EEIST

POWER AND INDUSTRY CASE STUDIES

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Contents

About

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

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

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

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

Contributors

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CASE STUDY:

Unstoppable Renewables and Marginal Pricing in China, India and Brazil

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

Region: Brazil, China, India

Methods: E3ME-FTT:Power

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

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

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

Introduction

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

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

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

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

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

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

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

[80] IEA. (2019). World Energy Balances 2019. www.iea.org/statistics/.

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

[82] IRENA (2021). Renewable Power Generation Costs in 2021, International Renewable Energy Agency, Abu Dhabi. https://www.irena.org/publications/2022/Jul/Renewable-Power-Generation-Costs-in-2021

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

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

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

Description of E3ME-FTT:Power

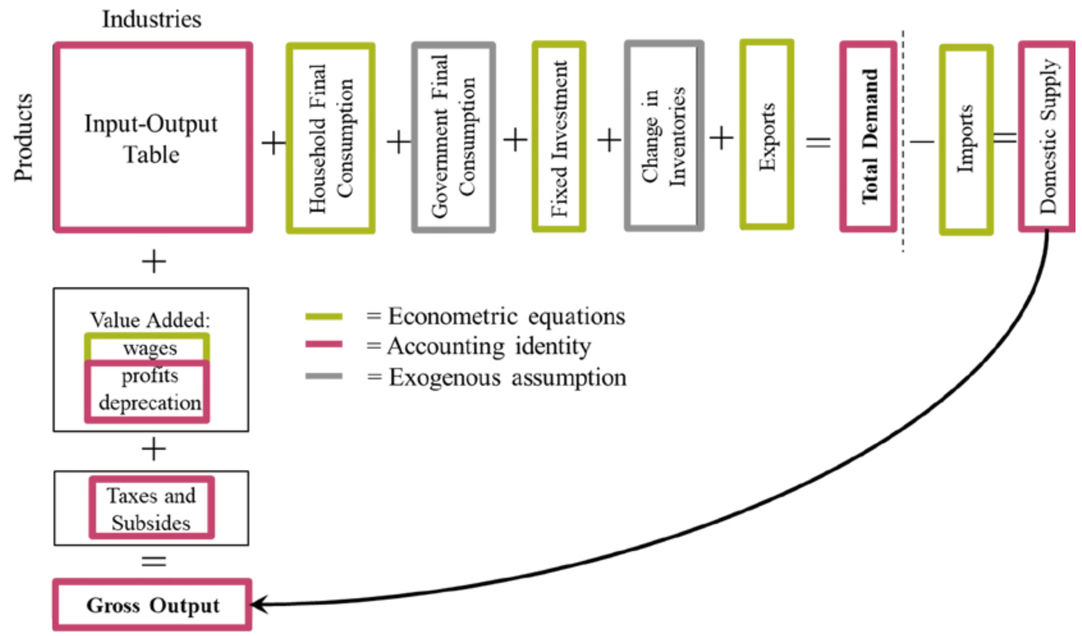
Description of E3ME
E3ME is a computer-based model of the world's economic and energy systems and the environment. Economic activity undertaken by persons, households, firms and other groups in society has effects on other groups (possibly after a time lag) and the effects may persist into future generations.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

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

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

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

Figure 18: National accounts structure of E3ME.



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

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

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

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

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

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

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

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

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

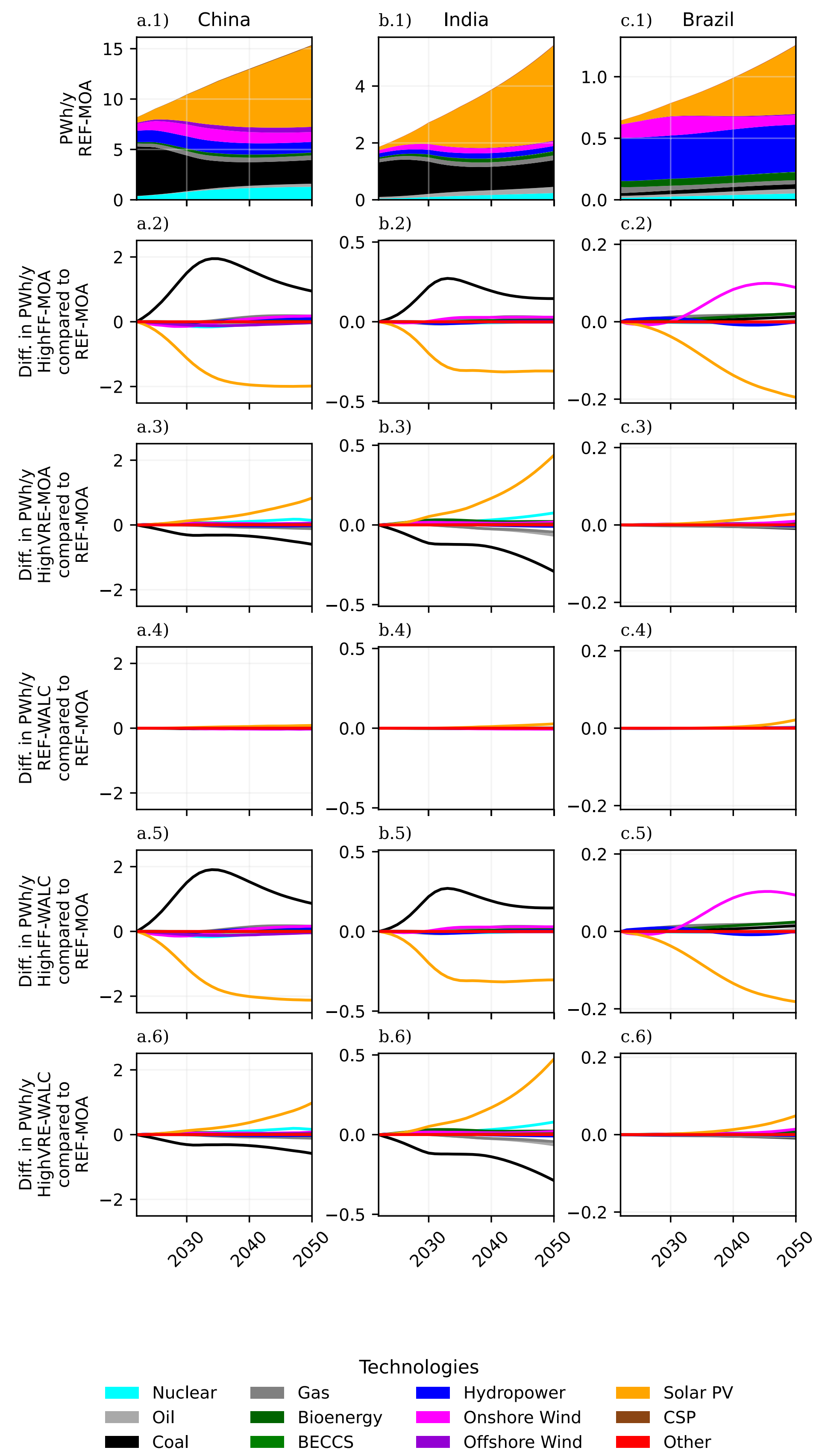
Results

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

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

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

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



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

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

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

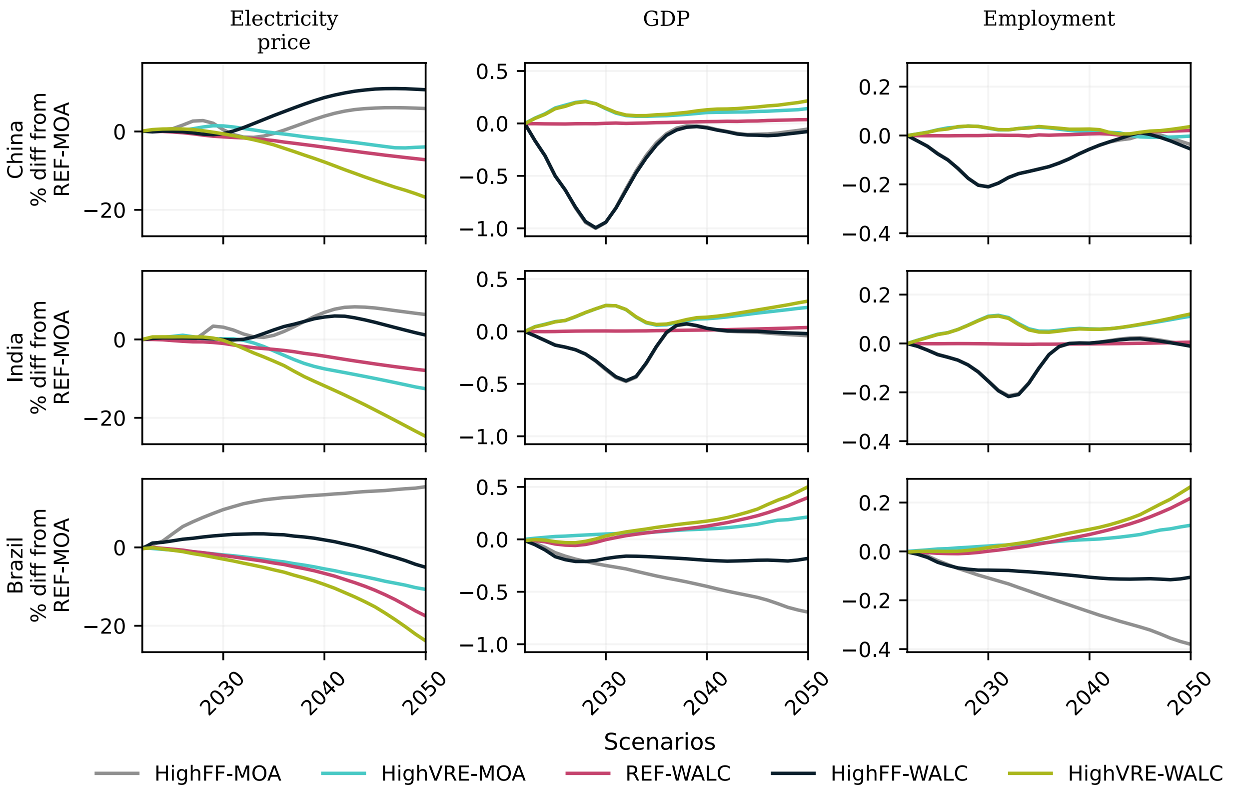
Electricity prices

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

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

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

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



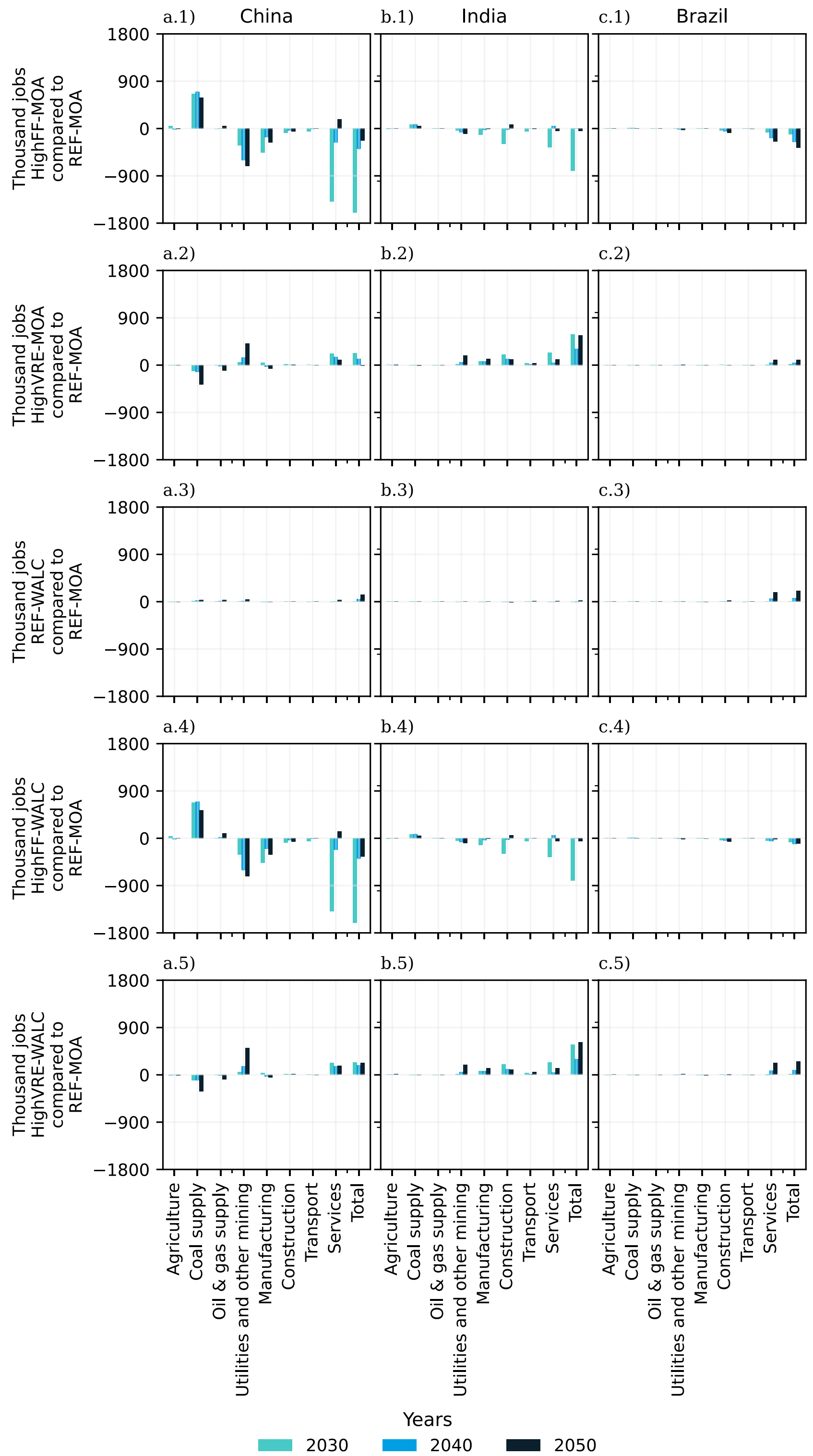
Macroeconomic effects

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

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

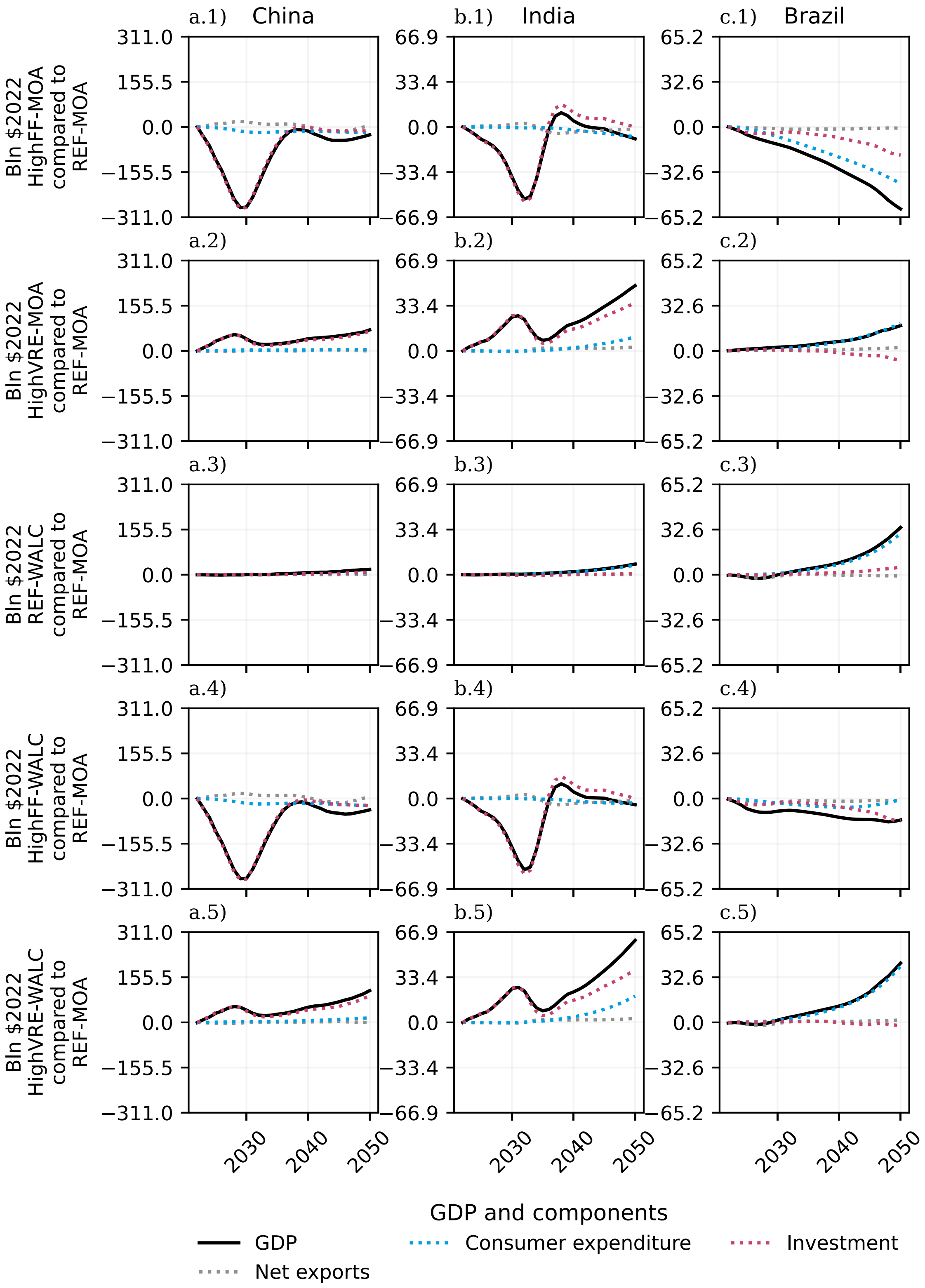
The effect on employment is similar. In the High-VRE scenarios and the WALC market design, we see increased employment in many sectors, and net gains overall. The employment gains are the highest in the scenario of high variable renewables and the WALC market design. There are significant net job gains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

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



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

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



Discussion & conclusion

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

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

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

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

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

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

CASE STUDY:

Modelling Sector Coupling of Hydrogen and Ammonia in India

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

Region: India

Methods: Complexity-extended traditional energy system model.

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

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

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

Introduction

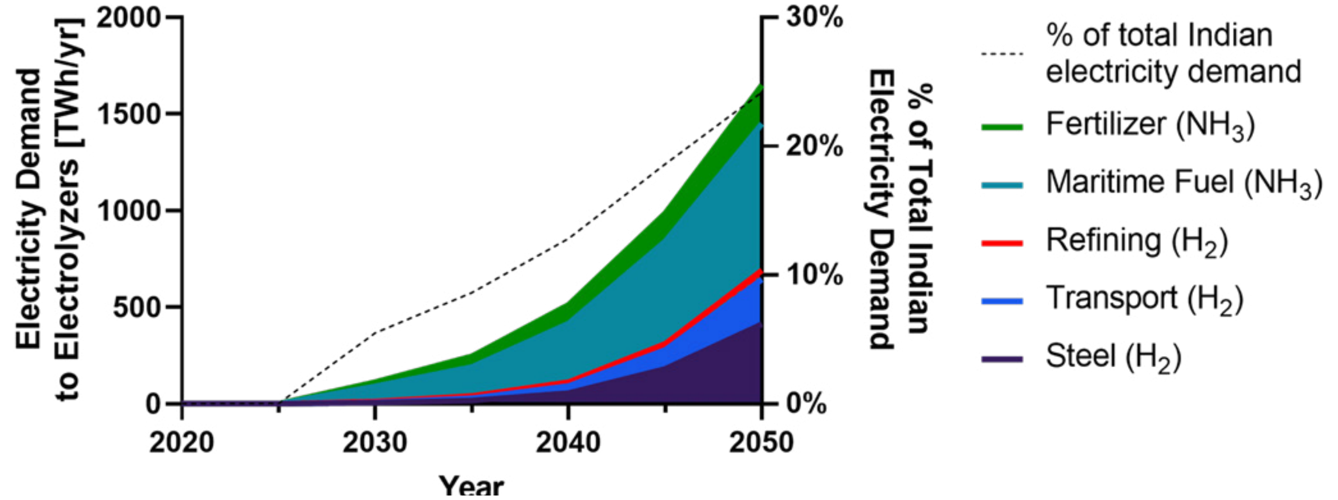
At a global level, the International Renewable Energy Agency (IRENA) forecasts that the production of green hydrogen and its derivatives (mostly green ammonia) will account for 30 per cent of the global electricity demand in 2050.[94] Yet, analyses published using Energy System Models (ESMs), the dominant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

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

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

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

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



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

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

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

Model summary

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

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

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

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

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

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

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

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

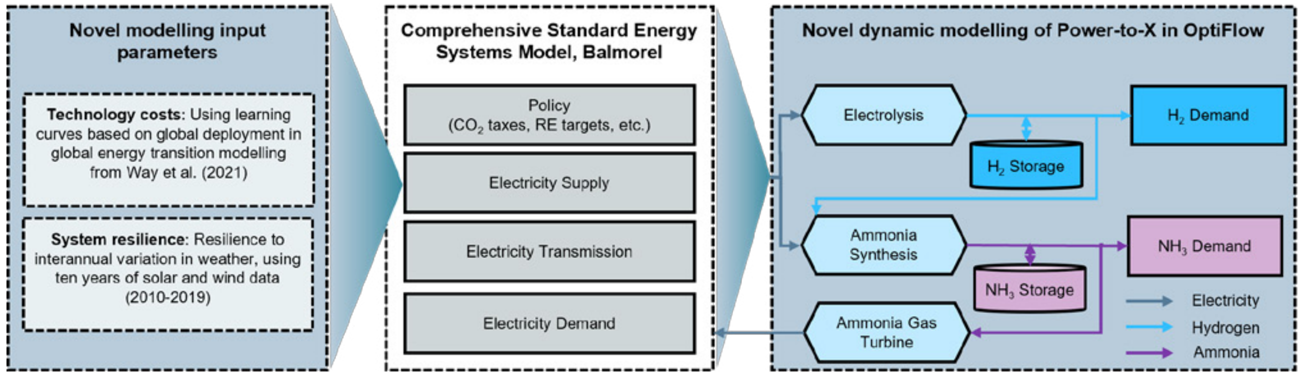
[104] Indian Ministry of External Affairs (2021) National Statement by Prime Minister Shri Narendra Modi at COP26 Summit in Glasgow.

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

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

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

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



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

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

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

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

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

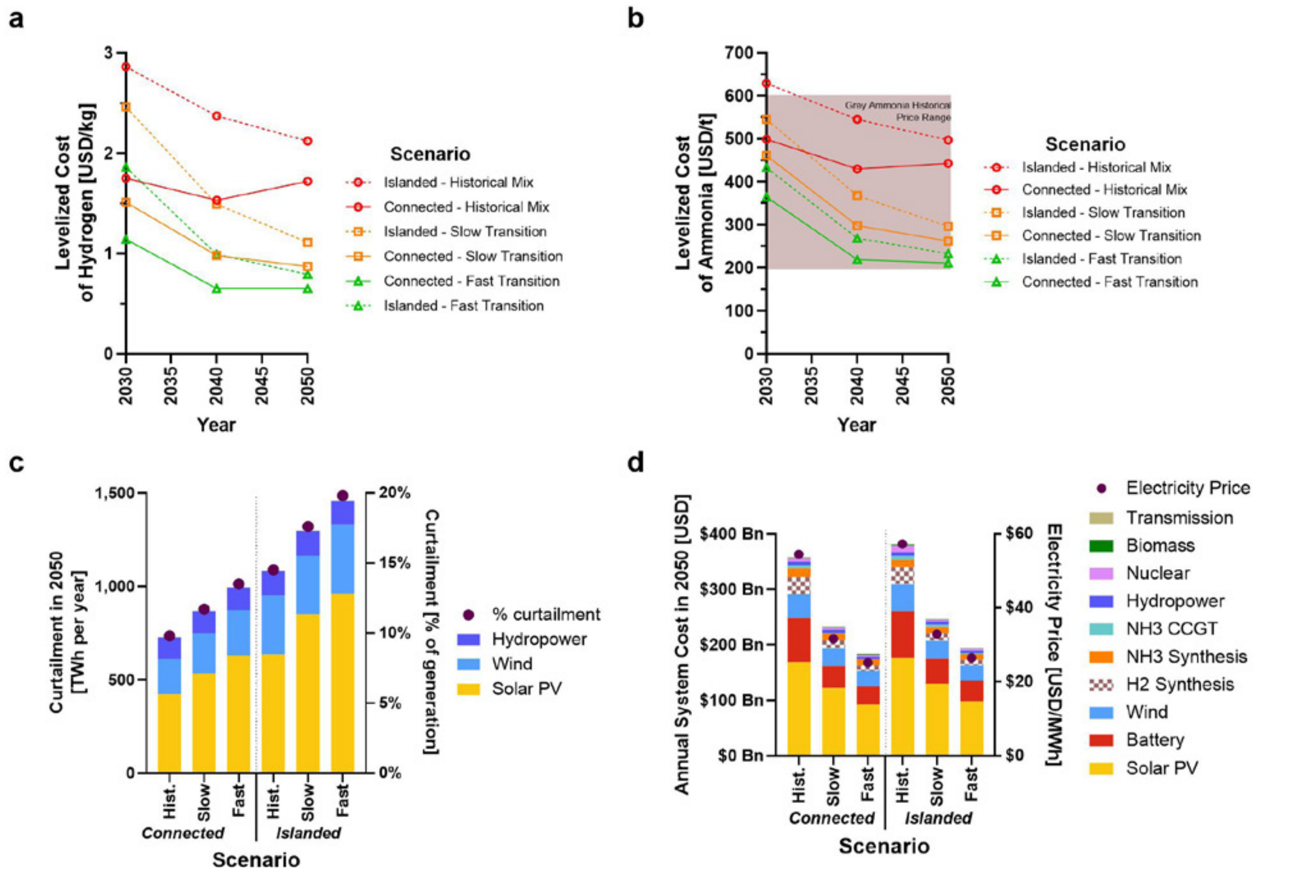
[111] Bramstoft, R. et al. (2020). Modelling of Renewable Gas and Renewable Liquid Fuels in Future Integrated Energy Systems. Applied Energy 268: 114869.

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

Results

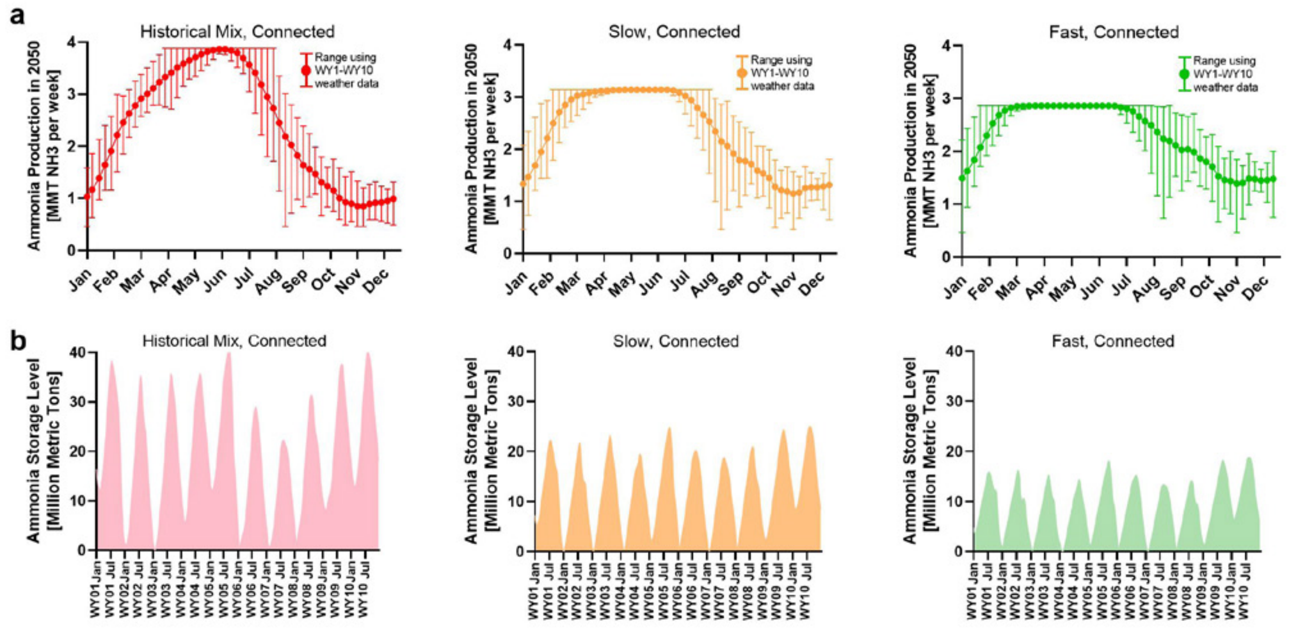
A key finding shown in the results is that there are significant benefits to connecting the hydrogen and ammonia production to the electricity grid rather than having islanded production sites. Islanded plants, which are independent from the grid and have their own dedicated renewables, are the current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

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



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

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



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

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

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

Our results also inform policy on two points. Firstly, the findings support the idea that green hydrogen and ammonia can dramatically improve energy security and reduce imports. India's NHM explicitly states: "The implementation of this policy will provide clean fuel to the common people of the country. This will reduce dependence on fossil fuel and also reduce crude oil imports."[115] Indeed, the level of LCOH and LCOA achieved are more competitive than importing fossil fuels for the steel and fertiliser sectors in India. In fertiliser, India is effectively 80 per cent reliant on imports for ammonia production today: 25-30 per cent of the country's consumption of fertiliser is imported ammonia (costing more than US$ 1.3bn per year) and over 60 per cent of the domestically produced ammonia is produced used imported LNG.[116] This reliance on imports is a major strategic reason for India to shift towards domestic green ammonia production for fertilisers and the results of this ESM suggest that this is possible in the near term without a subsidy or a CO2 pricing mechanism.

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

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

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

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

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

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

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

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

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

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

CASE STUDY:

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

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

Region: China

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

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

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

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

Introduction

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

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

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

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

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

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

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

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

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

Part 1: Systems mapping of carbon pricing options

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

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

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

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

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

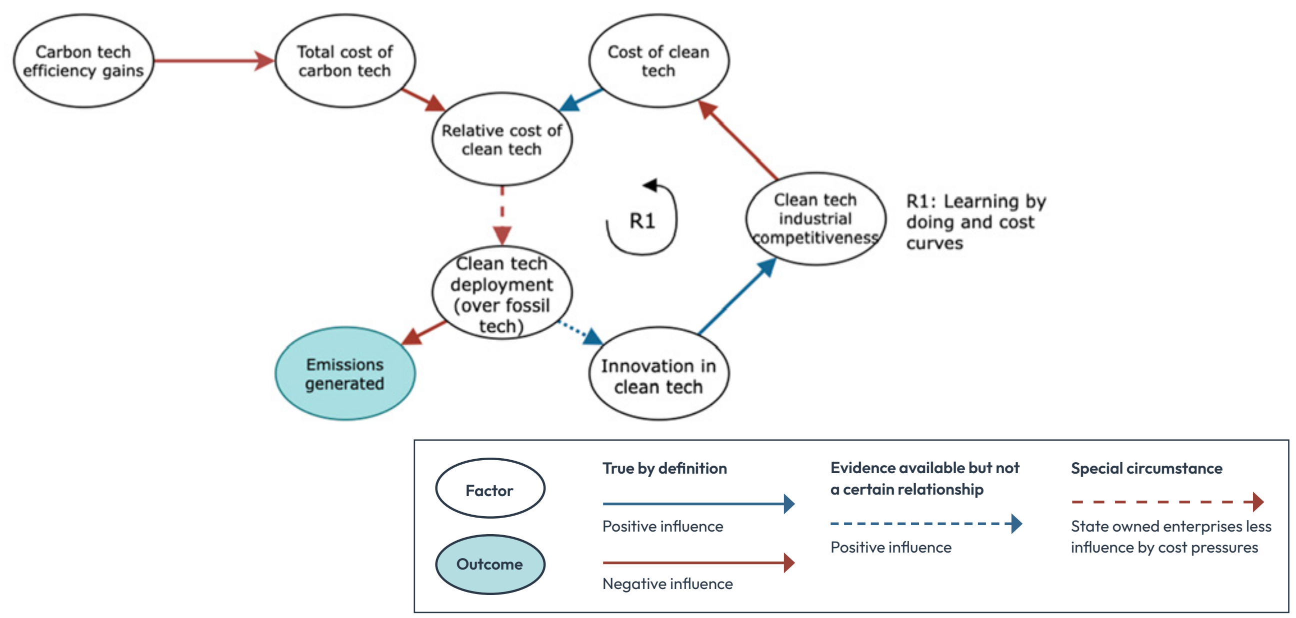
System maps of different carbon pricing mechanisms
We developed system maps of five carbon pricing policy scenarios: (i) no intervention, (ii) carbon tax, (iii) ETS, (iv) renewable portfolio standard, and (v) combinations of these. We describe only the first three here.

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

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

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

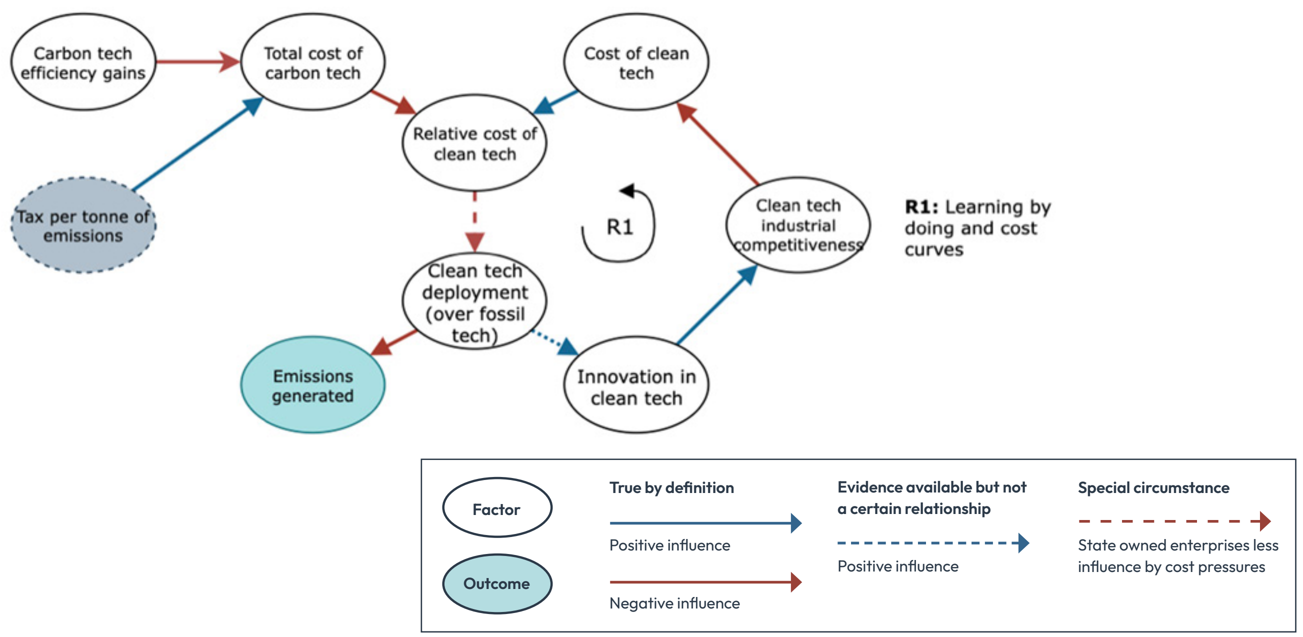
Figure 27: No intervention – historical deployment of clean tech has increased learning-by-doing and reduced costs, thus encouraging more deployment, which in turn further supports learning-by-doing in a reinforcing feedback (R1). Note: positive and negative influence refers to mathematical relationship,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



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

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

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



Emissions trading scheme

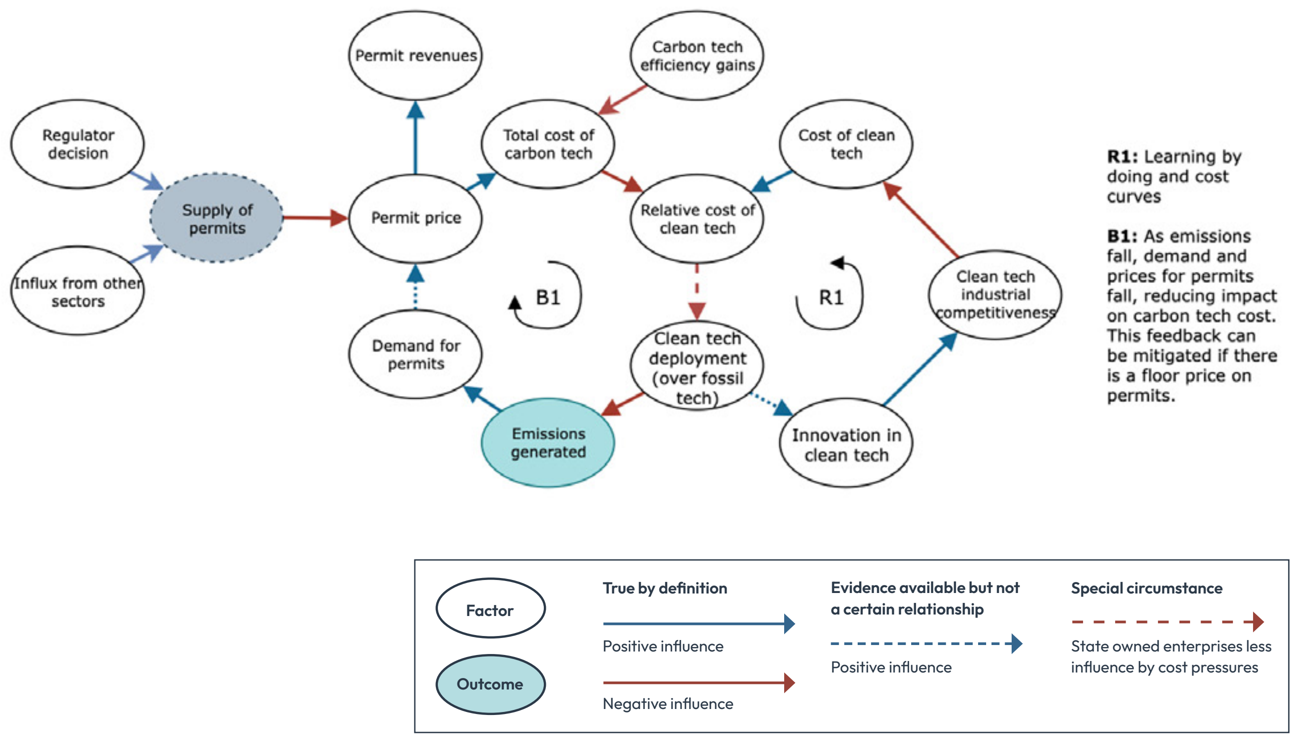
The next system map shows a different picture, with Figure 29 presenting the same diagram but for a standard ETS. Here the structure of the map changes, with the introduction of a balancing feedback (i.e. where a change induces an effect which in turn reverses the first change, thus acting in a self-regulating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

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

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

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

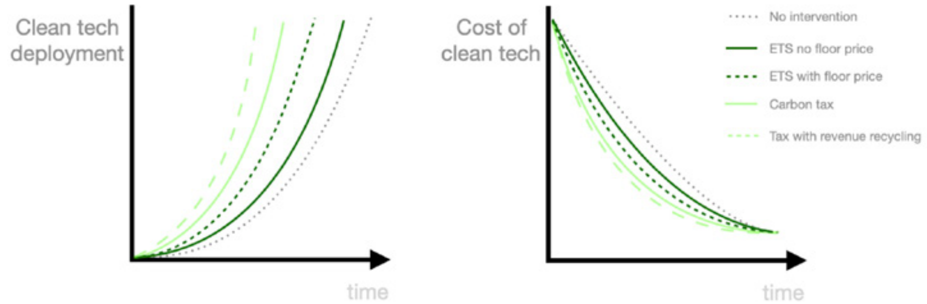
Figure 29: ETS – the scheme supports the reinforcing feedback of learning-by-doing (R1), but also introduces a balancing feedback. As emissions drop, there is less demand for permits, tending to reduce the effect of the carbon price on the costs of carbon tech (B1).



Behaviour-over-time (BOT) graphs

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

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



Policy conclusions from the system mapping exercise

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

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

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

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

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

Design of the agent-based model

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

The model runs three scenarios:

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

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

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

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

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

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

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

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

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

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

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

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

Results

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

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

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

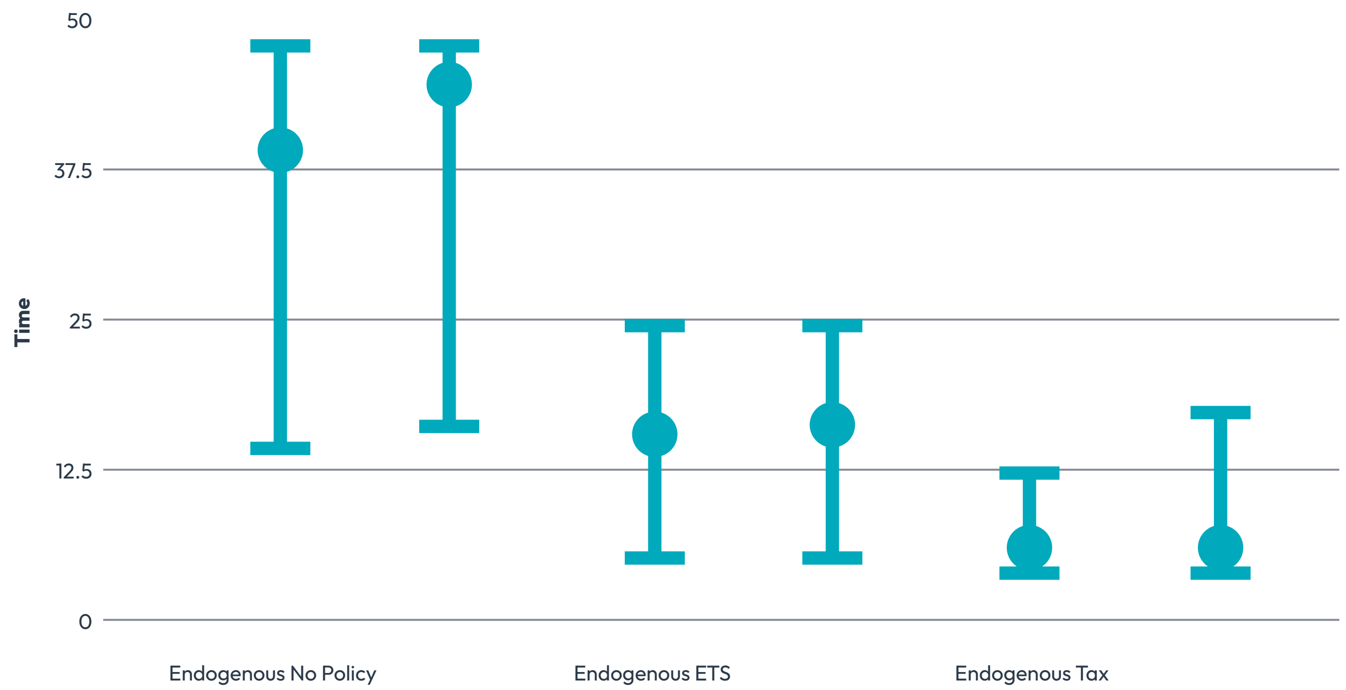


Table 9: Cumulative emissions (range) before reaching zero emissions (in tons CO2).

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

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

Discussion

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

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

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

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

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

Context and history of carbon pricing in China

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

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

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

Previous studies

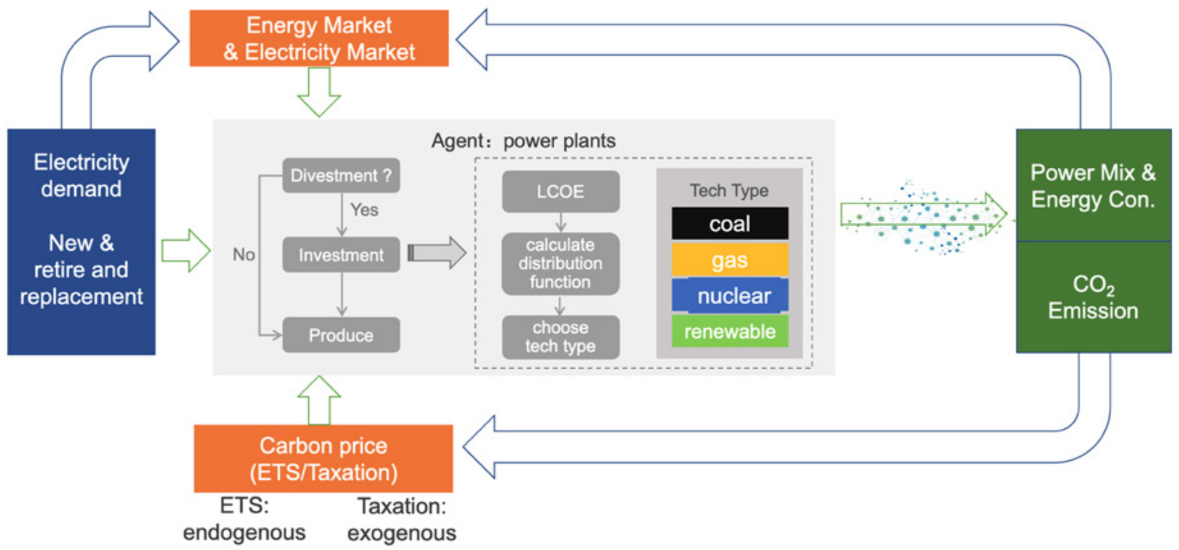
Many studies have compared these two carbon pricing instruments in applied contexts. Some have focused on specific issues such policy efficiency, cost-effectiveness, institutional feasibility or distributional impacts,[133 134] while others have used modelling approaches, such as equilibrium models or cost-optimised models, for assessing policy options.[135 136 137]

There are studies of carbon pricing specifically in China using ABM to look at this ETS,[138 139] as well as IEA and Tsinghua University's work on the scheme.[140] However, all these studies focus on only one policy option at a time, and do not compare tax and ETS.

Design of the China agent-based model

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

Figure 32: Illustration of ABM-power transition model.



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

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

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

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

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

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

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

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

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

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

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

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

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

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

The model begins with 14,960 power plants, including both fossil (around 3,000 of which are covered by the ETS) and non-fossil based, with a total capacity of 2,200 GW and total electricity generation of 7,700 TWh in 2020 (the first year). CO_2 emissions in the first year are around 4,500 Mt. Attributes of power plants include capacity, fuel type, construction year, lifespan, average working hours per year, energy efficiency, and emission intensity, based on open information sources and related assumptions. Technological progress in renewable technologies (and thus, cost assumptions) is treated as an exogenous variable, based on learning curves. The capacity, power generation and CO_2 emission distribution in the base year are shown in the appendix.

The following policy options were tested in the model:

a) No policy (business as usual).

b) A carbon tax at CNY 30/tCO_2 (~US$4.3/t$CO_2$).

c) A carbon tax at 50 Yuan/tCO_2 (~US$7.2/t$CO_2$). Note: these two levels for the carbon tax have been chosen to be similar to the average carbon price currently generated by China's ETS (CNY 51.20/tCO_2 over the period July 2021 to December 2021).

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

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

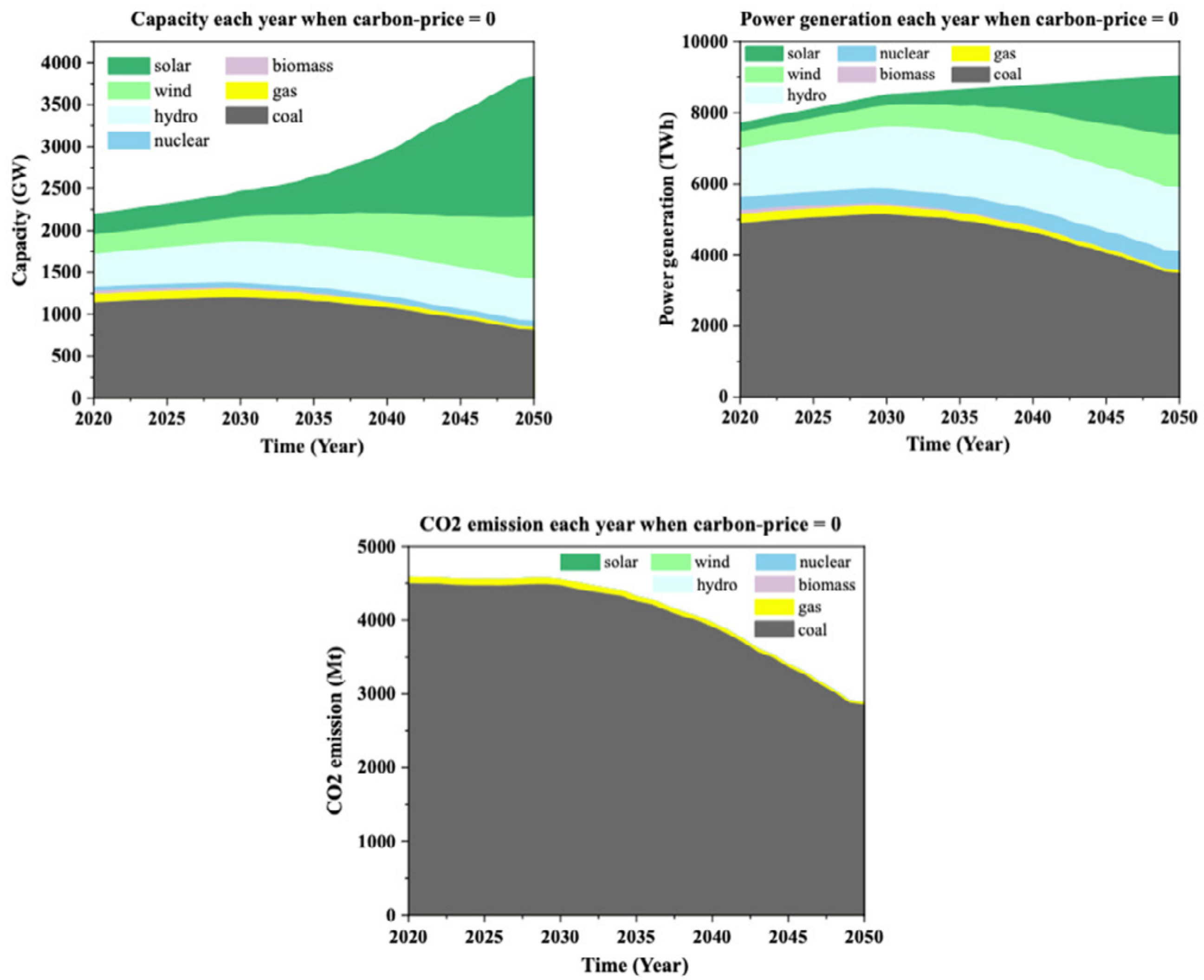
In all cases, the base year was 2020, and the model simulated the evolution of the power system until 2050.

Results and discussion

Business as usual
In the BAU scenario, there is no carbon pricing or other policy intervention. The power capacity, power generation and CO_2 emissions by fuel type are shown in Figure 33.

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

Figure 33: Technology evolution over time in BAU scenario: capacity (top left), power generation (top right), CO_2 emission (bottom).



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

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

The technology mix of power generation follows the same pattern as that of power capacity, since the model assumes the load factor of each technology remains unchanged. CO_2 emissions, which mainly come from coal and gas power plants, especially coal, tend to keep stable before 2030 and then decline significantly to below 3,000 Mt in 2050 – about two thirds of the level in 2020.

Carbon tax

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

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

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

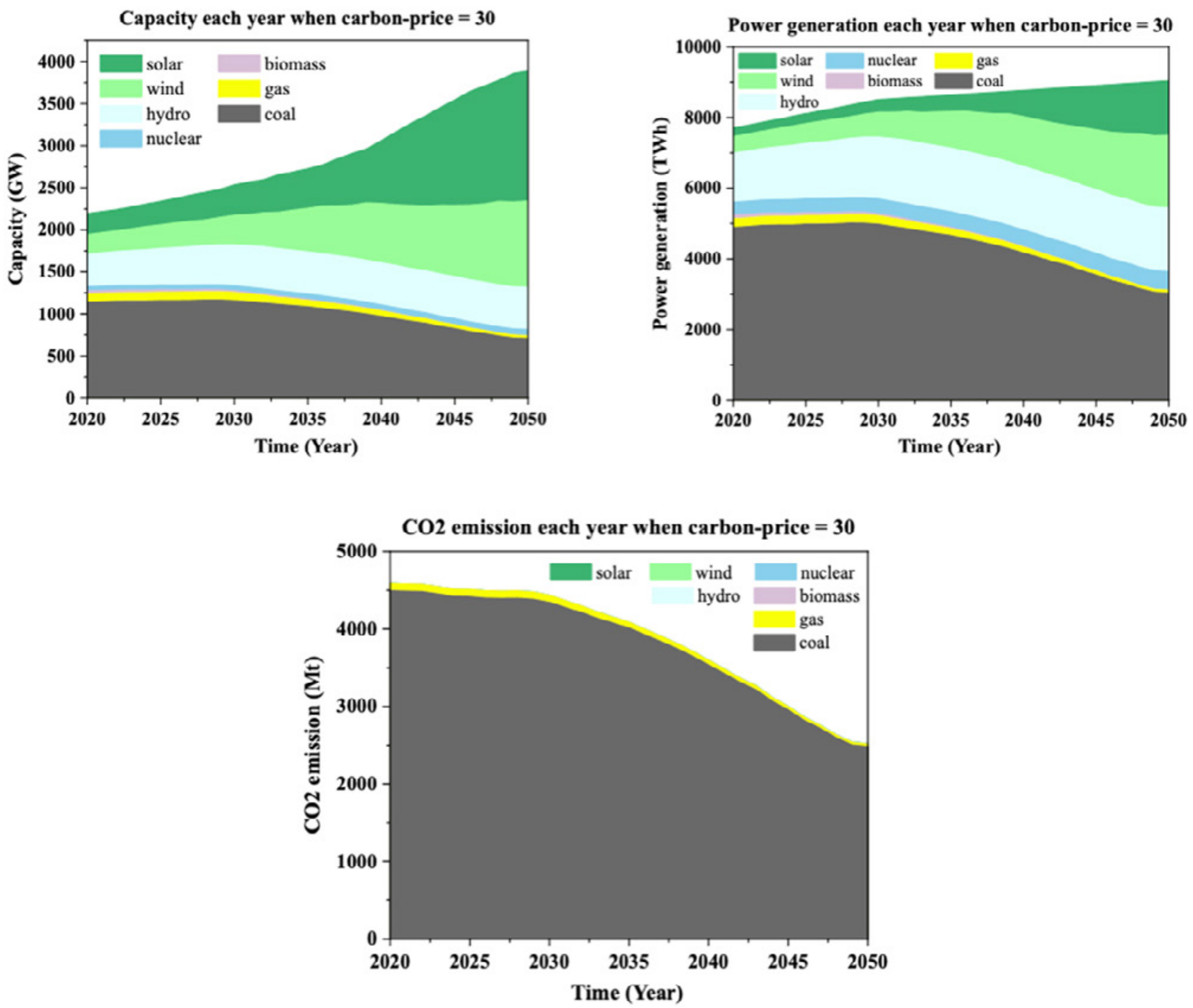
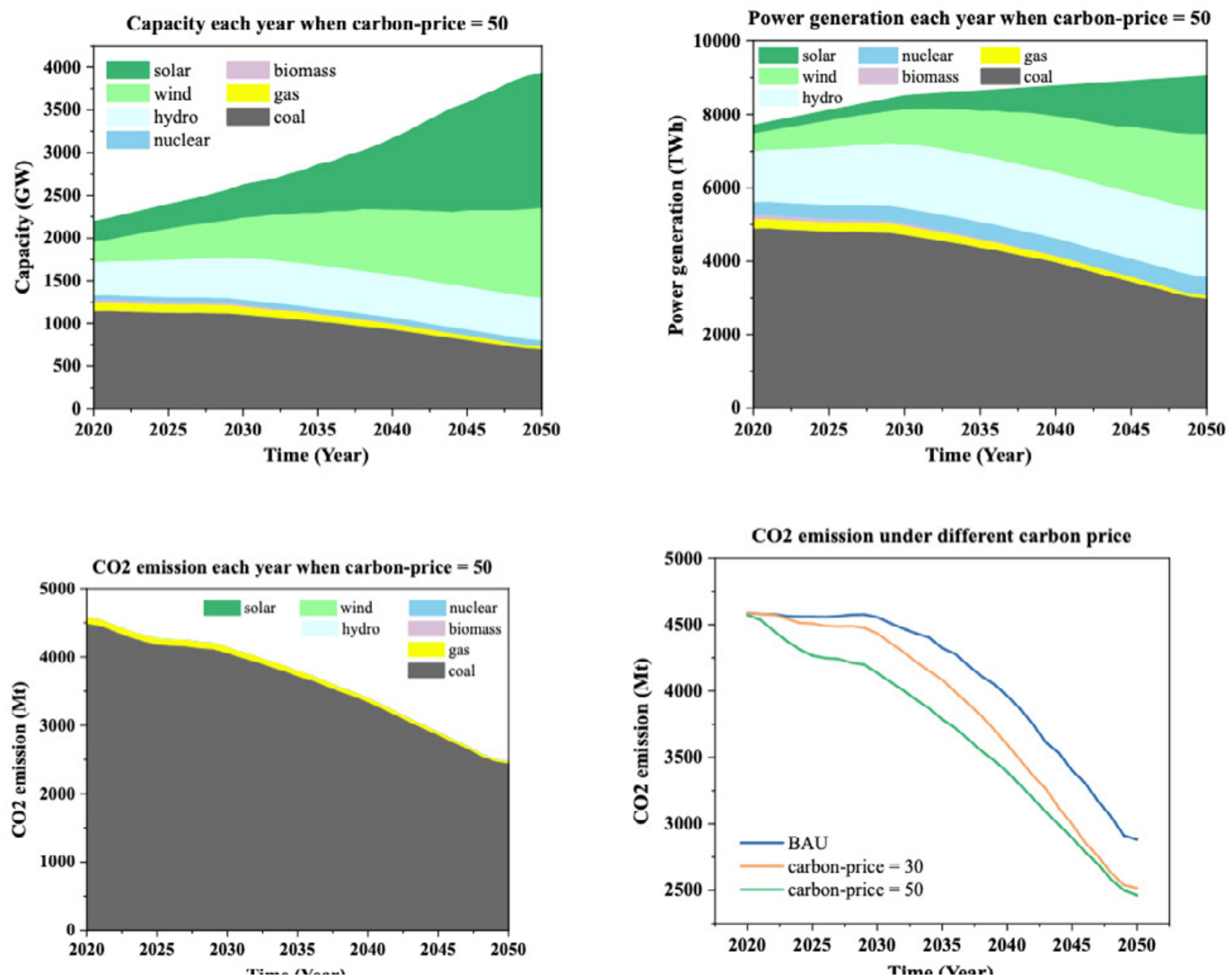


Figure 35: Technology evolution in CT-50 scenario: capacity (top left), power generation (top right) and CO2 emission (bottom left); comparison of BAU, CT-30 and CT-50 on CO2 emission (bottom right).



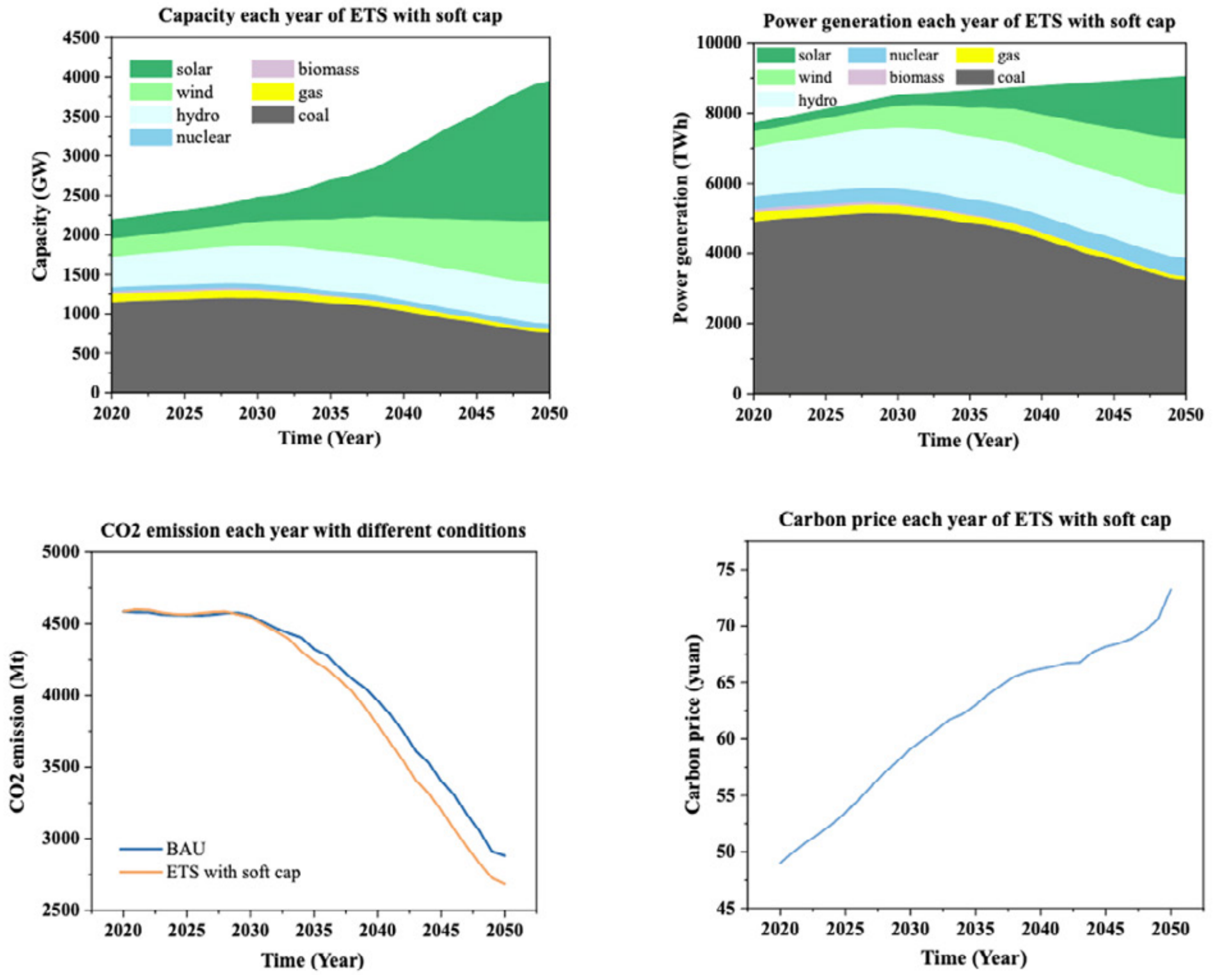
The high carbon tax has much greater impact in the first decade, with emissions declining quickly in the period of 2020-2030, during which the low carbon tax has little influence. However, the advantage of the high carbon tax decreases in later years, with its impact on the technology mix and annual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

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

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

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

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



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

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

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

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

Figure 37: Illustration of CO2 emissions in all scenarios.

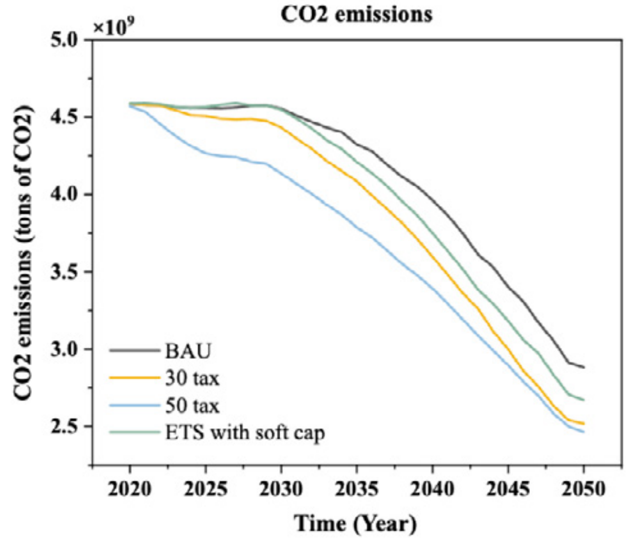
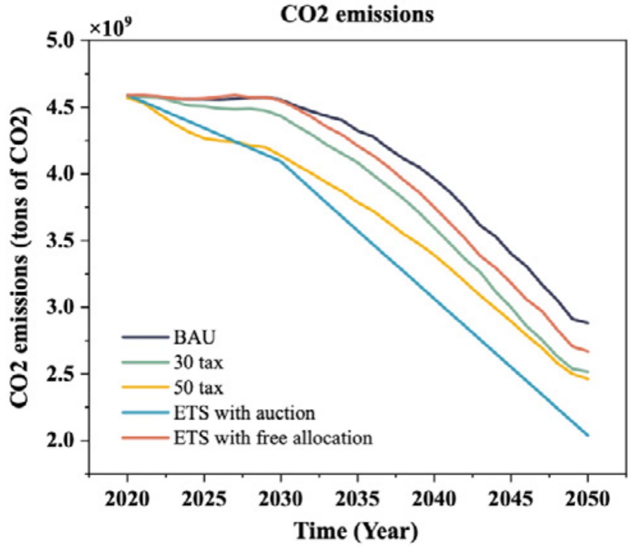


Figure 38: Emissions over time for the ETS with permits allocated by free allocation and auction, compared to low and high carbon taxes and BAU.



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

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

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

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

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

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

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

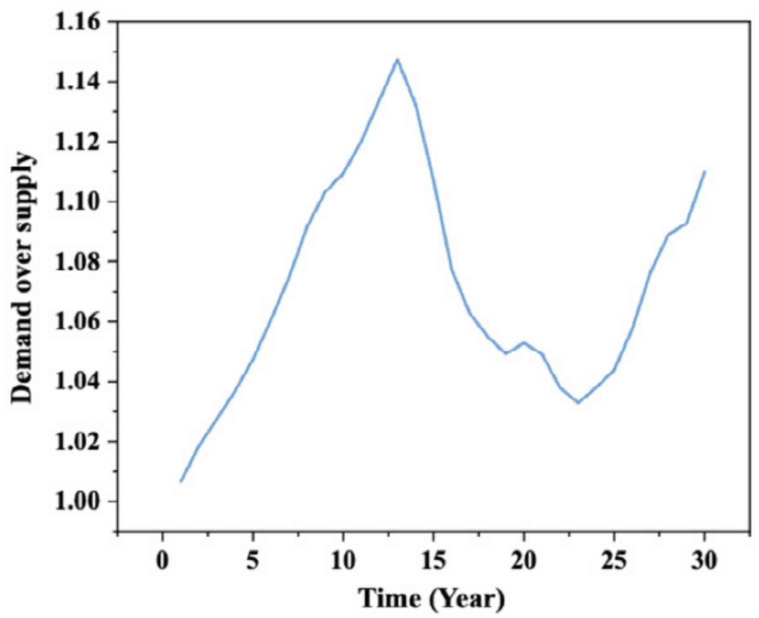
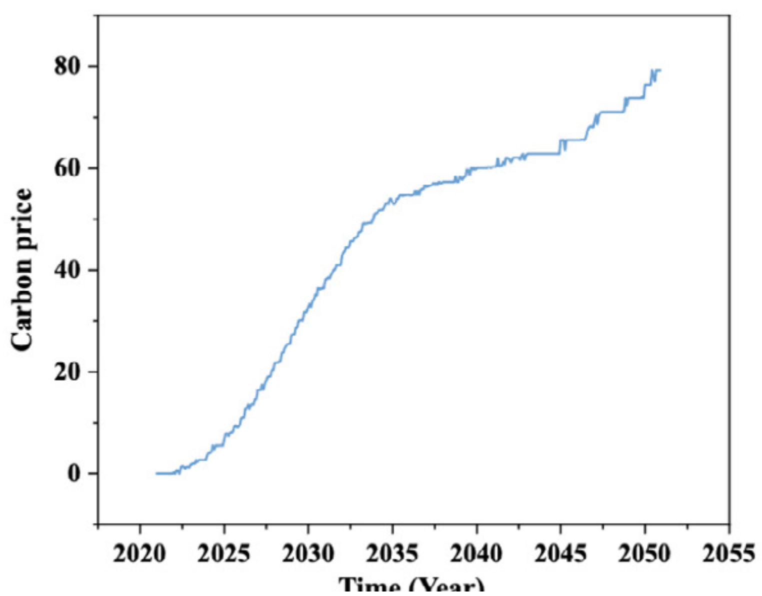


Figure 40: Carbon price through time.



Policy conclusions from Part 3

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

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

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

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

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

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Economics of Energy Innovation and System Transition

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