Title: Policy Robustness & Uncertainty in Model-based Decision Support for the Energy Transition

Authors: Ian J. Burton, Femke J.M.M. Nijsse, James M. Salter

Keywords: uncertainty quantification, energy modelling, uncertainty analysis, power systems, emulation, climate policy, policy analysis, decision-making

Abstract

Climate policy modelling is a key tool for assessing mitigation strategies in complex systems and uncertainty is inherent and unavoidable. We present a general methodology for extensive uncertainty analysis in climate policy modelling. We show how emulators can identify key uncertainties in modelling frameworks and enable policy analysis previously restricted by computational cost. We apply this methodology to FTT:Power to explore uncertainties in the electricity system transition both globally and in India and to assess how robust mitigation strategies are to a vast range of policy and techno-economic scenarios. We find that uncertainties in transition outcomes are significantly larger than previously shown, but strong policy can narrow these ranges. Globally, plant construction and grid connection lead times dominate transition uncertainty, outweighing regional price policies, including policy reversals in the US. Solar PV proves most resilient due to low costs, though still sensitive to financing and infrastructure limits. Wind and other renewables are more vulnerable. In India, we find that policy packages including even partial phaseout instruments have greater robustness to key uncertainties although longer lead times still hinder policy goals. Our results highlight that reducing lead times and phasing out fossil fuels are critical for faster, more robust power sector transitions.

1. Introduction

The purpose of policy design is to develop lasting solutions for shared problems (Giliberto Capano and Woo 2018). Making such policies in a complicated and unpredictable environment is challenging, and different forms of decision support are used to assess available options. Analysts often use computational models of the system of interest which show how policy options function within the model and provide insight into their likely effects in reality (Kwakkel et al. 2010; Walker et al. 2003). However, as the relationship between models and reality is not fully known, uncertainty is inevitable, limiting the ability to predict policy performance. Some policies may work well in default model settings but lose their effectiveness under other plausible conditions. In complex policy environments, such as climate or energy policy, uncertainty is pervasive and there is need for more in-depth analysis that goes beyond assessing effectiveness under a narrow set of circumstances.

Designing policy that remains effective under uncertainty—so-called robust policy—has emerged as a key goal in policy studies (Dewulf and Biesbroek 2018). (Giliberto Capano and Woo 2018) define policy robustness as a property of policies that allows them to ‘respond to, and retain functionality amid, uncertainty’. Howlett et al. (2018) expand on their definition by adding that robustness allows policies to ‘continue to deliver, over time, their intended functions, purposes and objectives’ across probable or possible contexts. Robustness differs from resilience which emphasises ‘returning to a stable equilibrium point after a shock’ (Capano & Woo 2018; 2017) rather than the ability to attain goals under shocks and uncertainty. A distinction is also made between robustness of policy ‘output’ and ‘process’. Output refers to the policies themselves and policy process refers to the wider policy formulation and implementation cycle such as institutional decision-making frameworks. For example, decision-making under deep uncertainty (DMDU) provides systematic frameworks which seek to guide policymaking across both dimensions (Marchau et al. 2019). Policy processes often include structural and institutional features that, whilst crucial, are typically beyond the remit of policy analysts (Kwakkel et al. 2010). This paper focuses on the ‘output’ aspect of policy robustness from a modelling perspective.

Robustness has long been recognized as a vital attribute in policy design across multiple fields (Dadson et al. 2017; Van der Steen and van Twist 2018) and studies have examined the qualitative characteristics of robust policies (Wilson and Kirman 2016; Kwakkel et al. 2016). However, these are rarely complemented by computational modelling tools. Uncertainty analysis often features in climate policy modelling but the application of such analysis for designing robust policies is rare. Several authors have called for better treatment of uncertainty in the field (Workman et al. 2021; Hepburn et al. 2025; Panos et al. 2023) as uncertainty analysis to date has consisted of a few well-established methodologies (Pastor et al. 2020). However, few studies attempt to use it to identify which policies are robust to uncertainty (Rezai and van der Ploeg 2017; Cai and Sanstad 2016). Several qualitative frameworks have been developed that categorise uncertainty (Kwakkel et al. 2010; Stirling 2010). From a modelling perspective, these uncertainties have been broadly categorised into ‘parametric’ and ‘structural’ uncertainty (Pastor et al. 2020). Existing methods typically capture these uncertainties to estimate ranges of outcomes under broad assumptions about policy ambition (Iyer et al. 2015).

Parametric uncertainty concerns the values of a model’s parameters and how closely they reflect aspects of reality. This can be analysed readily and receives most attention, primarily through scenario or sensitivity analysis (Pastor et al. 2020). Scenario analysis simulates different futures based on alternative assumptions (Brugnach et al. 2008), but it often requires assigning specific values to parameters and perhaps their standard deviation, which themselves may be uncertain. Sensitivity analysis (SA) supplements scenario methods by estimating the influence of parameter uncertainty on model outputs, identifying which inputs drive the most variation and defining uncertainty bounds (IEA 2024). However, it remains subject to the computational cost of the model in question, which limits the application of the method. Structural uncertainty refers to the discrepancy between a model and the system or process it is used to investigate. Inter-model comparisons and ensembles are common techniques for analysing structural uncertainty but remain relatively rare (Simmonds et al. 2022; Pastor et al. 2020; Jaxa-Rozen and Trutnevyte 2021).

Scenario and sensitivity analysis are common in climate policy modelling at the global and regional level. For example, the International Energy Agency (IEA) models several global scenarios of ambition in decarbonisation of the energy sector. In their modelling they find that rapid renewables deployment could put pressure on supporting activity such as permitting or supply chain resilience as well as inducing further cost declines as has already been seen in key technologies (Luderer et al. 2022). They project that emissions will fall nearly 30% by 2035 and approximately 50% by 2050 in their 2024 analysis on stated policies (STEPS, IEA 2024). They find uncertainty in electricity demand is driven by transitions in other industries, unpredictable weather patterns, and the rapid growth of new sectors such as AI data centres. In the accompanying SA, they explore the impact of variation in certain key factors, such as EV sales, on electricity demand, fuel use and subsequent CO_2 emissions. This analysis suggests 2030 emissions could be 1.6% higher or lower than projected due to key uncertainties. More ambitious scenarios are also projected with varying assumptions about renewables deployment, coal phaseouts, energy storage support and demand flexibility.

These types of analyses are also applied to regional transitions also. India is the third largest absolute energy consumer and faces rapidly rising energy demand with electrification in multiple sectors, a growing population, and limited domestic gas reserves (Vijayalaxmi and Manthanwar 2024; Bhatia 2023). Policy instruments have included feed-in tariffs, renewable purchase obligations, tradable renewable energy certificates or transmission cost waivers (Sawhney 2021; Vijayalaxmi and Manthanwar 2024). Scenario projections show solar will continue to expand rapidly and may come to dominate the system (Singh and Idrisi 2020). The Central Electricity Authority (CEA) in India projects between 53-55% renewables energy share (of capacity) by 2030 depending on demand levels, hydropower availability and the cost of batteries (CEA 2023). Previous studies examined key uncertainties affecting renewables uptake such as electricity demand and technology costs (Chaturvedi et al. 2021; Dasgupta and Sarangi 2021). Many studies highlight the need for supporting infrastructure such as transmission upgrades and storage (Singh and Idrisi 2020) and reducing the costs of finance (Shrimali et al. 2013). Critics have argued that modelling performed for India provide widely varying projections, without being explicit about assumptions (Bhatia 2023).

The field of Uncertainty Quantification (UQ) is one avenue for addressing the need for understanding model uncertainties and limitations. UQ replaces complex models with 'emulators' that approximate the true model (O'Hagan 2006), whilst being much more computationally efficient, enabling flexible and robust uncertainty analysis otherwise limited by computational cost (Lee et al. 2011). UQ has been framed as the connection from the mathematical and statistical analysis of complex models to the real world, using a suite of methodologies across fields (Swallow et al. 2022). Emulators are currently not widely used in climate or energy policy modelling. For example, the modelling framework used in this paper, FTT, has adopted uncertainty analysis based around model runs, whether by varying the inputs systematically (SA, Lam et al. 2018) or randomly (Monte Carlo, Nijsse et al. 2023). For policymakers to construct climate policy robust to uncertainties concerning assumptions and model parameters, a first step is developing tools that emphasise this conditional uncertainty within modelling frameworks (Stirling 2010).

This study develops a general methodology, based on uncertainty quantification (UQ), to identify key uncertainties in climate policy and to assess the robustness of policy outcomes. We provide a thorough analysis of model uncertainties at the global and regional level and use this to explore what policy packages show more robustness to key uncertainties for achieving certain policy goals. In section 2, we describe our method and its application to the power system transition model, FTT:Power. We use this framework to analyse key uncertainties in the global electricity system transition and analyse policy robustness for India, with results presented in section 3. In section 4 we discuss our findings in relation to similar research, highlight our contribution and conclude.

2. Methodology

We explore uncertainties affecting the power system transition globally and regionally, and investigate how different policy packages in India perform across a broad range of scenarios. By constructing emulators for different outputs of the model, we explore future scenarios, their uncertainty and the performance of policy packages under thousands of plausible techno-economic and political contexts by varying the values of the relevant unknown or uncertain parameters. This allows us to assess policy robustness to these uncertainties, without requiring infeasible amounts of simulations of the model itself. Our study applies this general methodology to FTT:Power, but it could be applied to a broader set of models and questions.

2.1 FTT:Power

The model family known as Future Technological Transformations (FTT) uses dynamic simulation modelling to understand how technology mixes in various sectors are set to develop in the coming decades (Mercure 2012). FTT:Power is a 71-region model of power sector investors and dispatchers and features 22 electricity generation and storage technologies. Residual load-duration curves are used to model load bands and storage needs; dispatchers decide on which generation asset to use by comparing marginal costs. The model is based on evolutionary dynamics simulating the uptake of technologies in S-curve processes characteristic of innovation. The central aspect is a set of replicator dynamics equations (Lotka-Volterra equations) which model the diffusion of technologies based on comparisons of levelized costs in chains of binary discrete choice models. The model incorporates a wide array of policy instruments, including regulations, taxes and subsidies. Innovation is incorporated by adding technology-specific cost reductions proportionate to cumulative global capacity. A term is added to costs to capture non-financial factors through calibration to historical shares data. This implicitly accounts for non-captured policies.

2.2 Emulation

The analysis uses emulators that are trained on input and output data from FTT:Power model runs at varied inputs. Whilst it is possible to emulate the entirety of FTT:Power, this would be computationally intensive due to the large numbers of potential model inputs and outputs. We focus on inputs and outputs relevant to the current study, but these could easily be substituted for alternatives within the emulation framework for studying different questions. Focusing on specific parts of models is common for all such methods.

2.2.1 Simulator configuration

We conduct a series of model simulations, systematically varying key policy and techno-economic parameters known to significantly influence four energy transition outputs:

1. Electricity generation capacity (onshore wind, solar PV)
2. Power sector emissions
3. Shares of renewables in the electricity mix (by capacity)
4. Weighted costs of electricity generation

Techno-economic inputs determine key aspects of the energy system and the context within which policies function. Table 1 shows some of those varied here, their assumed ranges and whether these vary generally, regionally or by technology. The specification of all 15 techno-economic inputs can be found in the Supplementary Information (SI). We use simplifying parameters that apply to multiple FTT:Power inputs. These can apply uniformly across all regions, like learning rates for technologies, or modify sets of pre-existing values. For example, discount rates have a baseline value for each region-technology combination, and our single discount rate parameter acts on all these, assuming they vary in a correlated fashion. This is a simplifying assumption we choose here for flexibility and tractability.

Input	Technologies / Regions	Ranges	Description/Sources
Learning Exponent	Solar PV	(-0.473) – (-0.165) Mean -0.319	Key parameter for the learning rate (% price decline per doubling of capacity) (Way et al. 2022)
	Onshore wind Offshore wind	(-0.3) – (-0.088)	
Lifetimes	Solar PV	25–35 (years)	(Way et al. 2022; Krey et al. 2019)
	Onshore wind Offshore wind		
Lead times	Solar PV	0.5–1.5 (years)	Lead times split into technology specific and system-wide timescales. Ranges devised from Gumber et al. (2024)
	Onshore wind	1–2 (years)	
	Offshore wind	2–4 (years)	
	Grid connection / commissioning	0-1 (years)	
Discount Rate	Region x Technology	+/- 3% (2% minimum)	IRENA, BNEF
Electricity Demand	Regional	+/- 20% to growth rate of projected demand	E3ME results based on IEA projections
Fuel Prices	Coal Gas (CCGT)	+/- 2 standard deviations from regional mean	Average over last 5 years (IEA)

Table 1. Techno-economic input details. *Each input is listed with the technology/region it applies to within FTT:Power. Ranges provided as well as their sources.*

The learning exponent determines the rate at which costs decline with deployment. Learning rates for similar technologies, e.g. onshore and offshore wind, are varied together. Bringing a generation plant online involves multiple stages (Gumber et al. 2024). We define lead times as the period from construction start to electricity generation. This combines technology- and system-level timescales, including grid connection delays. The discount rate is the rate at which investors discount future costs and revenues, reflecting the opportunity cost of capital and investor preferences for risk (Nasr et al. 2025). It relates to interest rates: cheaper finance means lower discount rates, making long-term and riskier projects more viable.

There are many ways policies could be parametrised in the model, with values specified by year, country, instrument, and industry. To simplify and avoid the simulation of unrealistic scenarios, we group by region and sets of policies determined likely to be correlated, such as upfront subsidies and feed-in tariffs. For each region-instrument combination, we define a single policy parameter that varies on [0,1] and maps onto these groupings. Through combining these policy ambition levels in different ways, certain types of instruments can be switched off entirely or simulated at any rate up to their regional maximum, allowing flexibility in the composition of policy packages simulated.

Table 2 details the three groupings of policy instruments, applied to technologies according to what is most common, depending on aspects such as the maturity of the technology. Phase-outs are applied to fossil fuel-based technologies such as coal, gas and oil. Subsidies are applied to nuclear, biomass, pumped hydro, geothermal and carbon capture and storage (CCS) technologies, and are correlated with feed-in tariffs applied to solar PV, onshore and offshore wind. Feed-in tariffs are differentiated based on the relative costs of these technologies, with wind technologies receiving a larger tariff. Carbon pricing is applied to all emitting technologies.

For regional groupings, China, the United States (US) and India are treated individually while the rest of the world is categorised into Global South or Global North based on World Bank classifications, giving 15 policy parameters (5 regions, 3 policy groupings) controlling levels of policy ambition. For example, the phase-out parameter for China can vary from no phase-out (0) to total phase-out (1), with mid-level phase-out (0.5) resulting in half the capacity additions that would occur under no phase-out. One exception is the feed-in tariff for the US which can also capture rollbacks of policy supporting renewables. For the US, parameter values between 0.5-1 represent the instrument levels in Table 2, values between 0.5-0 represent baseline policy for all instruments except feed-in tariffs which become negative. This is designed to capture removal of tax credits under the Inflation Reduction Act (IRA). Whilst the policy instrument is not identical, it has a similar effect in making renewables less attractive.

Overall, our analysis features 30 variable parameters, split between 15 techno-economic and 15 policy inputs. To produce training data for emulation, 500 runs of FTT:Power are performed at input sets generated by Latin Hypercube Sampling, ensuring comprehensive exploration of the 30-dimensional parameter space (Urban and Fricker 2010). Additional runs can be performed if regions of parameter space are predicted poorly, with validation checks to assess this. Once trained and validated, predictions from the emulator can be made at any combination of inputs.

Instrument	Baseline policy	Mid-level policy	High-level policy
Parameter value (excl. US)	**0**	**0.5**	**1**
Phase-outs *(sales restricted)* *Oil, CCGT, Coal*	0%	50%	100%
Feed-in tariffs Onshore/Offshore	$0/MWh	$20/MWh	$40/MWh
Solar PV	$0/MWh	$15/MWh	$30/MWh
Subsidies (upfront cost reduction)			
Nuclear	0%	10%	20%
CCS (coal, gas, waste)	0%	25%	50%
Biomass (+ CCS)	0%	30%	60%
Geothermal	0%	25%	50%
Pumped Hydro	0%	25%	50%
Carbon Pricing *Oil, CCGT, Coal*	Current regional levels	$\$31/\text{tonCO}_2$ (2022) – $\$345/\text{tonCO}_2$ (2050)	$\$62/\text{tonCO}_2$ (2022) – $\$564/\text{tonCO}_2$ (2050)

Table 2. Policy instrument levels. *Each row signifies what instruments are assumed to be correlated and are varied with the same parameter. Three levels are shown, but parameter values can vary between 0 and 1.*

The more ambitious policy levels are additional to the baseline which implicitly captures current policy for feed-in tariffs, subsidies and phase-outs. The carbon price is the actual level of the policy, if regions have previously existing carbon pricing, such as in the EU, this is replaced with the new level rather than added to it.

2.2.2 Emulator Fitting

Given the model runs generated by the space-filling design above, we train a Gaussian Process (GP) emulator for each output of interest. A GP is a flexible statistical model that can be used to approximate the true, expensive model, producing efficient predictions of the output at any set of inputs. Importantly, a GP provides uncertainty on these predictions, with interpolation at known points and uncertainty increasing as prediction points move further away (in input space) from observed simulations.

Denoting by $f(x)$ a particular output given when FTT:Power is simulated at vector of inputs x in parameter space, the GP emulator has the general form:

$$f(x) \sim \mathrm{GP}(m(x), C(x, x'))$$

with mean function, $m(x)$, and covariance function, $C(x, x')$. The mean function can be used to capture the main trend of the relationship between the inputs and output, for example through a regression on the inputs. The covariance function models correlations in the residuals, with parameters controlling the correlation in each input and the overall variance (Oakley and O'Hagan 2002). Given parameter estimates and data, the predictive mean and variance of $f(x)$ at any unseen inputs $\boldsymbol{x}$ can be written down using properties of the multivariate Normal distribution, and hence predictions are fast.

Emulators were trained for capacity of onshore wind and solar PV, and power sector emissions, at the global level for 2030, 2040 and 2050. For India, emulators were built for these outputs as well as the weighted average cost of electricity generation and shares of the energy mix made up by renewables, for the same years. For each, we use 80% of the 500 simulations for training and 20% for testing. Performance is validated using the test data and leave-one-out prediction (Dunne et al. 2022) (see SI). The emulation framework can be extended to higher dimensional output, for example the full time series of the above outputs, by combining GPs with dimension reduction techniques (Higdon et al. 2008; Salter et al. 2019).

2.3 Sensitivity analysis

Using the above emulators, we perform 'one-at-a-time' (OAAT) sensitivity analysis (SA) to evaluate the inputs that are the main drivers of variability in the model outputs (McNeall et al. 2024). Each input in turn is varied across its entire range whilst the remaining parameters are kept constant. For the non-varied parameters, policy inputs are held at baseline levels (0, representing current policy), and techno-economic parameters at their mean. The relative sensitivity across all outputs is calculated and inputs ranked according to how much variation they drive. The results identify the most important drivers of variability and guide the rest of the analyses.

2.4 Uncertainty Analysis

We can assess a range of policy scenarios rapidly by evaluating the emulators at different sets of inputs. By fixing certain inputs at chosen values, within subranges, or according to some probability distribution, we can sample from the input uncertainty under different scenarios and use the emulators to propagate this uncertainty through the model to give a probabilistic assessment of the output. By placing different assumptions on inputs, the emulators allow for the efficient and rigorous comparison and assessment of the robustness of policy scenarios under uncertainty.

The following describes the specific scenario comparisons. For each scenario, 20,000 samples are drawn from the distributions over the unfixed inputs, with the emulator mean and variance evaluated for the relevant outputs and sampled from to account for emulator uncertainty. Policy parameters are set at certain levels for each of the analyses. For these policy scenarios, the most important techno-economic parameters, for each analysis, are sampled uniformly from specific subranges whilst the remaining inputs are varied normally, therefore we can explore uncertainty across and within scenarios. Lead times are varied by dividing the full range into sub-ranges and then varying uniformly within each, with either 3 (fast, medium, slow) or 2 (fast, low) sub-ranges that partition the original range.

We investigate the global power sector emissions in 2030 and 2050 under several scenarios featuring different levels of global ambition under different assumptions about lead times. The policy scenarios feature one at current policy levels, and two with unified global response at mid and high levels as detailed in Table 2. These more ambitious policy levels are additional to current policy for feed-in tariffs, subsidies and phase-outs and the carbon price is the actual level of the policy. If regions have previously existing carbon pricing, such as in the EU, this is replaced with the new level rather than added to it.

For India's power sector, we first analyse how different policies perform at achieving capacity levels for 2030. A series of policy packages are designed for India's national power system that feature combinations of instruments at different levels. We predict capacity levels of onshore wind and solar PV at each combination of three levels of each instrument, shown in Table 2, and analyse what proportion exceed 393 GW, the combined capacity projected by the CEA (2023).

Next, we analyse the interaction between lead times, electricity demand and phase-out instruments over time. We compare a mid-level phase-out to current policy. For electricity demand, a scenario is classed as having 'low demand' if the growth rate is 0-20% lower than the mean level or 'high demand' if it is 0-20% higher year-on-year.

The final analysis examines a wider range of policies and their robustness in achieving multiple policy objectives under uncertainty. Objectives are represented by chosen target levels for outputs for 2030: 1) the CEA projection of 55% renewables share of generation, not including nuclear and large hydropower, 2) the weighted average cost of electricity generation equal to or below \$68/GJ, the value under current policy derived from the FTT:Power baseline scenario, 3) power sector emissions below 1000 $MtCO_2$/year, representing a reduction of approximately 30% from 2024 levels (Ember 2025). The policies include combinations of all instruments at mid-level (Table 2). We examine the robustness to inputs that are most important across all outputs by comparing the proportion of predictions that achieve the targets under each policy package subject to variation in the techno-economic parameters.

3 Results

We present our results in two parts. Firstly, we explore the key relationships in the model at the global and national level through sensitivity analyses, highlighting the main inputs driving variation, and uncertainty, for energy transition outputs. Secondly, we explore sets of scenarios to compare policy impact and robustness to key uncertainties.

3.1 Sensitivity Analyses

At the global level, we focus on the outputs of cumulative capacity of key technologies, solar PV and onshore wind, and power sector emissions. The SA presented in Figure 1 shows the relative importance of inputs in 2030, 2040 and 2050.

Variation in system-wide grid connection times has the most impact across outputs, particularly for emissions and solar PV capacity in the near term. This is also the case for variation in solar construction times. For onshore wind, whilst construction periods have the most impact on capacity it does not drive much variation in emissions except in 2030. This suggests that onshore additions are not primarily replacing fossil fuels except in the near term. Onshore is less affected by variability in grid connection times than solar as construction times are longer and investment costs are larger, so the impact of faster grid connection has a smaller impact on investor appraisal. In the longer term the learning rate for onshore wind drives most of the variation in capacity as costs decline. This highlights that onshore additions are often at the expense of other renewables, most likely solar. The learning rate of solar has a much smaller relative impact on solar capacity levels. This indicates that costs are already so low that further declines brought about by learning-by-doing only have a marginal impact. Discount rates play a substantial role in the rollout of both technologies in 2040 and 2050, while electricity demand drives substantial variation in all outputs.

Regarding policy inputs, phase-outs have a substantial impact on the level of emissions. In China, phase-outs have a larger impact in the near term as they determine how quickly China reduces its reliance on coal, while longer term, the level of phase-outs in the Global South drives more emissions variation as electricity demand continues to grow. Phase-outs in both regions also propel some variability in onshore capacity. Chinese subsidies drive much variation in onshore expansion particularly in the longer term. US subsidies or rollbacks drive variation particularly in the near term but relatively low amounts. Solar capacity seems not to vary heavily in response to phase-outs, subsidies or carbon pricing but is affected by factors that can be influenced by other policy not modelled here. For example, grid expansion support or monetary policy would influence lead times and discount rates, which here induce much of the variation.

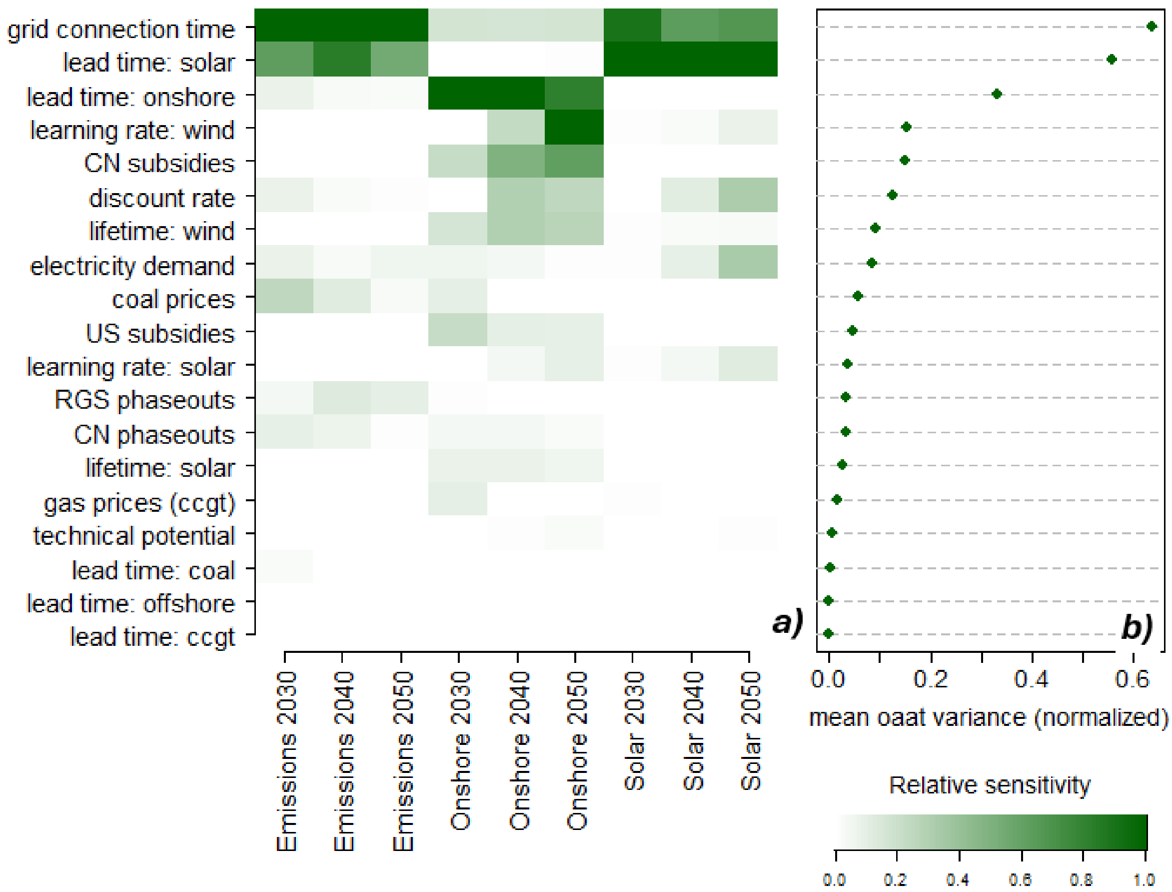

__Figure 1. OAAT sensitivity analysis for global outputs across time__. Panel __a)__ shows the relative sensitivity of outputs (x-axis) to policy and techno-economic inputs (y-axis), policy parameters below 0.001 effect excluded. Panel __b)__ shows the average sensitivities across all outputs shown ordered by importance. Abbreviations: China (CN), Rest of Global South (RGS), Solar PV Capacity (Solar), Onshore Wind Capacity (Onshore). Figure generated using code adapted from McNeall et al. (2024).

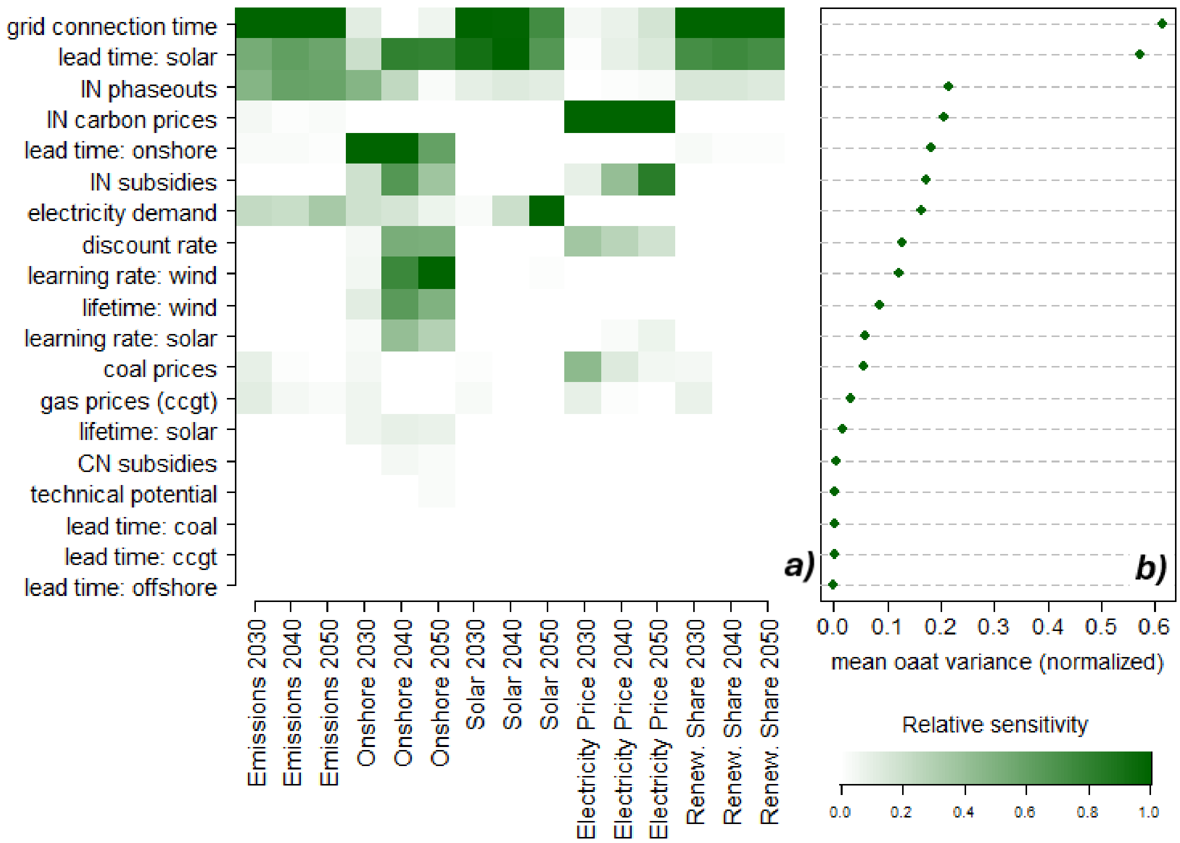

__Figure 2. OAAT sensitivity analysis for India outputs across time__. Same as Figure 1 for Indian outputs. Electricity price refers to weighted average generation price, Renew. Share refers to share of total capacity provided by renewables excluding nuclear and large hydropower.

Figure 2 shows the SA for India. Grid connection and solar lead times drive most variation across outputs, in particular emissions, solar capacity and renewables share, although onshore capacity is less sensitive to grid connection times. Emissions and capacity levels for both technologies are also sensitive to variation in electricity demand. Demand has less influence on the cost of electricity generation and renewables share, implying that greater demand alone is met proportionately by both renewables and fossil fuel-based technologies.

Phase-outs have a strong impact on emissions and near-term onshore capacity and a relatively minor impact on solar capacity, renewables share and the price of electricity generation. The influence on generation costs increases over time and this is also the case for subsidies, but they are most highly affected by carbon taxation. Carbon taxation has a low effect on emissions. Whilst carbon taxes will increase the costs of coal-based generation, India's main source of electricity currently, the discount rate for coal is high so much of this cost is discounted away over time. There is also low availability of other less intensive fossil-based technologies, such as gas, so the tax encourages mostly a shift towards renewables but not as effectively as subsidies which are not discounted. Subsidies drive substantial variation in onshore capacity but not solar.

The results of the above SA provide insight into what inputs drive most variation, and therefore uncertainty, in outputs of interest. This informs which inputs feature more prominently in subsequent analyses. For example, as capacity levels in India are mostly sensitive to phase-outs and subsidies, this is what features in the below instrument comparison.

3.2 Uncertainty Analyses

3.2.1 Global Power Sector Emissions Over Time

Figure 3 shows how the lead times and different levels of global policy ambition interact to influence the level of emissions in 2030 and 2050, under uncertainty in all other techno-economic inputs. Increased policy ambition leads to lower median emissions in all scenarios as well as greater predictability, displayed by the range and shape of the distributions. Scenarios featuring slow leads have greater emissions but are more predictable in the near term. When leads are fast, we see much greater emissions reductions, even under current policy, resulting in an approximate halving of 2050 emissions levels compared to slow rollout scenarios. High global ambition results in even greater reductions and far more predictable 2050 emissions levels. Comparing the impact of lead times to the impact of global policy, we see that fast leads under current policy have an approximately equivalent impact to mid-level policy under slow rollouts.

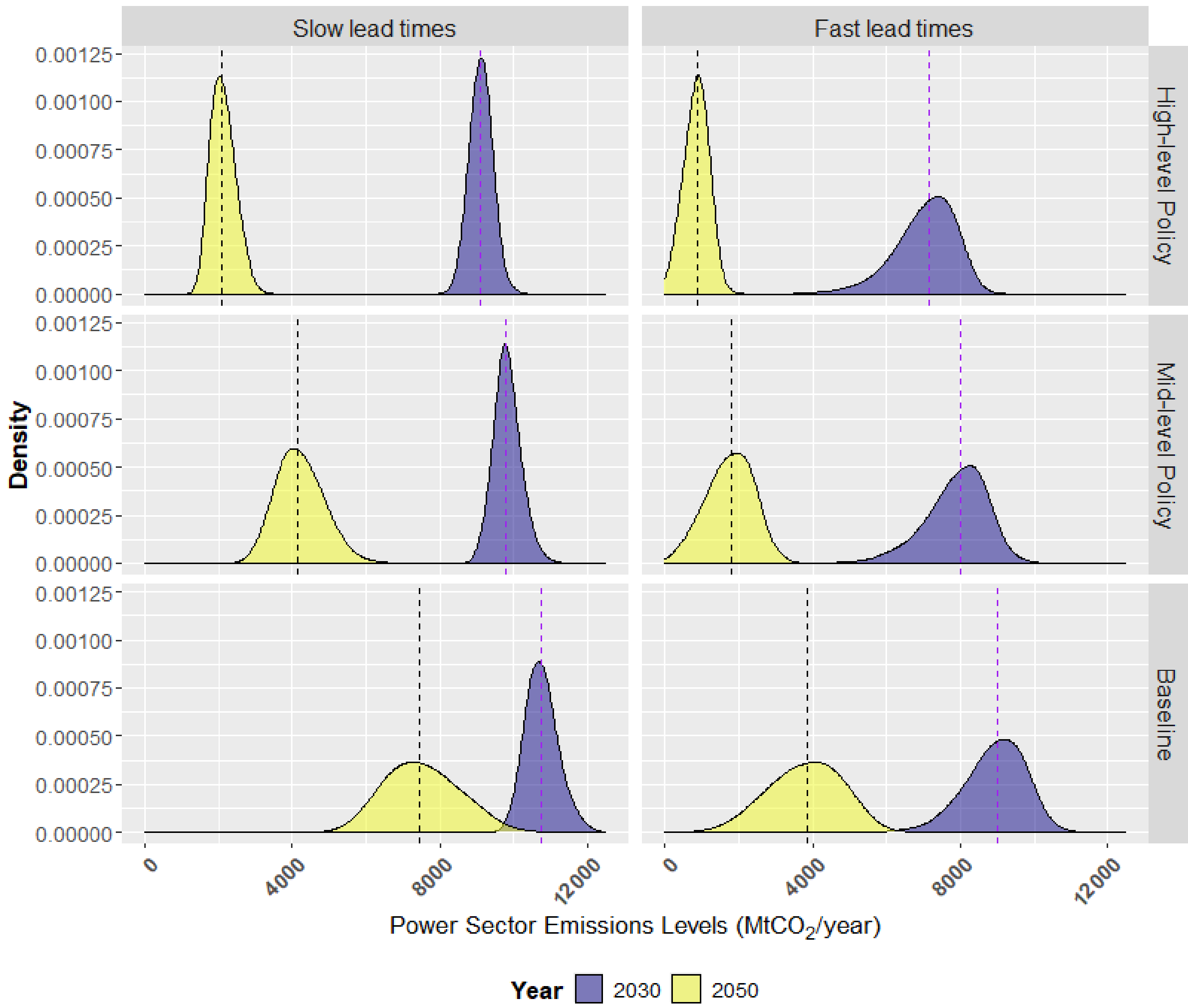

Figure 3. Power sector emissions distributions under different policy-techno-economic scenarios*. Distributions represent the variation due to the uncertain techno-economic inputs within that scenario. Dotted lines are median levels.*

Under fast lead scenarios we see skewed distributions for 2030 emissions levels with a portion of scenarios achieving disproportionately high emissions reductions. These scenarios feature the very fastest speeds where they interact with particularly favourable conditions such as high coal prices and low discount rates which increase investor preferences towards renewables.

3.2.2 India Policy Instrument Comparison for Capacity

Figure 4 shows the uptake of solar PV and onshore wind under different policy instrument combinations in India in 2030. We focus on phase-outs and subsidies only, as carbon pricing was shown by the SA to have little effect on capacity levels in India. We observe that fossil fuel phase-outs significantly drive uptake of solar PV and marginally increase onshore capacity. Subsidies drive greater onshore capacity but have a less pronounced effect on total capacity as in some scenarios, greater subsidies lead to less solar uptake. Under our baseline scenario, bottom left panel of Figure 4, the median combined uptake reaches approximately 390 GW, almost equal to that projected by the CEA (2023), implying a good alignment with government projections for capacity levels. However, we show the large uncertainty associated with these figures and only in 50% of our predictions is that value reached or exceeded in the baseline scenario.

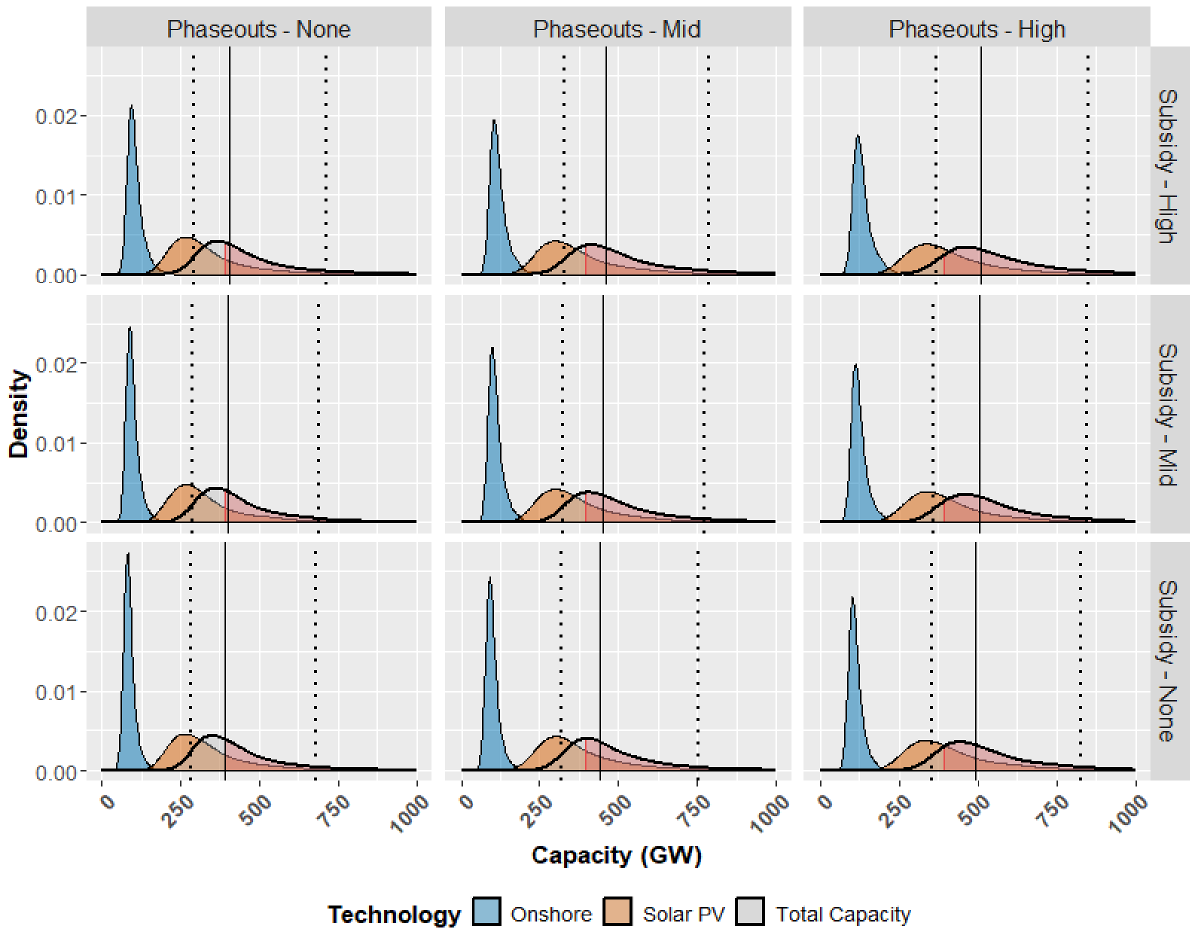

Figure 4: Distributions for Indian renewable energy capacities in 2030 across national policy packages. *Panels represent different policy instrument combinations. Each distribution represents the capacity of onshore, solar PV and their total under variation in techno-economic inputs. The total has 90% ranges marked by dotted lines with black solid lines representing the median total capacity. Red sections represent predictions above 393 GW.*

A high phase-out achieves a 28% increase in median total capacity. Beyond median levels, the number of scenarios where the 393 GW level is exceeded increases substantially as the phase-out strength rises with high phase-outs exceeding this level in just under 95% of scenarios. The skew of the total capacity distributions inherits the skew of solar capacities which is far stronger than that for onshore wind due, primarily, to the impact of lead times. We can infer that scenarios featuring faster leads will result in capacity levels toward the upper portions of the distributions.

When subsidies alone are added to current policy, the median combined capacity level increases marginally. The increase is stronger when focusing solely on uptake of onshore wind, but this is accompanied by a reduction in uptake of solar resulting in a less substantial increase in total capacity. Under our assumptions, which feature larger subsidies for onshore than solar, greater subsidies result in some additions of onshore wind replacing additions of solar PV as opposed to fossil fuels. When subsidies are used in conjunction with phase-outs, this swapping between onshore and solar is mitigated at certain subsidy levels.

These results show not only the impact of policy but also the variability of any policy scenario when subjected to a comprehensive treatment of plausible variability, and therefore uncertainty, in the techno-economic context. This has substantial implications from a planning perspective and in the next subsection we perform more systematic exploration of these uncertainties for emissions.

3.2.2 Phase-out Robustness for Emissions Reduction

Figure 5 shows Indian power sector CO_2 emissions as a function of phaseout levels, lead times, electricity demand and year. Informed by the SA, we focus on phase-outs as the most important instrument for achieving emissions reduction. We compare between our baseline scenario and a mid-level phase-out only as partial phase-outs appear more politically feasible in the near term. We see that even partial phase-outs significantly reduce median emissions and the sensitivity of emission levels to electricity demand levels. Without any phase-out policy, emission levels are more influenced by demand and this sensitivity increases substantially over time. In 2050 under current policy, emissions levels could be anywhere between 0-1800 $MtCO_2$/year . With a partial phase-out this range is restricted to 0-1000 $MtCO_2$/year, a reduction of 45%.

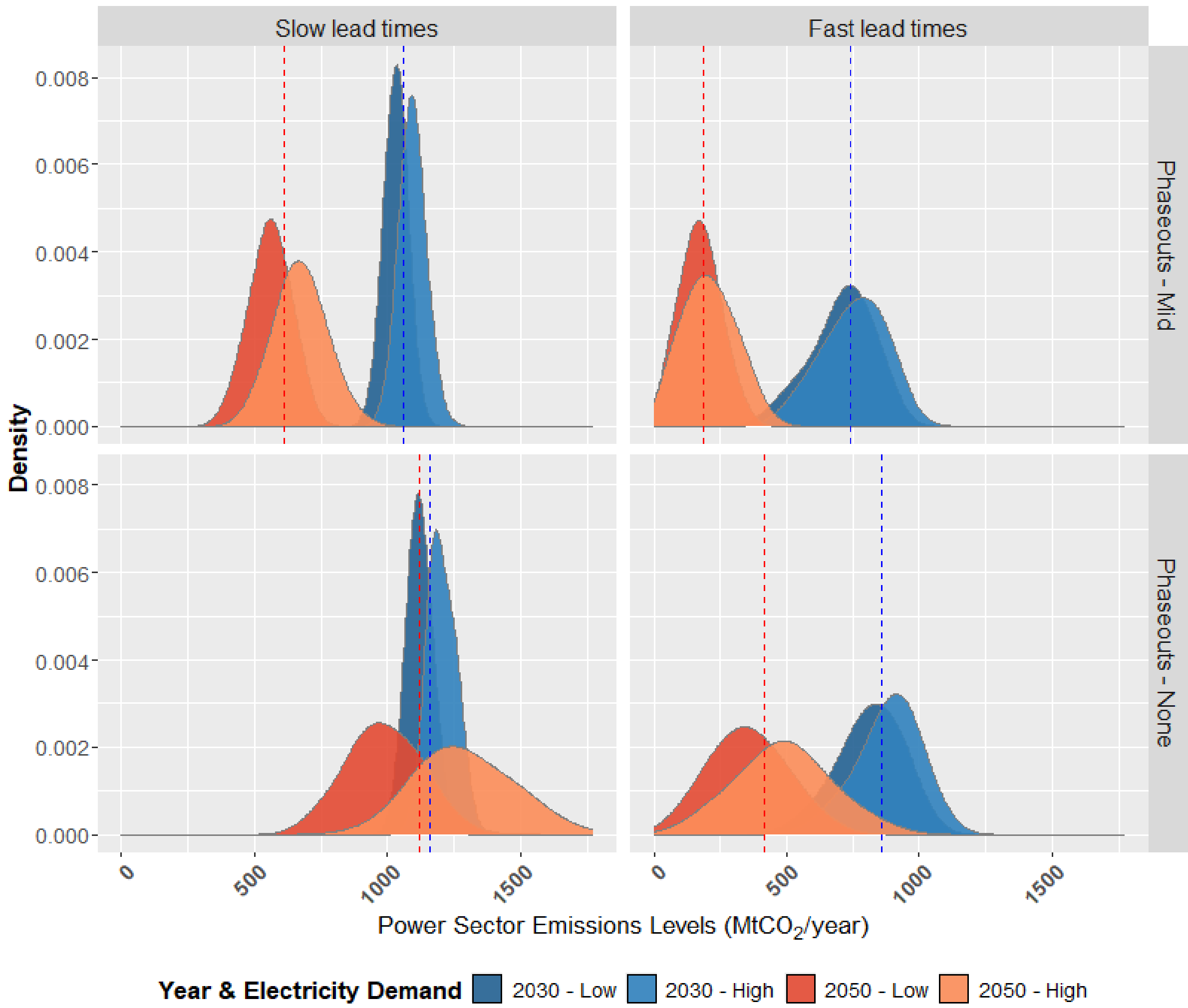

Figure 5: Distributions of Indian power sector emissions under policy and electricity demand variation across time. *Rows represent different levels of phase-outs, columns represent different lead times. The coloured curves represent different years; the shades represent levels of electricity demand. Dotted coloured lines represent the median for all demand levels for that year-leads-policy scenario.*

The sensitivity of emissions to demand increases over time, but less so with a partial phaseout. The wider 'tails' seen in the distributions under no additional policy are substantially decreased under a partial phaseout scenario. Without additional policy, India's power sector emissions could rise substantially by 2050 in scenarios with high demand and slow lead speeds. If construction and connection proceeds quickly then, even under current policies, emissions look set to decrease by 2050. However, if electricity demand is high then there is significantly greater uncertainty. This is shown in the significant difference between the spread of the distributions for 2050 in a fast lead, high electricity demand scenarios. In scenarios with slow leads, high electricity demand results in higher levels of emissions than under fast lead times. The uncertainty driven by electricity demand and its interaction with leads is significantly less under phase-outs, as are median emissions levels.

3.2.3 Policy Robustness Over Multiple Policy Goals

Our results from the two analyses above show phase-outs having substantial impact on the transition in India for individual policy goals. In this section we examine a broader set of policies and goals for India in 2030. Figure 6 displays the proportions of emulator predictions under techno-economic variability that achieve target levels for each policy goal, and the trade-offs. We observe lead times are the uncertainty that all policy packages have the least robustness to, as indicated by the large differences between the panels when compared vertically. However, some policies are robust to other uncertainties for certain targets, observed when comparing horizontally.

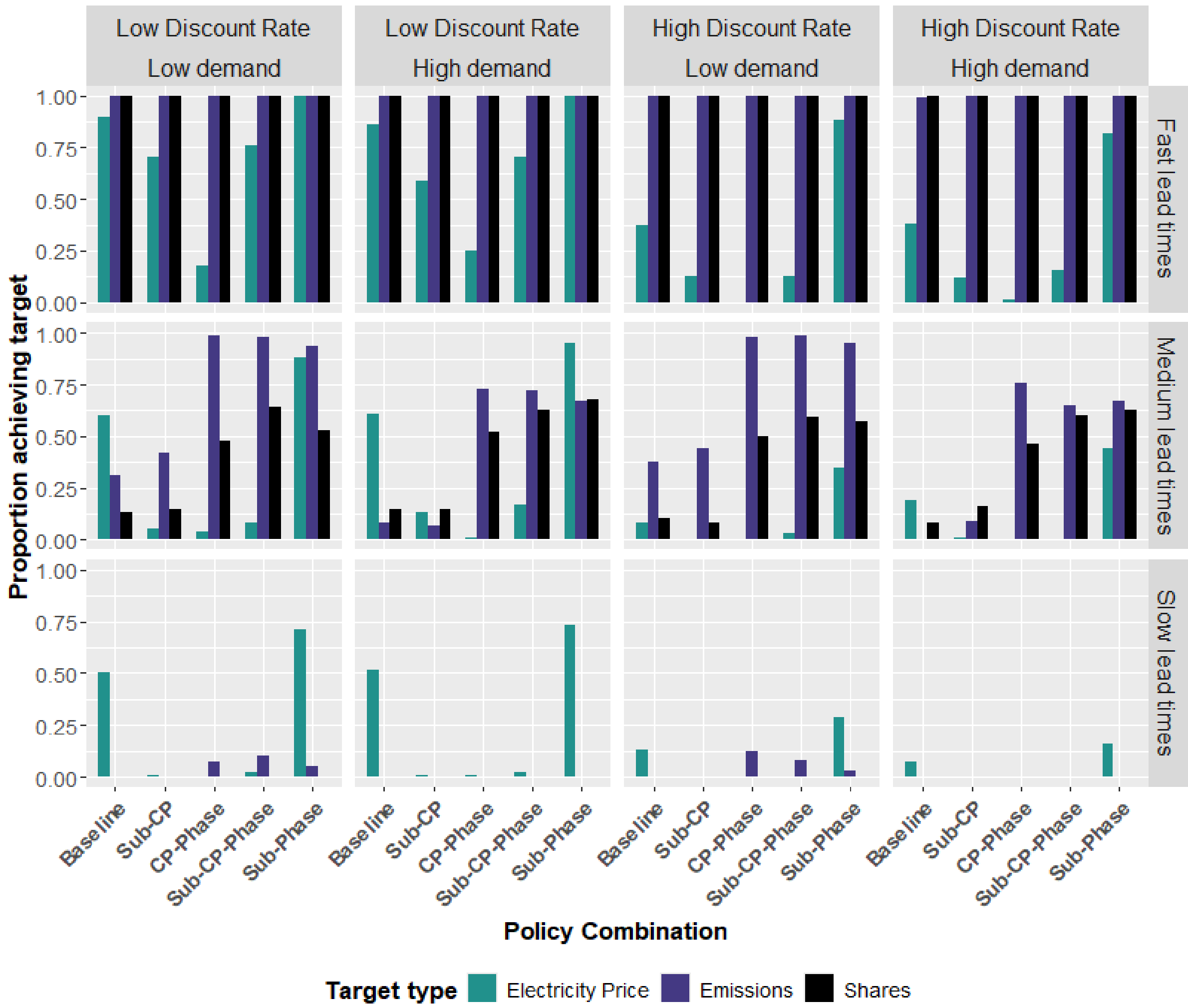

Figure 6. Proportions of predictions meeting 2030 targets in India. *Panels represent different combinations of ranges of techno-economic parameters. Lead times, discount rates and demand are varied uniformly within their subranges, identified by the panel, and all other techno-economic parameters are varied normally. Bars represent the proportion of predictions that achieve targets. Bars are separated into different policy packages: baseline, subsidies-carbon price (Sub-CP), carbon price-phase-outs (CP-Phase), subsidies-carbon price-phase-outs (Sub-CP-Phase), subsidies-phase-outs (Sub-Phase).*

In scenarios where plant integration moves at pace, all policies analysed are robust in achieving goals on emissions and renewable energy share. However, the average levelized price of electricity generation is more sensitive to other uncertainties, particularly discount rates. The policy that is most likely to achieve the cost target are subsidies-phase-outs. With fast leads, current policy also achieves many of the targets under low discount rates but not high ones, particularly if they are accompanied by high electricity demand. This is also the case for other policies except subsidy-phase-outs which remain relatively robust.

Under medium lead times, policy packages that do not include a phase-out instrument reached the emission target far less often. Packages including a phase-out, however, remain relatively robust although higher demand results in a smaller proportion achieving the thresholds. Phase-out-based packages show greater robustness in achieving the renewable energy share target and this is less affected by variability in demand. Carbon pricing-based packages result in higher costs of electricity generation and most predictions have generation costs above baseline levels. Subsidy-phase-outs result in costs staying below target levels in most predictions but this becomes much less likely in scenarios featuring high discount rates and medium or slow lead times. Under slow leads, most policies fail to achieve any goals in most scenarios but if discount rates are low then subsidy-phase-outs result in around 75% of predictions achieving the cost of generation target, greater than current policy. We can infer that even in unfavourable techno-economic contexts this policy would still result in cheaper electricity production as well as a greener power system.

Lead times are clearly the most impactful variable, and all policies have limited robustness to this. Phase-out based instruments exhibit strong robustness to discount rate and electricity demand uncertainty for energy share and emissions goals. When coupled with a subsidy this makes the package more robust to all uncertainties, including lead times, in achieving the generation cost target. These results show that the robustness of policy would be increased significantly if accompanied with policies aimed at decreasing lead times.

4. Discussion & Conclusion

Our methodology enables new treatments of uncertainty that are typically too computationally costly to perform using simulations alone. Using emulators we replicate established methods, incorporate in-depth uncertainty analysis and apply this to policy design. We demonstrate a general methodology for uncertainty analysis in modelling research and apply it to the power system transition model, FTT:Power, with a focus on policy robustness. In this application, we adopt flexible assumptions about policies, regions and general input parameterising to explore the energy transition globally and in India.

We find that variability in plant construction and grid connection speed, or lead times, drives most uncertainty in the global transition, outweighing price policies by individual regions, predominately due to the low cost of solar PV. For selected policy goals in India, partial fossil fuel phaseouts coupled with subsidy support for renewables showed robustness against a wide range of uncertainties. Generally, we infer that policy packages that focus on decreasing lead times, alongside regulation constraining fossil fuel expansion results in quicker, more predictable and more robust transitions in the power sector. However, this predominately favours solar PV expansion and further support for other renewables is necessary.

We show that future global capacity levels of key technologies and power sector emissions are highly sensitive to lead times. Within FTT:Power, longer lead times delay revenue creation, which limits the speed of reinvestment into the next generation of power plants. In other words, the longer lead time impacts the maximum growth rate. Technologies with fast lead times can most rapidly fill in market gaps compared to technologies with longer lead times (Mercure 2015). Given the strong path dependency in the model, with growth proportional to existing shares, this has long-term impacts (Mercure et al. 2014). In earlier stages of the transition, lead times for renewables were relatively low. These have been increasing over time for most renewables, but solar PV remains the quickest to commission (Gumber et al. 2024). Coupled with our findings, this suggests that lead times are a new key and growing driver of uncertainty in the global transition.

Regional energy policies, both supportive and adversarial, now drive relatively less uncertainty at the global level for the expansion of solar PV. This supports previous work highlighting the momentum of solar expansion (Nijsse et al. 2023) and this limits the impact of regional rollbacks, for example, the US's removal of aspects of the Inflation Reduction Act. We show that this has a limited impact on the global transition and that solar PV is particularly resilient due to recent cost declines and strong historical support. Onshore wind is still impacted by market-leading regions like China, but the US impact is minor and only in the near term. However, this does not include all policy levers and does not capture how the US might exert political pressure on other countries (MacNeil and Paterson 2020), or the US's role in international financial institutions (Merling and Forster 2024; Helleiner 2025). Further research is needed into policy affecting enabling factors to give insight into how regional policy exerts influence and drives uncertainty.

By 2030, we see lower median emissions under current policy than IEA projections (2024), though their projections fall within our uncertainty range. We include a broader set of uncertainties, showing that both shorter lead times and fossil fuel phase-outs are critical. Our results reveal much higher sensitivity than the IEA's analysis, underscoring our contribution. Our findings suggest policies focusing on decreasing lead times and enabling financing are critical. Fast lead times is dependent on factors such as permitting regulations, resilient supply chains, grid expansion and other accompanying infrastructure such as storage capacity (IEA 2024). Our contribution highlights the scale of the potential acceleration if progress is made in these areas.

To reduce the costs of capital, financial derisking tools such as contracts-for-difference and green finance remain important to accelerating renewables (Beiter et al. 2024; Christophers 2024) especially for wind, given its higher upfront costs and longer lead times. Whilst we find solar PV is increasingly resilient to financing constraints, it still currently depends on investor confidence and predictable revenues. The influence of investor preferences has also prompted calls for greater public ownership of energy systems (Christophers 2024), underscoring the importance of structural uncertainties beyond our analysis.

India is a growing player in global climate change mitigation. Whilst there is strong alignment between median estimates from our analysis and previous projections (Thambi et al. 2018; Das et al. 2023), our findings show how plausible variability in techno-economic parameters can lead to substantial uncertainty in those estimates. Our results confirm that the large uptake of solar and other renewables is already displacing coal at an accelerating pace (Joshi et al. 2025; Das et al. 2023). The pace of the transition remains uncertain, and conventional methods struggle to assess the likelihood of meeting defined levels. Our approach makes these uncertainties more transparent and enables clearer evaluation of how different policies perform against policy goals.

Our median results suggest a larger renewables share of the energy system by 2030 than previous studies, but this is subject to high uncertainty that is not analysed (Laha and Chakraborty 2021; Fern Lobo et al. 2023). Previous scenario modelling performed for India often produces widely differing results without detailing assumptions (Spencer and Dubash 2022). Our results show explicitly how this is possible as well as how policy design can incorporate this uncertainty.

We show that subsidy-phasedown packages show significant robustness to many uncertainties, but slow lead times still jeopardise policy targets. This aligns with previous research citing the expansion of supporting infrastructure as a key obstacle (Debanjan and Karuna 2022; Vijayalaxmi and Manthanwar 2024). The expansion of solar PV is now resilient to some uncertainties but if this is not accompanied with policies supporting other renewables, storage or flexibility mechanisms than this could slow uptake and endanger grid stability (Debanjan and Karuna 2022). Efforts focused on the justice implications of phase-outs should also be considered (Pandey and Kumar 2025; Vishwanathan et al., n.d.). In contrast to previous work, we do not find that carbon pricing has a substantial impact (Benitez et al. 2023).

Our analysis has the limitation of addressing parametric uncertainty only, and thus it reflects the structural uncertainties of the model (Pastor et al. 2020). For example, FTT:Power depends on generalised LCOE comparisons of technologies, however this concept has been criticized for misrepresenting what investors are interested in and that profit should be the priority (Christophers 2024). To make the methodology more robust, it could be applied to questions of structural uncertainty across models. The use of models implies particular interpretations of policy problems, and other valid interpretations could be overlooked and a comprehensive treatment of uncertainty would consider this (McLaren and Markusson 2020; Stirling 2023; Brugnach and Ingram 2012). Nevertheless, we argue that our methodology provides a more extensive treatment of uncertainty than is seen in much modelling research and it could be applied to structural uncertainty in future work.

We have shown that taking uncertainty seriously has important implications for modelling results. Equally plausible contexts or assumptions lead to dramatically different results. When considering policy targets this becomes especially important. Given that, we highlight new priorities for policy, particularly that of reducing lead times for renewable generation technologies as well as the importance of phase-outs at both the global and Indian national level. Our approach offers a novel way of analysing uncertainty for climate policy and evaluating the policy robustness to those uncertainties.

Acknowledgements

For the purpose of open access, the author has applied a Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version arising from this submission. This project was supported by a UKRI Centre for Doctoral Training in Environmental Intelligence PhD studentship hosted by the University of Exeter (EP/S022074/1).

Supplementary Information

Code and data used for the analysis can be found in the following repository:

https://github.com/cpmodel/FTT_StandAlone/tree/data_update_main_emulation

References

Benitez, L E., M Brinkerink, A Shivakumar, and P Deane. 2023. 'Modelling the Impacts of Carbon Pricing in India's Power System Using a Dynamic Optimization Approach'. *The Electricity Journal* 36 (6): 107291. https://doi.org/10.1016/j.tej.2023.107291.

Bhatia, P. 2023. 'India's State-Led Electricity Transition: A Review of Techno-Economic, Socio-Technical and Political Perspectives'. *Energy Research & Social Science* 102 (August): 103184. https://doi.org/10.1016/j.erss.2023.103184.

Brugnach, M, A Dewulf, C Pahl-Wostl, and T Taillieu. 2008. 'Toward a Relational Concept of Uncertainty: About Knowing Too Little, Knowing Too Differently, and Accepting Not to Know'. *Ecology and Society* 13 (2). https://www.jstor.org/stable/26267972.

Brugnach, M., and H. Ingram. 2012. 'Ambiguity: The Challenge of Knowing and Deciding Together'. *Environmental Science & Policy* 15 (1): 60–71. https://doi.org/10.1016/j.envsci.2011.10.005.

Cai, Y, and A H. Sanstad. 2016. 'Model Uncertainty and Energy Technology Policy: The Example of Induced Technical Change'. *Computers & Operations Research* 66 (February): 362–73. https://doi.org/10.1016/j.cor.2015.07.014.

Capano, G, and J J Woo. 2018. 'Designing Policy Robustness: Outputs and Processes'. *Policy and Society* 37 (4): 422–40. https://doi.org/10.1080/14494035.2018.1504494.

Capano, Giliberto, and Jun Jie Woo. 2017. 'Resilience and Robustness in Policy Design: A Critical Appraisal'. *Policy Sciences* 50 (3): 399–426. https://doi.org/10.1007/s11077-016-9273-x.

Capano, Giliberto, and Jun Jie Woo. 2018. 'Designing Policy Robustness: Outputs and Processes'. *Policy and Society* 37 (4): 422–40. https://doi.org/10.1080/14494035.2018.1504494.

CEA. 2023. *REPORT ON OPTIMAL GENERATION CAPACITY MIX FOR 2029-30 Version 2.0*. Central Electricity Authority, Ministry of Power, Government of India. https://cea.nic.in/wp-content/uploads/notification/2023/05/Optimal_mix_report__2029_30_Version_2.0__For_Uploading.pdf.

Chaturvedi, Vaibhav, Poonam Nagar Koti, and Anjali Ramakrishnan Chordia. 2021. 'Pathways towards India's Nationally Determined Contribution and Mid-Century Strategy'. *Energy and Climate Change* 2 (December): 100031. https://doi.org/10.1016/j.egycc.2021.100031.

Christophers, Brett. 2024. *The Price Is Wrong: Why Capitalism Won't Save the Planet*. Verso.

Dadson, Simon, Jim W. Hall, Dustin Garrick, Claudia Sadoff, David Grey, and Dale Whittington. 2017. 'Water Security, Risk, and Economic Growth: Insights from a Dynamical Systems Model'. *Water Resources Research* 53 (8): 6425–38. https://doi.org/10.1002/2017WR020640.

Das, Anjana, Vinay Saini, Kirit Parikh, Jyoti Parikh, Probal Ghosh, and Mario Tot. 2023. 'Pathways to Net Zero Emissions for the Indian Power Sector'. *Energy Strategy Reviews* 45 (January): 101042. https://doi.org/10.1016/j.esr.2022.101042.

Dasgupta, Diya, and Gopal K. Sarangi. 2021. 'Meeting India's Electricity Demand in 2030'. *Energy and Climate Change* 2 (December): 100038. https://doi.org/10.1016/j.egycc.2021.100038.

Debanjan, Mukherjee, and Kalita Karuna. 2022. 'An Overview of Renewable Energy Scenario in India and Its Impact on Grid Inertia and Frequency Response'. *Renewable and Sustainable Energy Reviews* 168 (October): 112842. https://doi.org/10.1016/j.rser.2022.112842.

Dewulf, Art, and Robbert Biesbroek. 2018. 'Nine Lives of Uncertainty in Decision-Making: Strategies for Dealing with Uncertainty in Environmental Governance'. *Policy and Society* 37 (4): 441–58. https://doi.org/10.1080/14494035.2018.1504484.

Dunne, Michael, Hossein Mohammadi, Peter Challenor, et al. 2022. 'Complex Model Calibration through Emulation, a Worked Example for a Stochastic Epidemic Model'. *Epidemics* 39 (June): 100574. https://doi.org/10.1016/J.EPIDEM.2022.100574.

Ember. 2025. *Global Electricity Review*. https://ember-energy.org/app/uploads/2025/04/Report-Global-Electricity-Review-2025.pdf.

Fern Lobo, Hannah, Rudolf Yeganyan, et al. 2023. *Modelling Clean Energy Transition Pathways for India's Power Sector Using OSeMOSYS (Open-Source Energy Modelling System)*. March 31. https://doi.org/10.21203/rs.3.rs-2753628/v1.

Gumber, Anurag, Riccardo Zana, and Bjarne Steffen. 2024. 'A Global Analysis of Renewable Energy Project Commissioning Timelines'. *Applied Energy* 358 (March): 122563. https://doi.org/10.1016/j.apenergy.2023.122563.

Helleiner, Eric. 2025. 'International Finance and the Global Polycrisis'. *Finance and Space* 2 (1): 221–36. https://doi.org/10.1080/2833115X.2025.2514272.

Hepburn, Cameron, Matthew C Ives, Sam Loni, et al. 2025. 'Economic Models and Frameworks to Guide Climate Policy'. *Oxford Review of Economic Policy*, July 28, graf020. https://doi.org/10.1093/oxrep/graf020.

Higdon, Dave, James Gattiker, Brian Williams, and Maria Rightley. 2008. 'Computer Model Calibration Using High-Dimensional Output'. *Journal of the American Statistical Association* 103 (482): 570–83. https://doi.org/10.1198/016214507000000888.

Howlett, Michael, Giliberto Capano, and M. Ramesh. 2018. 'Designing for Robustness: Surprise, Agility and Improvisation in Policy Design'. *Policy and Society* 37 (4): 405–21. https://doi.org/10.1080/14494035.2018.1504488.

IEA. 2024. *World Energy Outlook*. IEA. https://www.iea.org/reports/world-energy-outlook-2024, Licence: CC BY 4.0 (report); CC BY NC SA 4.0 (Annex A).

Iyer, Gokul, Nathan Hultman, Jiyong Eom, Haewon McJeon, Pralit Patel, and Leon Clarke. 2015. 'Diffusion of Low-Carbon Technologies and the Feasibility of Long-Term Climate Targets'. *Technological Forecasting and Social Change* 90 (January): 103–18. https://doi.org/10.1016/j.techfore.2013.08.025.

Jaxa-Rozen, Marc, and Evelina Trutnevyte. 2021. 'Sources of Uncertainty in Long-Term Global Scenarios of Solar Photovoltaic Technology'. *Nature Climate Change* 11 (3): 266–73. https://doi.org/10.1038/s41558-021-00998-8.

Joshi, Pratik, Anand B. Rao, and Rangan Banerjee. 2025. 'Review of Solar PV Deployment Trends, Policy Instruments, and Growth Projections in China, the United States, and India'. *Renewable and Sustainable Energy Reviews* 213 (May): 115436. https://doi.org/10.1016/j.rser.2025.115436.

Krey, Volker, Fei Guo, Peter Kolp, et al. 2019. 'Looking under the Hood: A Comparison of Techno-Economic Assumptions across National and Global Integrated Assessment Models'. *Energy* 172 (April): 1254–67. https://doi.org/10.1016/j.energy.2018.12.131.

Kwakkel, Jan H., Sibel Eker, and Erik Pruyt. 2016. 'How Robust Is a Robust Policy? Comparing Alternative Robustness Metrics for Robust Decision-Making'. In *Robustness Analysis in Decision Aiding, Optimization, and Analytics*, edited by Michael Doumpos, Constantin Zopounidis, and Evangelos Grigoroudis. Springer International Publishing. https://doi.org/10.1007/978-3-319-33121-8_10.

Kwakkel, Jan H., Warren E. Walker, and Vincent A.W.J. Marchau. 2010. 'Classifying and Communicating Uncertainties in Model-Based Policy Analysis'. *International Journal of Technology, Policy and Management* 10 (4): 299. https://doi.org/10.1504/IJTPM.2010.036918.

Laha, Priyanka, and Basab Chakraborty. 2021. 'Low Carbon Electricity System for India in 2030 Based on Multi-Objective Multi-Criteria Assessment'. *Renewable and Sustainable Energy Reviews* 135 (January): 110356. https://doi.org/10.1016/j.rser.2020.110356.

Lam, Aileen, Soocheol Lee, Jean-François Mercure, et al. 2018. 'Policies and Predictions for a Low-Carbon Transition by 2050 in Passenger Vehicles in East Asia: Based on an

Analysis Using the E3ME-FTT Model'. *Sustainability* 10 (5): 1612. https://doi.org/10.3390/su10051612.
Lee, L. A., K. S. Carslaw, K. J. Pringle, G. W. Mann, and D. V. Spracklen. 2011. 'Emulation of a Complex Global Aerosol Model to Quantify Sensitivity to Uncertain Parameters'. *Atmospheric Chemistry and Physics* 11 (23): 12253–73. https://doi.org/10.5194/ACP-11-12253-2011.
Luderer, Gunnar, Silvia Madeddu, Leon Merfort, et al. 2022. 'Impact of Declining Renewable Energy Costs on Electrification in Low-Emission Scenarios'. *Nature Energy* 7 (1): 32–42. https://doi.org/10.1038/S41560-021-00937-Z.
MacNeil, Robert, and Matthew Paterson. 2020. 'Trump, US Climate Politics, and the Evolving Pattern of Global Climate Governance'. *Global Change, Peace & Security* 32 (1): 1–18. https://doi.org/10.1080/14781158.2020.1675620.
Marchau, Vincent A. W. J., Warren E. Walker, Pieter J. T. M. Bloemen, and Steven W. Popper, eds. 2019. *Decision Making under Deep Uncertainty: From Theory to Practice*. Springer International Publishing. https://doi.org/10.1007/978-3-030-05252-2.
McLaren, Duncan, and Nils Markusson. 2020. 'The Co-Evolution of Technological Promises, Modelling, Policies and Climate Change Targets'. *Nature Climate Change* 10 (5): 5. https://doi.org/10.1038/s41558-020-0740-1.
McNeall, Douglas, Eddy Robertson, and Andy Wiltshire. 2024. 'Constraining the Carbon Cycle in JULES-ES-1.0'. *Geoscientific Model Development* 17 (3): 1059–89. https://doi.org/10.5194/gmd-17-1059-2024.
Mercure, Jean François. 2012. 'FTT:Power A Global Model of the Power Sector with Induced Technological Change and Natural Resource Depletion'. *Energy Policy* 48 (September): 799–811. https://doi.org/10.1016/j.enpol.2012.06.025.
Mercure, Jean-François. 2015. 'An Age Structured Demographic Theory of Technological Change'. *Journal of Evolutionary Economics* 25 (4): 787–820. https://doi.org/10.1007/s00191-015-0413-9.
Mercure, J.-F., H. Pollitt, U. Chewpreecha, et al. 2014. 'The Dynamics of Technology Diffusion and the Impacts of Climate Policy Instruments in the Decarbonisation of the Global Electricity Sector'. *Energy Policy* 73 (October): 686–700. https://doi.org/10.1016/j.enpol.2014.06.029.
Merling, Lara, and Timon Forster. 2024. 'Climate Policy at the International Monetary Fund: No Voice for the Vulnerable?' *Global Policy* 15 (3): 539–53. https://doi.org/10.1111/1758-5899.13367.
Nasr, Amro, David Tan, and Tarek Mohamed. 2025. 'Scenario-Dependent Discounting for Climate Change Adaptation Decisions for Infrastructure'. *Climate Policy* 0 (0): 1–16. https://doi.org/10.1080/14693062.2025.2549563.
Nijsse, Femke J. M. M., Jean-Francois Mercure, Nadia Ameli, et al. 2023. 'The Momentum of the Solar Energy Transition'. *Nature Communications* 14 (1): 6542. https://doi.org/10.1038/s41467-023-41971-7.
Oakley, Jeremy, and Anthony O'Hagan. 2002. 'Bayesian Inference for the Uncertainty Distribution of Computer Model Outputs'. *Biometrika* 89 (4): 769–84. https://doi.org/10.1093/BIOMET/89.4.769.
O'Hagan, A. 2006. 'Bayesian Analysis of Computer Code Outputs: A Tutorial'. *Reliability Engineering and System Safety* 91 (10–11): 1290–300. https://doi.org/10.1016/j.ress.2005.11.025.
Pandey, Jay Ganesh, and Atul Kumar. 2025. 'Navigating India's Energy Transition: A Systematic Literature Review of Risks in the Coal Phase-down Process'. *Renewable and Sustainable Energy Reviews* 210 (March): 115260. https://doi.org/10.1016/j.rser.2024.115260.
Panos, Evangelos, James Glynn, Socrates Kypreos, et al. 2023. 'Deep Decarbonisation Pathways of the Energy System in Times of Unprecedented Uncertainty in the

Energy Sector'. *Energy Policy*, June 29, 113642. https://doi.org/10.1016/j.enpol.2023.113642.
Pastor, A. V., D. C. S. Vieira, F. H. Soudijn, and O. Y. Edelenbosch. 2020. 'How Uncertainties Are Tackled in Multi-Disciplinary Science? A Review of Integrated Assessments under Global Change'. *CATENA* 186 (March): 104305. https://doi.org/10.1016/j.catena.2019.104305.
Pollitt, Hector, and Jean-Francois Mercure. 2017. *Climate Policy The Role of Money and the Financial Sector in Energy-Economy Models Used for Assessing Climate and Energy Policy The Role of Money and the Financial Sector in Energy-Economy Models Used for Assessing Climate and Energy Policy*. https://doi.org/10.1080/14693062.2016.1277685.
Rezai, Armon, and Frederick van der Ploeg. 2017. 'Climate Policies under Climate Model Uncertainty: Max-Min and Min-Max Regret'. *Energy Economics*, Seventh Atlantic Workshop in Energy and Environmental Economics, vol. 68 (October): 4–16. https://doi.org/10.1016/j.eneco.2017.10.018.
Salter, James M., Daniel B. Williamson, John Scinocca, and Viatcheslav Kharin. 2019. 'Uncertainty Quantification for Computer Models With Spatial Output Using Calibration-Optimal Bases'. *Journal of the American Statistical Association* 114 (528): 1800–1814. https://doi.org/10.1080/01621459.2018.1514306.
Sawhney, Aparna. 2021. 'Striving towards a Circular Economy: Climate Policy and Renewable Energy in India'. *Clean Technologies and Environmental Policy* 23 (2): 491–99. https://doi.org/10.1007/s10098-020-01935-7.
Shrimali, Gireesh, David Nelson, Shobhit Goel, Charith Konda, and Raj Kumar. 2013. 'Renewable Deployment in India: Financing Costs and Implications for Policy'. *Energy Policy* 62 (November): 28–43. https://doi.org/10.1016/j.enpol.2013.07.071.
Simmonds, Emily G., Kwaku Peprah Adjei, Christoffer Wold Andersen, et al. 2022. 'Insights into the Quantification and Reporting of Model-Related Uncertainty across Different Disciplines'. *iScience* 25 (12): 105512. https://doi.org/10.1016/j.isci.2022.105512.
Singh, Ayush Kumar, and Amir Hussain Idrisi. 2020. 'Evolution of Renewable Energy in India: Wind and Solar'. *Journal of The Institution of Engineers (India): Series C* 101 (2): 415–27. https://doi.org/10.1007/s40032-019-00545-7.
Spencer, Thomas, and Navroz K. Dubash. 2022. 'Scenarios for Different "Future Indias": Sharpening Energy and Climate Modelling Tools'. *Climate Policy* 22 (1): 30–47. https://doi.org/10.1080/14693062.2021.1973361.
Stirling, Andy. 2010. 'Keep It Complex'. *Nature* 468 (7327): 1029–31. https://doi.org/10.1038/4681029a.
Stirling, Andy. 2023. 'Against Misleading Technocratic Precision in Research Evaluation and Wider Policy – A Response to Franzoni and Stephan (2023), "Uncertainty and Risk-Taking in Science"'. *Research Policy* 52 (3): 104709. https://doi.org/10.1016/j.respol.2022.104709.
Swallow, Ben, Paul Birrell, Joshua Blake, et al. 2022. 'Challenges in Estimation, Uncertainty Quantification and Elicitation for Pandemic Modelling'. *Epidemics* 38 (March): 100547. https://doi.org/10.1016/j.epidem.2022.100547.
Thambi, S., A. Bhatacharya, and O. Fricko. 2018. 'India's Energy and Emissions Outlook: Results from India Energy Model'. Other. Energy, Climate Change and Overseas Engagement Division, NITI Aayog (National Institution for Transforming India). https://pure.iiasa.ac.at/id/eprint/15536/, https://iiasa.dev.local/.
Urban, Nathan M., and Thomas E. Fricker. 2010. 'A Comparison of Latin Hypercube and Grid Ensemble Designs for the Multivariate Emulation of an Earth System Model'. *Computers & Geosciences* 36 (6): 746–55. https://doi.org/10.1016/j.cageo.2009.11.004.
Van der Steen, Martijn, and Mark van Twist. 2018. 'Strategies for Robustness: Five Perspectives on How Policy Design Is Done'. *Policy and Society* 37 (4): 491–513. https://doi.org/10.1080/14494035.2018.1520782.

Vijayalaxmi, J., and Dhananjay Manthanwar. 2024. ‘A Review of Policies, Energy Resources Towards a More Sustainable Economy: A Study on Renewable Energy in India’. In *Reducing the Effects of Climate Change Using Building-Integrated and Building-Applied Photovoltaics in the Power Supply*, edited by Ali Sayigh. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-42584-4_12.

Vishwanathan, Saritha Sudharmma, Chris Bataille, Erika Carvalho Nogueira, et al. n.d. ‘Towards Net-Zero Electricity Sector in Emerging Economies – Brazil, India, Indonesia and South Africa’. *Climate Policy* 0 (0): 1–18. https://doi.org/10.1080/14693062.2025.2550588.

Walker, W. E., P. Harremoës, J. Rotmans, et al. 2003. ‘Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support’. *Integrated Assessment* 4 (1): 5–17. https://doi.org/10.1076/IAIJ.4.1.5.16466.

Way, Rupert, Matthew C. Ives, Penny Mealy, and J. Doyne Farmer. 2022. ‘Empirically Grounded Technology Forecasts and the Energy Transition’. *Joule* 6 (9): 2057–82. https://doi.org/10.1016/j.joule.2022.08.009.

Wilson, D, and A Kirman, eds. 2016. ‘Robust Institutional Design: What Makes Some Institutions More Adaptable and Resilient to Changes in Their Environment Than Others?’ In *Complexity and Evolution: Toward a New Synthesis for Economics*. The MIT Press. https://doi.org/10.7551/mitpress/9780262035385.003.0010.

Workman, Mark, Geoff Darch, Kate Dooley, Guy Lomax, James Maltby, and Hector Pollitt. 2021. ‘Climate Policy Decision Making in Contexts of Deep Uncertainty - from Optimisation to Robustness’. *Environmental Science & Policy* 120 (June): 127–37. https://doi.org/10.1016/j.envsci.2021.03.002.