Transition scenario to provide very high levels of reliable energy supply, which are above regulated requirements (99.97% in the US). We may also imagine how interconnectors here will play a substitutable role, in allowing electricity to flow across different grids – although this is not explicitly modelled here to maintain simplicity.

The explanation provided here on the PTEC model is a very brief overview. Readers interested in investigating the model in more detail are encouraged to refer to the much more comprehensive explanation in (Way et al., 2020).

The two PTEC energy transition scenarios

Constructing a scenario in PTEC

Despite its simplicity there is an almost infinite set of scenarios that could be constructed using the PTEC model, which must somehow be systematically narrowed down. For this report, we required scenarios that are (i) physically feasible given current trends, and (ii) allow for meaningful comparisons with each other, (iii) provided insights regarding the potential for our alternative approach to technology forecasting to be contrasted with the scenarios of the major mitigation models of the IEA and IPCC.

Many other studies rely on least-cost optimisation to produce scenarios, finding the lowest possible cost or emissions scenario out of an incredibly large possible set. However, this approach has been criticised for not reflecting real-world energy transitions (Trutnevyte, 2016) and is also very computationally intensive. Instead, to generate its scenarios the PTEC model essentially works 'backwards', using a few simple rules that constrain the supply, growth, and substitutability of technologies, to enable deployment of technologies to determine costs, in line with the probability distributions taken from historical trends.

To achieve this the PTEC model first fixes how much useful energy the global system will demand in the future, making the stringent assumption for both scenarios presented here, that every sector will continually grow their useful energy at 2% per annum. That is, there is no slowdown in energy demand from average historic levels, and therefore no requirements for economic growth to decline. By contrast, many other model scenarios that achieve net-zero emissions in the 21st century, necessitate a dramatic reduction in energy demand or a slowdown in economic growth. In doing so, they must make strong assumptions on demographic, economic, or policy changes to achieve the required drastic turn-around in global emissions.

There are multiple reasons to fix the growth rate of energy demand directly for both our scenarios. For one, it allows us to make a clear like-for-like comparison. Because each scenario must produce the same amount of useful energy, we can clearly distinguish other key differences between these scenarios, particularly in regards to technologies and policy, rather than being skewed by an implicit trade-off between CO_2 emissions and GDP. Additionally, our approach can be interpreted as imposing a strict conservative condition, in line with the model's overall conservative approach. Our 'green' Decisive Transition scenario must achieve its aims only through supply-side solutions, rather than relying on demand-side innovations or limiting economic growth. In some cases, demand reduction efforts will be very cheap and efficient, as shown with the widespread adaption of LED lighting (Creutzig et al., 2018). By making such strict and conservative assumptions regarding demand management, we are able to better test the relatively untouched area of the climate mitigation solution space involving probabilistic technological change forecasting (see Section 2).

Having fixed energy demand, the second step is then to specify the final carrier mix in each sector and the technology mix that supplies these carriers. For example, this would include determining how much electricity the transport sector demands versus oil and where that electricity is generated.

Any combination of energy technologies that meet these carrier constraints each year (and thus global demand) is theoretically a valid scenario in PTEC. Hence, it is crucial to ensure that the implicit growth rates specified here are consistent with current trends. This is thus reviewed again in the last step.

The third step is to place further constraints to address the 'intermittency problem' with any variable renewables (VRE), as described above. In PTEC this constraint requires that the adoption of solar, and wind energy must always be accompanied by significant increases in storage capacity to reliably provide dispatchable energy when making up a medium to large proportion of the global energy supply. This cap means implicitly that the cost of VRE deployment relies on growth in batteries, P2X fuels, and electrolyser technologies, which themselves have their own growth rates and cost declines based on empirical trends.

Lastly, given the final carrier and electricity mix, we then calculate the exact growth rate and length of time needed to achieve this mix from current levels. To ensure these growth rates are feasible, they are smoothed out to follow a general S-curve and adjusted to avoid unrealistically sharp transitions, using historical data as a reference. The energy storage requirements to deal with the 'intermittency problem' may further bind these growth rates. Further information on the details of this methodology can be found in Way et al. (2020).

Through this four-step process, we develop our two contrasting scenarios, each having very different final mixes and thus different growth rates of associated technologies, but each consistent with a set of explicit constraints based on physical limits and historical trends.

The Stalled and Decisive Transition Scenarios

Having outlined above how we construct scenarios generally; we provide more details on the Stalled Transition and the Decisive Transition scenarios, which are the focus of this remaining sections of the report and are assessed and discussed in contrast to other major climate mitigation scenarios.

The Stalled Transition scenario

This scenario represents a minimal change to the current energy system. That is, we assume that the current high rate of deployment of renewable energy technologies is stalled, slowing down over the next decade to the system-wide growth rate, and fossil fuels supplies continue to grow to meet global energy demand.

Such a scenario means that fossil fuels continue to meet most of the annual useful energy growth of 2% per annum across all sectors. By contrast, wind and solar PV generation respectively grow at a low 8% and 4% for a decade, before falling to 3% per annum. In such a scenario, solar and wind's electricity generation share falls from their current 7% to less than 2% over the next 50 years. Without the impetus of dispatchable renewable energy, there is no need for P2X fuels or battery technologies to take off. Note that, to begin with, daily batteries still grow at 2% per annum, in large part due to electrification of the transportation sector (i.e., EVs), which occurs even under this general slowdown.

It is worth emphasising just how extreme these decreases are. For reference, solar PV has seen an annual growth rate of 42% over the past 30 years, so even growing at 8% over the next decade is a significant downward revision. This is also a good illustration of why we call this a Stalled Transition, rather than "business as usual". Trends are not passive, but there is an active slowdown of multiple promising energy technologies.

Even if this scenario is not considered a realistic depiction of what we expect to happen in the future, we use it as our baseline due to several useful properties. We can compare other transition scenarios against it, essentially representing a stalling of current growth trends, freezing the energy system in its current configuration, and assuming pro-rata growth of technologies to match the 2% increase in total useful energy demand. Also, as Section 4 will demonstrate, this Stalled Transition scenario is very similar in terms of emissions and energy mix in 2070 to the SSP5-RCP8.5 scenario – a scenario that was initially seen as a "business-as-usual" but is now regarded more as a "worst-case" scenario – allowing us to contrast our results more easily with those of the IPCC.

The Decisive Transition scenario

In this scenario, investment in clean technologies with a high historic reduction in costs is pushed decisively and globally. These technologies grow at rates consistent with their recent historical trends until they become dominant and slow down to the system-wide rate.

Solar PV dominates due to its consistently steep experience curve. It grows at 32% per annum for the next decade, before descending to 10% per annum by 2040, and the system-wide 2% per annum by 2045. Likewise, wind grows at 20% per annum for the next decade, before declining to reach 6% by 2040, and the system-wide 2% per annum by 2045. This scenario subsequently sees solar and wind account for a substantial share of the energy mix by 2040. At this point, 90% of electricity will be generated from zero-carbon sources, and 81% of final energy is provided by zero-carbon sources, rising to 91% in 2050 and 97% in 2060.

The rise in variable renewables is met by a rapid increase in storage capacity to manage the intermittency problem. This sees a temporarily initial spike in the 2030s when capacity needs to be drastically built up to match the rise in renewables' storage requirements. These technologies' deployment rates are around 60% for these initial decades, which is high but below current rates. This is not unusual in the early phase of technologies where deployment is orders of magnitude lower than where it might end up. By 2040, enough short-term battery capacity exists to store and shift 20% of all solar and wind electricity generated each day. Likewise, there is enough multi-day storage to hold 10% of daily solar and wind generation. Enough P2X fuel is produced to cover one month's worth of solar and wind's contributions to the power grid if there is an extended lull in output due to the natural seasonal or inter-annual variation of these sources.

Overall, the rise in renewable energy – enabled by a rapid scale-up in storage technologies – allows for the global energy system's deep decarbonisation. Fossil fuels are displaced from all sectors by 2045, mostly through electrification, including replacement of difficult to electrify sectors with electrolytic P2X fuels (particularly in industry and transport). Oil consumption falls dramatically due to the rapid electrification of transportation.

This is one of the first significant transitions in this scenario because, while EVs grow at a similar rate to the other storage technologies, they start from a much higher level, so reach mass scale sooner. After five decades of sustained 2% growth of transport services, final energy in the sector is still below current levels due to the much higher efficiency of electric vehicles.

This scenario results in a global energy system that is very different from the one we currently have. This change is drastic in every way – in terms of the pace of change. Yet, as we have detailed throughout this section, the growth rates embodied in this scenario are close but lower than those experienced in the past few decades. As Section 4 will illustrate, the Decisive Transition suggests that simply sustaining the status quo will bring about a revolutionary change.

Section 4: Comparing our emission scenario projections with the IEA and IPCC scenarios, to 2040 and beyond

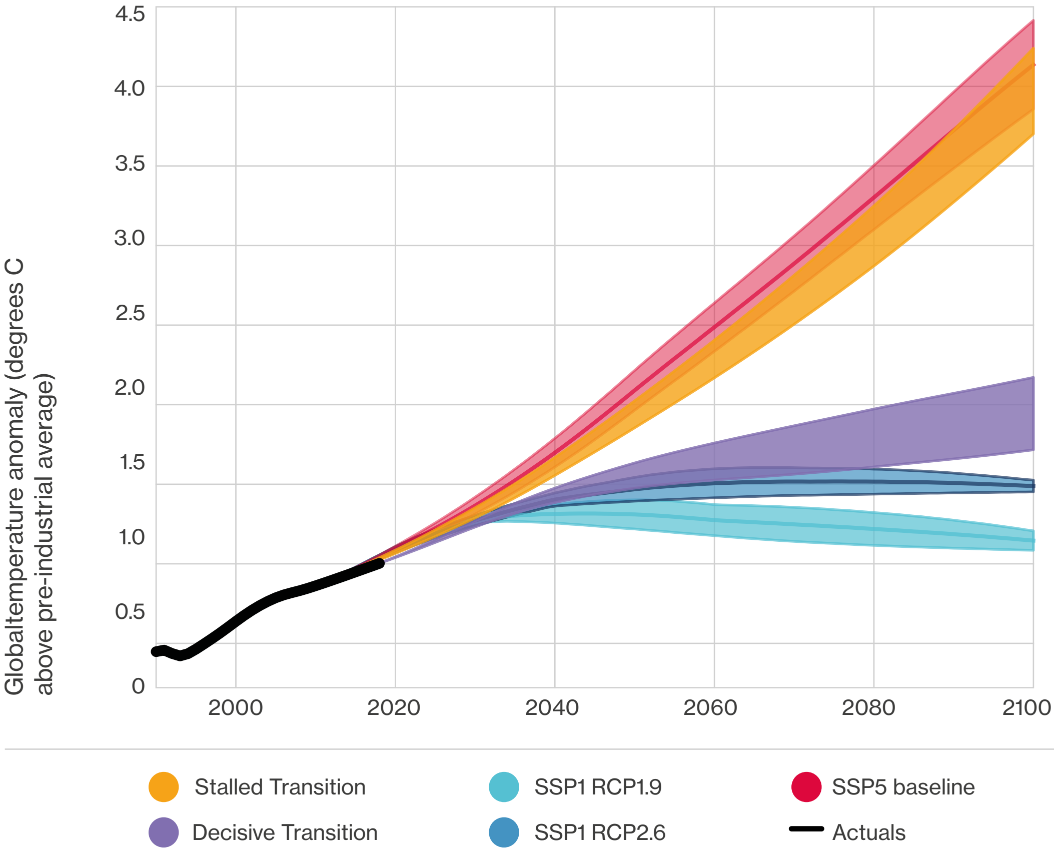
Introduction

Having outlined the Probabilistic Technological Change model (PTEC) in Section 3, we can now compare the results of the Decisive and Stalled Transition scenarios to some of the leading climate mitigation scenarios used by policymakers. For this comparison, we focus chiefly on models by the International Energy Agency (IEA), given its leading role in modelling the global energy sector, and the most recent scenarios of the Intergovernmental Panel on Climate Change (IPCC), being the most prominent and respected source for global climate mitigation scenarios.

We will summarise how the PTEC scenarios were equilibrated with the IEA models to ensure the PTEC scenarios represent the full global energy system. We then discuss the similarities and differences between the PTEC scenarios and those of the IEA. Finally, we provide a summary of how these enhanced global energy system scenarios were then equilibrated with the IPCC scenario by adding a non-energy system and non-CO_2 greenhouse gas emissions to the enhanced Stalled and Decisive Transition scenarios.

To convince our readers that it might be worth the trouble reading how our scenarios compare to the other mitigation models, we will begin with the headline results – which tell a remarkable story. Figure 9 presents the global warming associated with the final equilibrated Stalled and Decisive Transition scenarios compared to three key IPCC warming scenarios. As we can see our Stalled Transition scenario is most closely aligned with what is regarded as the 'worst-case' IPCC scenario (SSP5 RCP8.5) and the Decisive Transition is comparable to the SSP1 RCP2.6 high mitigation ambition "Taking the Green Road" scenario.

What is remarkable about this image is that it suggests the Decisive Transition achieves almost all the reductions in greenhouse gas emissions necessary to match these ambitious IPCC scenarios. This is remarkable because, in contrast to the SSP1 RCP1.9 and SSP1 RCP2.6, it achieves this result without any significant deployment of nuclear, carbon capture storage, or energy-saving technologies, and without a reduction in energy demand or economic growth. It merely is a result of extending current technological growth trends for another decade.



- **Figure 9**: Comparisons of Temperature Anomalies (using FaIR) from the estimated global emissions of two PTEC scenarios Stalled and Decisive Transition and three IPCC scenarios SSP5-RCP8.5 baseline, SSP1-RCP1.9 and SSP1-RCP2.6.

Despite such an interesting result, the analysis presented here is mostly a comparison exercise, to convince our readers of the legitimacy of these results. Where relevant, we highlight critical assumptions in the PTEC model that explain its differences from other models' scenarios. An examination of the potential obstacles to the technological progress presented in the Decisive Transition being realised and the policy implications of this "unexplored solution space" are given in Section 5.

Equilibrating PTEC scenarios with those of the IEA and IPCC

As explained in Section 3, the PTEC model focuses on simplicity and thus the energy flows included in it only accounts for 82% of current CO_2 emissions. To make a meaningful comparison with other global energy system models, we need to "add-in" everything else included in these IEA scenarios. This way, we can ensure that we are comparing like-for-like and can focus only on the critical assumptions regarding technological change.

Appendix C provides a detailed step by step guide to generating emission scenarios equivalent to those offered in the IEA World Economic Outlook 2019. In summary, we first match PTEC with the various components that make up the IEA global energy system and account for any missing parts. We then develop a methodology for projecting these missing components into the future in each PTEC scenario. To capture the inherent uncertainty associated with such an equilibration process (e.g., differences in assumed primary to useful energy efficiencies, regional carbon intensities for specific fuels, non-energy emissions etc.), we produce bands of emission estimates for each scenario, rather than exact values. Although lacking in precision, such an approach allows our readers to fully appreciate the uncertainty associated with our equilibrated emissions estimates so they can decide for themselves if such uncertainty alters any conclusion we may draw from this exercise.

A comparison with the IEA emissions scenarios

Background on the IEA World Energy Outlook

We begin by comparing the future projections of the PTEC global energy system model with those of the World Energy Outlook Report (2019) by the International Energy Agency (IEA). In particular we focus our analysis on the following two IEA scenarios:

- **Sustainable Development Scenario (SDS)**: This scenario defines a future where we hit global net zero in CO_2 by 2070 and fulfil the United Nations Sustainable Development Agenda's key energy-related goals. It then works out how to achieve such a scenario. The Sustainable Development scenario is the most ambitious scenario laid out by the IEA's WEO 2019 report and thus serves as a useful benchmark to our Decisive Transition.
- **Stated Policies Scenario (STEPS)**: This scenario is designed with the intention of "holding up a mirror" to the plans and ambitions announced by policymakers. It considers only specific policy initiatives that have already been announced and projects these forward to 2040. Although this is the least ambitious of the IEA scenarios, it is not as pessimistic as the PTEC Stalled Transition scenario. However, it does provide a useful benchmark for comparison with more and less ambitious climate mitigation scenarios.

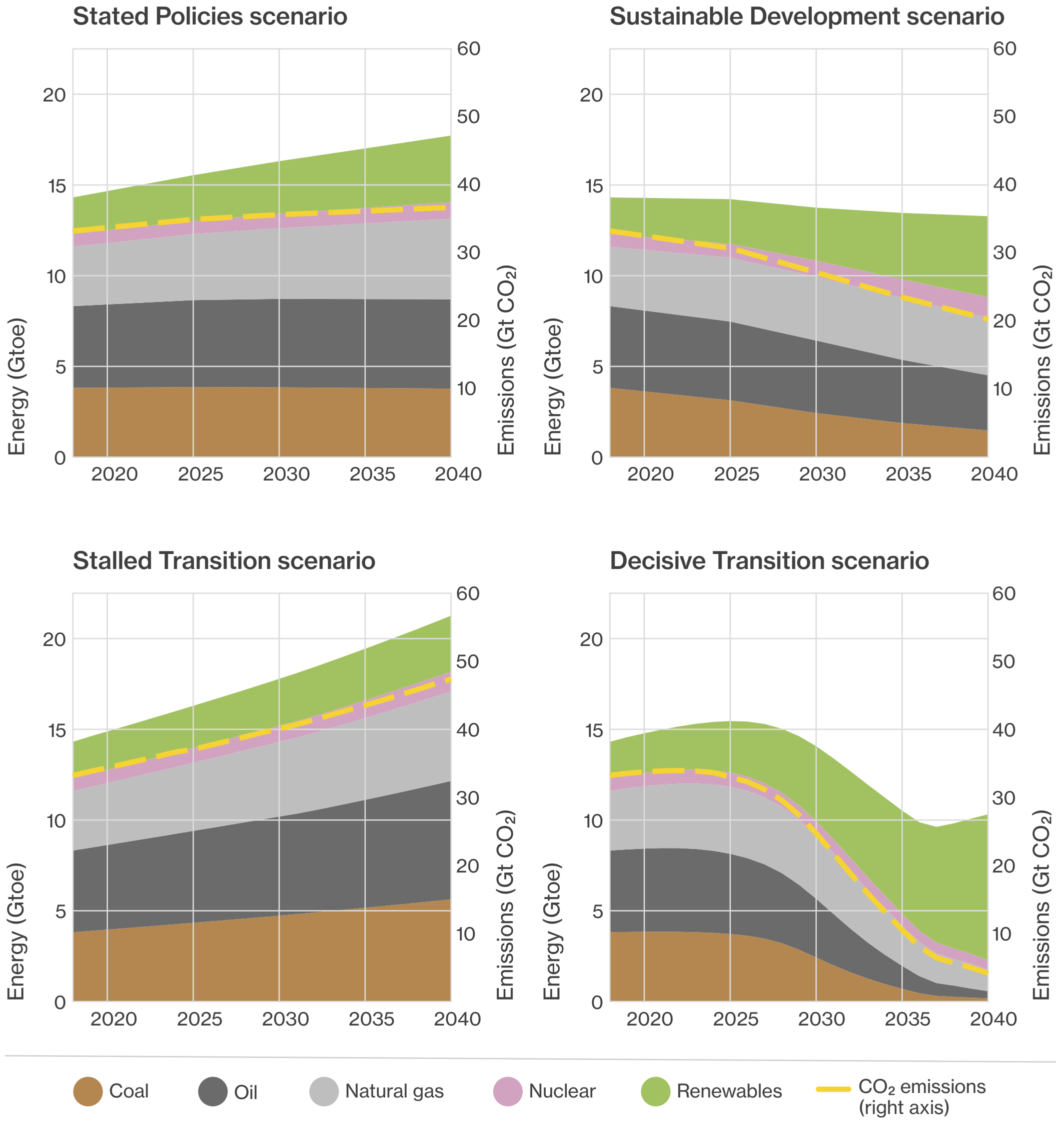
As discussed in Section 1, all IEA scenarios rely on identical underlying socio-economic scenarios, from which they can then work out energy demand. These include setting the growth rate of global gross domestic product (at an average of 3.4% per annum to 2040) and population (to around 9 billion people by 2040). This is similar to the PTEC scenarios in that both have the same drivers of demand, but different in that the IEA scenarios can still have different levels of total energy demand. The PTEC scenarios instead do not explicitly specify any macroeconomic outcomes but instead merely maintain a constant 2% per annum increases in *useful* energy.

Primary energy demand

Primary energy is defined as the energy embodied in nature that has not been subjected to any human engineering, and is used to present energy demand by primary energy source by the IEA. Providing a comparison with these published IEA primary energy demand figures is somewhat problematic as electricity made from solar and wind is treated differently to other sources of primary energy (as discussed in Section 3). However, it is still useful to compare primary energy as the emissions estimates can more easily by calculated by simply multiplying primary energy estimates by the emission intensities of each fuel. Figure 10 presents a comparison of the global primary energy demand by each fuel type for each of the two IEA and two PTEC scenarios. Comparing the two least ambitious scenarios (the two left-most graphs in Figure 10), we see that both increase primary energy demand linearly. However, the magnitude is somewhat different. Under the IEA's Stated Policies scenario primary energy demand grows by approximately 24% to reach 17,723 Mtoe in 2040; under PTEC's Stalled Transition it grows by over 50% to reach almost 21,846 Mtoe by 2040. This is to be expected given each scenario construction – in IEA's Stated Policies scenario, policymakers can at least fulfil their current pledges, whilst the PTEC's Stalled Transition is much more pessimistic. It would require an active effort to stifle technological progress. We should also note that a 2% increase in useful energy can require a greater increase in the supply of primary energy than a 3.4% growth rate in GDP, depending on how efficiently the energy is used. This is particularly the case here. The PTEC scenarios do not make any assumptions about energy-saving technologies and maintain the final-to-useful conversion efficiencies of each fuel type fixed throughout the scenarios (see Section 3 and Appendix A). In contrast, the IEA's Stated Policies scenario contains a tripling of energy efficiency investment by 2040. The Sustainable Development scenario relies heavily on energy efficiency as the critical policy lever for reducing emissions with the conversion efficiency for coal rivalling that of natural gas by 2040.

Comparing the two ambitious mitigation scenarios (the two right-most graphs in Figure 10), we see that in both cases primary energy demand generally decreases but with significant differences between the two. Under the IEA's Sustainable Development Scenario, the decrease is linear up to 2040, declining by 7% to 13,272 Mtoe. Under PTEC's Decisive Transition, primary energy demand initially falls but then actually increases from 2036 onwards. By 2040 it reaches 10,315 Mtoe – a 27% decline, more than three times that of STEPS.

In the Sustainable Development Scenario, energy demand in 2040 is 25% lower than in the Stated Policies Scenario due to efficiency improvements in conversion from final to useful energy. The lower primary energy demand in the Decisive Transition scenario is primarily explained by efficiency gains from electrification brought on by the increasingly cheap renewable energy. This is seen across all sectors, but especially transportation. Electricity generation from renewables only has moderate losses in converting it to useful energy; by contrast, at least half of the primary energy is lost in converting fossil fuels to electricity, torque in an engine, or heat. Once deployment in renewables starts falling beyond 2040, primary energy demand resumes a steady increase.



● **Figure 10**: Comparing primary energy by energy type to 2040 for the two IEA scenarios (top row) and the two PTEC scenarios (bottom row). Note that renewables are represented as 100% conversion from primary to final. Source: this report and IEA 2019 (Figure 1.1).

We present the change in the primary energy mix in Figure 10 to match with similar figures presented by the IEA in their World Economic Outlook 2019. However, it may at first appear somewhat confusing to see total primary energy declining so much in the Decisive Transition scenario. This is partly due to the conventions on how solar and wind are converted from primary to final energy by the IEA (and UN convention), as discussed in Section 3.

Final energy demand, and electricity generation in 2040

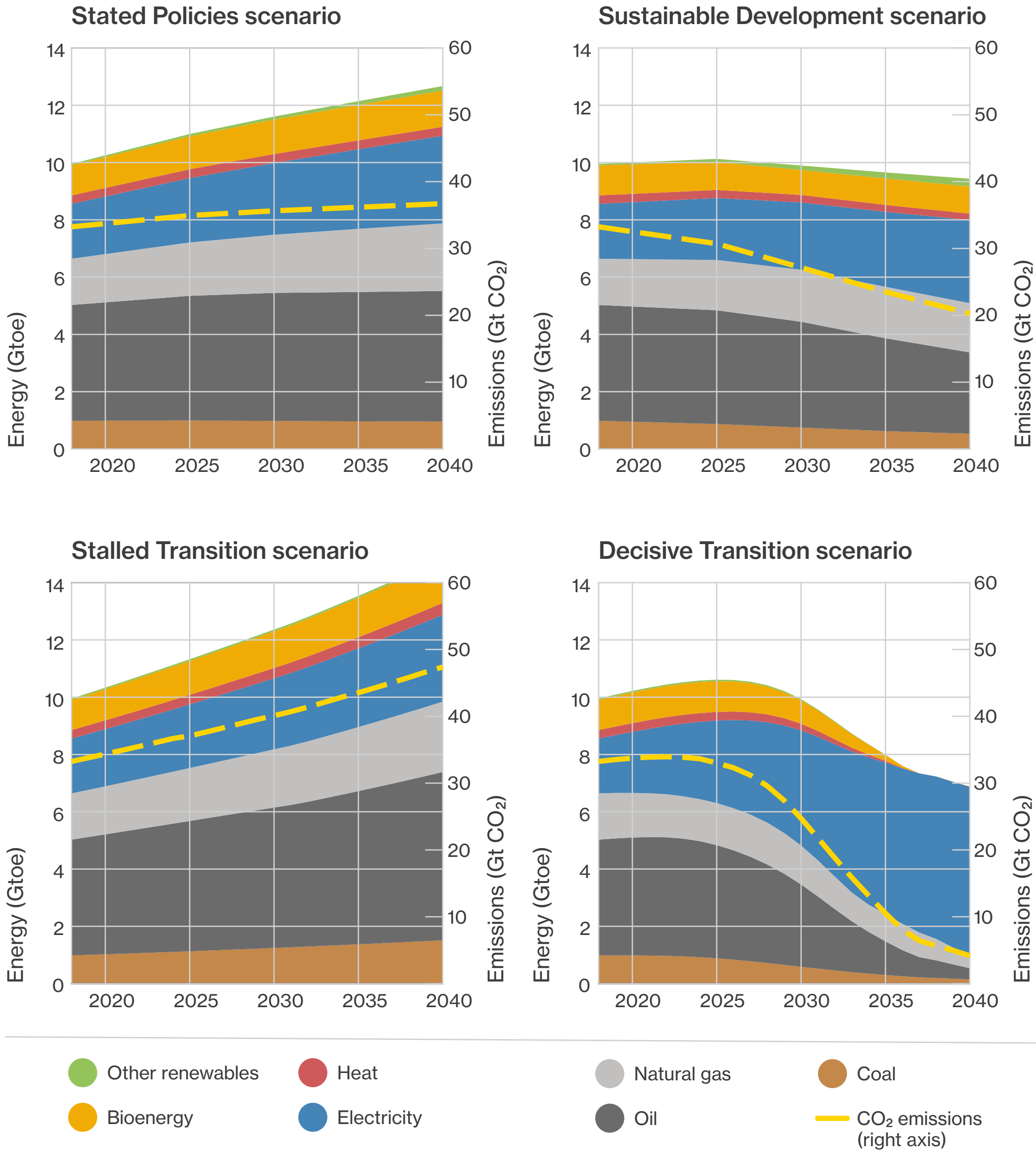
To get a better understanding of how the energy mix changes through time we can look instead at how global final energy changes between the scenarios. Applying the IEA conversion factors to each fuel produces the total final energy consumption for each scenario through time shown in Figure 11.[19] This Figure provides the same information and scenarios as Figure 10 with primary energy converted to final energy (including electricity) as described above. In the least ambitious scenarios, we see that, as per their definition, the mix of all fuel types remain essentially fixed under both IEA's Stated Policies scenario and PTEC's Stalled Transition, with the former including a modest increase in the share of fossil fuels. Turning to the more ambitious scenarios, we see that under IEA's Sustainable Development scenario fossil fuel usages declines by around 25% against 2018 levels by 2040. However, fossil fuels decline much quicker in the Decisive Transition scenario, supplying less than half the total final energy by 2035 and less than 20% by 2040.

The comparison of emissions between the two most ambitious scenarios shows that by 2040 annual emissions in the Decisive Transition are less than half those of the most ambitious IEA scenario. The contrast is stronger than Figure 11 suggests because the IEA's Sustainable Development scenario assumes extensive adoption of carbon capture and sequestration on coal-fired power stations worldwide, providing coal usage with a 40% reduction in emissions by 2040 (see IEA (2019) for more details). Such a significant global change in coal emission efficiency would be quite expensive and difficult to justify if renewable costs get any lower.

Although the transformation of the energy system shown in the Decisive Transition scenario may appear drastic, it is merely the continuation of a lower deployment growth rate than the exponential growth rate at which it has been deployed over the past 30 years. For instance, solar PV has experienced an annual deployment growth rate of 42%. This rate is assumed to continue at a lower 30% for the next decade before gradually slowing down.

Historically, the most widely cited obstacle to non-dispatchable technologies like solar PV and wind becoming dominant energy sources was their cost, and more recently, their reliability under changing weather conditions. As discussed earlier, this latter obstacle is overcome in PTEC by building up storage capacity, first in batteries and then in P2X fuels. This dynamic means that the deployment renewables become more expensive for a period until storage technology costs decline. This, however, is not the reason for the more gradual decrease in total final energy we see in this Decisive Transition scenario over the first ten years. The deployment of clean fuels is constrained by the rate of deployment for this scenario. As of 2019 growth in renewables is still lower than the energy demand growth assumed in the PTEC scenarios, resulting in renewables not being able to meet all the demand associated with the 2% p.a. increase in useful energy. For this reason, we also see an increase in natural gas during this early period in the Decisive Transition scenario, as natural gas acts as a "slack" energy source in the model meeting any demands that are unmet by other sources. Thus, the largest increase in renewables does not occur until after 2030 (55,000 TWh), once both the deployment in renewables and storage technologies is sufficiently large.

19 We use IEA's stated primary to final energy conversion factors to convert PTEC scenarios from primary energy to final energy, which are: coal 0.496, gas 0.575, nuclear 0.332, bioenergy 0.411, oil 1.0 (transport), wind & solar 1.0.



- **Figure 11**: Comparing IEA vs PTEC total final energy supply by energy type to 2040 2040 for the two IEA scenarios (top row) and the two PTEC scenarios (bottom row). Source: this report and IEA 2019 (Figure 1.1) using IEA stated primary to final energy conversion factors.

Figure 12 provides a comparison of the changes in electricity generation in each of the scenarios. This Figure is not presented in the IEA WEO (2019) but is added here to show how dramatically the electricity power sector changes in the Decisive Transition compared to all the other scenarios. Under the Decisive Transition scenario, renewables in 2040 provide over 60,000 TWh of electricity, more than double the total electricity generation from all sources in 2018 (26,000 TWh).

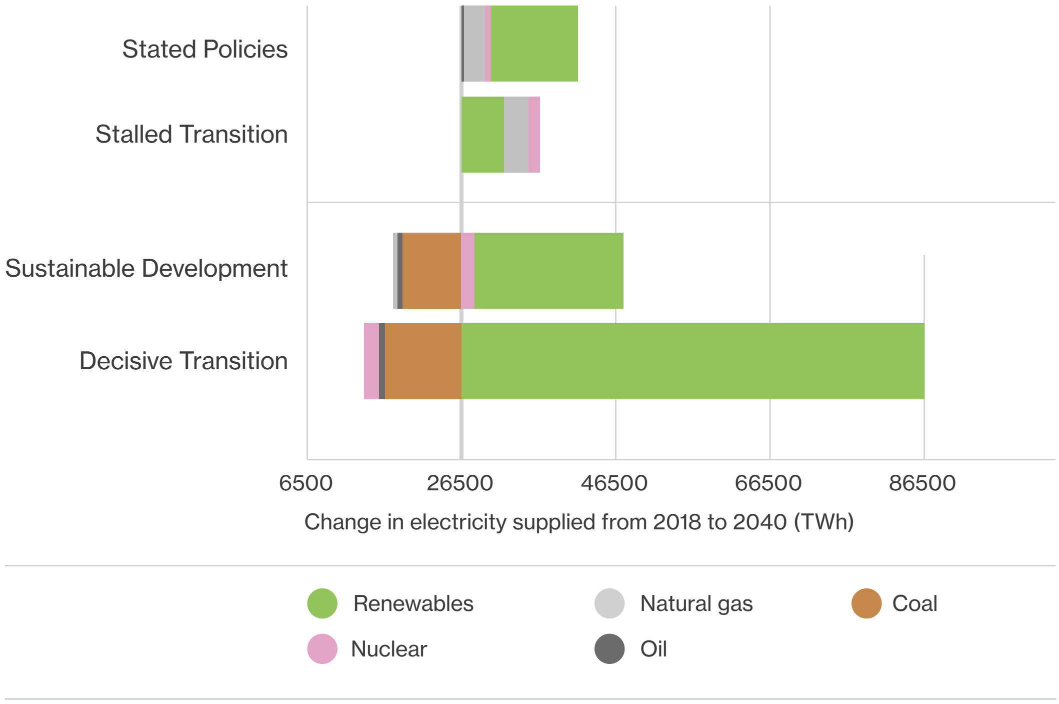
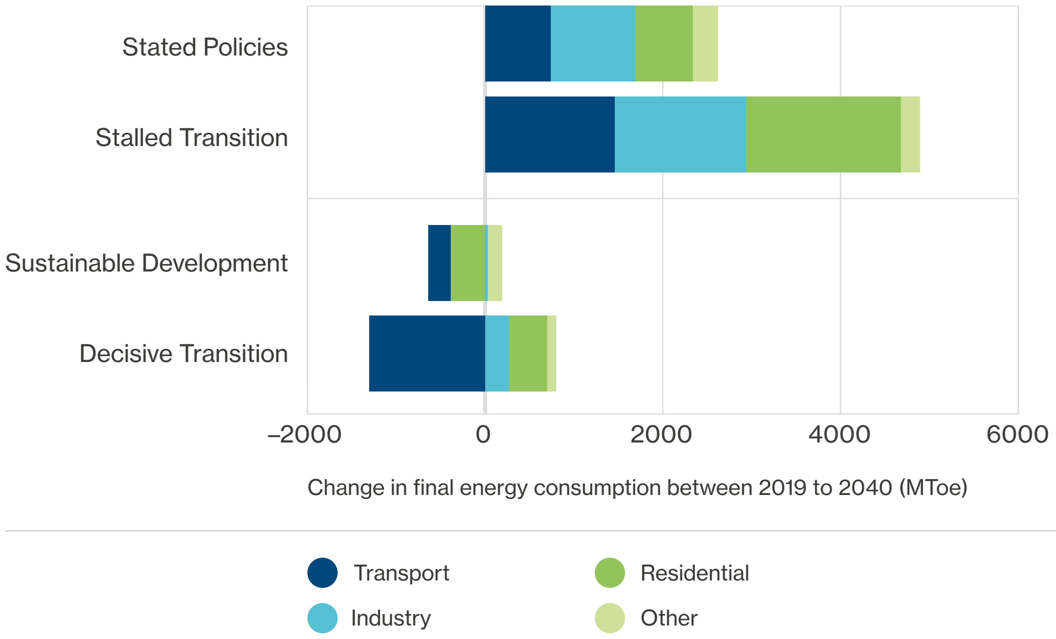


Figure 12: Cumulative change in electricity generation to 2040 relative to the 26,560 TWh in 2018 for IEA's Stated Policies scenario and PTEC's Stalled Transition scenario (left), and PTEC's Decisive Transition and IEA's Sustainable Development scenario (right).

Change in final energy consumption by scenario

Figure 13 illustrates the levels of final energy consumption by sector for each scenario from 2018 to 2040. Again, we can see a stark contrast between the IEA and PTEC scenarios. Because each of the PTEC scenarios requires a 2% p.a. increase in useful energy, the change in energy consumption in the Stalled Transition scenario is much higher than the others. Its focus is on maintaining the use of less efficient fossil fuels. All sectors increase in this scenario based on the size of each sector. This is to be expected, given the construction of the PTEC scenarios. The reduction in energy demand in the IEA Sustainable Development scenario is due to energy efficiency gains over this period. The same is true of the Decisive Transition scenario except that for the latter the only efficiency gains are from electrification. Unlike the Sustainable Development scenario, the PTEC model does not include any changes in conversion efficiencies.

The energy consumption reductions are most significant in the transport sector for the Decisive Transition scenario. This can again be related to PTEC's scenario construction. Remember that the Decisive Transition scenario picks winners. As the storage used in electric vehicles is already advanced transportation takes a significant transition towards electric vehicles. Electric vehicles are more energy-efficient than internal combustion engines and when powered with low-cost renewable electricity in the Decisive Transition become cheaper than internal combustion engines within a decade. Therefore, this sector sees the largest decrease in energy consumption (1,400 Mtoe). As will be discussed in Section 5, this might have implications for transition risk and the stranding of assets in this sector.



- **Figure 13**: Comparing the change in final energy consumption by sector between 2019 and 2040 in the IEA 2019 (Figure 1.4) and PTEC scenarios.

Cost per MWh by technology across scenarios

Whilst there are large upfront investments in renewable energy and storage technologies in the Decisive Transition, we can also see considerable savings over the long-term. This is illustrated in Figure 14, which traces out the median forecast LCOE for both PTEC scenarios (we could not obtain full data to compare LCOE costs to those used by the IEA). As explained in Section 3 and Appendix B, the technology cost forecasts are generated stochastically 100,000 times based on the historical record, and so we present the median value here. This illustrates the "learning-by-doing" dynamic that PTEC explores through calculating future costs based on technological progress (see Appendix A).

One purpose in presenting this information is to demonstrate the influence of deployment on cost in PTEC, with more learning leading to greater potential for cost savings per unit of energy. Thus, as there is considerably more deployment of Solar PV and wind in the Decisive Transition than in the Stalled Transition scenario, we see their respective LCOEs falling by more in the former. For Solar PV, the final cost is $30/MWh in the Stalled Transition in 2040 and only $15/MWh in the Decisive Transition. For wind, the final cost is $40/MWh in the Stalled Transition in 2040 and only $35/MWh in the Decisive Transition. This is a simple concept, but one that is consistent with the empirical evidence (Farmer & Lafond, 2016) and the key differences that separate the PTEC results from those of the IEA and IPCC (Creutzig et al., 2017).

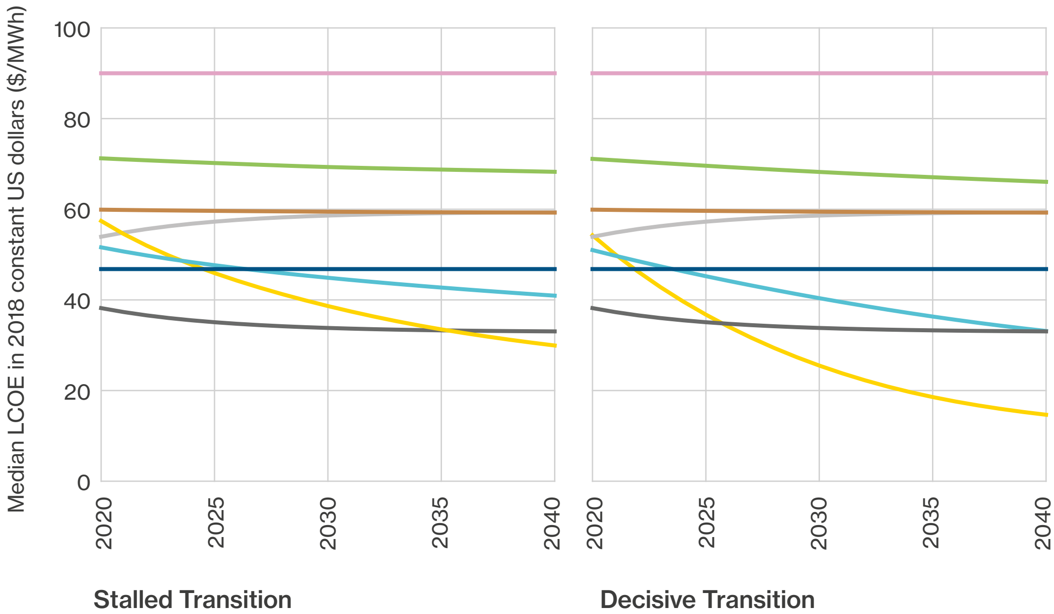


Figure 14: Median global forecast costs of various technologies in the two PTEC scenarios showing the contrast in improvements that arise when more solar PV and wind are deployed in the Decisive Transition scenario.

Annual emissions by fuel

Finally, we will compare how each model fairs in terms of greenhouse gas emissions. That is, how including a more probabilistic-based appraisal of technological progress, or lack thereof, might translate into greenhouse emissions and eventually global warming. Figure 15 provides a graphical representation of the emissions associated with each fossil fuel source in each scenario. Comparing the two sets of low ambition and high ambition scenarios from this perspective shows the two pairs to be remarkably similar. The two PTEC scenarios lie on either side of the IEA scenarios in terms of cumulative emissions, and consequently have a larger impact on climate change, but not by much.

The IEA Sustainable Development scenario and Decisive Transition, both achieve around 2,000 Gt CO_2 by 2040. Both will therefore see a similar impact on global warming by 2040. However, remember that these two scenarios have very different strategies and likely very different costs. For the IEA Sustainable Development scenario, the reductions are gained through extensive demand reduction, with final energy consumption, some 2,000 Mtoe lower than the Stated Policies scenario (as shown in Figure 15). There is also a somewhat remarkable reduction in the emission factors from some fossil fuels, particularly coal, which by 2040 is on par with natural gas in terms of global tonnes of CO_2 emitted per Mtoe of energy. This is achieved either through retrofits, carbon capture and storage or through co-firing with biomass (IEA, 2019), both of which are quite expensive options and would struggle to compete with renewables today, let alone in 2040.

By contrast, PTEC's Decisive Transition scenario allows an increase in energy demand and does not rely on any new and technologies that have not been tested at scale, like carbon capture and storage. Instead, as we have documented throughout this section, this scenario reduces emissions through a drastic shift towards renewable technologies, enabled by endogenous technological change. The electricity would be considerably cheaper in the Decisive Transition scenario (as suggested by the renewable energy costs shown in Figure 14), which can lead to a "rebound effect" and increased electricity demand (Gillingham et al., 2016).

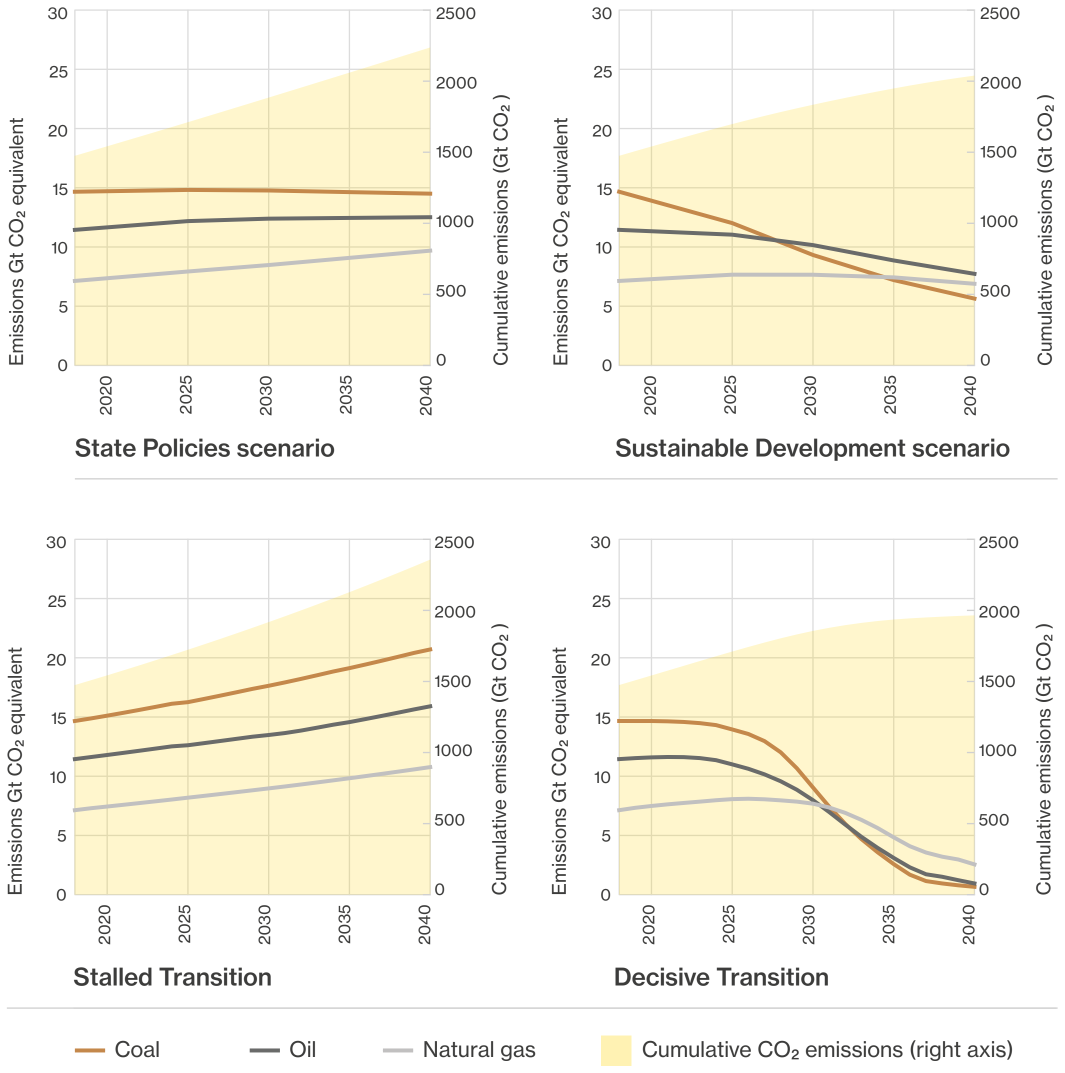


Figure 15: Comparing IEA and PTEC annual global energy system emissions by fossil fuel type (left axis) and total cumulative emissions (yellow shading – right axis) to 2040. Source: this report and IEA 2019 (Figure 1.6).

Although the fuel emission time-series of the Decisive Transition scenario look steeper and ends at a lower annual emissions level, the cumulative emissions over this time are quite similar. This is mainly because whereas the combined emissions go down steadily in the IEA Sustainable Development scenario from 2018, they initially increase in the Decisive Transition scenario because natural gas is used to maintain the 2% p.a. growth in useful energy while renewable and storage production ramps up. The benefit is that by 2040 the annual emissions are much lower going forward in the Decisive Transition scenario.

Total global energy system cost comparison

Although not the key research question being examined in this report it is likely that the reader is curious to know whether there might be a cost benefit associated with the Decisive Transition scenario. We lack the information necessary to compare the cost of the PTEC scenarios with the IEA scenarios, however Way et al. (2020) provide a comprehensive total energy system engineering cost comparison between the Decisive Transition (fast transition) and the Stalled Transition (no transition) scenarios. Using the 1.4% discount rate promoted in the Stern Review (2006), they estimate the expected net present savings of the total engineering cost of the Decisive Transition over the Stalled Transition would be roughly $6 trillion by 2040 and $11 trillion by 2070. Those interested in gaining a better understanding of how such estimates are calculated are encouraged to examine the details provided in Way et al. (2020).

Comparison to IPCC future emissions scenarios

The IPCC Scenario Matrix

As discussed briefly in Section 1 (and in further detail in Appendix C), the IPCC present their emissions scenarios in the form of a Scenario Matrix that combines the Shared Socio-economic Pathways (SSP) with their impact on global warming represented by the Representative Concentration Pathways (RCPs). The SSPs provide scenarios of possible future developments of emissions and their main socio-economic drivers and include projections of different growth rates of population, urbanisation, and GDP per capita. Depending on the amount of climate ambition applied to each of these SSPs (in the form of a social price on carbon), they are made to achieve the warming levels associated with each RCP.

As the PTEC model does not use an underlying socio-economic scenario and the IPCC use many, it is quite challenging to compare the two in a like-to-like fashion as we did with the IEA scenarios. However, the sets of SSP-RCP combinations that appear closest to our Decisive and Stalled Transitions scenarios in terms of emissions are SSP1-RCP2.6 and SSP5-RCP8.5, respectively. Under **SSP1 Sustainability (Taking the Green Road)**, the world population grows at 0.98% p.a. to reach 8.24 billion people by 2100 (Riahi et al., 2017). The global GDP per capita increases for this scenario is the lowest of all with the highest rates experienced in the developing countries (Dellink et al., 2017). Under **SSP5 Fossil-Fuelled Development (Taking the Highway)**, the world population grows at 1.21% p.a. to reach 8.47 billion (Riahi et al., 2017), whilst GDP per capita grows seven-fold by 2100 (Dellink et al., 2017). In their Baselines (no explicit climate ambition) the SSP1 has the lowest impact on warming and SSP5 the highest. Thus, we can see that the Scenario Matrix contains an implicit trade-off between meeting the Paris climate targets and a reduction in primary energy demand and a slowdown in population and economic growth. See Appendix C for more information on these scenarios and the IPCC Scenario Matrix.

This approach contrasts with the IEA and PTEC scenarios presented in this report, which hold these macroeconomic outcomes constant across each of their scenarios (the former explicitly and the latter implicitly via a fixed 2% p.a. growth in useful energy). However, this provides one of the more notable results from comparing the PTEC scenario with the IPCC scenarios.

Comparing the PTEC and IPCC emissions scenarios

We began this chapter with Figure 9 which presented the estimated warming (temperature anomaly) calculated for the PTEC scenarios alongside the least (SSP5-RCP8.5) and most ambitious scenarios from the IPCC SR1.5 Special Report (SSP1-RCP2.6 and RCP1.9). Starting with the most pessimistic scenarios, we see that the Stalled Transition scenario matches the SSP5 Baseline scenario quite well. This socio-economic scenario involves the global economy growing five-fold to 2100, and places no limit on emissions (Riahi et al., 2017). Thus, they fail to meet the Paris goals and send the world into a very non-optimal 4 degrees of warming. This result tells us two things that would be relevant for policymakers. Firstly, the 2% p.a. increase in useful energy required for both PTEC scenarios enables an enormous amount of economic growth – equivalent to the IPCC socio-economic pathway with the highest economic growth. Secondly, what is generally regarded as the "worst-case" scenario for decision-makers, RCP8.5, requires global technological progress in clean energy to essentially be stalled. Which means all the promising technologies currently in research and development, such as perovskites and printable organic solar cells (Hörantner et al., 2017; Xie et al., 2020), that have the potential to increase the efficiency of renewables further and lower costs, are all essentially mothballed. It is difficult to believe that even the fossil fuel industry, with all its wealth and influence, could achieve this. The use of RCP8.5 as a "business-as-usual" scenario has already been criticised (Pielke & Ritchie, 2020). Given the IEA and others, have recently declared solar PV electricity to be the cheapest form of energy in history (IEA, 2020c) – and very likely to get even cheaper in the future, our analysis would agree with this criticism given that RCP8.5 matches so closely to our Stalled Transition Scenario.

In contrast, the Decisive Transition appears to get close to achieving a temperature of around 2 degrees by 2100. Whilst not as low as SSP1-RCP2.6, this is quite a remarkable result given that the Decisive Transition scenario maintains the same 2% p.a. increase in useful energy demand through to 2100 as the Stalled Transition and SSP5-RCP8.5 scenarios. This is possibly the most evident contrast between the Decisive Transition scenario, and the SSP1-RCP2.6 which we estimate has an annual useful energy growth of only about 1.2% p.a. (see Appendix C). The Decisive Transition scenario also contrasts with SSP1-RCP2.6 and SSP1-RCP1.9, in that it does not include any carbon capture and storage or negative emissions technologies or other unproven technologies. Nor does it rely on a significant increase in nuclear energy or high carbon prices (although it could be argued there is an implicit carbon price associated with the continued near term growth in renewables deployment). The results presented in Figure 9 suggest that continued technological progress in clean energy technologies, driven by continued high deployment growth rates, can profoundly impact emissions and dramatically reduce warming by 2100. This, we believe, has not been shown in any IPCC model outputs to date.

Section 5: The barriers to a decisive transition and the opportunities presented by this research

Introduction

Based on the results presented in the previous section we have evidence to suggest that technological progress in clean energy might get us to a Paris-compliant world much more easily than is being suggested by the models of the IEA and IPCC. In this section we explore some of the potential barriers to the realisation of the Decisive Transition scenario, and counter with some opportunities for optimism.

Barriers to a decisive transition

Mainstream climate mitigation models

The mainstream climate mitigation models, such as the energy systems models (ESMs) used for the IEA World Economic Outlook, and those embedded within the integrated assessment models (IAMs) featured heavily in the IPCC outputs, are the dominant source of information provided to decision makers around the world on the speed, costs, and other requirements of climate mitigation efforts (Gambhir, 2019). We have already shown how such models can contain quite unrealistic assumptions around certain clean energy technologies, and the results of such models have been shown to be quite sensitive to such specification of clean technology costs (Barron & McJeon, 2015). Hence, adopting advice based on the results of such models must be done with caution. By setting expectations that climate mitigation will have a considerable cost, action on mitigation may be delayed (Aghion, Hepburn, Teytelboym, & Zenghelis, 2019). Early and decisive action has been identified by many studies as key to reducing the cost of climate change (Bosetti, Carraro, and Tavoni 2009; Jakob et al. 2012; Preston and Jones 2006; Rogelj et al. 2018; Warren et al. 2013). We therefore face the dilemma that if action is delayed because of expectations that climate mitigation will be too expensive – then this will be a self-realising prophesy, even if such expectations are based on a false premise. The major mitigation models might themselves be a fundamental barrier to decisive action on climate change and minimising the costs of mitigation.

The development of these mitigation models involves the analysis of hundreds of technologies that can interact with one another. Because experience curves of such technologies can be non-linear, it becomes impossible to apply standard optimisation methods to such an ensemble of technologies. Consequently, as discussed in Section 2, while such models are constantly being updated with new cost estimates, they appear reluctant to base such costs on historic trends. They either bring in exogenous deterministic forecasts for costs or employ devise rules that actively stifle the continuation of historic trends in key clean energy technologies, such as renewables. In either case, technological progress is not captured internally by the model. In addition, traditional models rarely focus on technological growth rates, which results in low-cost scenarios being relatively unexplored. Such models are also difficult to fine-tune with current data due to their fine-grained consideration of technologies and geographies (Way et al., 2020). And to our knowledge, no published work has applied the empirically based probabilistic technological change approach embodied in PTEC to the problem of mitigating climate change. The ultimate irony of this situation is that it is the use of optimisation in such major mitigation models that makes incorporating non-linear technological change so difficult (Grubb et al., 2021), and a potential reason for why their models are not able to correctly determine the least cost solution.

Identifying such problems is made difficult by the complexity of these models and the lack of transparency around the assumptions embodied in the many thousands of lines of code. There is a general paucity of information available to understand what assumptions have been used in many of these models (Gambhir et al., 2019). By hiding such questionable assumptions from the peer-review process they make it difficult to challenge the conclusions. This is a trend we have consciously tried to avoid with the development of PTEC. Ironically, the transparency of the PTEC model makes it more open to scrutiny and criticism from the established modelling community.

PTEC was deliberately developed in such a way as to simplify the energy system as much as possible to focus on the key process of endogenous technological change. It is therefore fundamentally different from most major mitigation models. Firstly, it is deployment-driven, meaning the deployment rates of various technologies drive the costs, and expected temperatures and emissions. Additionally, the problem of intermittency of power generation from variable renewables is solved by the simplifying assumption of combining variable renewables with sufficient storage technologies. The dynamics of competition, demand, consumer adoption, and the influence of supply and demand on price are all avoided by focussing the time series of historic costs for the various technologies. It could however be argued that the experience curves at the heart of PTEC themselves embody some of these dynamics in they are a reflection of such dynamics impacting on the rate of deployment and costs of these technologies.

Because PTEC is built differently it is not surprising that the results from PTEC provide considerable contrast to the incumbent models. Unlike other major mitigation models the PTEC model results suggest that compliance with the Paris agreement could be cheaper and easier than indicated by the many alternatives, and potentially cheaper than the current system. Furthermore, the Decisive Transition sees the energy system decarbonise rapidly while requiring no reduction in energy demand, no explicit carbon price, very little nuclear power, or little need for mostly unproven-at-scale technologies such as carbon capture and storage.

However, it is going to be a herculean task to convince the modelling and policymaking community that our simple, transparent model is right and most of the major mitigation modelling community are wrong – time will tell – as the continuing decrease in renewable costs will fairly quickly make the results from the major mitigation models difficult to defend.

Navigating the socio-technical transition

Despite the inclusion of ever greater complexity most climate mitigation models focus on only a few of the many elements necessary for a transition towards low-carbon systems (Geels et al 2019). That is, they lack a careful enough representation of the complex web of technologies, infrastructures, organisations, markets, regulations, and user practices that deliver services to society (Geels et al 2019), all of which must be transformed for any meaningful reduction in global energy emissions. Such accusations might also be levelled at the PTEC scenarios presented in this report. We attempt to assess the implications of such potential criticisms here.

From the socio-technical transitions (STT) "multi-layer perspective" (MLP), any major socio-technical transition will be the outcome of three mutually reinforcing processes "*increasing momentum of niche innovations, weakening of existing systems; and strengthening exogenous pressures*" (Geels et al., 2017), all of which must be navigated before a transition is complete – a process that has historically taken over a century for other major technologies e.g. from sail to steam shipping (Geels, 2002). The MLP approach provides a plausible narrative to the "random shocks" discussed in Section 2 that experience curve researchers find in the data and can hinder or accelerate technological progress. According to the MLP viewpoint, accelerating technological progress requires not just greater investment in research and development, but also a way of managing the impacts of such "random shocks". That is, accelerating a socio-technical transition requires a great deal of political support, widespread market and social acceptance, and a weakening of the existing incumbent regime.

We do not dispute the assertions of the STT community. Our scenarios are named the Stalled and Decisive Transitions as a recognition of the role the global community must play in ensuring the deployment of clean technologies necessary to drive the technologies down their experience curves. STT proponents have also acknowledged that electricity generation has to date experienced a particularly rapid transition to clean technologies (Geels et al., 2017). There are several reasons for this, including electricity supply transformation not requiring significant consumer involvement, unlike the food, buildings, and transport sectors. Also, as electricity is an undifferentiated product, consumers are likely to experience little impact from the switch in energy sources. Finally, it has been easier for policy makers to deal with this sector due to the relatively small number of utilities involved, in contrast to the millions of small farmers/owners/builders in the food, transport and building sectors (Geels et al., 2017). In fact, the analysis presented by Geels et al. (2017) suggests that for some early adopters like Germany and the UK the uptake of renewables into the electricity system is already past many of the impediments that might slow down the widespread adoption of these technologies and they are now in their final MLP phase, with wider adoption of these new technologies now requiring adjustments in the infrastructures, market structures, and views on what is normal.

Kramer & Haigh (2009) have argued that there are “societal laws” that necessarily slow exponential growth once an energy technology passes 1% of primary energy supply. However, very little historical data is presented in their paper, with no supporting analysis or validation. The main argument for why growth must slow is that only 2-4% of existing capital stock needs replacing each year, and “industry will only consider early retirement of the existing capital stock if the total cost of the new technology (capital and operating costs) falls below the operating cost of the old”. If we assume a lifetime of the current energy generation systems that ranges from 25 to 50 years, the usual replacement rate of such structures ranges from 2% to 4% per year. Coupled with the historical yearly energy demand growth rate of 2%, this means that renewables could grow to meet roughly 5% of the energy demand without needing to force the retirement of any existing assets. With such a growth rate, renewables would replace most of the current energy generation systems in 20 years, with a small share of it to be phased out in the decades to follow (Way et al., 2020).

There can be little doubt however that the transition of the entire energy system away from fossil fuels is still likely to impose enormous challenges for society. For example, a rapid transition away from fossil fuels, as presented in the Decisive Transition would likely lead to a major devaluation of fossil fuel assets and subsequently a destabilisation of global financial markets. A recent study by Rempel and Gupta (2020) found that pension funds from OECD countries still have an aggregated 10.58% of their portfolios invested in the fossil fuel sector. The problem that such pension-fund managers, and other financial investors face is that a rapid, disorderly shift away from carbon-intensive assets might exacerbate transition risks through weakened earnings for carbon-intensive asset operators, which, given their central role in the economy are a source of systemic risk for the financial system. This major source of risk has already been identified as a concern by the Financial Stability Board (Carney, 2015; TCFD, 2017a). Providing investors with the information necessary to incorporate all such forms of climate risks in their investment decisions can lower the economic, social, and political costs of transforming the energy industry by reducing the likelihood of stranded assets (Ansar et al., 2013; Farmer et al., 2019), as can increasing the credibility of climate targets and associated expectations (Aghion, Hepburn, Teytelboym, & Zenghelis, 2019).

Considerably more literature could be cited here expounding on the many social, institutional, and economic barriers to a decisive low-carbon transition. One particularly powerful counter to all such claims is that the modelling approach used in PTEC is actually closer in theory to the STT perspective than those used by the major mitigation models. The latter models tend to optimise on a single dimension, such as cost or social welfare, identifying optimal pathways, and include technologies that have yet to gain social acceptance or are not yet feasible at scale, such as bio-energy with carbon capture and storage (Geels et al., 2017). In contrast, PTEC relies on decade-long empirical deployment and cost trends for known technologies – trends that incorporate their transition through niche markets, user acceptance, incumbent resistance, political wins, and losses, and changes to infrastructure detailed by the STT approach. The very slope of the experience curve represents the aggregation of all such future barriers being overcome in different markets, regions, and political environments, at different rates and times across the globe. The experience curves employed in PTEC represent the complexity of the socio-technical transitions they undertake and hence provide a defensible probabilistic estimate of the rate of that progress.

Unlike other optimisation models, the global system represented in PTEC will not automatically switch to these new technologies as soon as clean dispatchable technologies become cheaper than their fossil fuel counterparts. In PTEC the rate of deployment sets the scenario, and hence PTEC does not require assumptions around floor costs. Once the new technologies begin to dominate the market their deployment rates slow down, along with their cost declines.

Even if experience curves correctly reflect future socio-technical transition trends there is still much to be gained from the STT perspective in advising future policies. As the existing socio-technical energy systems have co-evolved with markets, governments, and our daily lives, continuing the changes necessary to decarbonise will undoubtably challenge society. The STT perspective provide valuable insights necessary to identify those policies that can promote widespread public and political acceptance of the new technologies, including the collection of reliable and comprehensive data, community involvement in the innovation process, and engagement with relevant stakeholders to understand their needs (Sovacool & Griffiths, 2020) and research into: "*(1) environmental performance, (2) financing and business models, (3) user behaviour, (4) natural resource use, (5) visions and narratives, (6) social justice concerns, (7) gender norms, and (8) urban resilience*" for all technological solutions promoted by such policies (Sovacool et al., 2018).

The "just" transition, gender and inclusiveness, and energy insecurity

Once key concern for policymakers in promoting a rapid clean transition, such as presented in the Decisive Transition scenario, is their impact on global equality and sustainable development goals. Notwithstanding that the research in this report suggests a decisive transition will lead to lower electricity costs, and the fact that many climate mitigation policies also provide valuable co-benefits (A. Smith, 2013), the simple fact that our socio-economic system is a complex, dynamic system means that adverse side-effects are inevitable. This includes the potential for some climate mitigation policies to create or compound inequalities. One clear weakness of using such a simple, high-level model, such as PTEC, is that it does not provide the granularity to really assess the structural regional change and redistributive questions associated with the "just" transition.

Probably the most obvious and difficult adverse impact to manage for policymakers will be the loss of jobs in the fossil fuel and related industries (Rosemberg, 2010). Although many of the jobs related to these industries are already likely to be adversely impacted by increased automation in the future (del Rio-Chanona et al., 2021; Frey & Osborne, 2017), this only adds to the complication as it is not merely the loss of fossil fuel occupations that might impact on workers but also the probability that automation or climate policies might also impact on those jobs to which they might have transitioned (del Rio-Chanona et al., 2021). Regardless of whether automation or the green transition is the cause, strong protests in several countries around the world speak to the potency of feeling that can be generated against measures to reduce fossil fuel use that are not seen as 'just'. Prominent examples are the coal union protests in the UK in the 1980s and more recently the 'gilets jaunes' protests in France in 2018.

To counter such deleterious impacts some countries have offered large pay-outs, investments and retraining, such as Canada, Spain and Germany (Piggot et al., 2019), while others, like Poland simply refuse to commit to ending coal mining, and actively veto policies to increase climate ambitions (Jankowska, 2016).

There is therefore likely to be resistance, and an added social and financial costs, to any decisive transition that may not be captured in the cost focused PTEC model, and that should be carefully managed by policymakers. However, given that the current high growth in renewables has occurred while subsidies for fossil fuels are still around double what they are for renewables (IEA, 2019) it appears inevitable that policymakers will have to deal with such transition pains regardless.

Climate change is itself a potential cause of gross inequalities with the most vulnerable and least able to adapt more likely to be exposed to climate impacts. The developed countries could do much to redress the imbalance of past emissions being generated by their economic growth by providing foreign aid in green investments and by sharing new technologies. Such new technologies will also come with new material requirements and sources of waste that also tend to have a disproportionate negative impact on developing countries (Liu & Agusdinata, 2020; UNCTAD, 2020).

From a gender and inclusiveness perspective it is likely that the majority of workers impacted in the fossil fuel industry, particular mining, are male (Piggot et al., 2019) and mostly in developing countries, such as China and India. The transition to clean energy provides an opportunity to move towards greater gender balance, but the energy industry needs to prioritise such efforts now to avoid perpetuating existing gender inequalities (Pearl-Martinez & Stephens, 2016). For instance, women and migrants are over-represented in indirect, supportive roles, such as lower-paid service work and unpaid care work and as they are usually under-represented in the industry, they are less likely to be covered by any proposed worker compensation and re-training policies (Piggot et al., 2019).

Social equity concerns also go well beyond the implications for coal miners and include communities tied to coal-fired power stations and communities linked to oil extraction and refinement (Carley & Konisky, 2020). Policymakers must also be cognisant of the distributional impacts of various policy instruments used to promote new technologies (Peñasco et al., 2021), and the need for coordinated programmes to target the many causes of energy insecurity (Carley & Konisky, 2020). Much depends on contextual factors but through the application of good policy design, including multi-stakeholder engagement, adaptive policy strategies, and careful monitoring, many of the most deleterious impacts can be mitigated or prevented (Markkanen & Anger-Kraavi, 2019).

Transition risks and stranded assets

The PTEC model is by necessity an abstraction from reality and a much more simplified model than those it is being compared to in this report. It therefore only provides a highly aggregated estimate of the capital investment associated with the current and future global energy system. It is not a capacity expansion model and does not directly track the cost of assets that may be stranded by an ambitious climate mitigation strategy.

The extensive analysis of existing global assets by Tong et al (2019), suggests that the potential cost of stranded assets of a transition pathway that has a 50 per cent chance of limiting warming to 1.5 degrees (580 Gt CO_2) could be between \$5 to 17 trillion. The high side of this estimate results from stranding those assets with the highest asset value per committed emissions, which is primarily in transport.

The Decisive Transition scenario has electric vehicles becoming cost competitive with internal combustion engines (ICE) in a decade, which maps well to analyses by other organisations (CCC, 2019; Hagman et al., 2016), suggesting that some stranding or early retirement of transport assets is possible. Given the growing numbers of municipalities requiring zero carbon transport in the coming decades, the end of the ICE-age might come sooner than later (IEA & IRENA, 2017) suggesting a significant transition risk for the transport sector.

Despite this risk, it should be made clear to decision-makers that stranded assets are only a one-off cost to the system. Once replaced by clean technologies, possibly when the combined capital and operating costs of the new technologies fall below the operating cost of the old, there are no further transition costs. In contrast, the physical costs associated with increased extreme weather, wildfires, floods, droughts, and hurricanes resulting from a slow transition are likely to be orders of magnitude higher, and will be continual, long term, and potentially permanent (Cohen et al., 2020). To put the estimated transition costs in perspective we produced a conservative estimate for climate damages from each of the PTEC scenarios using the FUND-Hector model (Appendix D), with the Stalled Transition estimated to cause at least USD\$330 trillion more in climate damages that the decisive transition from 2020 to 2100 – an order of magnitude greater than any estimates of transition risk.

Regional differences in the costs of technologies

The probabilistic estimates of the cost of technologies included in PTEC are based on their deployment rate and their historical record. We use global averages in PTEC from the most reliable sources available. It might nevertheless be argued that such averages do not adequately reflect the costs experienced in all countries on earth. The most recent solar PV installation costs for India and China are some of the lowest per kW costs in history (IRENA, 2019), with low margins, low labour installation costs and access to low interest finance. They appear in the lowest 5% extremes of the LCOE probabilistic forecasts generated by PTEC for 2020. On the other hand, solar PV installation costs in Russia and Japan are almost three times those seen in India (IRENA, 2019). In these latter countries new solar deployment will be slow without significant policy support. All such regional differences are incorporated in the data used to generate the global average cost estimates used in PTEC, but global averages can hide the range of costs that might be experienced in different countries.

The regional differences in the costs of deploying renewable energy technologies is generally dominated by local conditions, solar irradiance[20] and wind resources, and local operating costs – particularly interest rates, as capital costs far outweigh operating costs for most renewables (Ondraczek et al., 2015), and labour costs (Lang, 2018). It would be reasonable to assume that most of the global deployment to date would have occurred in locations with the most favourable conditions (low interest rates, high winds and irradiance, low labour costs), thereby skewing our empirical record.

For instance, Yuan et al. (Yuan et al., 2014) assessed the LCOE of distributed solar PV in China and found that solar PV only broke even with fossil fuel electricity generation in those regions with the best solar resource or high commercial/ industrial retail electricity prices even with subsidies.[21] However, the current deployment of renewables by country does not match well with renewable potential, suggesting political will is also a stronger determinant of where renewables are currently being deployed.

What is most relevant is that our experience curves reflect these very regional differences, not just in the location of the global average but in the slope of the experience curve. If regional differences did not exist, then the moment renewables plus storage became cheaper than the fossil fuel alternatives the global energy system would almost immediately deploy only such cheaper alternatives. This is a key problem with entering continually declining cost curves into the cost optimising major mitigation models. However, as discussed above regarding socio-technical transitions, any technology will initially grow through a series of niche markets where the new technology has an advantage, even at a higher price. Some of these niche markets will be regional. For solar PV that market was originally in space and other remote locations such as offshore oil rigs and remote communities (Perlin, 1999). It was in part due to favourable interest rates that Germany was able to invest heavily in capital intensive solar PV during the *Energiewende* of the early 2000s. However, as the price declined, and different actors in different regions learned how to finance, deploy, and integrate solar PV, the deployment has increased, and with the experience this brings, the costs have decreased.

The story of regional differences is therefore represented in the very slope of the experience curve as the new technology wins out in various regional markets, either through cost, or decreased air pollution, or political objectives such as decarbonisation targets. The slope of the experience curve therefore represents the aggregation of the technology becoming favoured at different rates in the different niche markets, regions, and political environments, across the globe.

20 A recent evaluation of regional LCOE difference with the key technology PV solar suggests the economic potential varies between \$0.06/kWh and \$0.14/kWh in most countries of the world with over 75% of the evaluated global area below \$0.12/kWh (World Bank 2020).

21 It is possible the picture has changed for China since 2014, given the rate of decline in renewable costs, but such studies demonstrate that regional conditions within and between countries will dictate the pace of global renewable deployment.

Energy security and the intermittency problem

The intermittency of most renewable generation options will result in additional costs to the grid once renewables go beyond 40% of grid capacity (Franco & Salza, 2011). As discussed in Section 4, the PTEC model deals with this problem directly by costing the addition of sufficient storage investment necessary to match variable renewable energy (VRE). However, unlike other studies that have applied this methodology (Barron & McJeon, 2015), we also allow costs in storage to decline probabilistically in-line with their historical trends.

In the last 23 years, the production of lithium-ion batteries has grown at a rate 30% per year, while costs have dropped 12% annually. Such trends bode well for the future of storage, but there will be a need for long-term storage once VRE penetration reaches around 80%. Energy dense fuels, such as electrolytic hydrogen may be part of this solution, and as around 85% of its costs is electricity the reduction in costs of solar PV and wind power will reduce the cost of electrolytic hydrogen.

This in turn can further promote other P2X fuels such as ammonia or methane which are more easily stored and transported, and already widely used (Cesaro et al., 2021). Suggesting there exists a viable path for dealing with intermittency while moving towards deep decarbonisation. This is however the most speculative part of the analysis on which this report is grounded, as there exists only limited time series of data for the mass production of clean fuels.

The problem of incorporating a greater share of VRE into regional electricity networks is also obviously more complex than our representation. Most distribution grids have been built for energy to be sent in a single direction from a small number of large energy providers. There will therefore be additional costs to upgrading distribution networks not suited for more distributed energy generation resources that are not included in this assessment. This will be less of a problem for countries where a large portion of the renewable energy is being generated at large renewable installations, such as offshore wind in the UK, and hydroelectric power in Brazil.

Is an interim solution required?

There appears to be a vocal push, primarily from the fossil fuel industry, for an "interim solution" to any clean energy transition given the still low levels of deployed renewable energy (Gürsan & de Gooyert, 2021; Stephenson et al., 2012). With electricity generated using efficient natural gas turbines producing roughly half the emissions of dated coal-fired power stations, some early gains could be made from such an interim solution. This was in fact how the UK made early ground in meeting its climate mitigation targets. However, given the current low prices of renewables this is likely to be a risky solution for most countries going forward., particularly if the rest of the world focuses on deploying renewables with their better experience curves. Adding "bulky" long-lived energy infrastructure increases switching costs and slows down change (Wilson et al., 2020). Hence, any proposed interim solutions should first be assessed for their potential to create carbon lock-in and exacerbate transition risk (Aghion, Hepburn, Teytelboym, Zenghelis, et al., 2019; Gürsan & de Gooyert, 2021; Pfeiffer et al., 2018).

Competition from fossil fuels

One potentially limiting assumption that the PTEC scenarios in this report make, is that fossil fuel prices do not respond to the competitive pressures of renewables beyond their behaviour over the past 50 years. That is, we assume the price of fossil fuels will remain within the bands of historical trends and the uncertainty created by random shocks. For example, under a scenario where solar energy becomes widely deployed and significantly cheaper, we may reasonably expect that fossil fuels will be forced to innovate to remain relevant. However, Way et al. (2020) compares the Decisive Transition (fast transition) scenario with one in which fossil fuels are only supplied from regions with the least costs and still finds the Decisive Transition more cost effective over a range of discount rates.

It is therefore entirely possible that renewables are competitive even in regions with very cheap fossil fuels. Aghahosseini et al. (2020) undertook a highly detailed analysis of transforming the energy system in the Middle East and North Africa (MENA) region and found a system based on wind and solar PV, similar to our Decisive Transition scenario, to be their least cost solution.

Similarly, using natural gas instead of P2X fuels might result in cheaper scenarios, but this would not lead to carbon neutrality. Therefore, even acknowledging that Decisive Transition is cheaper than a Stalled Transition, as well as a scenario in which the fossil fuel companies produce only at their lowest costs, the decarbonisation of the energy system will still likely require policies tailored to curb the use of fossil fuels.

The opportunities presented by the Decisive Transition

The justification for the application of technological trends in PTEC has already been given a great deal of attention in this report, with more available in Way et al. (2020). However, given the above counterarguments for why a decisive transition might not manifest we feel it is important to provide some counter arguments, and to stress the opportunities that the PTEC approach to projecting technological progress into the future offers decision makers.

PTEC's conservative assumptions about costs and tech growth

It is important that readers are aware of the number of ways in which the PTEC results were made conservative in terms of the low cost of renewables. We only made use of those technologies that had well documented cost time series, and hence new technologies in development that show great promise but do not offer the same historic record were not considered, irrespective of their being well regarded by experts. We assume renewable energy capacity grows over the next decade at rates that are lower than their consistent historic record. The growth of PV output between 1998 and 2018 was at an exponential yearly average of 44%, while for wind power it averaged 23% per annum. For the Decisive Transition PTEC conservatively adopts 32% per year for PV, and 20% for wind power.

The PTEC scenarios allows a 2% annual increase in useful energy demand, a level of growth only matched by the most aggressive shared socio-economic pathway – SSP5 “Take the Highway”. In contrast, the SSP1 “Taking the Green Road” scenario against which the Decisive Transition was compared to assumes only about a 1.2% annual increase in useful energy. Finally, although the model lacks precision in specifying the exact operational details of the entire electricity system it more than compensates for this by an oversupply of storage technologies able to meet all electricity and energy demands and assumes the use of storage even though in many cases demand management or expanding the grid would be a cheaper alternative.

The empirical evidence

If we just look at the empirical evidence, the cost of oil, coal, and nuclear energy has remained within one order of magnitude or has actually increased (in the case of nuclear), over the last 50 years. In stark contrast, the costs of some renewable technologies have dropped 3 orders of magnitude over that same 50 years. Just as the constant year-on-year declines in computing costs have taken most people, including those in the industry, by surprise, the same can be said of these new energy technologies.

Solar PV was a very niche technology 20 years ago, mostly used in remote locations or on small, low power devises like calculators and watches (Perlin, 1999). It is not surprising that most people have a bias against the idea that such a niche and seemingly simple technology could grow to become the dominant form of electricity generation on the planet. However, if we take a probabilistic approach the cost declines in solar were predictable, and was predicted ten years ago by a co-author of the PTEC model (Ferguson et al., 2010). In fact, based on those same technological trends, the future dominance of solar is quite likely.

There exists therefore sufficient compelling evidence that these long-term energy technology cost trends appear to be consistent and predictable (Farmer & Lafond, 2016; McNerney et al., 2011). Alongside advances in the technologies themselves, we have seen advances in our understanding of how technological change unfolds in the economy more broadly and of the characteristics that fast-progressing technologies have in common with each other (Wilson et al., 2020). As discussed in Section 2, several new methods that are statistically validated and firmly grounded in data have been developed for forecasting technological progress (Nagy et al., 2013; Way et al., 2019). The empirical evidence clearly supports the trends used to develop the scenarios presented here.

There exists social, material, and production barriers on the horizon for all the current versions of these technologies, but there are also potential solutions and new fundamentally different versions of these technologies that will allow their growth to continue. As discussed already in this section, the experience curves used to predict the future costs of these technologies embody many of these past obstacles and solutions. They are thus still the best predictors available for future trends. Finally, we can be confident that societies currently experiencing high levels of pollutions will not find clean energy sources too difficult to accept.

As discussed in the previous sections, the results presented here are based on predictions of future costs. This approach sets these PTEC scenarios apart from the other major scenarios examined in this report as the other major mitigation scenarios make no such claims (in fact, they state quite the opposite), and yet their conclusions depend almost entirely on the costs used by the model (Creutzig et al., 2017). What this makes abundantly clear is that there exists an opportunity here for an improvement in the range of solutions that are currently being provided to decision makers. At the very least the major mitigation models should be required to present the cost assumptions explicitly and transparently for all their energy technologies, including renewables, along with the empirical evidence on which such assumptions are based.

A methodology for incorporating probabilistic technological change

As with any model, PTEC has its limitations (which we discuss later in the report). However, these limitations do not undermine the model's ability to offer a glimpse of a broader range of possible energy futures and climate mitigation solutions than those captured in the current energy and climate mitigation models used to inform policymaking. At the very least the probabilistic technological change forecast (PTEC) model provides a defensible methodology by which empirical-based non-linear trends in technologies can be incorporated into climate mitigation models and given an accommodating framework, into decision making processes (Sharpe et al., 2020).

The PTEC model is simple and would need enhancement to provide sufficient information to match the outputs of the major mitigation models. We have done our best here to add components of the energy and total economic system on to the PTEC results to enable a defensible contrast. However, such additions are set to the specific scenarios used in this report and they are post-processed, so do not include dynamics between the modelled components and those not modelled. We have therefore had to by necessity incorporate a large range of uncertainty around these components in our presentation of the resultant emissions scenarios.

Despite the need for further work, we hope that through this exercise we have demonstrated the value of incorporating more realistic representations of technological change into climate mitigation models. As discussed in Section 2 there is a vast and exciting area of the solution space that is not being explored by the major mitigation models which may not require decision makers to choose between climate mitigation and economic growth, between future and current generations. With the right technology we can potentially have our cake and eat it too.

Section 6: Conclusions

The implications of this work

The choices we make in energy investment in the next decade will define the world we will live in for many decades to come. Making the right energy investment choices constitutes a sensitive intervention point that can tip the system towards a cleaner, smarter, and cheaper world (Farmer et al., 2019). A little can go a long way, but why wait? In fact, waiting might well just be a waste of money (Way et al., 2020).

As discussed in Section 5, the modelling results presented in this report are sufficiently robust to prompt a re-evaluation of current assumptions around the expected cost and speed of transition; the current quantification of each country's NDCs; expectations around mid and long-term energy generation mix; and the potential transition risk of current technological trends. We provide here a brief commentary on how we understand these implications and wrap up with some concluding remarks.

Expectations around the overall cost of transition to a Paris Compliant Scenario

The current thinking about renewable energy makes significant assumptions about the cost of future energy which influences the speed at which the transition happens.

There also appears to be a general belief that renewables are too expensive; or are unlikely to continue to drop in price for much longer; or due to intermittency, have an absolute limit to the fraction of our energy needs they can meet; or provide no solution for difficult to abate energy and non-energy emissions.

An alternative, perhaps overly simple, but nonetheless meaningful narrative, is that renewables plus storage can provide dispatchable, baseload energy; that renewables plus hydrogen (e.g., green ammonia) can provide clean fuels; and that an energy system made up of renewables plus storage plus hydrogen can replace our entire fossil fuels dominated energy system. What is more, if renewable energy gets cheap enough, as cheap as their experience curves suggest they will, then such a clean energy system could actually be less expensive than the current system (Way et al., 2020), without the pollution and associated morbidity and mortality (Vohra et al., 2021), and without the current increasing rate in global warming and associated climate risks which are orders of magnitude greater than any estimates of transition risk (Appendix D) (Cohen et al., 2020).

These are two very different narratives, and the evidence from empirical-based technological trends favour the latter.

Expectations around the speed of transition

Similarly, this research offers the opportunity to revisit thinking around the most financially effective speed to transition to a Paris compliant scenario.

We have found no evidence that shows renewables will not continue their current decreasing cost trends, despite this being assumed in most, if not all, of the major climate mitigation models. If they continue to fall, then electric vehicles would most certainly be cheaper than internal combustion vehicles in less than a decade (Sharpe & Lenton, 2021). Which will in turn likely drive electricity costs down even further. There is a positive feedback dynamic here and it is arguably already underway (Farmer et al., 2019), whereby renewables get cheaper, and electricity gets cheaper, and electric transport gets cheaper. This increases demand for electricity, and the deployment of more renewables. Making renewables cheaper...and the feedback repeats.

Such a technology trend-based energy transition will not get us all the way to our Paris Targets. There are still non-energy sectors and rogue emissions that will have to be dealt with. But with cheap electricity even the task of pulling carbon dioxide out of the atmosphere will be considerably cheaper.

Access to low-cost energy drove the industrial revolution and brought more prosperity to more people than the world has ever seen before. Energy is set to get even cheaper, which sounds like a good start for enabling prosperity for even more people around the world.

Nationally Determined Contributions (NDCs)

At a national level, the research may act as a catalyst for governments to reassess their NDCs at COP26. This is especially true for nations which expect a large growth in energy demand and, therefore, are already considering new investment in energy infrastructure. A better understanding among national policymakers of the cost reductions which have already happened in renewables, and how a Paris-style collaboration to be ambitious on action – through investment in renewables and storage in national targets – might benefit all concerned. To understand whether such a collaborative strategy is risky for individual countries might require more regional granularity than the model presented here – national policymakers will possibly want to see regional differences in the cost of renewables reflected in the analysis. We intend to tackle this question in a national model for China in 2021.

Expectations around the make-up of energy technologies in the future

It is generally agreed that electrification of energy is one of the three pillars of deep decarbonisation strategies, along with fuel switching and efficiency measures (Sachs, 2015), and that even without the imperative to decarbonise, electricity is likely to become our primary source of energy in the future (Jones et al., 2018). A key reason why the Decisive Transition scenario is so successful is simply a product of the efficiency gains from electrification. Once electricity is generated by the renewable source it only suffers moderate losses when converting that electricity to useful energy; by contrast, at least half of the primary energy is lost in converting fossil fuels to electricity, or torque in an engine, or to heat.

In the short- and medium-term, situations may arise where energy demands cannot be met by renewables. In these situations, there might be an argument for investment in interim fossil-fuel based solutions, such as natural gas. However, it should be kept in mind that such investments would not contribute to the overall transition, can lead to carbon lock-in, and generate further transition risk. Not only will choosing renewables where possible likely lead to lower cost energy but also fewer assets that will have to be discarded before the end of their engineered lifetime. It is very likely that any fossil fuel assets built in the future will be replaced even before their even shorter financial lifetime, as it is possible their operating costs alone could be above the cost of building new renewable generation, even without a price on carbon.

This model also calls into question the continued investment in nuclear. As the results set out in previous chapters show, it may be possible to get close to Paris compliance without continued investment in nuclear power generation. Nuclear energy can itself create a greater energy security risk due to the high generation losses when individual sites go down (Schneider et al., 2019) and it does not mix particularly well with renewables at low usage rates (Cesaro et al., 2021). Also, to restate the major premise of this report, the more we invest in renewables, the faster they ride down their experience curves. The UK's investment in Hinkley Point C nuclear reactor is already looking like a very expensive legacy given how cheap and reliable offshore wind has become.

Finally, current thinking around the future mix of technologies, expressed in the major mitigation models, is that a Paris compliant pathway must rely heavily on underdeveloped technologies such as carbon capture and storage (CCS) and Bioenergy with CCS (BECCS). The transition scenarios in this research decarbonises the energy system without relying on these technologies.

Expectations around the transition risk

There is still a lot of work to be done to understand and limit the risks associated with the transition of the global energy system. As discussed in Section 5 we need to ensure institutional and social barriers are countered; financial stability is maintained; and concerns around job losses in the fossil fuel industries are addressed. The IEA has itself shown that renewables have the potential to provide far more jobs than other energy related investments (IEA, 2020b), but these jobs may not be created in the areas where coal mines are being closed and so industrial strategies will need to be developed to counter such transition risks (Mealy & Teytelboym, 2020).

Transition risks are real and are likely given how rapidly technological trends are moving, but it must be remembered that stranded assets are a one-off cost. If we don't put an end to climate change, the more frequent and damaging extreme hurricanes, floods, droughts, and wildfires will potentially cause orders of magnitude more costs that will be constant, long-term, and potentially permanent.

Concluding remarks

Current energy transition models are important, but there is space for a wider view

As set out in Section 1 of this report, existing climate mitigation models have offered decision-makers with useful insights into the complexity of the transition process for decades. However, this complexity frequently requires compromises in model construction that can narrow the possible range of outcomes produced. As the results from the PTEC scenarios presented in this report, such compromises can occlude a wider view of alternative futures that might deliver a decisive decarbonisation of the energy system with greater financial efficacy. However, if such alternative views are not given a seat at the table, the current modelling results restrict the solutions policymakers are offered, ultimately slowing down the transition and society's ability to mitigate climate change.

New collaborative thinking is needed around delivering a decisive transition

This report has set out key assumptions in energy transition policy that bear re-examining. What is needed next is another Paris-style global collaboration, but this time not just on ambition, but on action – and specifically on investment in clean energy technologies with good reliable experience curves. COP26 in November 2021 offers a ripe opportunity for a *Glasgow Accord* on action. Renewables are clear "runners" in the technology race and those that bet on it early will very likely capture more of the prosperity this green industrial revolution has to offer (Farmer et al., 2019).

Much work to be done, but the future looks much better

There will inevitably be pains to such a major global transition. But the good news is that with renewables we can have our cake and eat it too. It is possible to have economic growth while achieving emissions reductions. There need not be a trade-off, and after the Covid-19 pandemic we cannot afford business-as-usual, it is too risky and too expensive. The major mitigation models informing decision makers are not exploring all options and might very well be missing the best. When coupled with storage, expanded transmission networks, and smart grids, renewable energy provides a solution to the energy trilemma that the fossil fuel system might never be capable of solving – an energy system that is affordable, secure, and sustainable.

Appendix A: Climate mitigation models and authorities

Climate impact, mitigation, and adaptation models

We provide here a brief overview of each of the various models that are used by the climate modelling community to provide information to decision-makers relevant to action on climate change. Note that the categorisations of models we present here are not mutually exclusive and there are many examples of crossovers (Dickinson, 2007).

Earth Systems Models (ESMs) (sometimes broadly known as 'climate models') are complex tools used to explore future physical and biogeochemical responses to changing atmospheric composition and radiative forcing. ESMs can be General Circulation Models (GCMs) or Atmosphere–Ocean General Circulation Models (AOGCMs, the key components of GCMs), which both use three dimensional grids over the globe to represent physical processes in the atmosphere, ocean, cryosphere and land surface (IPCC data, n.d.). Lower resolution ESMs, known as Earth Systems Models of Intermediate Complexity (EMICs), and even simpler reduced-form 'emulators' of full climate models such as FAiR and MAGICC, can also be used, especially to investigate longer timescales and improve model-run speed.[22] ESMs simulate the response of the climate system to increasing GHG concentrations to produce consistent depictions of climate change needed for impact analysis. ESMs are the basis for the construction and interpretation of emissions scenarios that provide modelled trajectories of global anthropogenic emissions, and conceivable consistent patterns in the physical climate. These physical climate scenarios are essential to inform the metrics for targets, which might include temperature (e.g., the Paris Agreement), emissions budgets of future GHG emissions (e.g., the UK's Climate Change Act 2008), stabilisation levels of atmospheric GHG concentrations and anthropogenic radiative forcing of the climate system (e.g., the RCPs see below).

Energy Systems models are used for synthesis, and simulation of aspects of the global energy system. Since energy is at the core of emissions productions, energy system models are often (in simplified form) both a component of emissions modelling, and central to mitigation and adaptation scenarios used to analyse response strategies (Hall & Buckley, 2016).

22 For example, the emulator MAGICC calculates the annual mean global surface air temperature and global mean sea level implications of emissions scenarios, and is linked to SCENGEN, a database containing a large number of GCM experiments. This allows for greater exploration of both climate change scenarios and the uncertainties associated model parameter settings, including carbon cycle feedbacks is possible (Palmer et al., 2018).

They can include models for forecasting, energy planning, energy supply & demand simulation, as well as analysing the behaviour of energy equipment or behaviour of entire systems, power flows, and energy system optimisation (Kondili, 2010). Some examples include MARKAL (Fishbone & Abilock, 1981), MESSAGE (Schrattenholzer, 1981), and POLES (Keramidas et al., 2017). Energy System Models are crucial to formulating legislation on energy supply (e.g. the promotion of renewables) and/or energy demand (e.g. industrial or residential energy efficiency), which are addressed by around 60% of climate laws (S. M. Eskander et al., 2020).

Land Use Models are used to model other emission-related systems, such as land use and ocean productivity and biodiversity. Such systems are usually pooled together in IAMs under what are known as Agriculture, Forestry and Other Land Uses (AFOLU). Each of these have their own equivalent modelling efforts. The purpose of such land-use models is to downscale the aggregated land-use projections of IAMs to obtain a spatial land-use distribution, which could subsequently be used by Earth system models for global environmental assessments of ecosystem services, food security, and climate policies.

Integrated Assessment Models (IAMs) are an attempt to bring together the processes of the aforementioned earth system models, energy system models, global economic models, and in some cases other land use and biodiversity models. There is an enormous range in the level of detail, complexity and interconnections considered in IAMs, ranging from a collection of a small number of equations (cf. Nordhaus 2014) to the syntheses of thousands of equations from physics, chemistry, biology and economics (cf. Reilly et al. 2012). The 'simple' IAMs, such as DICE, POST and FUND aim to identify 'optimal' climate policies by calculating the costs and benefits of proposals (Weyant, 2017), such as estimating values for the social cost of carbon (SCC), and generally optimise for a global social welfare function.

The more 'complex' or 'process driven' Integrated Assessment Models (IAMs) couple the sub-models described above together in a complex model-of-models that each run against a consistent set of initial variables and exogenous drivers. Much of this work of creating and running IAMs is performed at leading scientific institutes around the world. The more 'complex' IAMs seek to simulate the costs of mitigation through a detailed projections of the economic costs of mitigation efforts at regional and sectoral levels, based on a framework of linked "modules" representing each of the sectors of the economy, energy systems, agriculture and the climate, each of which can interact (CarbonBrief, 2018). Examples of the more complex IAMs include AIM-CGE, GCAM, IMAGE, MESSAGE-GLOBUM, REMIND-MAgPIE and WITCH (all of which are used in the IPCC AR5). More recently, the process of model development has been integrated with the intended users, with calls for greater collaboration from climate scientists and economists with stakeholders in the development of scenarios (Hall & Buckley, 2016).

Despite the increasing complexity of these 'complex' IAMs, some difficult processes have typically been emitted. The feedback of economic damages and reduced economic growth from extreme weather events, such and flood losses, and any adaptation costs are not generally included in complex IAMs. This obviously makes using their results to estimate the costs of inaction misleading for policy-makers as the economy grows at the rate defined by the scenarios, regardless of the impacts of climate change (CarbonBrief, 2018).

Another, cause for concern is that complex IAMs struggle to incorporate non-linear system dynamics, such as endogenous technological change, and non-technical mitigation barriers and opportunities, such as changing consumer behaviour (CCC, 2019). Given the potential for such non-linear components of the socio-economic system to enable rapid decarbonisation (Farmer et al., 2019) such an omission could result in key areas of the solution space being underrepresented in their results. The non-linear growth in clean energy technologies is one such omission that we hope to address in part with this report.

More recently, there have been efforts to develop more consistent modelling frameworks for climate impacts, known as the coupled/integrated human-earth system (CHES/IHES) models, in which IAMs, ESMs and impacts, adaptation and vulnerability (IAV) models can be united (Monier et al., 2018). Such a coupling strategy could provide solutions to some of the criticisms aimed at IAMs to better synthesise impacts, adaptation and mitigation, but at the cost of ever greater complexity.

Regional and National-Scale Models are used for the development of national adaptation plans, and identification of short and long-term needs. They can involve the downscaling of global climate scenarios to produce regional models, e.g. through CORDEX (Ashfaq et al., 2020). Influential sector systems models, ESMs and IAMs can also be found on a national scale, which allows for a more tailored approach to impact, mitigation, and adaptation potential. The UK's UKCP18 , Swiss CH2011 (2011), Dutch KNMI scenarios (2015), US National Climate Impact Assessment (Melillo et al., 2014), South African LTAS (Department of Environmental Affairs, 2013), and German Klimaatlas (DWD, n.d.) are among the hundreds of national projects that may be more accessible and responsive to the needs of local policy-makers and users (Grantham Research Institute on Climate Change and the Environment, 2019). Additionally, some models began as national but have been extended for wider use (Skelton et al., 2019), and, conversely, some global IAMs are well suited towards single-country analysis. (For example, AIM/CGE, which is foundationally built as an economic model with a national economy and energy system, and trade relationships with the rest of the world at its core.) Even moving beyond the national scale there have been calls for greater granularity and more local-based modelling. Since local evidence-driven policy actions can have wider international mitigation benefits (Estrada et al., 2017), robust local evidence is critical to inform local resilience and adaptation (Howarth et al., 2020). Nevertheless, given that the challenges and impacts of climate change will be global in character, there should be caution against regional-only optimisation which excludes impacts in other regions, and global models will continue to be most useful in answering a range of trade, innovation, and resource issues.

The key authorities that produce scenarios

The key authorities of climate scenarios modelling are known for their thoroughness, expert authors, and alignment with international goals, such as the Paris Agreement and UN SDGs, despite differing in their methodologies and outputs. We provide here a brief overview of each and the work that they do in providing the world's decision-makers with climate mitigation information.

The IPCC

The most extensive, well-known and widely used body of projections and pathways are those of the IPCC, which has issued five comprehensive Assessment Reports (ARs) to date (in 1990, 1996, 2001, 2007, 2013). The IPCC has a wide audience but is intentional in informing policy makers and the media,[23] with content made to be deliberately policy-relevant, but not policy-prescriptive. The IPCC reports are widely trusted and demonstrate exceptional scientific credibility, due to their extensiveness and inclusive process.[24] AR5 and the 2018 Special Report for Global Warming of 1.5°C (IPCC SR1.5), in response to the new ambitions set by the Paris Accords, are used as a basis in much of the below described policy.

The physical science of the IPCC AR5 report (WGI), relies heavily on the results of the CMIP5. The adaptation assessment (WGII) attempts to summarise climate risks in the form of expert judgement integrated with empirical evidence. The mitigation assessment (WGIII) builds on the use of the five SSPs, described above, employing six different complex IAMs to translate the socioeconomic conditions of the SSPs into estimates of future energy use characteristics and GHG emissions. To combine these with mitigation targets (defined by radiative forcing levels RCP2.6, RCP4.5, RCP6.0 and RCP8.5), additional modelling presents how different levels of climate mitigation and adaptation would fit into the future described by each SSP. The IPCC 2018 Special Report 1.5 takes the mitigation target of RCP1.9, corresponding to the Paris Agreement's target of limiting warming to below 1.5°C.[25] Like the AR5, it also utilised both MIPs[26] and the low-computational-cost emulators such as MAGICC,[27] which allows for greater exploration of both climate change scenarios and the uncertainties associated model parameter settings, including carbon cycle feedbacks.

In terms of (potentially controversial) outcomes, the SR1.5's 78 emissions pathways and system transitions can either be a temperature stabilisation at or just below 1.5°C, or temporarily exceeding 1.5°C ("overshoot") before returning below 1.5°C through the application of negative emissions technologies; while emissions reductions can be achieved with different portfolios of mitigation measures, balances between lowering energy and resource intensity, rate of decarbonisation and reliance on the removal of CO_2 (IPCC, 2018).

23 Noting that "climate policy design is influenced by how individuals and organisations perceive risks and uncertainties and take them into account" the IPCC reports also have an SPM (summary for policymakers) to highlight the most critical developments and and ensures presentation of level of certainty in its pathways is well understood with classifications such as "high confidence", "medium confidence" etc, such that it can also provide clear and consistent communication.

24 AR5 had experts from over 80 countries, 830 lead authors and review editors, 1000 contributors, and 2,000 expert reviewers.

25 The report warns limiting the global average temperature to a maximum of 1.5°C "require[s] rapid and far-reaching transitions in energy, land, urban and infrastructure [systems] (including transport and buildings), and industrial systems."

26 For example, HAPPI-MIP was used for SR1.5.

27 The 'Model for the Assessment of Greenhouse Gas Induced Climate Change' is a reduced complexity carbon-cycle, atmospheric composition and climate model that calculates the annual mean global surface air temperature and global mean sea level implications of emissions scenarios, and is linked to SCENGEN, a database containing many GCM experiments. The 'Finite Amplitude Impulse Response', FaIR, is an even simpler model than MAGICC but with updated methane radiative forcing was also used. Both were fit against MIPs: with FAIR's near-term temperature trends potentially being more realistic than MAGICC (Leach et al., 2018). FaIR is used in this report.

This requires transformations in energy, including for renewables to supply 70-85% of electricity in 2050, prevention of emissions from industry, and urban and infrastructure, global and regional land use transition. However, according to the IPCC models, all pathways that achieve 1.5°C by 2100 require carbon dioxide removal (CDR) on the order of 100-1000 $GtCO_2$ to compensate for residual emissions.

The IEA World Energy Outlook and energy technology perspectives

The International Energy Agency (IEA) World Energy Outlook (WEO) is an annual 700-page publication of the large-scale simulations of the global energy system. It uses multiple scenarios to present different futures under the changes of key variables, including climate policy of governments worldwide, and aims to guide energy management, policy, and investment decisions. The IEA WEO 2019 addresses the climate question with both a goal oriented and descriptive approach: the Current Policies Scenario (CPS) and the Stated Policies Scenario (SPS) model the world's present path without any changes in policy, and incorporating today's policy intentions and targets, respectively. The Sustainable Development Scenario (SDS) maps out a path to meet the relevant sustainable energy criteria of the UN's Sustainable Development Goals (SDGs).[28]

The IEA also takes an energy innovation approach to present modelling of pathways to highlight areas for critical technology solutions in its Energy Technology Perspectives (ETP) reports. Its latest 2020 report is complementary to the WEO scenarios, including the SDS, as well as possibilities for faster innovation (IEA, 2020a). In terms of (potentially controversial) outcomes, the SDS and the earlier B2DS (Beyond 2 Degrees Scenario) do not align with climate goals of the Paris Agreement, and rely heavily on negative emissions and carbon capture technology. Cumulative capital expenditure on oil and gas under its scenarios are higher than some other estimate, and even in the IEA 450 scenario, by 2035, the level of oil and gas is a similar level to today (Greenpeace, 2018).

Other sources of scenarios and climate mitigation modelling

Beyond the IPCC and IEA, energy and transition scenarios have also been constructed and deployed by government agencies (e.g., US EPA), NGOs (e.g., Greenpeace, WWF), and private companies, especially in the energy sector (e.g., BP, Shell). Their varying perspectives provides an array of anticipated mitigation possibilities, emissions levels, and technological progress.

The United States Environmental Protection Agency (US EPA) has for decades relied on 'simple' IAMs to compute the Social Cost of Carbon (SCC), achieve optimal policy outcomes, and calculate the costs and benefits associated with nonoptimal climate policies. The DICE IAM (Nordhaus, 2014) has been an influential early approach to cost-benefit optimisation modelling, seeing the problem of climate change as the problem of investing in uncertainty. DICE estimates the costs and benefits associated with the mitigation of GHG emissions, aiming to balance near term costs of emissions reductions with future benefits of climate avoided damages, aggregating different countries into a single level of output, capital stock, technology, and emissions.

28 An early peak and rapid subsequent reductions in emissions, in line with the Paris Agreement [SDG 13]; universal access to modern energy by 2030, including electricity and clean cooking [SDG 7]; and a dramatic reduction in energy-related air pollution [SDG 3.9]. (IEA 2019)

As relatively simple IAMs, DICE, FUND (Anthoff & Tol, 2009) and PAGE can incorporate climate damage functions via a monetisation of the temperature increase to translate physical impact into economic damages and a discount rate, converting a stream of economic damages over time into a single value (Greenstone et al., 2013). These have provided a wide range of estimates for the optimal SCC, between USD$1 and $2400 (Tol, 2008), with the huge differences in estimates derived in part from their alternative climate damage functions (representing damages from more extreme events e.g. hurricanes, floods, wildfires), and their assumptions around the ability of different regions to adapt to climate change. They all take highly simplified approaches to estimate the SCC: translating emissions into changes in atmospheric GHG concentrations, atmospheric concentrations into changes in temperature, and changes in temperature into economic damages. However, these models have been criticised for two highly uncertain yet very influential elements: firstly, their dependence on the choice of discount rate parameters, which, if too high, lead to excessive discounting of the estimates of future damages. Secondly, on the scope and design of their damage functions: by omitting global damages beyond the US, omitting non-market damages, and omitting the risk for low-probability, high-impact catastrophes, this can also lead to underestimates of the SCC (Hänsel et al., 2020).

BP and Shell provide some of the most well-known Energy System models of any private company. Shell was one of the earliest to establish scenario analysis in a business context in the early 1970s (TCFD, 2017b), and has continued to produce their own scenario modelling, as well as joint studies with national institutions that have been very influential (used by the Chinese, Singaporean and South African governments among others) (Shell and DRC, 2017). In terms of outcomes, Shell's "Sky" scenario aims to align with the Paris Agreement goals, by achieving net zero emissions by 2070, with the first national net zero targets met by 2040. High energy demand into the second half of the century is a central feature of this model, as is the large scaling-up of solar energy as a primary source, coupled with extensive CCS/BECCS -- 10,000 large facilities by 2070 (Evans, 2018). BP releases an annual Energy Outlook to explore the energy transition that considers a range of scenarios through three lenses: sectors in which energy is used, regions in which it is consumed and produced, and the consumption and production of different fuels. While BP does not use the SSPs, its scenarios assume growth in living standards, partially offset by increasing energy efficiency so that global energy demand grows at 1.2% pa (which would roughly align with SSP2). The BP EO 2019 emphasises that its baseline "Evolving Transitions" scenario is not consistent with meeting increased energy demand, nor with meeting climate goals of lower carbon, with its alternatives for each lens contributing towards a "Rapid Transition" instead. Even under Rapid Transition, however, the BP scenario remains conservative, where oil and gas account for 50% of primary energy, and carbon emissions increase by 7% by 2040 (BP, 2019).

By contrast, climate NGOs and think tanks have tended to be more aggressive in their suggested mitigation pathways. Greenpeace's 2005, 2010, 2012 and 2015 Energy [R] evolution (E[R]) scenarios (Teske et al., 2015) aimed to be an alternative to the IEA WEO scenarios it criticised, with less reliance on CCS than WEO scenarios, has higher renewables share, lower fossil fuel use, and lower total energy demand from equivalent exogenous population assumptions. The most recent 2015 E[R] uses results from the IPCC AR5 for its climate system model but combines this with the Mesap/PlanNet simulation model[29] for mitigation.

29 The Mesap/PlanNet which does not include cost optimisation, as other models do, but rather uses consistent exogenous definition of feasible developments). Energy Plan, EU.

The mitigation pathways in Greenpeace scenarios have key characteristics: (1) the E[R] and ADV E[R] scenarios discount nuclear, coal and CCS technologies; (2) including specific directions for policy implementation, (3) a greater emphasis on energy efficiency than equivalent energy systems models, (4) aggressive growth projections for renewables, which it validates against past pathways for the real development of global cumulative capacity of PV and wind, which it highlights has outstripped all of the less aggressive short term projections (Teske et al., 2015).

Other providers of climate and energy modelling and scenarios include:

National institute level:

- IEEJ: Institute of Energy Economics Japan, Outlook 2019-Energy transition and a thorny path for 3E challenges, Tokyo, Japan, Oct. 2018
- EIA: US Energy Information Administration, International Energy Outlook 2017, Washington, D.C., United States, Sep. 2017 CNPC:
- CNPC Economics & Technology Research Institute, Energy Outlook 2050, 2018

Industry level:

- Equinor: Energy Perspectives 2018 – Long-term macro and market outlook, May 2018
- ExxonMobil: 2018 Outlook for Energy: A View to 2040, Feb. 2018
- DNV GL: 2019. Energy Transition Outlook. (Produces an independent 'Energy Transition Outlook' annually, as well as produces regional reports and reports relevant to the Maritime Industry)
- IHS: IHS Markit, Rivalry: the IHS Markit view of the energy future (2018-2050), Jul. 2018

International level:

- OPEC: Organization of the Petroleum Exporting Countries, World Oil Outlook 2040, Sep. 2018

Academic modelling:

- Climate econometrics: Climate econometrics is an academic Research Network based in Oxford that has produced numerous economic forecasting models of the climate system.
- S&P's "Heat is on": report quantifies the impact of climate change on the drop in GDP per capita following major weather events. This builds on a specialised database that gathers the damages, in monetary values, due to major weather events across the world (Swiss RE Sigma Explorer database), and a forward-looking climate model (Climada). S&P Global Ratings developed an ESG Risk Atlas, and its Carbon Efficient Indices has been used as a benchmark by the world's largest pension fund GPIF.

Other uses of climate mitigation scenarios

Determining risks, regulations, and recommendations

Increasingly, there has been an acknowledgement of risks of the changing world on global systems: most prominently the financial system that urgently needs more resilience to anticipated changes. While on the national scale, this has involved government action (Vermeulen et al., 2018), the private sector also faces uncertainty, especially since not all net zero targets are supported by detailed sector policy pathways. They must address three lenses of risk:

- physical risk regarding susceptibility to climate shifts and extreme weather patterns such as flooding, drought, and fires,
- transition risk regarding anticipated vulnerability (or advantage) in the light of policy and market transformations, and
- reputational risk of engagement with what are perceived to be environmentally harmful activities.

Transition risk, which has (thus far) been most relevant to strategic and financial considerations, can be further divided into three:

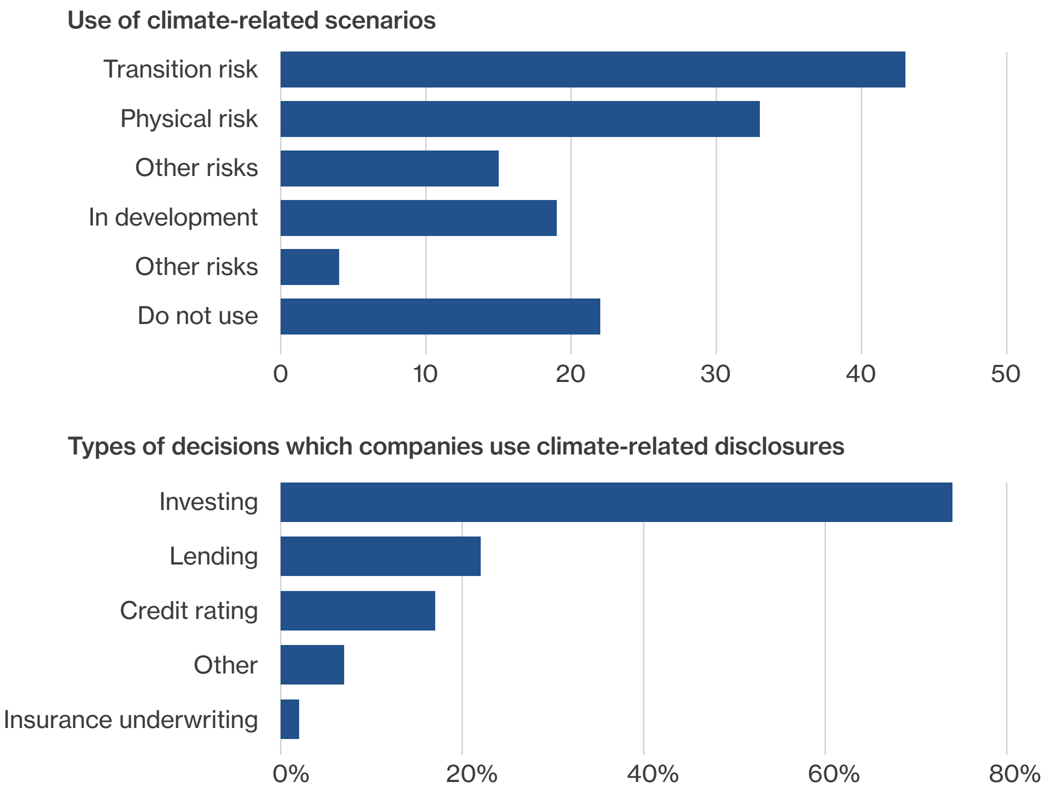
- policy risks, from policies aiming at decreasing GHG emissions in line with the Paris Agreement (e.g., carbon pricing) which threaten the viability of carbon intensive industries,
- technology risks, arising from the uncertainty in technological development and deployment and
- legal risks, a function of climate litigation, such as in the context of damages (Ralite & Thomä, 2019).

Demands for stress-testing of investment decisions against multiple futures, which requires scenario analysis by companies and financial institutions, have been increasing. Alongside the industry-led Task Force on Climate-Related Financial Disclosures (TCFD, 2017a), the 2018 IPCC SR1.5 also highlights the importance of directing finance towards investment in infrastructure for mitigation and adaptation which requires the removal of barriers in access to adaptation finance, while national regulatory initiatives such as the French Energy Transition for Green Growth Law (2015), regulatory standards bodies such as the California Insurance Commissioner's Office (2018), and investor networks and coalitions such as 2° Investing Initiative (Ralite & Thomä, 2019), and now also international standardisation bodies, such as the ISO 14097 Working Group (ISO, 2020), have been urging for greater use of scenario analysis in assessments of climate-change related risks across the board (Ramirez et al., 2017).

Transition and physical risk estimation based on scenario modelling has multiple applications to investment, insurance, and credit decisions. Insurance and credit industries can act as a barometer of climate risk, establishing values for climate risk based on perceived likelihood and severity (Hawker, 2007).

For investment, guided direction is critical for not 'locking in' carbon, and either ending up with stranded assets if policy changes or preventing necessary policy developments to move away from carbon.

Although traditional reference decarbonisation scenarios are not designed for financial analysis, industry associations, NGOs and consulting firms have developed guidance and tools to assist companies in using climate scenarios and assessing climate risks, including to provide sector-specific approaches.



● **Figure 16**: Use of Climate Related Scenarios in Company decision-making. From TCFD Status Report, Figure 67.

The TCFD reports that by 2018, 76% of organisations surveyed used climate-related financial disclosures for decision making, with investing and lending decisions being the primary uses. While only 9% of companies disclosed the resilience of their strategies considering different climate-related scenarios (TCFD, 2017b), there was an increased adoption of scenario analysis (IPIECA, 2018). As recommended by the TCFD, many companies have used IEA analysis and the IPCC's "meta-scenarios" (TCFD, 2017b). Some companies combine modelling from several sources (see Oil Search in Table 4). Others have produced their own set of socioeconomic scenarios integrated into an IAM. Many of the private companies examining these scenarios and models are insurance firms, who by their nature may have a particular interest in understanding climate risks.

Table 4: Utilisation of climate scenarios and modelling by private organisations.

Name	Type of organisation	Scenarios and models used	Uses and output
Oil Search	Private Company (oil and gas exploration)	Greenpeace Advance Energy [R]evolution, IEA 450, IEA NPS	• Impact on expenditures, assets, and revenues • Transition risk for specific projects • Physical risk for facilities
Citi	Investment Bank and financial services	Transition risk scenario, 2°C and 4°C physical risk scenarios corresponding to IPCC RCP2.6 and RCP8.5	• Transition risk: calculation of scenario-implied probability of default from key risk factors: direct & indirect emissions costs, capex and revenues • Physical risk: incremental change and extreme weather events on assets
AIIB (2017)	Multilateral Development Bank in Asia	IEA WEO 450S and NPS, UN Advisory Group on Energy and Climate Change	• Establish what investment trends would be needed to reach the Paris Agreement goal (e.g. in Renewable Energy, Energy Efficiency investments, Power T&D, pollution management) • Establish six guiding principles to guide the build-up of the bank's energy portfolio
HSBC (2020)	Commercial bank and financial services	Scenario: Paris NDCs for policies, SSP2 for population and GDP IAM: TIAM-Grantham MSCI All Country World Index ACWI, Vivid Economics, Trucost, Rystad Energy, IPCC SR1.5 2018	• Company valuation and company-level climate related risk and opportunities • Ientify common characteristics of 'climate winners' and 'climate losers' across scenarios • Projected changes in credit ratings across emissions-intensive industries
2° Investing Initiative (Ralite & Thomä, 2019)	Think Tank, funded by the European Commission H2020 Programme	S&P Trucost, IEA B2DS, OECD's "Delayed Action", Mercer, UNEP FI	• Stress testing given that 'too late, too sudden' scenarios are more likely than 'smooth transition' • Produced Energy Transition Risk (ET Risk) Project • Modelled potential credit effects and found credit rating movements of 0.5 for utility sectors, 2 for cement and 1 for the steel sector

Source: TCFD Status Report, 2 Degrees Investing Initiative, HSBC 2020.

Determining adaptation requirements

Further risks are also encountered through communities, companies, assets, economies, and ecosystems exposed to physical risks (both incremental temperature changes and vulnerability to extreme weather).

The exposure of human and natural systems and their ability to adapt has implications for local planning and insurance as well as national, international and private intervention.[30] For this, localised modelling is of prime importance; despite the potential of producing huge variation in modelled projections that allows for selection of preferred outcomes (Warren-Myers et al., 2018). For example, sea level rise, which in worst-case IPCC scenarios is up to 7m by 2100, displacing hundreds of millions of people (Stocker et al., 2013), demands response from the insurance sector and local planning. An Australian national assessment considers 1.1 m by 2100 as its high-end scenario, still finding that A$226 billion worth of commercial, industrial, road, rail and residential properties are anticipated to be exposed to inundation and erosion hazard (Australian Government, 2011). Other physical threats include food security risks, biodiversity and species extinction risks, human health problems, and population displacement.

Litigation

Modelling also has a role to play in climate change litigation cases brought before courts around the world. These can include topics such establishing causation of harm; incorporating climate change risks into investment strategies; forcing disclosure of climate risks by government organisations and publicly traded companies, assessing the impacts of carbon pricing and stranded assets, which both utilise (and identify neglect or manipulation of) transition risk projections.[31] Plaintiffs can include companies, NGOs, investors, individuals, and government agencies (including institutions such as the US Securities and Exchange commission (SEC), for example holding polluting companies liable for costs that local authorities had incurred to protect residents from the impacts of climate change.[32]

Assessing the costs and benefits of proposed projects

An indication of expected costs is an invaluable function of climate modelling for policymaking and in industry. Benefit-cost IAMs have been used by the US government to compute a Social Cost of Carbon (SCC), defined as the incremental damage caused by one additional ton of carbon emissions. The monetisation of climate damages (such as changes in net agricultural productivity, human health, property damages from increased flood risk, and the value of ecosystem services) aim to facilitate the incorporation of social benefits of regulation that is expected to reduce these emissions. The US Interagency Working Group (IWG) uses the damage function modules of the DICE, PAGE and FUND IAMs (see below) to obtain a range of projections of the SCC that must be included in all project approvals (IWGSCC, 2010). However, the value of the SCC is heavily dependent on the discount rates, and whether global or national damages are considered. Scientific literature can also help to assess the size of co-benefits and to maximise these and reduce the adverse side effects in climate and sectoral plans and strategies (Lucon et al., 2014) and to identify low-cost options through sensitive intervention points (SIPs), such as financial disclosure and certain technology investments (Farmer et al., 2019)

30 Heat stress, landslides, storms, extreme precipitation, inland and coastal flooding, air pollution, drought, water scarcity, sea level rise and storm surges can impact on productivity, energy demand for cooling, water availability, food security, infrastructure, and agricultural incomes.

31 For example: NYAG (NY state Office of the Attorney General) accused Exxon Mobil in October 2018 of failing to apply a "proxy cost" of carbon because it would have resulted in "substantial write-downs" of Exxon's assets (Clifford Chance, 2019).

32 City of New York v. BP plc, et al; City of Oakland v. BP plc; Rhode Island v. Chevron Corp.

Appendix B: additional PTEC model details

This Appendix contains additional information regarding the workings of the PTEC model. For the complete methodology, see (Way et al., 2020).

Endogenous technological change

Wright's Law

Endogenous technological change, referred to as an experience- or learning curve, was first formalised by Wright (1936), who showed that the cost of aeroplanes fell as a power law of their cumulative production (see Figure 17). "Wright's law" has since been applied to a wide array of contexts, as detailed by Thompson (2012).

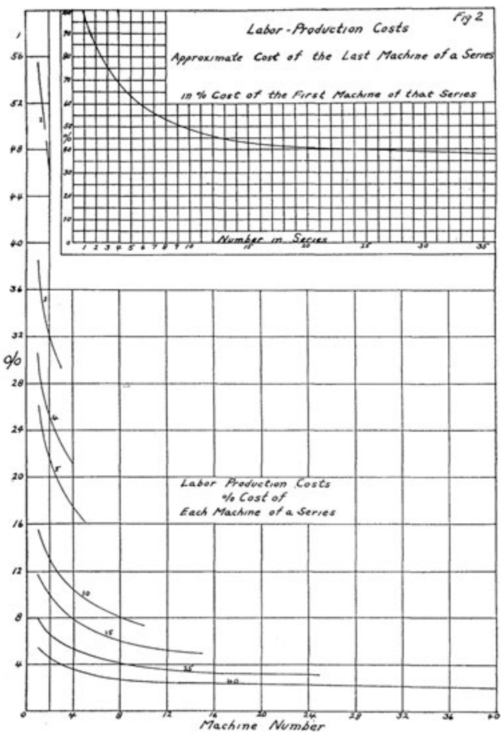


Figure 17: Source: Wright (1936).

Wright's law does not prescribe an exact causal mechanism; it is an empirical relationship that can be widely observed and applied. Indeed, because our model extrapolates existing trends, the issue of causality is not critical to our results. However, it is conceptually important to clarify that it is not literally 'experience' (i.e. cumulative production) that decreases costs, but rather any number of correlated factors. These may differ depending on the exact context. One potential factor is "learning-by-doing", whereby organisations become more proficient in producing a technology through practice (Arrow, 1962). Another is "economies of scale", whereby once a large quantity of production is reached, firms can spread out fixed costs and standardise procedures.

Wright's law is akin to a generalised form of Moore's law, the latter originating as an observation that the number of transistors in a microchip doubles about every two years.

A key difference is that under Wright's law, it would not be 'time' *per se* that causes the number of transistors to double, but rather the R&D, knowledge, and proficiency that increases with time.

Indeed, in the special case where experience grows exponentially with time, Moore's and Wright's law are in fact equivalent. Generally, there is an essential difference between the two. Taking Moore's law strictly allows no role for policy or demand since the rate of time passing is always constant, and thus the amount of technological change will always be constant too. This fact is not the same under a strict interpretation of Wright's law, since we can actively change the amount of experience by stimulating production through demand (or other factors correlated to it). For example, if we cut all R&D spending to reduce the production of microchips, then we would expect advances in the number of transistors to slow down.

This difference allows us to test the two laws against each other. Lafond et al. (2020) do this by examining 675 different types of military equipment produced by the US during WWII. Here the war marked a sharp change in funding allocations overwhelmingly driven by demand rather than costs. Under Moore's law, this rise in demand should have no effect; under Wright's law, it should. Their analysis suggests an approximately half-to-half split between cost decreasing due to exogenous exponential trends (Moore's law) and experience (Wright's law).

This finding has important implications for modelling endogenous technological change within the global energy sector. Under Moore's law, all scenarios would bring forth the same dynamic since the passing of time is identical. Under Wright's law, scenarios would drastically differ between each other. For example, where there is more deployment of PV cells, there is more 'experience' acquired, meaning that per-unit costs should fall further.

Moore's law is much more optimistic under our model. This is because even under a Decisive Transition, the growth rate of renewable energy eventually slows down and with it the experience that drive's Wright's law. Time, however, does not slow down, and so prices would continue to drop rapidly, regardless of how mature the renewable energy sector becomes. This is empirically demonstrated by Way et al. (*forthcoming*) in their supplementary material.

Applying Wright's Law to renewable technologies

To forecast learning curves, we want to model the relationship between costs and cumulative production (i.e., experience) of a technology over time. To do this we write costs as some function of cumulative production, using log differences to express everything in terms of growth rates, as per Wright's law. Let c_t be the cost and z_t the cumulative production of a technology in period t. This gives the following equation:

$$\log c_t - \log c_{t-1} = f(\log z_t - \log z_{t-1})$$

Following Lafond et al. (2018), there are two sources of uncertainty that we must incorporate into our forecasts. To model random changes in the future we include periodic noise shocks η_t with IID $\eta_t \sim N(0,\sigma_\eta^2)$. Additionally, to show that we do not know the true experience exponent ω we model this as a variable rather than a fixed parameter. This thus gives the following equation:

Equation 1: $\log c_t - \log c_{t-1} = -\omega(\log z_t - \log z_{t-1}) + \eta_t$ with IID $\eta_t \sim N(0, \sigma_\eta^2)$

A last component to add is that the above-mentioned random shocks tend to persist beyond a single period t as shown by Farmer & Lafond (2016). For example, if there is a shortage of materials for PV cells, it may take several years for things to gradually return to normal. This can be modelled by using positive autocorrelations, whereby the total shock this period η_t is a combination of the new shock this period u_t plus some persistence ρ of last period's shock u_{t-1} (which in turn depends on the persistence of all the shocks from period before that). This can be written as:

Equation 2: $\eta_t = u_t + \rho u_{t-1}$ and thus $\sigma_u^2 = \sigma_\eta^2 + (1 + \rho^2)$

Substituting these in we get our final equation:

Equation 3: $\log c_t - \log c_{t-1} = -\omega(\log z_t - \log z_{t-1}) + u_t + \rho u_{t-1}$ with IID $u_t \sim N\left(0, \frac{\sigma\eta^2}{1+\rho^2}\right)$

To solve for ρ we refer to Lafond et al. (2018), who found that the persistence of fluctuations in cost improvements averaged at 0.19 across over 50 different technologies. We thus also use this as our estimate across all technologies.

The two remaining parameters are thus the distribution of periodic noise shocks, σ_η^2 and the experience exponent, ω. We solve for these by calibrating Equation 1 on the full set of historical data available, assuming exponential exponents are normally distributed $\omega \sim N(\widehat{\omega}, \widehat{\sigma^2})$. This then gives us best estimates for $\widehat{\omega}$, $\widehat{\sigma_\omega}$, $\widehat{\sigma_\eta}$. From this, we can then plug in our values in Equation 2 to also get the best estimate for $\widehat{\sigma_u}$.

A slight nuance to this comes in the case of nuclear power. As previously outlined, there is substantial reason to believe that costs may rise in the future, since the experience exponent has been negative across several datasets. However, in line with our general conservative approach, we assume that ω is close to zero and $\widehat{\sigma_u}$ small. This assumption means that the Slow Nuclear Transition is somewhat optimistic when comparing it to counterfactuals, where solar and wind are rising instead.

Solving for a Cost Path

The above parameters then get estimated through a random sampling process. By repeating this a large number of times, we account for inherent future uncertainty and ambiguity in evaluating the experience exponent, obtaining a distribution of possible outcomes for each given scenario.

Suppose we wish to forecast the cost of a technology ahead *T* periods under a given scenario (i.e. conditional on certain z_t values). First, we randomly pick an exponential exponent from $\omega \sim N(\widehat{\omega}, \widehat{\sigma^2})$. We then randomly pick *T* successive noise shocks from $u_t \sim N(0, \sigma_u^2)$. Together with our z_t scenarios, we can thus calculate c_t at each step until period T. This is a single cost path for a given scenario.

We repeat this whole stochastic process 100,000 times, simulating what would happen under different random future shocks and exponential exponents. Combining all these cost paths, thus gives an array of possible outcomes, which are distributed according to our uncertainty.

Outcomes with higher probability predicted by our model will have many cost paths around it; outcomes with lower probability predicted by our model will only have outlier cost paths around it.

Forecasting accuracy: mean versus median

Two counteracting factors generally determine forecasting accuracy. Firstly, as the forecast horizon τ grows, our forecast accuracy decreases. Intuitively, this is because the further ahead we attempt to predict, the more critical random shocks become: As time progresses, there is more potential for unexpected shocks to diffuse and build on each other, thereby deviating from the overall trend. This reason is why the confidence interval tends to grow further into the future. By contrast, our forecast accuracy decreases the more historical data points m we have to fit parameters. This is because more data helps to reduce the overall uncertainty around misestimating our equations.

Lafond et al. (2018) note that for models like Wright's Law, these two factors combine so that forecasting accuracy for the mean scales at $\tau + \frac{\tau^2}{m}$. This equation leads to an important dynamic. When we reach a point where we forecast more periods than we have historical data on ($\tau > m$) then the forecasting error becomes dominated by parameter estimation $\frac{\tau^2}{m} > \tau$. Because this term contains a quadratic, the error then starts growing ever more quickly, and the mean deviates from the median. For example, in cases where we have 30 data points, the forecast error grows reasonably slowly until about 2050 and then grows faster after that.

Experience curves for fossil-fuels

Fossil fuels are placed into a different category because, as outlined above, they appear to behave fundamentally differently in having remained at a close to constant price over the last century. We thus choose to model it using an autoregressive time series – or AR(1) – that can be formally written as follows:

$$X_t = \phi X_t - 1 + \in_t + \text{ with } \phi \in (0,1]; \in_t \sim N(0, \sigma_\in^2); \kappa \neq 0$$

Here the cost of fossil fuels in period t is dependent on its price in the previous period t–1 subject to a random shock $\in_t$, which again represents the inherent future uncertainty. The parameter ϕ determines how quickly such a shock will dissipate over time and $\sigma_\in^2$ how volatile these shocks are. Solving, we can see there is a long-term mean $\frac{\kappa}{1-\phi}$, which represents the constant price. The decision to model fossil fuels using AR(1) appears substantiated by the literature. For example, Pindyck (1999) found that fossil fuel prices demonstrated a strong mean reversion dynamic to a stochastically fluctuating trend line.

Using historical data, we can thus fit this equation for each fossil-fuel-based technology, obtaining estimates for ϕ, σ, κ accordingly. Since there was a temporary break in the price level in the mid-1970s due to the OPEC shock, we decide to calibrate using data from 1975 onwards, as this would otherwise skew our results into suggesting that fossil fuels are becoming more expensive.

Note that in theory, we could also apply Wright's Law, whereby the experience exponent would become close to zero after calibrating this variable on historical data. Indeed, on short timescales of around ten years or so, such a model behaves approximately the same as AR(1). However, over longer timescales, such as in our case where we make predictions to the year 2100, these small differences cumulate and predict very volatile results. Whilst this did seem appropriate for nuclear power, which has demonstrated large fluctuations in price, this contradicts the remarkable price consistency in fossil fuels that we observed over the last century. We thus believe that fossil fuels are better captured over the long-term by an AR(1) process.

Levelised cost of energy and vintages of capital stock

Each scenario specifies how much energy is produced by a given technology i in a particular year t, denoted as q_i^t. We are interested in calculating how much it costs to deploy this quantity. To measure the cost of a unit of technology we use the LCOE. This is defined as the average net present cost of electricity generation for a generating plant over its lifetime.

The LCOE for a given technology remains constant throughout the lifetime of a unit of technology. This helps make for easy comparison across technologies. However, this annuitisation also means that LCOE is not simply the same as dividing annual costs by annual production. Annual costs can change drastically year-by-year. For example, all the instillation costs happen upfront but LCOEs "spread these out" over a lifetime. LCOE can thus be likened to an investor taking out a loan for the total costs of the asset over its lifetime and paying that loan back at a certain interest rate.

Whilst the LCOE of given a unit of technology does not change over time, it can change across different "vintages" of that same technology. For example, as Section 2 shows, there has been a clear trend in PV cells becoming ever cheaper at producing electricity. Thus, whilst a PV cell produced in 2020 will have the same LCOE across its lifetime, this may be higher than the LCOE of a PV cell produced in 2025.

To work out the cost of producing q_i^t, (Way et al., 2020) note that we must "add up the individual costs associated with panels of every vin-tage in the installed capacity base (each with a different LCOE), as well as any new annual addi-tions". This occurs for each technology as follows.

We assume that each technology's capital stock has a lifespan L^i and functions perfectly until it is then removed from the system. For simplicity, we also assume that to begin with (i.e., in the year 2020) the existing capital stock had been installed linearly over the previous L^i periods. Our scenarios then define q_i^t for all future periods. Thus, we can subtract from the production of capital stock that has already been installed in the past and not yet expired ($t < L^i$). From this we can infer how much new capital stock must be installed to make up the remaining shortfall.

Appendix C: Creating the PTEC emission scenarios

Introduction

The purpose of this appendix is to demonstrate how the estimates of energy and total anthropogenic emissions, radiative forcing, and ultimately temperature anomaly presented in this report are generated from the PTEC scenarios. The aim is to demonstrate how the outputs of the PTEC scenarios are converted to match transition scenarios developed by the IEA and the IPCC. This not only allows a comparison of our scenarios with major modelling efforts by these key organisations, but also generates emissions scenarios relevant to the exploration of climate risk for the other workstreams of the UK-China Climate Risk Assessment project.

Our intention is not to provide emission scenarios that are precise, as the PTEC scenarios are not predictions of the future. This is also the case for the both the IEA and IPCC scenarios, although the latter uses an ensemble of models to provide some measure of uncertainty around their scenarios. The primary goal here is to provide defensible estimates of the emissions associated with each of our scenarios, once again for comparison purposes, and to examine the potential impact that endogenous technological change could have on mitigating climate change. To this end we also include our best representation of the uncertainty in our estimates.

Producing emissions scenarios from the PTEC model requires several steps. Firstly, we undertake a like-to-like comparison of the PTEC energy system components with those provided by the IEA, in the starting year of the analysis, 2018. Secondly, we produce an estimate of the emissions generated by the PTEC energy system for every timestep in each of the PTEC scenarios. For any components found to be omitted from the PTEC model (in comparison to the IEA model), we also develop a trajectory of future emissions based on the narrative of the scenario, including bands of uncertainty around these components. Thirdly, we conduct a similar like-to-like comparison with the IPCC scenarios in 2018. We then add any anthropogenic emissions that are not included in the IEA/enhanced PTEC energy system models and produce future projections of these additional anthropogenic emissions for the PTEC scenarios, based on the IPCC Scenario Matrix. Finally, we project each of the global energy system scenarios through to 2040 for comparison with the IEA scenarios, and total anthropogenic emissions through to 2100 to provide a comparison with the IPCC scenarios.

Calculating the emissions from the global energy system

The PTEC system was originally designed to generate probability-based estimates of the future costs of technology deployments and energy production based on empirical data. The model was therefore not necessarily built with emission scenarios in mind. However, there is a simple methodology, with a clear set of transparent assumptions, that we can use to generate our estimates of the emissions from the components of the energy system modelled in PTEC.

In each of the scenarios the PTEC model calculates the necessary deployment and retirement of new technologies to meet a 2% annual increase in supplied useful energy. To match total primary energy demands with those of the IEA scenarios requires the conversion of final electricity demands to primary energy demands by fuel. Primary energy is a difficult concept for non-fossil fuel sources. For the conversion of renewable electricity (e.g., renewable energy input for P2X), and the conversion of nuclear electricity to primary energy we simply use a 100% conversion. That is, we are not converting these technologies back to their primal fuel source 33% from uranium to electricity in nuclear reactors or 15% conversion of solar irradiance to electricity from solar PV panels. However, a conversion factor in the form of a thermal efficiency was used to convert final energy of coal/oil/gas-fired electricity to primary energy of coal/oil/gas.

Converting back to primary energy demand allows us to generate emission calculations by simply multiplying the energy usage (EJ/GWh/Mtoe) of each polluting energy source by the emissions intensity for that source. For our emission conversion factors we use those presented in the IEA World Energy Outlook Stated Policies scenario to be able to match their emissions levels.

Equilibration with IEA 2018 emissions

The PTEC model is a medium complexity energy systems model, designed purposely to reduce the complexity of the energy system to allow the model to be transparent and to run quickly (for sensitivity and uncertainty analysis). To this end, some minor components of the energy system that were believed to require excessive complexity to be included in the PTEC model were excluded. The list of what is included and excluded from PTEC are shown in Table 5 below and described in more detail below, sorted by the size of the omission.

- **Intermediate/unspecified (9.9%)**: This refers to fossil fuel consumption, whereby energy gets 'spent' to produce even more energy. Examples of this include powering blast furnaces, petroleum refineries, and coal mines. Overall, such intermediate uses account for about 47.5 EJ worth of fossil fuels. Since modelling this is highly scenario-specific (depending on how much fossil fuels grow), we make the simplifying assumption to exclude this component entirely. Note that the same is not done for electricity generation, which is included in our model and through which all renewables -- but only some fossil fuels – flow through.

- **Traditional biomass (5.4%)**: The only substantial end-use sector not modelled are the 26.0 EJ that is mostly being used for cooking and heating. This includes technologies such as fuelwood, charcoal, animal dung and agricultural residues. We believe this omission is justified for two reasons. Firstly, this sector is shrinking in importance, as modern and more efficient technologies become widespread, especially in the developing world. Secondly, to model CO_2 emissions, it is no clear these are necessary as traditional biomass is close to carbon neutral. For example, to produce more charcoal over the long-term, one must plant more trees. Thus, even if there is an increase in EJ, this does not mean that emissions will increase too.
- **Petrochemical feedstock (4.8%)**: This refers to the 23.0 EJ of fossil fuels currently used as raw materials to produce plastics and other industrial products, such as lubricants. As these are not used as energy carriers in the usual sense, we exclude them from our model.
- **Bioenergy/biofuels (2.9%/0.8%)**: These components are excluded primarily because of their high environmental costs per unit of energy. If these sectors were to actively grow from their currently small size (13.8 EJ and 3.7 EJ respectively), this would not be compatible with a green transition. Additionally, the evidence about whether these technologies are commercially viable is mixed. This is therefore not something of interest for our analysis, and not included in the Decisive Transition or Stalled Transition.
- **Heat (2.6%)**: This refers to the small 12.3 EJ produced from fuel combustion, nuclear reactors, geothermal sources, sunlight as well as various industrial processes. It is thus more a by-product rather than an energy carrier in of itself. Because of this qualitative difference, it cannot easily be included in the same model framework. The model thus omits it to maintain simplicity. Where we to incorporate heat in our analysis, then there would likely be more energy produced under the same processes. This is akin to treating all heat generating technologies as more 'efficient', which, as per our argument above, implies lower CO_2 emissions throughout.
- **Other fuels (1.0%)**: A further 4.7 EJ is currently made up of mostly small and nascent technologies. These include solar thermal energy, marine energy, geothermal energy, tidal energy, and carbon capture storage. Whilst these all currently make up very negligible parts of the global energy system they are often cited as potentially critical for a green transition. This may be true, but either due to their high location dependency (e.g., geothermal energy) or lack of historical cost improvements (e.g., carbon capture storage), we choose not to make them part of our analysis. This again is a conservative assumption: our transition scenarios must meet the global energy demand without making use of any of these potentially promising energy technologies.

Table 5: Final energy and other major uses in 2018 by sector and energy carrier, as listed in the IEA WEO 2019, showing whether each component is included or excluded from our model. Each column for a given sector is split into two columns, one showing what is included and one showing what is excluded.

Total emissions estimate	In	Out	Total
t/CO_2	26,131,384,522	7,470,033,393	33,601,417,915
Gt/CO_2	26.1	7.5	33.6
Percentage	**78%**	**22%**	**100%**
Electricity (Energy sector)			
Technology	**EJ***	**EJ In**	**EJ Out**
Oil	8.0		8.0
Coal	73.5	73.5	
Natural gas	38.3	38.3	
Nuclear	29.5	29.5	
Hydro	15.1	15.1	
Biopower	5.6	5.6	
Wind	4.6	4.6	
Geothermal	0.3		0.3
Solar PV	2.1	2.1	
CSP	0.0		0.0
Marine	0.0		0.0
Total	**177.0**	**168.6**	**8.4**
Fraction		**95%**	**5%**
Transport (End use sector)			
Energy carrier	**EJ***	**EJ In**	**EJ Out**
Oil	110.1	110.1	
Electricity	1.3	1.3	
Biofuelds	3.7		3.7
Other fuels	4.7		4.7
Total	**119.8**	**111.4**	**8.4**
Fraction		**93%**	**7%**

Total emissions estimate	In	Out	Total
Industry (End use sector)			
Energy carrier	**EJ***	**EJ In**	**EJ Out**
Oil	12.5	12.5	
Coal	33.3	33.3	
Natural gas	27	27	
Electricity	33.6	33.6	
Heat	6		6
Bioenergy	8.9		8.9
Other renewables	0.0		0.0
Total	**121.4**	**106.4**	**15.0**
Fraction		**88%**	**12%**
Buildings (End use sector)			
Energy carrier	**EJ***	**EJ In**	**EJ Out**
Oil	13.8	13.8	
Coal	5.2	5.2	
Natural gas	29.3	29.3	
Electricity	42.3	42.3	
Heat	6.3		6.3
Bioenergy	4.9		4.9
Traditional biomass	26.0		26.0
Other renewables	2.0		2.0
Total	**129.8**	**90.7**	**39.2**
Fraction		**70%**	**30%**
Other uses			
Energy carrier	**EJ***	**EJ In**	**EJ Out**
Electricity	15.5	15.5	
Petrochemical feedstock	23		23
Unspecfiied (fossil)	67.2		67.2
Total	**235.5**	**106.9**	**129.7**
Fraction		**45%**	**55%**

Table 6 provides a summary of the missing components and their associated CO_2 emissions in 2018. In total, these components produced 8.1 Gt of CO_2 emissions in 2018, which represented around 18% of the CO_2 emissions from the global energy system in 2018. Although our ability to match the omitted components exactly is problematic given the level of disaggregation available in the IEA data, these are our best approximation of the emissions from the 18% of the energy system components that were identified as omitted in Table 5. Another difficulty is that the IEA scenarios have changes to the emission efficiency factors of their technologies through time.

To allow us to represent the uncertainty around how these missing emissions should be projected into the future for our two PTEC scenarios we generate a band of emissions for them. The lower bound of this emissions band is produced by either increasing or reducing each of these components at the same rate that the total primary energy demand for fossil fuels increase or decrease each year in each of the PTEC scenario. The upper bound is produced by applying the annual increases or reductions in each of these components from the IEA stated policies scenario. This appears to be a conservative estimate of the future fate of these components. For instance, the largest omission (9.9% of useful energy) is intermediate fossil fuel usage – whereby fossil fuels are needed to generate fossil fuels (e.g., powering coal mines). When fossil fuels are replaced, fewer CO_2 emissions will be attributed to these components. The more fossil fuel-intensive a scenario is, the greater this conservative bias will be.

Table 6: A breakdown of the components of the global energy system not represented in the PTEC model with IEA estimates of each component's CO_2 emissions in 2018

Energy system component	Excluded component 2018 emissions (Gt CO_2)
Oil for electricity	0.6
Biofuels for Transport	<0.1
"Other fuels" for transport	0.3
Heat in industry	0.5
Heat in buildings	0.5
Bioenergy in buildings	<0.1
Traditional biomass	<0.1
Petrochemical Feedstock	1.6
Unspecified fossil	4.7
Total	8.1

Finally, to be able to compare the energy use by fuel source between the PTEC and IEA scenarios the missing components in the Decisive Transition are electrified at the same rate at which the scenarios phase out dependence on fossil fuels. Normally, the process of electrifying final energy would lead to an efficiency improvement. For instance, the overall global energy system, we see a 30% reduction in final energy demand required by 2100 to meet the same useful energy demands in the Decisive Transition scenario compared to the Stalled Transition scenario. However, as these components are likely to be difficult to electrify, we have forgone any efficiency gains and transferred the full energy demand from the fossil fuel component to its electrified counterpart.

IEA full scenario comparisons

Figure 18 presents the resulting emission outputs for the IEA and PTEC scenarios. The most noticeable difference between the scenarios is that the uncertainty associated with the PTEC Decisive Transition is much greater. This is purely an artifact of the fact that emissions decline much faster in the Decisive Transition scenario than in the Stated Policies scenario with both being used to estimate the declines in the components of the energy system not included in PTEC. The second noticeable difference is the non-linear curvature to the PTEC Decisive Transition scenario. The emissions for this scenario increase in the first few years as the natural gas network grows to accommodate the 2% annual growth in useful energy demand with the growth in renewables not yet able meet demand growth. However, when the global factories' production capacity for renewables and associated storage technologies become sufficiently high the emissions begin to decline rapidly. Finally, there is a noticeable decline in this growth by around 2035. This is due to the additional energy required when transport electrification starts to demand more electricity before it is completely decarbonised.

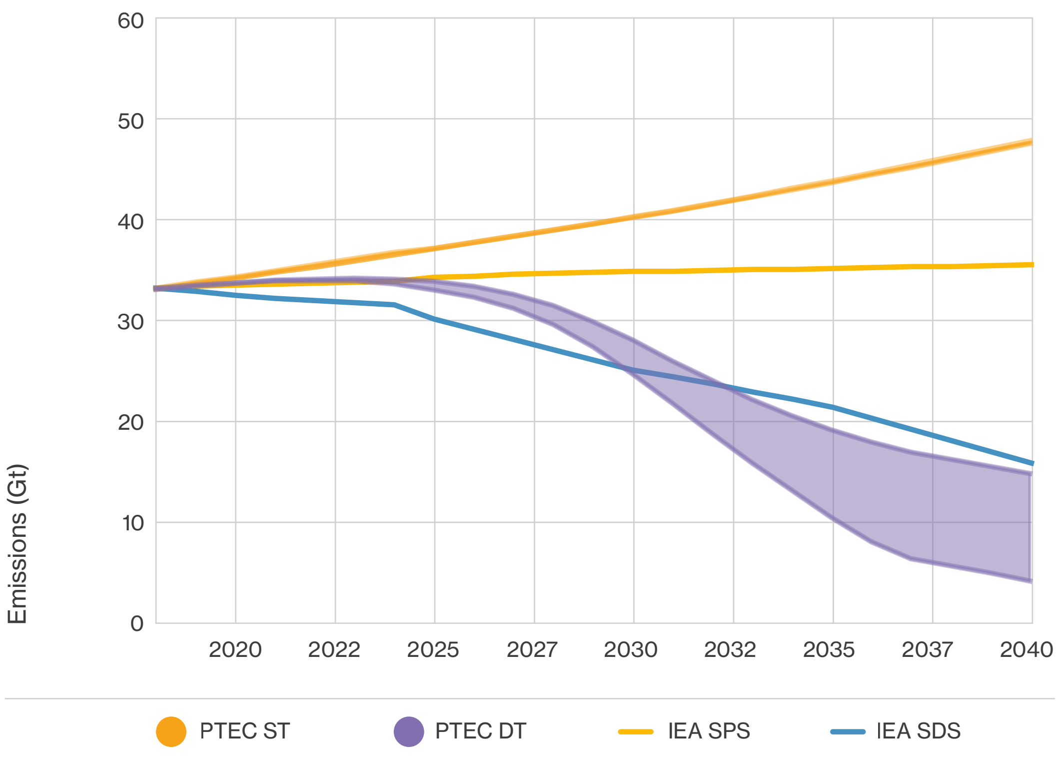


Figure 18: A comparison of PTEC to IEA Scenarios global energy system emissions. Source: this report and IEA World Energy Outlook 2019.

Equilibration with IPCC emissions in 2018

To equilibrate the PTEC scenarios with the full anthropogenic emission scenarios of the IPCC scenarios we must develop a method for adding non-energy system emissions. This is more difficult than equilibrating with the IEA modelled outputs, and hence involves greater uncertainty. PTEC is a model of the global energy system. It therefore provides little information about how other sources of anthropogenic greenhouse gas emissions could evolve in the scenarios generated using PTEC. We provide here the details of the steps we have taken to produce the results presented in Section 4.

Firstly, we provide some background information on the IPCC emission scenarios presented in this report.

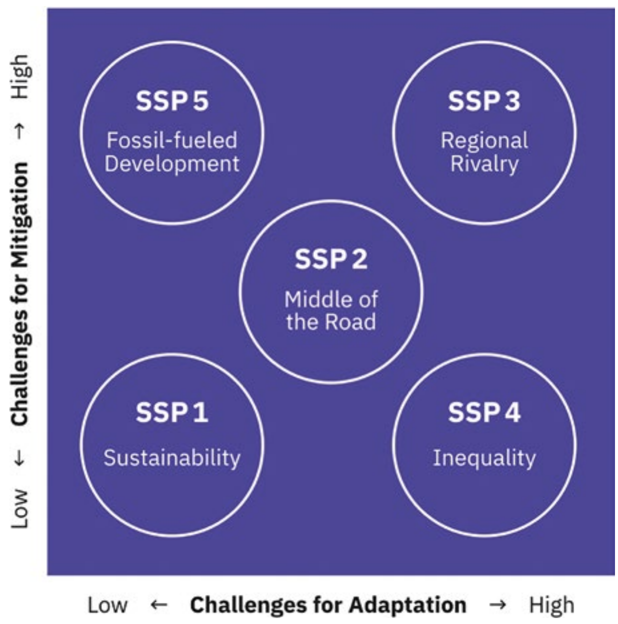
The Scenario Matrix architecture

To achieve some standardisation and comparability across climate research, two main sets of future scenarios or trajectories that were initially developed concurrently but separately, were combined into what is referred to as the Scenario Matrix Architecture. The first set of scenarios, the **Representative Concentration Pathways**, provide estimates of the radiative forcing on the climate system of various greenhouse gas emission pathways, and the other, the **Shared Socioeconomic Pathways**, provide plausible socioeconomic scenarios of global development that might produce such emission pathways (van Vuuren et al., 2014). These will be described in some detail here as the outputs of the modelling efforts presented in this report have been designed to be directly comparable to these standardised scenarios.

The first set of scenarios, known as Representative Concentration Pathways (RCPs), have been the standard reference to classify the stringency of different warming limits. They provide projections of the trajectory and cumulative greenhouse gas concentrations, with consequent radiative forcing. They originally ranged from the lower emission pathway RCP2.6 to the worst-case pathway RCP8.5, with the associated numbers representing the total radiative forcing in year 2100 relative to 1750 (from 2.6 W/m² to 8.5W/m²). This range corresponds to an increase in global mean temperatures above pre-industrial levels of around 2°C to 4.3°C in 2100. 9 An additional RCP1.9 was introduced following the Paris Agreement and captures pathways that achieve the 1.5 °C Paris warming target with some certainty.

For each category of emissions, RCPs contain a set of starting values and future emissions and include all greenhouse gas (GHG) emissions such as carbon dioxide (CO_2), water vapor, methane (CH_4), nitrous oxides (NOx), and ozone (O_3), aerosols, such as soot and dust, which can reduce warming. They can also include natural sources of radiative forcing change, including sun cycles and volcanic activity (which can also temporarily reduce warming). The RCPs provide information on all components of radiative forcing that are needed as input for climate modelling and atmospheric chemistry modelling (emissions of greenhouse gases, air pollutants and land use), that were constructed through a collaboration of the integrated assessment model (IAM), impacts, adaptation, and vulnerability (IAV) models; and climate modelling (CM) communities.

Initially the RCPs were created using emissions based on the Special Report on Emissions Scenarios (SRES) which cover a wide range of key drivers of future emissions (IPCC, 2000). This original ensemble of RCP scenarios were selected from the literature that existed at the time, and corralled into the RCPs on the basis of their emissions and associated concentration levels (van Vuuren et al., 2011). However, this approach for developing scenarios meant there was no consistent set of socio-economic narratives associated with each of these RCPs.



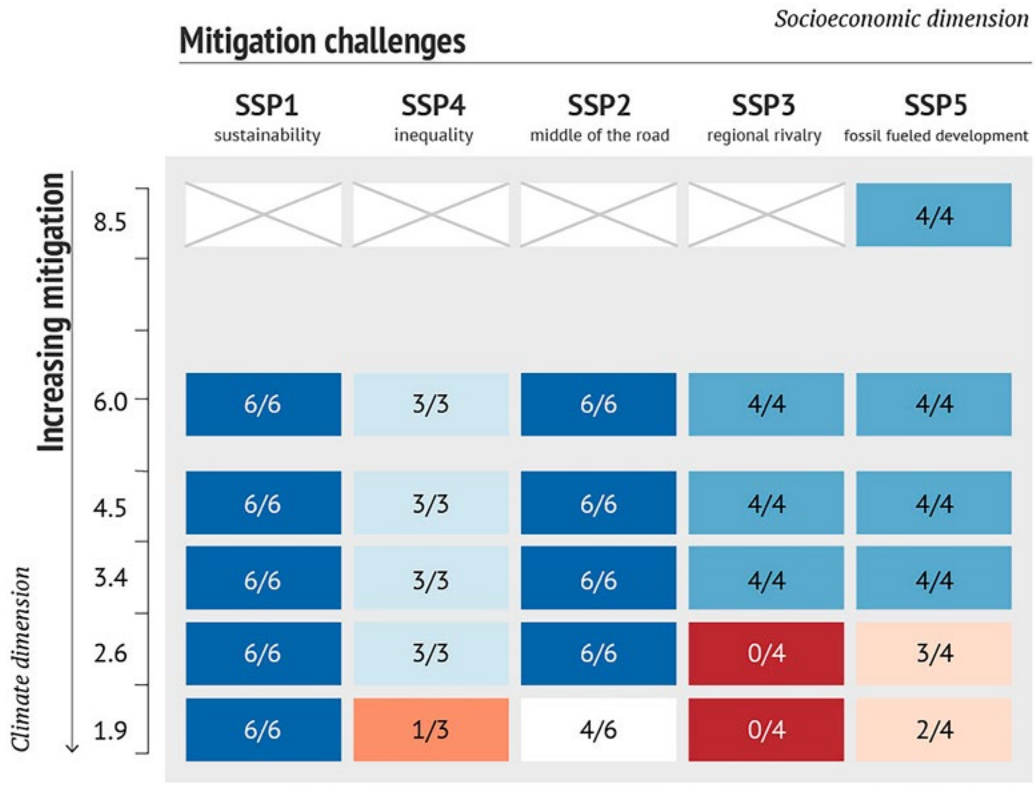
Since CMIP5 and IPCC AR5 the RCPs have been matched with a set of social-economic scenarios known as the Shared Socioeconomic Pathways (SSPs). They give a consistent 'baseline' storyline of future population, economic growth, societal attitudes, technology costs and the arena of international policy, that are independent of mitigation possibilities. Each is based on a different narrative, with qualitative 'low', 'medium', or 'high' capabilities to mitigate or adapt (see Figure 19).[33]

● **Figure 19**: SSPs classified by challenges for mitigation and adaptation. Source: Climate change scenarios.

The SSPs were originally developed separately from the RCPs, portraying the outcomes in terms of emissions given an absence of climate policy. However, they were designed to be complementary and during the CMIP5 process were eventually combined with the RCPs to form a Scenario Matrix (Figure 20). This was achieved using "shared policy assumptions" around the speed of international collaboration on climate policy in each of the SSPs, and a climate policy "lever".

33 SSP1 is the Sustainability scenario: a world in which the global population peaks mid- century, and there are strong and flexible global, regional and national institutions; SSP2 is the Middle of the Road scenario: a continuation of economic and technological trends with slow process to achieving the SDGs; SSP3 is a Resurgent Nationalism scenario: regional rivalry and conflicts with weak global institutions, and fossil fuel dependence; SSP4 is an ever-increasing Inequality scenario: modelling a growing divide between prosperous and well educated societies and the global poor; and lastly SSP5 is the rapid growth scenario: a world in which economic output and fossil fuel energy use are unconstrained by environmental consequences (van Vuuren et al., 2014).

Each IAM can combine socioeconomic scenarios and either mitigation-adaptation assumptions or emissions targets to produce this scenario matrix to provides a range of climate impacts for differing abatement rates. The underlying IAMs help identify socioeconomic and technological conditions under which the pathways may be attained in the real world. Some of the more extreme emissions scenarios are infeasible for certain IAMs (or all IAMs) given their parameterisation of the constraints under certain socioeconomic scenarios.[34] (For example, no IAM is able to achieve the climate goals of RCP2.6 in the SSP3 scenario – shown in red in Figure 20). This Scenario Matrix approach was central to the IPCC AR5, in which six IAMs were used [35] (see Figure 2) to generate 24 baseline scenarios, from which a single 'marker' was selected for each SSP and aligned with emissions targets in the form of the RCPs.



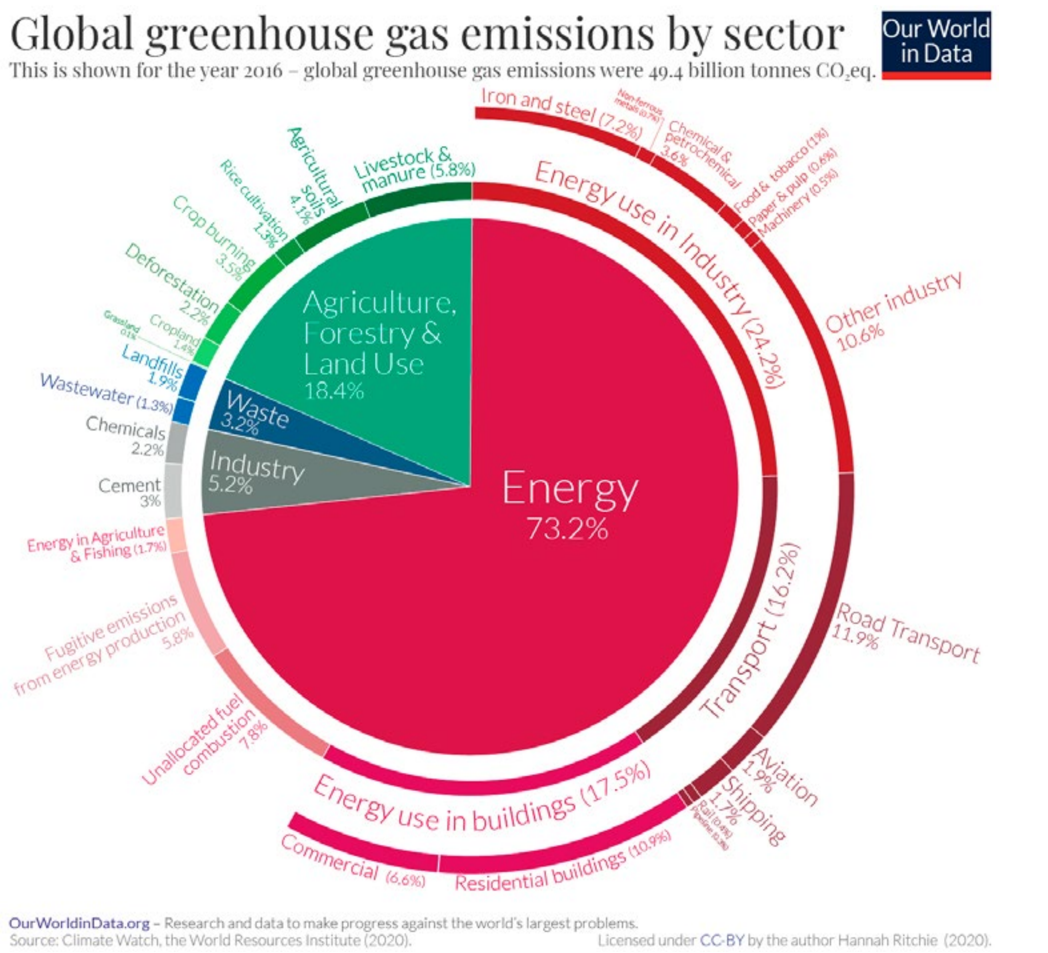
- **Figure 20**: The scenario matrix. Source: Carbon Brief, based on (Rogelj, Popp, Calvin, Luderer, Emmerling, Gernaat, Fujimori, Strefler, Hasegawa, Marangoni, Krey, Kriegler, Riahi, van Vuuren, et al., 2018).

34 These include human and financial resources, governance coordination, uncertainty about projected impacts, different perceptions of risk, competing values, absence of key leaders and advocates and limited monitoring tools, as well as "shared policy assumptions" about how quickly international collaboration on climate change could occur within each SSP.

35 Six IAMs used: AIM-CGE, GCAM, IMAGE, MESSAGE-GLOBIOM, REMIND-Magpie, and WITCH-GLOBIOM. IPCC AR5 WGIII.

Accounting for missing non-energy sector components

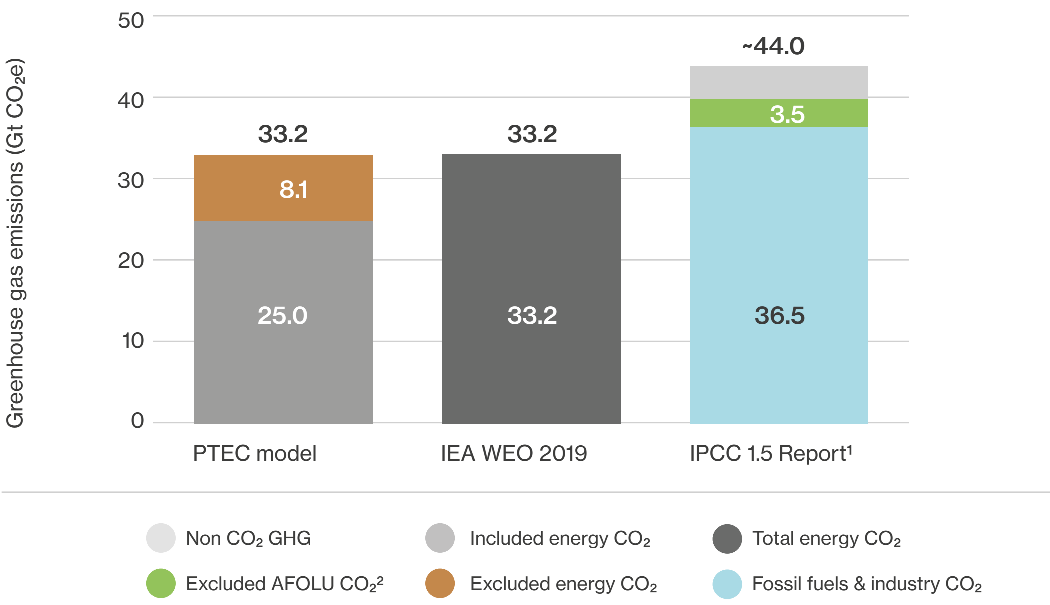
As shown in Figure 21 the energy system is responsible for around three quarters of the world's greenhouse gas emissions. Other major sources of anthropogenic emissions include Agriculture, Forestry and Land Use (AFOLU), waste management and GHG emitting chemical industries such as cement production. It includes non-CO_2 emissions from the energy sector, such as methane, nitrous oxides, and aerosols. The latter are problematic as aerosols can actually reduce the impact of warming by reflecting long-wave radiation from the sun and are a primarily produced from energy generation using fossil fuels and volcanoes.



● **Figure 21**: Gobal greenhouse gas emissions by sector for 2016. Source: Our World In Data.

When compared to the IEA emission estimates (Figure 22) we see that there are approximately 10 Gt of additional CO_2 equivalent greenhouse gas emissions in the IPCC scenarios that are not included in the IEA system model. Our approach to dealing with this uncertainty is to embrace it. That is, to incorporate the entire range of non-energy emissions from the IPCC SR1.5 Scenario Matrix in our estimates of non-energy emission for the PTEC scenarios. Future agriculture, forestry, and other land use (AFOLU) changes will be heavily dependent on key socio-economic drivers such population growth and economic growth. As each of the PTEC scenarios assumes a 2% annual increase in useful energy demand we are limited to socio-economic scenarios that achieve a similar consistent energy demand increase. Unfortunately, most of the SSPs involve reduced useful energy demand.

Only the SSP5 “Take the Highway” scenario has a comparable increase in useful energy demand. Thus, this does not provide us with a range of population and economic growth with which to capture the uncertainty around AFOLU changes that could occur in both PTEC scenarios. To solve this problem, we instead apply the emissions of the entire range of AFOLU estimates from the IPCC Scenario Matrix.



- **Figure 22**: The comparison of greenhouse gas emissions in 2018 between the PTEC Model, the IEA World Economic Outlook 2019 and the IPCC 1.5 degrees Special Report. Sources: This report and (IEA 2019); 1. IPCC SR15 Full report p.113, 2. CMIP6, 2018 figures.

A similar approach is taken to incorporating non-CO_2 emissions. Unlike the AFOLU emissions, most of the non-CO_2 emissions are associated with the energy system, particularly the generation of methane from leakage and aerosols from power generation in the high fossil-based Stalled Transition scenario. For reasons unclear, the IEA scenarios only provide CO_2 emissions. However, the degree to which such non-CO_2 emissions will be problematic will depend on the efforts of the society and the fossil fuel industry to reduce these additional emissions through leakage and pollution reductions efforts and legislation.

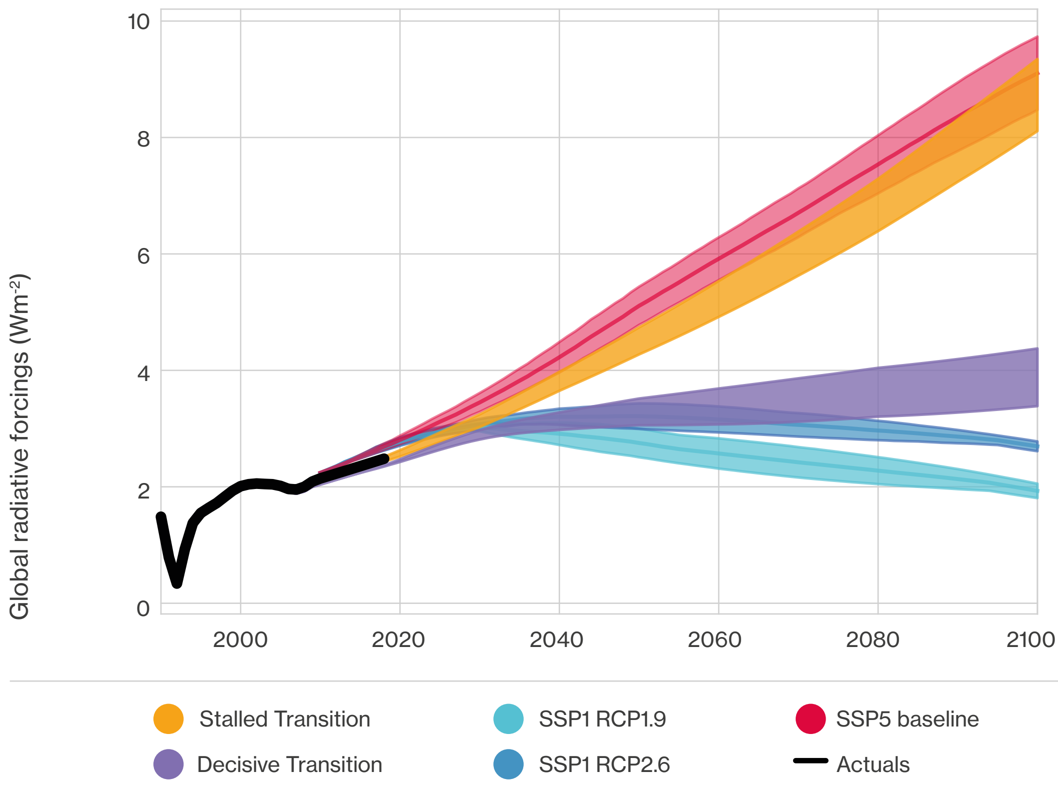
To accommodate the inherent uncertainty in the extent to which society will manage this problem in the future, we include the non-CO_2 emissions estimates for a range of RCPs for each of the PTEC scenarios. For the Decisive Transition scenario, we add the range of estimates of non-CO_2 emissions from RCP2.6 and RCP 4.5. To reflect the higher fossil fuel outputs in the Stalled Transition scenario, we add the range of estimates of non-CO_2 emissions from RCP6.0 and RCP8.5. SO2 levels were matched to RCP2.6 and RCP8.5 for the Stalled and Decisive Transition scenarios, respectively.

Finally, the bands of uncertainty created for each scenario from these additional full anthropogenic emissions are added to bands of uncertainty created by the addition of the missing components found during the equilibration with the IEA scenarios.

Calculating radiative forcing and global warming for each scenario

Finally, the FaIR climate emulator[36] was used to convert the anthropogenic emissions estimated for enhanced Stalled and Decisive Transition scenarios to radiative forcing and warming calculations (Boucher & Reddy, 2008; Joos et al., 2013; Millar et al., 2017b). A equilibrium climate sensitivity (ECS) of 2.7°C, a transient climate response (TCR) of 1.6°C, as given in (Millar et al., 2017a), and a base rate of 0.057 W.m-2 of natural forcings were included beyond 2010.

The estimated radiative forcings from each of these scenarios are shown in Figure 23 along with those of three IPCC scenarios, SSP5-8.5, SSP1-2.6 and SSP1-1.9. The values shown for the IPCC scenarios are the range of FaIR mean radiative forcings values from the five IAM models (AIM/CGE 2.0, GCAM 4.2, IMAGE 3.0.1, REMIND-MAgPIE 1.5 and WITCH-GLOBIOM 3.1) taken from the IIASA 1.5degrees Special Report database.[37] The equivalent warming scenarios are presented in Section 4. Readers should be aware that the FaIR model is a regarded as providing a reasonable fit to the IPCC Global Circulation Models for lower emission pathways and emulates near-term temperature trends more realistically than MAGICC (Leach et al., 2018), but underestimates the temperature response for RCP8.5 (Smith et al., 2018). Finally, readers should note that the disparity that can be seen in Figure 23 between the PTEC Scenarios and the IPCC Scenarios between the years 2005 and 2018 are due to the PTEC scenarios using actual data to 2018 and the IPCC scenarios using simulations that begin in 2005.



● **Figure 23**: The radiative forcing generated by the two enhanced PTEC scenarios in comparison to the IPCC SSP5-RCP8.5, SSP1-RCP2.6 and SSP1-RCP1.9 scenarios. Source: this report and IPCC 1.5 degrees special report (2018).

36 Using the ECM_OxfordSimpleIAM.xls tool version 0.2.

37 IAMC 1.5°C Scenario Explorer hosted by IIASA.

Appendix D – Estimates of physical climate damages

Climate damages analysis results

To provide a comparison of the estimated physical damages associated with the two PTEC scenarios we applied the range of calculated global emissions from the Stalled and Decisive Transition scenarios to the FUND-Hector model (Anthoff & Tol, 2013; Hartin et al., 2015). We incorporate some uncertainties included in the FUND-Hector climate module and damage module and apply a Monte Carlo method to randomly sample the uncertainty in the associated parameters with 10,000 simulations. The total global climate damage estimates are shown in Figure 24(a), and these damages as a fraction of global GDP Figure 24(b), assuming the GDP growth associated with the SSP5 Baseline scenario (which is shown in Appendix C to be the IPCC scenario closest to the useful energy growth applied to both the Stalled and Decisive Transition scenarios).

The mean global climate damage under the Stalled Transition scenario is estimated at nearly 13 trillion dollars at the end of this century, which accounts for about 1.5% of global GDP. Conversely, the estimated average global climate damages under Decisive Transition scenario are close to zero in year 2100. Integrating over the century the .Decisive Transition is estimated to avoid over 334 trillion dollars in climate damages from year 2020 to 2100.

The uncertain around estimates according to the FUND-Hector model have the 95th quantile of global climate damage in year 2100 under Stalled Transition scenario, at about 4% of global GDP, much higher than the average climate damage. However, it should be noted that the estimates for climate damages from the FUND model are considered quite conservative. An application of the empirical analysis of warming impacts on GDP from Burke et al. (2015) to the SSP Baseline scenario (which best matches the useful energy growth of the Stalled and Decisive Transition scenarios) provides estimates for climate damages in 2100 of around $520 trillion dollars (Cohen et al., 2020), close to 50 times the estimate given here.

The FUND-Hector model subdivides climate damage into 15 categories (appendix table 1), including the economic damage and non-economic damage. We analyse the climate damage in different sectors. Under Stalled Transition scenario, the impact of climate change on cooling energy demand is the main source of climate damage, which is about 5.7 trillion in year 2100 (about 45% of total climate damage). The agriculture sector benefits from the climate change before 2075 due to the of CO_2 fertilisation effect but suffers from climate change after then.

By the end of the century the climate damage in the agriculture sector accounts for about 25% of total climate damage under Stalled Transition scenario. The climate damage from loss of species and water resources is also significant under Stalled Transition scenario. For the Decisive Transition scenario, the agriculture sector continuously benefits from climate change to the end of the century, which offsets the negative impacts of climate change on energy demand, water resource, and biodiversity.

- **Figure 24**: Global climate damage under Decisive Transition and Stalled Transition scenarios in this century. (a) Total climate damage in constant $2019. (b) Climate damage as the fraction of global GDP assuming a SSP5 baseline economy. The climate damage estimated is uncertain. The pink region in each figure represents the results fall between 25th and 75th quantiles, the grey region represents the 5th and 95th quantiles. The red line and blue line represent the median estimate and average estimates respectively.

The FUND-Hector model

We use the FUND-Hector model to estimate the climate damage under Decisive and Stalled Transition scenario. The FUND-Hector model is constructed by coupling the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) model and a simple climate model Hector. The FUND model is widely applied to estimate the climate impacts in different regions and sectors, as well as to measure the Social Cost of Carbon (SCC).

We apply the FUND version 3.9 in this study, which include 16 regions and 15 sectors.[38] The Hector model is an open-source climate model developed by Pacific Northwest National Laboratory to project key climate variables (GMST, sea level rise, CO_2 concentration) caused by GHG emissions.

The FUND-Hector model includes parameters for which there is a great deal of uncertainty and regional differences. In the climate model Hector, we mainly consider the uncertain climate variable equilibrium climate sensitivity (ECS), and randomly sample the ECS from its AR5-consistent distribution as the input of Hector model. For the FUND model, we retain all the uncertain provided for the coefficients in damage functions. We use the Monte Carlo method to consider these uncertainties and run the FUND-Hector model 10,000 times for each scenario which produces the distributions of climate damage shown in Figure 24.

Scenarios and data

Both scenarios provide estimates of anthropogenic carbon dioxide (CO_2), methane (CH4) and aerosols (e.g., SO2) emissions from 1765 to 2100, which are input into the Hector model. The Hector model also requires other GHG emissions, such as N2O, PFC and HFC. We use the emissions from the similar RCPs as supplements. For Decisive Transition scenario, we use those from RCP2.6 and for Stalled Transition scenario, we use those from RCP8.5. The FUND-Hector model also requires socio-economic assumptions to estimate climate impacts. These socio-economic assumptions include GDP, population, and energy demand. The Decisive Transition scenario and Stalled Transition scenario are characterised by rapid economic growth and high energy demand in the form of 2% p.a. useful energy growth. To replicate this we adopt the socio-economic assumptions of SSP5 in the shared socio-economic pathways database for our analysis, which achieves a very similar 2% p.a. useful energy growth.

38 Water resources, Forests, Heating energy demand, Cooling energy demand, Agriculture, Dry costs, Protect costs, Enter costs, Hurricanes, Extra tropical storms, Species loss, Death costs, Morbidity costs, Wetland costs

Glossary

Term	Definition
Back-test	The process of testing a predictive model using historical data
Business-as-usual	A scenario in which the world continues on its “normal” trajectory, even though something unpleasant (like climate change) might happen
Carbon Capture and Storage (CCS)	The process of capturing, transporting, and disposing of waste carbon dioxide, such that it will not enter the atmosphere. This is primarily done to remove carbon dioxide from industrial and power generation flue gas; more recently there has been progress to remove carbon dioxide from the atmosphere directly
Climate Action Tracker (CAT)	The Climate Action Tracker is an independent scientific analysis that tracks government climate action since 2009 and measures it against the globally agreed Paris Agreement. https://climateactiontracker.org/
Climate Mitigation Models	This report uses this term to refer to a series of energy system models and ‘process-driven’ IAMs, such as those used by the IEA and IPCC that provide information to decision-makers on feasible climate mitigation scenarios.
Decisive Transition	A scenario used by PTEC to model a more environmental outcome than under the Stalled Transition. Under the Decisive Transition, energy services grow at the same rate, resolute policy and investment action maintains the deployment of renewable technologies near their current rates for another decade before they relax to the system-wide growth rate of 2% per year.
Deployment rate	The rate at which an energy technology is deployed and thus gains experience. For example, how many gigawatts of nuclear power generation is built each year
Direct-use primary energy resources	Forms of energy that do not need to be necessarily converted before being used. In PTEC the three direct-use resources are oil, coal, and gas
Earth System Model	A model that incorporates various physical processes to simulate the earth’s climate. This includes explicitly the movement of carbon and are thus essential to capturing the effects of climate change. It may be incorporated into an Integrated Assessment Model
Electric vehicle (EV)	A mode of transportation that is powered by electricity, rather than the common internal combustion engine that derives its energy from fossil fuels.

Term	Definition
Electricity generation technologies	Technologies that generate electricity as a primary energy. In PTEC the seven technologies considered are coal, gas, nuclear, hydropower, biopower, wind, and solar PV
End-use sectors	Sectors of the economy that use the final energy produced. In PTEC the three sectors considered are transportation, industry, and buildings -- making up 83% of the current total
Endogenous Technological Change (ETC)	When the rate of technical progress is determined within a model, rather than being assumed fixed (exogenous)
Energy carriers	Forms in which energy can be transported from generation to final use. In PTEC the five carriers considered are oil, coal, gas, electricity, and P2X fuels
Energy System Model	A model that captures the human use of energy, potentially including technologies, prices, end-use sectors. They can be used to evaluate the greenhouse gases produced by an economy and are thus essential to capturing the effects of climate change. It may be incorporated into an Integrated Assessment Model
Experience curve	The relationship shown when we plot the logs of total/cumulative experience and cost per unit against each other
Experience exponent / Learning rate	Defined as the exponent of log cost over log experience. It is used to capture the rate at which learning translates into cost savings. Using Wright's Law, we can derive it as follows: (Cost per unit) = (Total Experience) ^ (Experience Exponent). Thus (Experience Exponent) = (Cost per unit)/(Total Experience)
Fifth Assessment Report (AR5)	A report organised by the IPCC to provide an update of knowledge on the scientific, technical, and socio-economic aspects of climate change
Final energy	A measure of energy that is in usable form, such as gasoline or electricity. It will then be converted to useful energy
Final Energy Consumption (FEC)	The total amount of final energy used in a system. It is relevant in our analysis for determining if the demand in useful energy is satisfied
Greenhouse Gas (GHG)	Gas that absorbs and emits radiant energy within the thermal infrared range, causing the greenhouse effect. The primary gases are H_20, CO_2, and CH_4, N_20, and 0_3.
Gross Domestic Product (GDP)	A monetary measure of the market value of all the final goods and services produced in a specific time period. It is commonly used to assess the wealth or size of an economy
Integrated Assessment Models (IAM)	A modelling approach that combines the main features of society and economy with the biosphere and atmosphere into one framework. It thus combines many different systems and their interactions
Intergovernmental Panel on Climate Change (IPCC)	Intergovernmental body of the United Nations for assessing the science related to climate change

Term	Definition
Intermittency problem	The problem faced by non-dispatchable renewables by producing varying levels of energy at different times, causing risks of major blackouts. For example, Solar PV may produce surplus energy during the summer, but a deficit in winter. Storage technologies are the key feature of the PTEC model used to resolve the intermittency problem
International Energy Agency (IEA)	An international intergovernmental organisation established in 1974 to maintain the stability of the international oil supply. It produces the annual World Energy Outlook report
Learning by doing	A concept in Economics whereby productivity gains are achieved through increased practice. It was used by Kenneth Arrow to design endogenous growth theory
Least-cost optimisation	The process whereby a cost-model optimises over the space of all feasible scenarios to find the one with the lowest cost. Our PTEC scenarios are not derived from such a process and thus may represent a lower bound of the actual value from accelerating a green transition
Levelised Cost of Electricity	Defined as the net present value of the generated electrical energy over the lifetime of a electricity generating plant. It is used to compare different methods of electricity generation on a consistent basis
Model Intercomparison Projects (MIP)	Attempts to compare and evaluate different models, often using a standard experimental framework. This can be help identify each model's strengths and weaknesses as well as identify why they make different projections. For climate change, the most prominent example of this is the Coupled Model Intercomparison Project (Phase 6).
Moore's law	The observation that the number of transistors in a dense integrated circuit doubles about every two years
Nationally Determined Contribution (NDC)	Agreed upon efforts by each country of the Paris Agreement to reduce their national emissions and adapt to the impacts of climate change. This is intended to limiting warming to 1.5 to 2 degrees Celsius above pre-industrial levels
Power-to-X fuel (P2X)	A collection of electricity conversion, energy storage, and reconversion pathways. X stands for any form of chemical storage, such as hydrogen, ammonia, or methanol. They are used to store surplus electric power, typically during periods where fluctuating renewable energy generation exceeds load
Paris-compliant	A scenario or world outcome whereby we limit global warming to 1.5 to 2 degrees Celsius above pre-industrial levels
Policy Evaluation Models (PEM)	Models that use an underlying scenario to explore feasible pathways for mitigating climate change, such as 'process-driven' IAMs. This contrasts with the Policy Optimisation Models
Policy Optimisation Models (POM)	Models that determine the (globally) optimal pathway from the perspective of a social planner. This contrasts with the Policy Evaluation Models

Term	Definition
Policy Mood Music	The current range of policies being considered by decision-makers, including common assumptions and beliefs underlining these policies
Floor Cost	Set a lower bound for the costs that specific technology may attain over time. These can be hard bound or soft bound (i.e. asymptotic) and are used in several Climate Mitigation Models
Primary energy	A measure of energy as found in nature, such as the blocks of coal or barrels of crude oil. It will then get converted to final energy
Primary-to-final conversion efficiencies	The fraction of primary energy that is converted to final energy. For example, how much energy in a barrel of crude oil will be successfully transferred to power a internal combustion engine (as opposed to how much is lost on the way). Note that this may differ across technologies and across sectors.
Probabilistic Technological Change Model (PTEC)	A model produced by Way et al. (2020) to evaluate the cost of different global energy systems. It is used to derive the Decisive and Stalled Transition in our analysis
Process-driven	A term used to describe an IAM that quantifies future developmental pathways, including detailed sectoral information. These are frequently used by the IPCC, with prominent examples including IMAGE, MESSAGEix, and WITCH-GLOBIOM
Radiative forcing	The difference between solar irradiance absorbed by the Earth and energy radiated back to space. It is the scientific basis for the greenhouse effect and thus a major determinant of climate change
Replacement rate	The rate at which deployed energy technologies expire and thus need to be replaced, to maintain the same level of energy generation. It is usually determined by the expected lifetime of a current energy generation system. For example, if we assume that a given wind turbine has a lifetime of 25 to 50 years, the replacement rate of such structures would be 2-4% per year.
Representative Concentration Pathways (RCPs)	Four different greenhouse gas concentration trajectories They are commonly used to in climate modelling together with Shared Socioeconomic Pathways, including for the IPCC's AR5
Shared Socioeconomic Pathways (SSP)	Five different scenarios of projected socioeconomic global changes up to 2100. They are commonly used to in climate modelling together with Representative Concentration Pathways, including for the IPCC's AR5. For our analysis, we mainly focus on SSP1 and SSP5 to contrast the Decisive- and Stalled Transition respectively
Slack variable	A variable that is added to an inequality constraint to transform it into an equality. In PTEC scenarios, gas electricity is used to make up any shortfall in the 2% per annum growth in useful energy (e.g. if renewables and fossil fuels grow useful energy by 1.8%, gas electricity will make up the remaining 0.2%)

Term	Definition
Socio-technical transitions (STT)	The social and technical aspects facing an energy transition, such as infrastructure requirements, regulations, and organisation. These aspects are not explicitly considered in the PTEC model
Stalled Transition	A scenario used by PTEC. Under the Stalled Transition, the current energy mix remains approximately constant, whilst useful energy still grows by 2% per annum
Stated Policies Scenario (SPS)	A scenario used by the IEA in its most recent World Energy Outlook report. It considers only specific policy initiatives that have already been announced and projects these forward to 2040
Stochastic	Property of being well described by a random probability distribution. The opposite of this is deterministic.
Stranded Assets	Defined as assets that "have suffered from unanticipated or premature write-downs, devaluations or conversion to liabilities". In the context of climate change, this may be for example oil reserves that will no longer be used in a low-carbon economy
Sustainable Development Scenario (SDS)	A scenario used by the IEA in its most recent World Energy Outlook report. It is defined as a future where we hit global net zero in CO_2 by 2070 and also fulfil the key energy-related goals of the United Nations Sustainable Development Agenda
Total Primary Energy Demand (TPED)	The total amount of primary energy produced in a system. It is relevant in our analysis for determining how many carbon emissions are released under a given scenario
United Nations Climate Change Conference (COP26)	Yearly conferences held in the framework of the United Nations Framework Convention on Climate Change. In 2020, the 26th conference was intended to be held in Glasgow under the presidency of the UK. Due to Covid-19 it has not been postponed to November 2021.
Useful energy	The fraction of energy that is converted to useful purposes, such as moving a car or lighting a building. For both PTEC scenarios, we assume a 2% per annum growth rate in useful energy
Variable renewable energy (VRE)	Renewable energy that is non-dispatchable due to its fluctuating nature and may thus be limited by the intermittency problem. The main examples for our analysis include wind- and solar power.
World Energy Outlook (WEO)	An annual report by the International Energy Agency. It is widely recognised as the most authoritative source for global energy projections and analysis. We use it throughout the report and to draw important comparisons to PTEC
Wright's law	A relationship whereby cost declines as a function of cumulative production. It was first observed by Theodore Paul Wright, who observed that labour requirement fell by 10-15% for every doubling of airplane production. It has since been applied to many more areas

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